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Language editor, proofreader Karolina Beyer

Desktop publishing Patryk Wlekły

Cover design Joanna Dubois-Mosora

Scientific editors dr Karolina Beyer, ORCID 0000-0002-0437-1461
dr hab. Małgorzta Łatuszyńska, prof. US, ORCID 0000-0002-7847-0198
prof. dr hab. inż Kesra Nermend, ORCID 0000-0002-4309-7434
dr Mateusz Piwowarski, ORCID 0000-0003-2541-1909

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PREFACE

In an era marked by accelerating technological progress and far-reaching societal transformations, the importance of artificial intelligence (AI) and intelligent management systems is rapidly growing. These two areas – intertwining technological innovation with organizational effectiveness – are shaping the future of public institutions, enterprises, and societies. The dynamic development of AI technologies not only creates new economic and scientific opportunities but also generates a series of challenges related to ethics, law, education, and strategic decision-making. The need to comprehensively analyze these aspects becomes a priority for both academic communities and practitioners seeking to responsibly harness the potential of AI in various spheres of life.

This monograph constitutes a peer-reviewed collection of research articles presented during the international workshop Intelligent Management (InMan), organized within the framework of the 28th European Conference on Artificial Intelligence (ECAI 2025), which took place in Bologna, Italy, on October 25 – 30, 2025. The ECAI conference is one of the most important events in the field of artificial intelligence in Europe, gathering experts from diverse academic disciplines and fostering international cooperation and exchange of innovative ideas. The inclusion of the InMan workshop in the official conference program highlights the growing relevance of intelligent management in both academic discourse and applied research, where AI is increasingly seen as a transformative driver of competitiveness, innovation, and resilience in modern organizations.

The international and interdisciplinary character of this publication is reflected in the diversity of its authors, who represent scientific and research institutions from numerous countries, including Bosnia and Herzegovina, the Czech Republic, Hungary, India, Indonesia, Kosovo, Latvia, Lithuania, Poland, Spain, and Sweden. This global composition not only enriches the perspectives presented but also allows for a deeper understanding of how AI and intelligent management solutions are interpreted and implemented in different national, cultural, and institutional contexts. Such diversity provides a valuable comparative insight into the ways organizations and societies adapt to digital transformation and the ethical, social, and strategic dilemmas it brings.

Volume I of the monograph is divided into two complementary thematic sections. The first part, “The Role of Artificial Intelligence in Intelligent Management,” focuses on the theoretical foundations and practical applications of AI in the context of organizational strategy, process optimization, and innovation. The presented articles analyze how digital innovation and AI contribute to building competitiveness in the SME sector, the role of AI in branding and marketing activities, and the ways technological transformation is reshaping the functioning of contemporary enterprises. Particular attention is devoted to sector-specific applications, such as the use of AI in veterinary business or in the food service industry, as well as the emerging role of AI in auditing processes. Several contributions explore the relationship between trust and the adoption of AI technologies, digital maturity in enterprises, and the challenges of balancing private and open-source AI solutions. Taken together, these studies demonstrate the breadth of AI applications and the importance of intelligent management in fostering both efficiency and human-centered values, such as employee dignity, within organizational practices.

The second part, titled “Artificial Intelligence and Intelligent Management in the Social and Educational Context,” broadens the analytical lens by addressing the societal and humanistic implications of AI integration. Authors examine the utilization of AI tools in youth education, the generational differences in digital competencies, and the role of AI in shaping new learning environments, particularly in relation to Generation Z’s adoption of tools such as ChatGPT. Ethical

dilemmas are also a recurring theme, including the paradox of machines making moral decisions, the challenges of AI-driven consumer journeys, and the role of governance and public policies in ensuring fairness and accountability in algorithmic decision-making. Other articles investigate how universities use modern communication tools to build their image, how city councilors respond to cybersecurity threats in the era of hybrid warfare, and how intelligent management can improve public transport services for older adults. Collectively, these contributions illustrate the growing need to view AI not only as a technological solution but also as a social phenomenon with far-reaching consequences for education, public administration, and everyday life.

The editors of this volume would like to express their deepest appreciation to all the authors for their commitment and high-quality scholarly work. We also extend our sincere thanks to the reviewers and members of the Scientific Committee for their invaluable support in ensuring the academic integrity of this publication. It is thanks to their expertise, constructive feedback, and engagement that this volume could take its final, coherent shape.

We hope that this monograph will serve not only as a valuable academic resource, but also as a source of inspiration for further research, policy-making, and responsible innovation in the field of artificial intelligence and intelligent management. By combining theoretical insights, empirical research, and practical case studies, it provides a broad platform for reflection on how to harness AI responsibly while addressing the ethical, organizational, and societal challenges that accompany its rapid development.

Scientific Editors

Karolina Beyer
Małgorzata Łatuszyńska
Kesra Nermend
Mateusz Piwowarski

CHAPTER 1
The Role of Artificial Intelligence in Intelligent Management

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28th European Conference on Artificial Intelligence (ECAI 2025)

DIGITAL INNOVATION AND ARTIFICIAL INTELLIGENCE (AI) AS A TOOL FOR BUILDING COMPETITIVENESS OF THE SME SECTOR

Agnieszka Malkowska[a], Arkadiusz Malkowski[b], Jamila Jaganjac[c]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *West Pomeranian University of Technology in Szczecin, Faculty of Economics, Szczecin, Poland*
[c] *University "Vitez" Travnik, Faculty of Business Economics, Travnik, Bosnia and Herzegovina*

ABSTRACT

Purpose: *The main purpose of the article is to indicate the importance of digital innovation in the SME sector with a special focus on the role of AI in building the competitiveness of enterprises.*

Need for the study: *Digital transformation, including the use of artificial intelligence AI, is a relatively new area in which all the world's top developed economies are trying to find their edge. In order to win this race, investment in the development of digital and AI technologies and competencies is essential in the EU.*

Methodology*: Literature studies, secondary data analysis, comparative analysis, logical inference and deduction methods were used. In addition, the authors also shared their own knowledge and professional experience, including business.*

Findings*: Based on the research, a number of barriers were identified that SMEs in Poland face in their attempts to obtain financial resources from EU funds for the implementation of innovative projects. The most important ones include: the lack of product or process innovation in the presented projects at least on a national scale and the lack of ability to finance own contribution.*

Practical Implications: *The presented research and results should be used by institutions creating policies to support economic development at the level of countries and the European Union as a whole. The results of the research can also be used by institutions supporting the development of innovation, including digital innovation, in the SME sector in determining the terms of competitions and financial support.*

Keywords: Artificial Intelligence (AI); Innovation; SME sector; Industry 5.0; Digital transformation; Smarter Europe

Jel codes: F63; O3; L26

1. INTRODUCTION

Digital transformation and the development of modern technology are considered key to strengthening entrepreneurship and economic competitiveness. It is also of great importance in creating the economy's resilience to digital crime threats. Therefore, it is essential to support the development of digitization in

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both the public and business sectors as a tool for secure digital development of the economy. The complexity of the process and the seriousness of the challenges faced by the participants in this process require specific measures to support entities that, due to their financial and organizational potential, may have problems implementing innovative digital considerations into their operations. One of the many challenges facing modern enterprises is the process of acquiring, aggregating and selecting technical knowledge. In this context, special attention is paid to supporting SMEs (micro, small and medium-sized enterprises) by allowing them easier access to advanced technologies, including in the area of intelligent business management. This will enable companies to innovate more effectively, increase efficiency and better respond to the challenges of digital transformation.

The SME sector plays a key role in the global economy and is one of the most important pillars for the development of national economies. Its importance stems both from the number of enterprises in operation and their impact on job creation, innovation, competitiveness and regional development.

One of the main strengths of the SME sector is its flexibility and ability to adapt to changing market conditions. The size and structure of companies in this sector enable rapid decision-making, which allows them to take better advantage of opportunities and better adapt to new trends.

The main purpose of the article is to indicate the importance of digital innovation in the SME sector with a special focus on the role of AI in building the competitiveness of enterprises. The specific goal is to present the issue of innovation, including digital innovation, in the policies of the European Union and on the example of a selected member country. The research questions posed were: What are the opportunities for the development of digital innovation of SMEs in the EU? What are the barriers to the development of innovation in the SME sector in Poland?

2. LITERATURE REVIEW

Classical factors of production, i.e. land, labor and capital, are not the only ones that affect the construction of sustainable competitive advantage of enterprises, and consequently further economies. In today's global economy, entrepreneurship, knowledge, innovation of technological solutions play an important role in creating conditions for the development of competitive enterprises. A rich literature on the sources of competitive advantages in a globalized economy confirms this: Zysk (2024), Mariani et al. (2023), Widayanti and Meria (2023). According to numerous authors, e.g. in the third decade of the 21st century, artificial intelligence (AI) and its development, which can determine groundbreaking, innovative, important technological solutions such as ChatGPT, is definitely becoming a priority in creating competitiveness at the enterprise level. It has been a huge success and is considered here as, a landmark event in the development of civilization. ChatGPT was publicly released on November 30, 2022, largely as a technology demonstration. Two months later, it had already attracted an estimated 100 million active users – making it the fastest-growing consumer application in history, as highlighted by Hu (2023). This spectacular example of the digital revolution in the 21st century shows that time is of the essence when it comes to new technological solutions that can give a competitive advantage in the marketplace, which is no longer counted in years, but in months and weeks and perhaps sometimes in days.

In the dynamic and turbulent business system that makes up the global economy, the role of innovation, digitization and the use of artificial intelligence (AI) in creating competitive advantages is becoming a key element of management at the operational and strategic levels. This is reflected in the concept of building Industry 5.0 (Slavic et al., 2024; Wang et al., 2023), which is widely described in the literature. It is based on digital innovations and develops the ideas of Industry 4.0 with elements emphasizing the need to develop interaction between man and machine (Coelho et al., 2023). The new approach points to the vital importance of personalization, creativity and advanced cooperation between technology and people in all aspects of economic life. In this new concept of economic development, three key components are distinguished (Grabowska et al., 2022; Nahavandi, 2019):

- human-centric – shifting the focus from efficiency, production efficiency to employee welfare, competence and development,
- sustainability – indicating issues of circular economy, minimization of environmental damage and use of green energy,

- resilience – related to the operation of the organization in a turbulent technological, economic and geopolitical environment.

Numerous studies indicate that in the face of dynamic changes in the economic environment, the main factor determining the necessary changes that must occur in companies is the rapid development of technology, including innovation, artificial intelligence, the Internet of Things (IoT), data analytics and process automation (Jiang et al., 2024; Xu et al., 2021; Yavari & Pilevari, 2020). By implementing tools specific to Industry 5.0, companies can gain a competitive advantage by optimizing processes and eliminating inefficiencies. Analytical tools, such as predictive maintenance and real-time data analysis, reduce downtime, improve resource allocation and increase productivity (Goujon et al., 2024; Tyagi et al., 2023). This is particularly important for building the competitiveness of SME players.

Management of any organization is a complex and multifaceted process, and effective tools are needed for its proper and efficient implementation (Santalova et al., 2019). Griffin (2005) defines management as a set of activities, such as planning, decision-making, organizing and leading, and controlling, which are directed at human, financial, physical and information resources. In the era of globalization, the management of an SME enterprise covers many areas of activity and requires a high level of labor and coordination of many activities, which translates into time-consuming processes and involves certain financial outlays (Bashan & Kordova, 2021). The use of appropriately selected innovative tools can affect more efficient implementation of processes, lowering the labor input and time of performing activities. Chen at al. emphasize that in the face of progress in the area of digitization, traditional methods of financial management in the enterprise are becoming obsolete (Chen et al., 2023).

The application of AI in the SME sector covers a range of areas, from data analysis to forecasting market trends. With learning capabilities, AI-based management systems will continue to improve. Already, these systems have the ability to identify events that may reveal new business opportunities or potential competitive threats (Griesch et al., 2024; Kedi et al., 2024). The implementation of digital considerations using AI can support decision-making processes, providing decision-makers with comprehensive analysis and recommendations based on large amounts of data. The use of AI in SMEs can bring numerous benefits (Mohd Suki, 2024; Yurdagel & Baycur, 2024). First, it enables faster and more precise data analysis, thereby speeding up and rationalizing the decision-making process. Second, through continuous learning and expansion of databases, AI systems provide up-to-date and currently required information to managers. In addition, AI gains the ability to identify non-obvious trends, making it possible to create flexible strategies adapted to the changing business environment (Aslam & Martha, 2024; Morshed et al., 2024). In the area of management in the SME sector, where it is often impossible to hire adequate specialists, the use of artificial intelligence plays a key role, enabling a better understanding of the competitive environment. This can result in more efficient and smarter business management.

It is necessary to introduce into management practice tools that enable analysis of large data sets (Big Data), allowing to more accurately forecast demand, optimize the commitment of capital, inventory, human resources. The availability of real-time data from various sources allows effective monitoring and management of all processes occurring in the enterprise (Cao & Zhai, 2022; Gadde, 2024). The use of 'Big Data' also leads to the minimization of risks associated with the turbulence of the modern economy (Lagap & Ghaffarian, 2024). Big data is a term for very large, diverse and rapidly growing data sets that are too complex to analyze with traditional data processing tools and methods.

According to McKinsey (2021), companies using AI-based tools in production and supply chain management report optimizing operating costs and reducing them by about 10–20% through the implementation of AI. In addition, a study by Delloite Report (Dutt et al., 2024) indicates that among the other benefits companies expect from generative AI are: (1) improve efficiency and productivity; (2) improve existing products and services; (3) encourage innovation and growth; (3) shift workers from lower to higher value tasks; (4) increase speed and/or ease of developing new systems / software; (5) increase revenue; (6) enhance relationships with clients / customers; (6) uncover new ideas and insights; (7) detect fraud and manage risk. At the same time, the Delloite Report emphasizes that the greatest value and strategic differentiation will likely come from using the technology to innovate. First, by helping to generate new products, services and capabilities that wouldn't be possible otherwise. And second, by enabling new business models and ways of working across an enterprise.

In summary, AI is becoming an increasingly important tool in building the competitiveness of enterprises in the globalized economy and at the same time a requirement of modern management in the

strategic and operational dimensions. Using digital innovations including generative AI, companies increase their operational efficiency, make better strategic decisions and flexibly adapt their offerings to changing market conditions. Such activities are part of the definition of smart business management.

On the other hand, it should be remembered that artificial intelligence is not just "ordinary technology" and there are many risks associated with it (Kaur et al., 2023). The problem to be solved remains the question of its further development and control by, among other things, setting "specific boundaries" not only ethical (Bostrom, 2020; Müller, 2021) but also regulated by law (Buiten, 2019; Xenidis & Senden, 2020). This is important from the point of view of the functioning of humans, businesses, as well as societies (Makridakis, 2017), since it is known that AI is capable of simulating human thinking as well as behavior. Consequently, today one can identify many areas of AI threats such as cyber-attacks on the infrastructure of enterprises or critical infrastructure of countries, fake news, arms race, deliberate violation of the rights or freedoms of people/societies, among others. AI can be a useful tool in the creation and pursuit of sustainable socio-economic development of countries, but also a tool used in armed conflict, terrorism, struggle for influence and domination in the global economy (Polcumpally, 2024; Xue & Guo, 2024). Moreover, it is worrisome that AI leaders are pessimistic about the social impact of the technology. The concern is about serving only one organization or one country. when as many as 52% of AI leaders said they expected widespread use of generative AI to centralize power in the global economy, while 30% expected it to more evenly distribute global power. Similarly, 51% expected generative AI to increase economic inequality, while 22% expected it to reduce inequality (Dutt et al., 2024).

Taking into account the above risks, the following are indicated as important for risk management in the implementation of generative artificial intelligence (Dutt et al., 2024):

- monitoring regulatory requirements and ensuring compliance,
- establishing a governance framework for the use of generative AI tools/applications,
- conducting internal audits and testing on generative AI tools/applications,
- training practitioners how to recognize and mitigate potential risks,
- ensuring a human validates all generative AI content,
- using a formal group or board to advise on generative AI-related risks,
- keeping a formal invent of all generative AI implementations,
- using outside vendors to conduct independent audits and testing,
- single executive responsible for managing generative AI-related risks.

Observation of economic trends prohibits that artificial intelligence is being used in many industries in the area of customer relationship management as well. Thanks to digital transformation, Chatbots and recommendation systems implemented at the enterprise level enable companies to build strong customer relationships, personalize goods and services and create flexible offerings. Flexible personalized offerings that coincide with identified consumer expectations are the way to generate increased product sales, and thus higher revenues. Changes in the way we communicate and also gather and process information, which have occurred since the dissemination of tools such as ChatGPT developed by OpenAI, affect many areas of management, including the process of operational and strategic management (Ayinde et al., 2023; Wagner et al., 2022). The transformation and evolution of AI-based technologies, makes innovative digital technologies an increasingly integral part of competitive strategies, enabling the improvement of market analysis tools, identification of trends, and, above all, flexible adaptation to changes in the socio-economic environment (Abu-Alfoul, 2023). The high efficiency and speed of artificial intelligence is a potential for reducing employment in the long term and in the perspective of reducing wage costs, reducing costs relating to the entire value chain of the organization by means of streamlining business processes in the organization (Sofiyah et al., 2024). Artificial intelligence, in the context of its use in building the competitiveness of enterprises, is becoming a set of increasingly advanced technologies that enable an enterprise to understand its environment, process information and make decisions leading to the efficient use of its resources, including human resources. The implementation of AI allows the automation of repetitive tasks, which frees employees from routine and allows them to focus on more desirable activities for businesses (Abu-Alfoul, 2023; Ayinde et al., 2023). As a result, companies that use AI can better manage human capital, which is becoming an increasingly scarce resource these days.

Increasing the competitiveness of SME companies depends primarily on their innovations. Companies that more intensively implement innovative digital solutions are more likely to introduce such innovations. Collaborating in this process with IT and R&D entities (Lewandowska, 2021).

Deloitte's survey (Dutt et al., 2024) of business and technology leaders indicates that interest in the enterprise sector in artificial intelligence remains high. The impact of digital transformation is expected to be clearly visible in the next three years. The vast majority of respondents (79%) said they expect artificial intelligence to drive transformation in their organizations and industries over the next three years. Nearly a third expect significant transformation to occur now (14%) or in less than one year (17%). Most organizations rely primarily on off-the-shelf digital solutions using AI. This is characteristic of the SME sector which needs standard and low-cost solutions. This is due to the organizational potential of these companies as well as the amount of capital they have. Among these solutions, the most common are:

- productivity applications with integrated generative artificial intelligence (71%),
- enterprise platforms with integrated artificial intelligence (61%),
- publicly available large language models (LLMs) (56%), such ChatGPT.

So, it seems right to observe that AI is changing business, the economy and society, impacting experiences and relationships between stakeholders and citizens In the race to implement AI solutions in the enterprise, it is the characteristics of the organization, such as adaptability, flexibility, willingness to experiment, that will be crucial. Technology continues to evolve and influence the business landscape, so it is imperative for both current and future entrepreneurs to be proficient in using advanced tools such as AI (Giuggioli & Pellegrini, 2023).

3. METHODOLOGY

Verification of the research question and the realization of the stated goal was carried out on the basis of various research methods. Literature studies, secondary data analysis, comparative analysis, logical inference and deduction methods were used. Literature was reviewed and analyzed from the fields of mainly: innovation, artificial intelligence AI, entrepreneurship and competitiveness of SMEs, socio-economic development of the European Union.

Additional authors also shared their own professional knowledge and experience, and that of business. In particular, the theoretical and practical knowledge gained while working as an expert within the Evaluation Committees of Projects of small and medium-sized enterprises applying for European Union funding proved useful in the work. The projects were aimed at developing and strengthening the research and innovation capacity of enterprises, targeting the implementation of product or process innovations, as well as the digitization and transformation of enterprises (also as part of the construction of intelligent management systems) towards sustainable development, .

The research was also based on data available from national and international public statistics. Documents published by organizations such as the World Intellectual Property Organization (WIPO), Deloitte, the European Commission, the National Bank of Poland, the Polish Agency for Enterprise Development and Statistics Poland, among others, were used in this regard. The work mainly uses the latest available data. The territorial scope of the research covers the area of the European Union, with particular emphasis on Poland.

4. RESULTS

4.1. Innovation as an element of EU policy

Numerous studies indicate that innovation is key to the development of economies. Mendez et al. (2013), in their research, confirmed that it is innovation that can drive up to 80% of economic growth in developed countries, while investment by less developed countries in innovation can improve the export performance of a sector considered crucial in the context of low business competitiveness and domestic demand. Therefore, the amount of funding allocated in the European Union for research and development supporting innovation has gradually increased. Since 2000, the investments in research and innovation (R&I) under Cohesion Policy have grown exponentially: from €26 billion in the 2000-

2006 period to over €86 billion in 2007–2013, to €121 billion in the 2014–2020 period (Council of the European Union, 2021). In the latest financial perspective 2021–2027, a total of €137.5 billion is programmed for the innovation and digital economy priority alone. The first strategic objective of the EU Cohesion Policy for 2021–2027 is "A more competitive and smarter Europe" (so-called PO1). Under this objective, projects are planned and already underway to contribute to the following specific objectives:

- developing and enhancing research and innovation capacities and the uptake of advanced technologies (total budget €53.3 bn),
- enhancing sustainable growth and competitiveness of SMEs and job creation in SMEs, including by productive investments (total budget €37.2 bn),
- enhancing digital connectivity (total budget €3.6 bn),
- reaping the benefits of digitization for citizens, companies, research organizations and public authorities (total budget €15.9 bn),
- developing skills for smart specialisation, industrial transition and entrepreneurship (total budget €2.5 bn).

Italy is scheduled to receive the most funds for the OP1 objective (€17,325 bn), followed by Poland (€16,037 bn) and Spain (€13,058 bn). Luxembourg, on the other hand, will not receive EU funds for this purpose. Malta (€0.184 bn) and Cyprus (€0.245 bn) have the smallest budgets. Figure 1 shows the total budgets of individual EU members for the goal of building Smarter Europe.

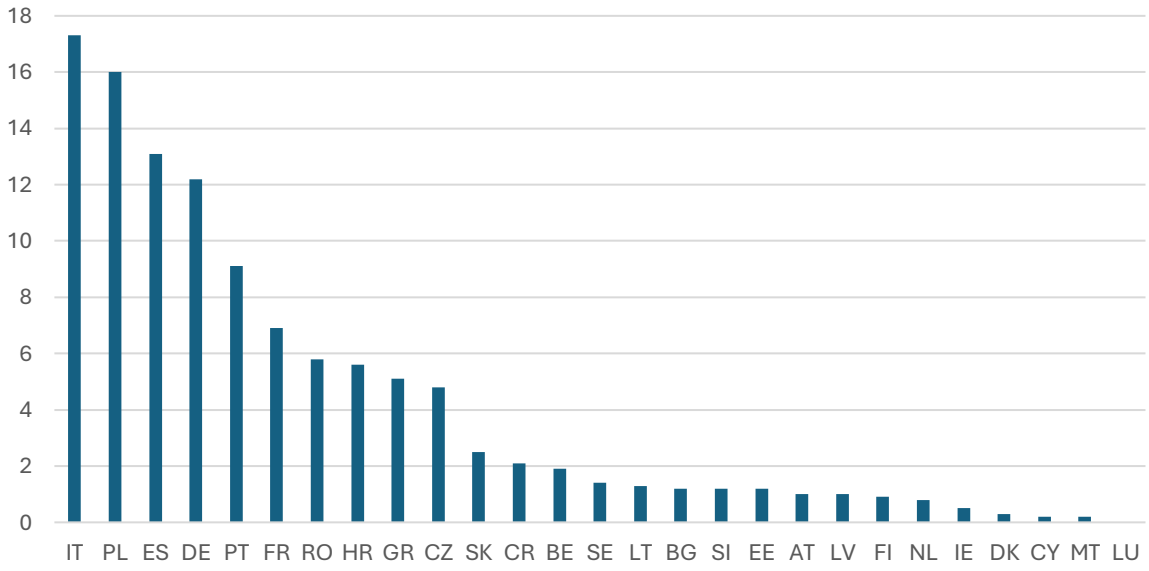


Figure 1. Total Budget by country UE: P01 – Smarter Europe, EUR Billion
Source: own elaboration based on Cohesion Open Data Platform.

One of the key barriers to the development of digital innovation in companies is the gap in good examples and their applications that could be benchmarked. A benchmarking strategy is a process in which an organization compares its processes, products, services or results with the best practices and performance of other companies, usually leaders in a particular industry. The goal of benchmarking is to identify areas that can be improved and implement solutions that will help the organization gain a competitive advantage. That is why it is so valuable to observe how companies in the European Union, especially Italian, Polish and Spanish entrepreneurs, will use the funds under PO1. Digital transformation projects and the use of AI to build competitive advantages will obviously be key in this regard, also in the area of smart SME management

4.2. Innovativeness of the Polish economy

According to the Global Innovation Index, from 2011 to 2024, Poland ranked between the lowest 49th (in 2013) and 38th (in 2017, 2020, 2022). According to the latest data, in 2024 it occupied the 40th position and this was one place higher compared to 2023. Increasing the level of innovativeness of the

Polish economy is possible only if SME entities are involved in the process. An analysis of statistical data on the development of the SME sector in Poland reveals it is an extremely important and dynamic element of the Polish economy. According to data from the Statistics Poland, in 2024 there were more than 2.3 million enterprises in Poland, of which up to 99.8% were SMEs. Details of the sector are provided in Table 1. SMEs generate 45.3% of Poland's GDP and employ more than 55.9% of workers in the private sector. They are therefore a key element of the Polish economy, affecting its stability and growth.

Table 1. Characteristics of the SME sector in Poland

Number and structure of enterprises	**Poland**		**EU-27**	
Number of enterprises	2 668 101	100%	31 997 696	100%
Micro	2 554 874	95,8%	30 119 467	94,1%
Small	93 624	3,5%	1 578 948	4,9%
Medium	16 002	0,6%	246 577	0,8%
Employees in enterprises	**Poland**		**EU-27**	
Number of employees in enterprises	11 489 622	100%	156 124 230	100%
Micro	4 265 808	37,1%	47 004 556	30,1%
Small	1 843 959	16,1%	29 467 249	18,9%
Medium	1 641 083	14,3%	24 009 260	15,4%

Source: own elaboration based on Zadura et al. (2024).

According to the latest available data Statistics Poland there were 2847 companies employing 10 people or more in the ICT sector in 2023, of which 92.7% provided ICT services. Slightly more than 80% of ICT service enterprises were IT service providers. The number of people working in the ICT sector was 324500. IT services constituted the area of enterprises with the highest number of employees among all those employed in ICT services (79.2%). The value of net sales revenue in the ICT sector in 2023 amounted to PLN 269.8 billion, with an annual increase of 2.6%. Services made the largest contribution to the ICT sector's revenue generation. Their share in the revenue of the entire ICT sector was 81.5%. In 2023, almost a third of enterprises provided their employees with training to improve ICT skills (31.4%). One in five enterprises used open public data (19.5%).

Among ICT companies in 2023, more than a third of revenues were generated by companies providing IT services (44.7%, up 4.7 percentage points from a year earlier). Telecommunications services companies came in second with a share of 18.6%. It is these enterprises that are also most responsible for the positive trade balance in the Polish services trade balance.

A systematic and rapid development of Poland's foreign trade in innovative and knowledge-based services was observed between 2010 and 2023. The total value of exports of these services increased from PLN 18.8 billion in 2010, to PLN 155.4 billion in 2023, or by 825%. In turn, the value of service imports increased from PLN 21.1 billion to PLN 112.9 billion. This represents a marked increase of 535%. The trade balance in this category was negative in 2010-2014, with a steadily increasing balance in subsequent years, reaching PLN 42.4 billion in 2023. As can be seen in the case of the analyzed group, the growth rate of imports was also much lower than the growth rate of exports of services.

An analysis of the innovative and knowledge-based components of Poland's trade in services shows that there were significant changes from 2010 to 2023, including an 825.1% increase in exports and a 289.4% increase in imports. It is significant that Poland achieved a trade surplus for 2023 of the following components: Telecommunication, IT and information services, Research & development services, and Services provided by professionals. Only the component Fees for intellectual property rights showed a negative trade balance, which worsened compared to 2010. Unfortunately, Polish entrepreneurs have to pay fees for copyrights, patents, trademarks or design rights in many cases (see table 2.).

The share of innovative and knowledge-based services increased in Poland's foreign trade in services in 2023 compared to 2010, with exports rising from 17.9% to 23.5% and imports from 34.0% to 40.7%. This is obviously a positive change. However, it should also be pointed out that the value of service exports as a proportion of GDP decreased in Poland in 2023 to 13.4% (compared to 13.7% in 2022). It remained at a lower level than the European Union average (16.3%). An additional barrier is the

dominance of equity-linked entities in both exports and imports of services. For example, in 2023, only 15.6% of domestic entities were responsible for the export of services of the Telecommunication, IT and information services component, and only 1.6% for the Fees for intellectual property rights component (Międzynarodowy Handel Usługami Polski w 2023 Roku, 2024).

Table 2. Poland's foreign trade turnover by the main components of innovative and knowledge-based services in 2010 and 2023 (PLN bln)

Service	2010			2023			2023/2010 [%]	
	Export	Import	Trade balance	Export	Import	Trade balance	Export	Import
Telecommunication, IT and information services	6,1	6,6	–0,6	70,7	46,3	24,4	1168,3	699,0
Research & development services	1,7	0,5	1,2	12,7	2,6	10,1	748,6	563,0
Services provided by professionals	10,4	7,3	3,1	66,2	44,4	21,8	638,2	611,0
Fees for intellectual property rights	0,7	6,8	–6,1	5,7	19,6	–13,8	811,2	289,4
Total	18,8	21,1	–2,3	155,4	112,9	42,4	825,1	534,6

Source: own elaboration based on National Bank of Poland data.

The authors' experience of working with the SME sector indicates that the reason for this state of affairs is the low awareness of entrepreneurs of the benefits of implementing innovative digital solutions The most frequently cited are concerns about the complexity of the entire process of implementing digital technologies and fear of using AI in business. The problem is the low level of knowledge regarding the implementation of digital innovations and the specific opportunities brought by the use of AI in business processes. Certainly, things are not made easier by the lack of credible examples of implementation of these technologies in similar companies in the industry. This also means a lack of competitive pressure to implement AI, which would certainly influence greater openness to swap.

Not surprisingly, according to the Digital Economy and Digital Society Index (DESI) in 2022, Poland ranked 24th among the 27 European Union member states. The report positively assessed the development of public services in Poland. Over the past few years, there has been an increase in the number of users using services provided by the administration electronically, from 49% in 2019 to 55% in 2022. It is also encouraging to see an increase in the number of ICT specialists1 from 3.1% of the working population aged 15–74 in 2019 to 3.5% in 2022, however, this result is below the EU average of 4.5% (European Commission, 2022).

The problem with the implementation of digital technologies in the SME sector in Poland is also evidenced by the value of the Digital Intensity Index. In 2024, more than two-thirds of Poland's enterprises are categorized as having very low or low digital intensity. Only 26.7% of SME enterprises were categorized as having high or very high intensity. Taking into account the type of business, high or very high intensity was most often characterized by entities engaged in information and communication (88.0%), while the highest percentage of enterprises with very low digital intensity was recorded in the construction section (46.9%).

One of the tools for developing the competitiveness of Polish enterprises under PO1 is a program called Smart Path, implemented by the Polish Agency for Enterprise Development (PARP). Its objective is to develop and strengthen the research and innovation capabilities of enterprises, aimed at implementing product or process innovations (at least at the national level) and the digitization and transformation of enterprises towards sustainable development, as well as the internationalization of enterprises and the increase of personnel competence. The program allows funding for digital transformation and ensuring cyber security of the Applicant's business operations. Activities planned in the module must lead to the implementation of a product or process innovation at least at the enterprise level. The Smart track is a comprehensive support for the activities of micro, small and medium-sized

enterprises, in particular, strengthening research and development capabilities and implementing innovations based on the results of R&D work.

The authors of the article, as PARP experts, participated in the evaluation of more than 100 projects under SMART. Own observations related to the process of implementation of the program and observations of other experts with whom discussions were held on this subject indicate the advisability of implementing such projects. This is because they are an opportunity for the SME sector to establish cooperation with the R&D sector and increase the innovativeness of their products and services. More than 5,600 applications submitted suggest that companies are looking for projects that allow them to finance the costly process of creating their competitiveness.

Table 3. Characteristics of competitions for SMEs in Poland supporting the development of innovation under the SMART and SMART Accessibility programs co-financed by the EU

Competition number	Number of applications submitted	Total budget in PLN	Number of projects with funding
1.	1540	1,883 bn	198
2.	2722	1,4 bn	201
3.	148	222 million	13
4.	1081	2,1 bn	unfinished
5.	91	222 million	unfinished

Source: own elaboration.

It should be pointed out that under the SMART Path programs, support can be given to projects that result in product or business process innovations relating to business functions (as defined in accordance with Oslo Manual 2018) in the production of products or services. Also eligible under the competition are costs that lead to the development of innovations in intelligent business management systems, which could then be sold on the market. In addition, as part of the planned tasks within the framework of research work and industrial research, entrepreneurs can apply for support for the purchase of modern enterprise management systems, if this is reasonable, rational and related to the purpose of the project. Thus, the SMART Path supports enterprises in the development of modern tools, including AI in support of intelligent management processes in two ways. Projects in the subject area were submitted by SMEs and the authors participated in their evaluation. It can be pointed out, for example, that one of the more common areas of evaluated projects was the use of AI in infrastructure and renewable energy management or the implementation of ERP systems.

At the same time, the small percentage of projects that have been recommended for funding indicates the numerous problems encountered by the SME sector in these activities. Mistakes made by Applicants at the application stage, jump to the variety of problems faced by entrepreneurs. Based on their own experience and observations, the following should be mentioned first and foremost:

- lack of product or process innovation in the submitted projects at least on a national scale,
- lack of ability to finance the necessary own contribution, including the applicant's poor financial condition or the scale of the project exceeding the applicant's financial capacity,
- lack of good knowledge of the competition documentation, which resulted in the preparation of applications with errors,
- overly complicated provisions of the project selection regulations,
- highly elaborate competition documentation,
- difficulties in prioritizing expenditures, including, most notably, the repeated overestimation of project staff salaries,
- erroneous assignment of tasks to industrial research and development categories,
- unclear cost eligibility rules for beneficiaries,
- inclusion in applications of unjustified expenses incompatible with the purpose of the project,
- lack of understanding of the idea and principles of cooperation between the entrepreneur and the R&D sector,
- requirement to develop complex financial models based on projections of future projected revenues,

- lack of qualified personnel, including qualified personnel to implement intelligent management systems in SMEs,
- difficulties in implementing intelligent management solutions in the process of energy transformation of the organization and the realization of sustainable development goals,
- low quality of services of consulting companies supporting the SME sector in obtaining grants,
- lack of proof of the presented model of the volume of planned sales of products/services of projects – declarative nature of assumed sales volumes, i.e. not supported by verifiable data, market analysis, market research or letters of intent from potential customers.

The possibility for SMEs to obtain support for the development and implementation of innovative products/services under nationwide competitions organized by PARP as an intermediary institution is only one of the ways to obtain EU funds under the 2021–2027 perspective. It should also be mentioned that Polish SMEs also have the opportunity to obtain European funds from, among others, the National Reconstruction Programme, as well as under sixteen Regional Operational Programs in accordance with the guidelines of individual competitions.

5. DISCUSSION

According to the International Monetary Fund (IMF), the world's largest economies in 2024 are still the US, China, India. The counterweight to these big economies in such a politically and economically turbulent world should be the economy of the European Union. However, this is not the case. An analysis of a range of economic data shows that Europe is growing too slowly in the 21st century, and its economy is not keeping up with its global rivals (Bavoso, 2024; Gonzalez Minguez, 2024). This is one of the conclusions of the Draghi Report (Draghi, 2024) commissioned by the European Commission. The main reason is the weak growth of productivity - that is, the ability of a worker to create added value. The analysis presented clearly shows that the European Union economy is no longer competitive with the United States and China. Without big investments, it faces “slow agony”. Constructive conclusions of the report indicate that in order to restore the EU's competitiveness, action is needed in three areas: (1) developing innovative solutions on the basis of mature technologies; (2) coupling climate goals with the development of European industry; (3) investing in security and making Europe less dependent on global partners. It has been estimated that an additional 750 to 800 billion euros per year are needed to meet these goals.

Europe's lack of growth potential is particularly pronounced in the area of innovative technologies. As much as 61% of total global funding for artificial intelligence ventures goes to US companies, 17% to Chinese companies. Only 6% of capital is raised by companies in the EU. The new plan for sustainable growth and competitiveness of the EU economy is the so-called “Competitiveness Compass for the UE” (2025) presented in January 2025 by the European Commission. It specifies that the key to competitiveness is to increase innovation by:

- creating an environment that enables young companies to start up and grow, through the EU's strategy for start-ups and scale-ups,
- helping large companies implement new technologies, such as artificial intelligence (AI) and robotics, through the strategy on the application of AI,
- making it easier for companies to do business across the Union by simplifying rules and regulations, including through the proposed so-called 28th legal system, which will guarantee one set of rules across the EU,
- supporting the development of new technologies through action plans for advanced materials, quantum technologies, biotechnology, robotics and space technologies.

One of the key barriers to the development of digital innovation in companies is the gap in good examples and their applications that could be benchmarked. In particular, this includes the implementation of smart roving solutions, including AI in the process of managing the energy transition and achieving the sustainable development goals. A benchmarking strategy is a process in which an organization compares its processes, products, services or results with the best practices and performance of other companies, usually leaders in a particular industry. The goal of benchmarking is to identify areas that can be improved and implement solutions that will help the organization gain a

competitive advantage. That is why it is so valuable to observe how companies in the European Union, especially Italian, Polish and Spanish entrepreneurs, will use the funds under PO1. Digital transformation projects and the use of AI to build competitive advantages will obviously be key in this regard.

In an increasingly globalized world economy, there is a widening gap that Europe is losing to digital powers like the US and China. Digital skills and innovation are key to creating a competitive economy as well as the prosperity, security and resilience of society as a whole. According to the European Commission, the Road to the Digital Decade Program, with specific goals and targets for 2030, is designed to strengthen the EU's digital leadership and, to that end, promote inclusive and sustainable digital policies serving citizens and businesses. To this end, specific digital goals have been set for the EU and its member states to achieve by the end of the decade in 4 areas: (1) strengthening digital skills and digital education; (2) secure and sustainable digital infrastructures; (3) digital transformation of businesses; (3) digitization of public services.

A new feature of the program is the introduction of a form of cooperative governance between member states and the Commission, so that the Union pursues its goals together. It creates favorable conditions for the development of cooperation among member states in the development of digital capabilities and technologies. The overarching goal is digital transformation that empowers citizens and businesses, in line with EU values. In the communication “Digital Compass for 2030: Europe's path in the digital decade” on March 9,2021. the Commission outlined a vision for the EU's successful digital transformation by 2030. It shows that the EU is striving for digital sovereignty in an open and interconnected world, and wants to pursue digital policies that ensure a human-centered, inclusive, sustainable and prosperous digital future for citizens and businesses.

In Poland, the problem of digital exclusion and low-quality IT infrastructure affects many SME entrepreneurs. Their competitiveness to date has been created on the basis of advantages related to low labor costs. According to PARP's data, in 2022 only 13.2% of Polish companies were engaged in innovative activities, and 86.8% were classified as non-innovative companies. The percentage of companies introducing product or service innovations was 7.0%. As for business process innovations, the percentage of companies implementing them was 12.6%, of which only 1.9% of companies implemented IT innovations. An analysis of the scope of innovations implemented shows that in the case of product innovations, 51.0% of them involved enterprise-scale innovations and only 7.4% involved global innovations. In terms of service innovations, as much as 80.2% concerned innovations on an enterprise scale and only 4.7% were innovations on a global scale. To a small extent, these entities implemented digitization activities, which puts them at a competitive disadvantage. This clearly indicates a deficit in building international competitiveness based on innovative products and services, which is characteristic of the Polish business sector.

According to the “Policy for the Development of Artificial Intelligence in Poland” from 2020, the key sectors in which artificial intelligence will be developed are public administration, construction (with a focus on smart building), cyber security, energy, trade and marketing, medicine, industry, agriculture, and transportation and logistics. These sectors stand to benefit 2.65% of GDP after implementing AI-based solutions. In order for this to become a reality, further development of the information and communication technology (ICT) sector enterprises that are the foundation of the digital transformation of the Polish economy is essential.

Small and medium-sized enterprises account for 99.8% of all enterprises in Poland. Surveys conducted indicate that organizations of this type are characterized by low maturity in implementing solutions based on new technologies. Therefore, it is necessary to support these entities in achieving a high level of digitization, including extensive use of AI in their operations. This is to be served by a pilot program to support the implementation of artificial intelligence solutions in SMEs (Drozdowicz & Węcławska, 2024). One of the key goals of the program is to increase the use of artificial intelligence by businesses in Poland from the current level of 2.89% to 10% in 2030, which is particularly important in the context of the relatively low level of digitization of the Polish SME sector.

Observations of the SME sector in Poland indicate that entrepreneurs are trying to invest in areas related to digital technologies, but these activities are mainly limited to implementing basic digital solutions at the enterprise level. Few companies choose to implement intelligent management systems. This is especially true for smaller organizations. There is a distinct lack of action on smart management for sustainable development.

Between 2020 and 2024, the percentage of enterprises with broadband Internet access nationwide exceeded 98%. The high level of the indicator testifies to the unflagging interest in the benefits of being able to connect to the global network. Among large enterprises, the value oscillated around 100%. In 2023, among EU member states, the highest percentage of employees with access to the Internet for business purposes occurred in Sweden (86.8%), while the smallest – in Bulgaria (39.7%). Poland with the value of the indicator 55.3% was below the EU average of 61.3% (Społeczenstwo Informacyjne, 2024).

The implementation of digital technologies in the SME sector in Poland is not integrated. It usually concerns selected aspects of the business, such as accounting, human resources, and warehouse management. Therefore, it is of an operational rather than strategic nature from the point of view of creating competitive advantages. The lack of integrated information systems means that information that is extremely important from the point of view of economic activity is scattered, and its analysis is difficult or even impossible. Insufficient digitization of processes does not allow them to be mapped and systematized, which makes it impossible to identify areas that should be optimized. This also prevents the implementation of AI-based digital innovations. Artificial intelligence implemented at the enterprise level is based on the high-quality data with which it is fed. The foundation of the AI model is high-volume and continuously collected and processed data.

6. CONCLUSION

The European Union is aware of the importance of digital transformation using AI artificial intelligence to build and enhance the competitiveness of economies across the organization. As a result, more and more funding has been allocated to innovation development in successive financial perspectives. Cohesion policy allocated EUR 26 billion for this purpose in 2000-2006 and nearly EUR 138 billion in the current programming period 2021–2027. Currently, the indicated funding is allocated to: developing and enhancing research and innovation capacities and the uptake of advanced technologies, enhancing sustainable growth and competitiveness of SMEs, improving digital connectivity and developing digital competencies.

The implementation of these goals is taking place within the framework of the European program "Smarter Europe," which is focused on digital transformation in the member countries in the broadest sense. We will be able to assess the effects of this program in a few years. However, it is already clear that in some sectors of the EU, innovation development activities must accelerate, for example, in the defense sector.

The paper makes a rather broad characterization of the SME sector and the level of innovation of one of the EU member countries. Poland was chosen because of the low level of innovativeness of its economy and the second largest budget in the EU for the implementation of the Smarter Europe PO1 program.

The structure of the enterprise sector in Poland indicates that SMEs should be considered the foundation of the Polish economy and a key catalyst from the point of view of the digital transformation of the Polish economy. A characteristic feature of the Polish economy is the percentage of microenterprises in the economy that is higher than the EU average. They also employ more people than the EU average. That is why it is so important to create conditions for the development of the competitiveness of these enterprises. Considering the low innovativeness of the entire Polish economy, it is necessary to take quick actions to change this state.

Actions taken in the field of digitization and innovation of the SME sector can quickly translate into Poland's competitive position, both in the business and social dimension. Thanks to digital transformation, small and medium-sized enterprises will be more open to new challenges and focused on searching for market advantages. However, the barrier to digital transformation is the undercapitalization of SME sector enterprises and the lack of specialized staff. This means that increasingly higher requirements in the field of innovation and digital technologies can be an opportunity and a threat to this market sector, determining the level of its current and future competitiveness.

The conducted research allowed to identify a number of barriers faced by SMEs in Poland. This concerns primarily difficulties in obtaining support from EU funds for the implementation of innovative

projects. This affects difficulties in creating innovative products and services on a national scale. Enterprises from the SME sector also have difficulties in indicating sources of coverage of the required own contribution. The situation on the labor market does not allow for obtaining specialists in the implementation of innovative projects, including digital ones. Low competences of project management staff mean that a significant number of entrepreneurs have problems understanding project documentation, distinguishing product innovation from process innovation, etc. In the authors' opinion, this is one of the reasons why the vast majority of application forms are prepared incorrectly. They contain numerous substantive errors and are usually characterized by low innovativeness of the proposed solutions.

New digital technologies, especially artificial intelligence and the Internet of Things, are currently treated as an important condition for strategic management of strategic importance, redefining business models, management processes or ways of using available resources. The speed of technological changes introduced, and the rationality of their implementation are becoming a determinant of the digital maturity of future business, in which humans and technologies will cooperate naturally. Digital excellence is not reduced to the implementation of subsequent solutions based on digital technologies. It is a catalyst for redefining those values that constitute the market advantage of an enterprise. Leading to the reconceptualization of methods and tools for competing in a globalized world.

The research also shows that issues related to the development of SMEs in the field of using new digital technologies have not been researched and verified to the extent allowing for their detailed assessment. The collected statistical data is scattered, and their processing is handled by a number of institutions. Available studies and analyses indicate that, compared to the European Union, Polish enterprises from the SME sector still face many challenges in the area of digital development.

The authors are aware of the study's limitations and implications. First, various data sources were used, which meant that the data were not always homogeneous. In addition, it was a problem to maintain a single time period of research for all aspects discussed, but efforts were made to include the most recent data. Secondly, the subject matter undertaken is very broad, so it was not possible to discuss all aspects more extensively. Thirdly, a limitation of the implication of the results may be the broader analysis and characterization of the level of innovation of only one EU member state, i.e. Poland, which may cause problems in generalizing the results of the research. However, the authors' own experience in terms of evaluating SME projects for EU funding in the implementation of digital transformation as well as expert insights into the problems associated with the process of digital and innovative transformation of the Polish economy, which makes some of the research results original, which is the value of this work.

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USE OF ARTIFICIAL INTELLIGENCE IN BRANDING AND MARKETING ACTIVITIES (ON THE EXAMPLE OF AGENZA COMPANY)

Katarzyna Włodarczyk[a]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*

ABSTRACT

Purpose: *The aim of the paper is evaluating the use of AI in branding and marketing activities in the operation of a company.*

Need for the study: *Building a recognizable brand is nowadays regarded as one of the most effective tools for creating a competitive advantage in the market. In this study, attention is focused on artificial intelligence, which can prove to be a source of inspiration for marketing creations, but also a tool to assist companies in the communication process and influence the behaviour of buyers.*

Methodology: *In the first part of the paper, theoretical considerations are undertaken on selected aspects of branding and marketing activities in modern business realities, as well as on artificial intelligence and the possibilities of its use in the described industry. The empirical part presents the case of a Polish company - the branding and marketing agency Agenza from Gryfice (in the West Pomeranian Voivodship) on the basis of qualitative research.*

Findings: *Based on the conducted qualitative research, it was established that artificial intelligence, used carefully, can provide significant support for specialists, but it will not replace human experience, intuition, creativity or education - humans still remain the key subject of the creative and decision-making process.*

Practical Implications: *The near future in branding and marketing activities using artificial intelligence means the ability to effectively use modern technologies and the tools they offer by humans, along with their combination with their creativity, ingenuity, intuition and feelings.*

Keywords: marketing, branding, brand, artificial intelligence, company

Jel codes: M31; M39; M15

1. INTRODUCTION

Technological development is continuously linked to contemporary economic development and growth. Technological development is the process of inventing, innovating and disseminating new and modern technologies. Technological development requires continuous improvement and the commercialization,

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accessibility and thus dissemination of the results obtained in the economy and society. The importance of technological development in shaping the modern economy is due to the fact that it is regarded as an important factor in changing the level of innovation and competitiveness at every level of activity, from the micro level to the macro level (Mateusiak & Stoma, 2020; Zakrzewska & Jarosz, 2022). Modern technologies are therefore the forces that stimulate and drive modern economies. As a result of their application, it becomes possible not only to produce goods and services faster, but also cheaper and often better in terms of quality. Technological development, the growth of modern technology and the associated process of digitalization of the economy and society is one of the most visible and dynamic changes in contemporary realities (Łaszek, 2018; Boratyńska, Cieślik, Kacperska, Łukasiewicz & Milewska, 2021; Chądrzyński, Gruziel, Kacperska, Klusek & Utzig, 2021; Kotler, Kartajaya & Setiawan, 2021).

Modern technologies provide companies with opportunities to improve the products they produce and the services they offer, to manage their resources more efficiently and to operate the organisation at all levels and in relation to various aspects. As far as households are concerned, modern technologies facilitate people's daily lives, both professional and private (Ratnicyn, 2016: Bartnik, 2016; DuVall, 2019).

The latest new technologies that are currently receiving a lot of attention in both scientific and popular science studies include: the development of mobile Internet, artificial intelligence (AI), the Internet of Things, virtual reality (VR) and augmented reality (AR), cloud solutions for storing and processing information, robotization, automation, the development of genomics and biometric technologies, blockchain, the development of quantum computers, and progress in green and sustainable technology (Stone, et. al., 2020; Puślecki, 2021; Marr, 2023).

In this paper, special attention will be focused on one of today's technological tools - artificial intelligence (AI). Its use will instead be shown in the branding and marketing industry. The aim of the paper is therefore to evaluate the use of AI in branding and marketing activities in the operation of a company, as a contemporary tool that is essential for the realisation of the activity undertaken and, with it, of short- and long-term goals, while at the same time fostering the competitiveness of the organization in the market. In the first part of the paper, theoretical considerations are undertaken on selected aspects of branding and marketing activities in modern business realities, as well as on artificial intelligence and the possibilities of its use in the described industry. The empirical part presents the case of a Polish company - the branding and marketing agency Agenza from Gryfice (in the West Pomeranian Voivodship) on the basis of qualitative research. Based on information obtained from in-depth interviews with agency employees, ways of using artificial intelligence in the company's operations are described, as well as the advantages and disadvantages of using this tool. The empirical part additionally uses internal materials provided by Agenza. The study provides a case study, while concluding with conclusions and recommendations regarding the prospects for the use of artificial intelligence in companies carrying out analogous activities to those presented in the article.

2. LITERATURE REVIEW

Branding is a marketing technique that involves creating and shaping a brand image and consolidating that image in the minds of consumers. Branding activities are aimed at creating positive associations among consumers with the brand and the products or services it offers. Today's customers expect specific goods and services not only in terms of the required basic and additional characteristics but also have specific requirements for these products and services in terms of accessibility, their level of quality and when and where they are purchased. Branding is also an important element determining the final choice of the modern consumer.

A brand is a set of distinctive characteristics and attributes that serve to identify a particular product or service in the marketplace and typically include: name, logo, symbol, colour, design or sound. Many definitions of a brand can be found in the literature, which are not entirely consistent with each other. One of the most popular is the definition proposed by P. Kotler in 1994 (Kotler, 1994; Kotler, 2006), which assumes that a brand is a name, symbol, design or a combination there of, used to identify a seller's goods or services, or a group of them, and to distinguish them from their competitors. According to the American Marketing Association, a brand is identified with a name, symbol, design or melody

("What is the brand?", AMA). A brand can therefore encompass various elements, such as a name, logo, colours, sound or advertising slogan, while in a broader sense it can additionally represent a set of associations, emotions and values associated with a particular product or company that influence the process of how both the brand and the company are perceived by customers. If a brand is effective then it defines the company and at the same time communicates the quality and experience, the values espoused and encourages effective promotion. However, despite the differences in defining the brand, it can be said that it represents a kind of communication between the company and its stakeholders.

S. Anholt believes that the brand is a value multiplier and provides the owner with a fundamental competitive advantage. S. Anholt emphasises that a brand "is as good as a deposit in a bank. It can be pledged, it can be bought, it can be sold, it can be invested in, and it can, through proper management, increase its value" (Anholt, 2006, pp. 7–8).

The components of a brand are the verbal part (name) and the non-verbal part (symbol, logo). The verbal part uses words, letter or letter-number combinations. Names are intended to evoke positive associations. Names of cities, countries or regions can also be used, but also names symbolising nature (i.e. names of plants and animals), historical, literary or musical names, etc. (Encyklopedia Zarządzania, 2025). Brand creation is a lengthy process that requires the manufacturer and the retailer to make many complex strategic decisions. Wrong branding decisions can lead to a state where a brand appears in the market and disappears after a short period of time. Achieving successful branding is contingent on proper management. In their efforts and decisions to shape a brand's position in the market, companies focus on a variety of aspects, such as, for example: shaping customer loyalty to the brand, customer perceptions of the brand, awareness of the brand and its associated characteristics, shaping the brand image, customer perceptions of brand quality, customer associations with the brand, shaping brand values (Witek-Hajduk, 2011). A brand contains, on the one hand, elements that describe the product and, on the other hand, indicates additional aspects such as symbols, relationships and relations with customers and the environment, perceptions of brand use or the country of origin of the brand. These elements can influence its image and external perception by regular and potential customers. Thus, the brand becomes a carrier of emotional values for the product, which provides the buyer with functional benefits (Szulce & Janiszewska, 2006).

The branding process can be divided into several stages. The first is to define it through the target group, as well as to define the brand values and its mission. Then begins the very important process of creating an identity – the character that the brand symbolises for the product or service and the company. At this stage, it is important to highlight the characteristics and emotions that customers should associate with the brand. This is followed by the creation of a communication process and the selection of channels to communicate about the brand. In the branding process, the most important role is played by tangible – visual – elements, such as the sign, logo, design, colours, slogans and slogans, décor, repetition of visual elements, etc. (Kocoń, 2008). It can therefore be concluded that the branding process consists of three successive stages (Moroz, 2008; Dolińska-Weryńska, 2015):

1. An analytical stage in which the initial work on the brand is undertaken, the aim of which is to identify internal and external communication conditions. In this stage, as a rule, the company profile is defined, the marketing policy assumptions are made, the product range is planned and, in addition, a market and competition analysis are carried out, distribution possibilities are identified, and the target group is defined. As a result, in the analytical stage, brand building starts with defining the brand, getting closer to the potential audience and developing brand values and its mission.
2. Conceptualisation, in which the brand identity is created, as well as its name and logo. As already mentioned, the identity should indicate the characteristics and emotions attributed to the brand.
3. The implementation stage, in which the brand is implemented in real action. At this stage, ways of presenting it and communication strategies are also developed. At this stage, elements such as the logo, the advertising slogan, the colour scheme, etc., are most often refined and finally take shape.

In the literature, the understanding of brand is constantly changing and evolving. The brand has become a dynamic concept, and its definition is constantly being modified. E. Glińska (2016) distinguished five stages in the evolution of the understanding of a brand and distinguished the stages on the basis of the functions attributed to the brand. In addition, the author points out that the

development of the brand concept is largely due to the expansion and addition of the original meaning of the brand by adding new values to the definition, which result from the functions attributed to the brand. The stages of understanding the concept of brand are (Glińska, 2016):

- the brand as an identifier,
- the brand as a differentiator of the company from the competition while maintaining the identifying function,
- the brand as a provider of added value,
- the brand as a financial value for the company,
- the brand as a tool for building relationships with customers.

Extensive marketing activities make it possible to manage brand value. The brand is treated in modern organisations as their intangible capital, in which lie the greatest opportunities for increasing the value of the company (Doyle, 2003). Among the main reasons for the growing importance of brands in the activities of organisations, M. Hereźniak includes (Hereźniak, 2011):

- the development and proliferation of modern technologies, which offer the possibility of rapidly copying a product, but also have the effect of shortening its life cycle,
- globalisation and integration processes, which intensify communication processes between companies and an ever-widening audience,
- the growing market offer, which influences the desire of companies to differentiate themselves from their competitors,
- the increasing role of information among customers about the market offer in order to reduce purchasing risks,
- the diversification and emergence of new customer needs,
- new trends and behaviours of contemporary consumers, with an emphasis on increasing demands for goods and services and treating consumption as a way of expressing one's identity, personality and lifestyle,
- the growing importance of intangible resources in the global economy as the most unique and hardest to copy assets of organizations.

The activity of a company that is carried out within the framework of brand value management is called branding. Branding, according to the definition proposed in the Encyclopedia of Management (Encyklopedia Zarządzania, 2025a), is identified with a marketing technique that consists in shaping a positive brand image in the perception by buyers and in their awareness, in order to arouse interest in the product, brand associations with it and allows the product to be identified among the products offered by competitors. Creating a positive brand ultimately translates into long-term relationships with customers. Building brand recognition, on the other hand, provides opportunities to shape product features, facilitates the introduction of new products and designs, and allows for continued collaboration with other market players. It can therefore be concluded that through branding, market relationships are created and, at the same time, the values that distinguish the brand are highlighted. In addition, through branding, trust is built in customers, and their loyalty is gained (Kall, 2001; Urbanek, 2002; Kall, Kłeczek & Sagan, 2013; Skrzypek & Pinzaru, 2017; Kotarbiński, 2021).

Building a recognizable brand is nowadays regarded as one of the most effective tools for creating a competitive advantage in the market. A strong brand generates value for both companies and customers (Kaplan, Yurt, Guneri & Kurtulus, 2010). In their marketing activities, companies communicate a set of offered values to customers through the marketing mix and awareness of the brand they represent. Offering customers the values represented by the brand represents a kind of investment that will have a return in the form of translation into the value of customer capital. Customer capital is understood as any relationship with the customer, which is an independent and individual category of capital (Adrianowski, 2013). Effective branding activities allow for the creation of a significant corporate asset, as well as continuously amplifying the impact on customers' purchasing behaviour. However, from the perspective of the modern consumer, thesis a rather large problem arises. Companies need to effectively reach out to the potential buyer with their messages, but it is worth noting that the average customer operates in a jumble of information and has a wide range of product and service choices, which does not make it easy for them to make a decision. Organizations are therefore faced with the challenge of matching the right communication channel with the potential customer (Kotler,

Kartajaya & Setiawan, 2023; Raji et al., 2024). In this study, attention is focused on artificial intelligence, which in modern times can prove to be a source of inspiration for marketing creations, but also a tool to assist companies in the communication process and influence the behaviour of buyers through the brand.

According to the information on the European Parliament website, artificial intelligence is the ability of machines to demonstrate human skills, such as reasoning, learning, planning and creativity. Artificial intelligence enables technical systems to perceive their environment, cope with what they perceive and solve problems, acting towards a specific goal. The computer receives data (already prepared or collected by its sensors, e.g. a camera), processes it, analyses it and reacts ("Sztuczna inteligencja: co to jest i jakie ma zastosowania?", European Parliament).

The term 'artificial intelligence' was first used and defined by J. McCarthy in 1955. According to his considerations, artificial intelligence is a science that encompasses the engineering of the creation of intelligent machines and, in particular, intelligent computer programmes. Artificial intelligence is seen as an 'approach' to solving complex and complicated problems, logical reasoning and inference identical to that which occurs in the brains of humans (McCarthy, 2007). J. McCarthy's approach has met, and continues to meet, with both support and criticism. One contemporary definition of artificial intelligence is proposed by N. J. Nilsson (2014), who assumes that artificial intelligence is an issue that structures and gives direction to methods of designing 'intelligent machines' so that they behave in ways that mimic the intelligence of humans. Another contemporary definition of artificial intelligence can be found in the Encyclopedia Britannica, where J. Copeland points out that artificial intelligence is "the ability of a digital computer or computer-controlled robot to perform tasks normally associated with intelligent beings. The term is often used to refer to the project of developing systems equipped with intellectual processes characteristic of humans, such as the ability to reason, discover meaning, generalize or learn from past experience." ("Artficial intelligence", Britannica).

Within the framework of contemporary theoretical considerations on artificial intelligence, certain coherent and recurring content can be noticed. It should certainly be associated with a computer programme or a machine that is controlled by a computer programme for a specific purpose, while the logic of reasoning and inference of the machine and the programme should coincide with the same functions and processes that occur in human brains. Hence, it is possible to distinguish sub-fields of artificial intelligence in theoretical considerations related to human activities, namely: natural language processing, image recognition, speech recognition, problem solving and inference, and machine learning (Warszycki, 2019).

Searching for information about artificial intelligence, one can find its division into three main categories: artificial narrow intelligence (ANI), general narrow intelligence (AGI) and super intelligence (ASI). Narrow artificial intelligence (ANI) specialises in specific tasks, such as speech recognition or data analysis, and examples of its use are voice assistants, recommendation systems or image processing software. Artificial intelligence in its narrow form (ANI), focuses on performing single tasks in a specific domain. This is the most common type of artificial intelligence used by the average person, and the defining characteristic of ANI is its limited ability to learn and function outside of its assigned field of operation. Unlike more developed forms of artificial intelligence, it cannot adapt to new circumstances or solve problems outside of its specialisation. Today, ANI, in the face of technological developments, is the most common type of artificial intelligence. It facilitates the optimisation of business and personal processes by automating routine tasks and assisting users in decision-making. In this way, it contributes to increasing productivity and saving time in various aspects of life. The second category of artificial intelligence, AGI, is a level of AI that for the time being remains in the realm of theory and is the subject of intensive research. AGI refers to systems capable of thinking and learning like humans. It is intended that this system would be able to think and solve problems independently, just like the human mind. AGI for the moment remains in the vision of the future, as the technology needed to realise it is currently lacking. AGI is intended to have the ability to think and adapt. AGI systems are capable of abstract thinking, planning and problem solving without being programmed for specific tasks in advance. This allows them to theoretically operate effectively across all industries and scientific disciplines. The creation of AGI systems, however, requires the creation of conscious machines with advanced cognitive abilities, which is one of the biggest challenges of modern artificial intelligence science. General artificial intelligence (AGI) has the potential to revolutionise many aspects of our lives with capabilities that match those of humans. The last of the AI categories mentioned is ASI

– super artificial intelligence. ASI surpasses humans in all intellectual aspects. It is a vision of the future in the development of artificial intelligence that has capabilities far beyond currently available systems. Such a system could operate autonomously at a higher level than today's technologies and humans, offering solutions to complex global problems through advanced information processing. The ASI is intended to achieve self-awareness and perform tasks more effectively than humans and is also intended to have the ability to solve problems, make decisions and have an advanced reading of human emotions and experiences. ASI is expected to surpass human intelligence in all areas, including problem-solving and thinking and decision-making processes, is expected to perform tasks faster and more accurately than humans, and is expected to independently generate and offer innovative solutions to complex challenges. With the ability to process massive amounts of data and continuously learn, ASI will self-improve and push current technological boundaries and open the way for the creation of autonomous operating systems with capabilities far beyond today's artificial intelligence standards (Niechciał, 2024).

However, regardless of the direction in which artificial intelligence will develop, it is certainly possible to speak for the time being of many advantages and benefits from its use in relation to various subjects and aspects of everyday life. Among the positive sides of the use of artificial intelligence are ("Sztuczna inteligencja: szanse i zagrożenia", European Parliament 2023):

- benefits to societies, as the widespread use of artificial intelligence in various areas of life gives people, for example, access to safer transport systems, safer cars, cheaper products and services, easier access to information, education and training, better opportunities to enter and perform jobs, and safer job performance,
- benefits for business, because artificial intelligence can enable the development of a new generation of products and services, as well as support environmental activities, increase sales, improve machine maintenance, production efficiency and quality, customer service, and save energy,
- benefits for public services, because the use of artificial intelligence can reduce costs and offer new opportunities for public transport, education, energy and waste management, as well as improve the sustainability of products,
- strengthening democracy, as the use of AI can increase control and prevent disinformation and cyberattacks, as well as objectively analyse data,
- strengthening a country's internal and external protection thanks to artificial intelligence through faster processing of data sets, more precise risk assessment, which would have an impact on crime prevention, anticipation and prevention of terrorist attacks, detection of illegal behaviour and rapid response to it.

However, the use of AI is not completely safe and, despite the indicated advantages from its use, risks are also pointed out. The main risks associated with the use of AI include the following ("Sztuczna inteligencja: szanse i zagrożenia", European Parliament 2023):

1. Underutilization or abuse of artificial intelligence. This threat results, on the one hand, from the fact that not everyone has full trust in artificial intelligence and is unable to fully use its achievements. Another issue seems to be the lack of infrastructure that allows the use of AI. Often, the limitation in the use of artificial intelligence may also result from low investments in digital development, low digital competences of society, or fragmented digital markets. On the other hand, it may turn out that the expenditure incurred on investments in the use of artificial intelligence in the future will prove useless, or that artificial intelligence will be used for tasks and purposes for which it is not suitable.
2. Lack of precisely defined liability for damages related to the use of artificial intelligence.
3. Use of artificial intelligence for activities inconsistent with its intended purpose, e.g. interference with protected data, violation of the right to privacy and data protection, creation of so-called information bubbles, etc.
4. Reduction of jobs through excessive automation and robotization.
5. Disruption of market competition activities, e.g. through excessive information gathering, dissemination of false information.
6. Threats to security through human error (e.g. improper use of weapons).
7. Inequalities in access to information and unfair manipulation of information.

Regardless of the future prospects, as well as the opportunities and threats that may result from the use of artificial intelligence, many of its solutions are currently used in many areas, including marketing

activities (Noble & Mende, 2023). The development and possibilities that artificial intelligence brings have become not only an assumption, but also a common practice supporting the marketing industry. The main AI tools that can be used in marketing are: voice processing technologies, text recognition, image recognition, decision-making, and autonomous vehicles and robots (Jarek, Mazurek & Hałas-Dej 2018).

The use of artificial intelligence in marketing may concern, among others, such aspects as: segmentation of recipients, personalization of content, automation of processes, prediction of trends in consumer market behaviour, or advanced customer service. Target group segmentation is one of the most important elements of activities in building marketing strategies. Defining customers and their needs is the basis for building an advertising campaign. In the face of the huge amount of information in the modern world, the use of artificial intelligence gives amazing effects in building a database of customers and grouping them in terms of selected features (e.g. demographics, preferences, purchase history, etc.), and also allows to detect similarities, differences and trends in their behaviour (Przegalińska & Jemielniak, 2023; Kumar, Ashraf, & Nadeem, 2024). Thanks to personalization processes, marketers are able to match the appropriate content to the expectations and needs of specific groups of recipients. Artificial intelligence supports not only the work on building messages, offers and news for specific people or groups, but also decides whether and what advertising messages will reach customers (Szews, 2024; Gujar, 2024; Rutkowski, 2020). Artificial intelligence can also be used in marketing by automating many activities, such as: sending emails prepared for a selected recipient, managing the time of introducing advertising content into circulation (e.g. in social media, on selected portals and platforms, etc.), as well as analysing the results of views and the effectiveness of advertising campaigns. Thanks to the automation of activities, companies manage their time rationally, and at the same time can increase the effectiveness of their marketing activities (Łapińska, 2019; Rutkowski, 2020). Another aspect of using artificial intelligence in the marketing activities of a company may be its use in building models predicting changes in consumer behaviour, as well as classifying customers in terms of selected characteristics and purchase intentions. customers. Thanks to accurate predictions using artificial intelligence, marketing strategies and offers can be adjusted to current goals and market demand, thus increasing the effectiveness of conducted marketing campaigns (Garbarski & Tkaczyk, 2023). It is also worth adding that due to the fact that consumers increasingly make purchases online, and draw their inspiration from information obtained online, artificial intelligence allows not only to observe such virtual consumer behaviours, but also to build communication channels and service channels tailored to customers. Many offers directed to consumers on the Internet are based on automation, which allows consumers to serve themselves independently, and if necessary, without the participation of a real seller, but using a virtual assistant, to obtain the missing information and make the final choice. All this is possible thanks to advanced technologies and the development of increasingly better algorithms and software (Sira, 2022).

It is undeniable that artificial intelligence has enormous potential in many areas, including marketing. It is a catalyst in the dissemination of information, data sources, improving software data management capabilities and designing complex and advanced algorithms. In addition, AI in marketing is changing the way sellers and manufacturers and customers communicate and interact with each other. Thanks to the use of artificial intelligence tools, people responsible for marketing activities in the company can focus more on the customer and their needs. Thus, companies appreciate the benefits of using AI, because it is easier to determine what and to whom advertising content to send, and on the other hand, the customer who receives a message in accordance with their expectations and needs, feels not only noticed, but also valued and cared for by the company (Haleem, Javaid, Qadri, Singh & Suman, 2022).

However, one should not forget about the limitations and threats resulting from the use of artificial intelligence in business activities, especially in the branding and marketing industry. The issues of weaknesses and disadvantages of using AI will be described later in the article. In the next part of the study, an example of a Polish company – the branding and marketing agency Agenza, which uses artificial intelligence tools in its activities, will be presented.

3. METHODOLOGY

3.1. Participants

Agenza, a branding and marketing agency, is a Polish company operating in the West Pomeranian Voivodship, headquartered in Gryfice. Agenza is a branding studio operating on the market since 2016, which combines creativity in decision-making and project implementation with the knowledge and experience of its employees. Its main scope of activity concerns the provision of comprehensive solutions in the field of visual identification, graphic design and building a strong presence of brands in the digital and offline space. The company specializes in logo design, creating coherent visual identification systems and developing modern websites that are not only aesthetically pleasing, but also meet the highest standards of usability and functionality.

Agenza's activity is based on a holistic approach to branding – each project is preceded by a thorough analysis of the market, competition strategy and the client's business goals. A team of specialists combines knowledge in the field of design, marketing and visual communication to provide solutions tailored to the specifics of a given industry. The company also offers a wide range of photographic services, including product, advertising and corporate photography, which support building a coherent brand image.

One of Agenza's key areas of activity is supporting companies in the process of introducing new brands and products to the market. The company provides advice on branding strategy, market segmentation and building competitive advantage through coherent and engaging visual messages. In this context, Agenza works with clients at the research and development (R&D) stage, helping to identify key product differentiators that can determine its uniqueness and competitive advantage.

Agenza actively supports entrepreneurs in the process of protecting intellectual property, including the registration of trademarks and industrial designs both in the Urząd Patentowy Rzeczypospolitej Polskiej (UPRP, Patent Office of the Republic of Poland) and within the European Union Intellectual Property Office (EUIPO). Thanks to cooperation with experts in the field of intellectual property law, the company helps clients develop unique graphic signs and their effective protection at the national and international level. In this way, companies gain legal certainty in the use of their brand and eliminate the risk of its infringement by competitors.

In addition, Agenza is involved in research and development (R&D) projects that allow for the improvement of branding and marketing strategies based on the latest market trends, consumer psychology and analysis of the effectiveness of visual communication. Working with experts from various fields, the company implements innovative solutions that increase the recognition and market value of created brands.

By combining creativity, marketing knowledge and support in the field of intellectual property, Agenza is a comprehensive partner for companies that want to not only stand out on the market but also protect their identity and innovations on a legal and business level. Working with both small companies and large enterprises, Agenza helps created brands not only stand out from the competition, but also effectively communicate the values and mission assigned to them in the planning assumptions. Thanks to an individual approach to each project and attention to detail, the company has gained the trust of clients from various market sectors. Agenza's mission is to create strong, recognizable and authentic brands that effectively reach their recipients and build long-term relationships with customers.

3.2. Research Protocol and Stimuli

Since 2023, Agenza has been supporting its operations with an artificial intelligence tool in the form of ChatGPT. The branding agency, which covers a wide range of services related to building brand identity, recorded intensive project activity in 2023. In the analysed period, 242 projects of varying scope and scale were implemented, the key element of which was the creation and development of branding. These projects included both the comprehensive implementation of new brands and products on the market, as well as more specialized services, such as logo design, visual identification, building and implementing websites, marketing activities and long-term service as part of a marketing subscription, including running clients' social media.

The analysis of the customer structure indicates significant geographic diversification. The company's location on the western coast of Poland probably had an impact on the fact that 30% of all orders carried out by Agenza were orders from investors in this location. Another 35% of projects were

carried out for clients from other regions of Poland, while the same percentage, i.e. 35%, concerned Agenza's cooperation with foreign companies. In 2023, in relation to the sectors of business activity, domestic clients were dominated by service and hotel companies, constituting 30% of the entities served. In the group of nationwide clients, a significant share was held by brands related to the production of cosmetics and home products, such as candles and bedding, as well as stationary stores moving to online sales, which constituted 35% of the projects carried out. In the foreign segment, cooperation focused on the markets of Belgium, England, Germany, Norway and Denmark. The clients were mainly representatives of the service industry, including accounting, transport and logistics companies, packaging manufacturers, as well as entities providing heating and air conditioning services.

In 2024, there was a decrease in the number of projects implemented in favour of increasing their size and complexity. 30% of cooperation with clients from the coastal region was maintained, but in the domestic segment, a significant trend was the acquisition of large projects covering the identification of cities and comprehensive branding services for foundations and events organized by these institutions. The demand for projects related to mental health and the introduction of health-promoting products to the market, especially ecological and based on hemp extracts, also increased. The share of projects on a Polish scale in Agenza in 2024 was still 35%. As part of cooperation with foreign clients, a 35% share in the project portfolio was maintained, with the dominant areas of activity being e-book publishing, transport and logistics services, and branding of animal supplements.

In summary, the evolution of branding projects in 2023–2024 indicates growing specialization and complexity of activities adapted to changing market needs and the growing importance of pro-ecological values and innovative solutions in building brand identity.

As already mentioned, since 2023, Agenza has been supporting its business activities with an artificial intelligence tool in the form of ChatGPT. In order to examine the real applications of this artificial intelligence tool in these areas, interviews were conducted with specialists in marketing, graphic design, photography, project management and audio-visual production. In-depth interviews were conducted in February 2025 among Agenza employees.

3.3. Analysis of Measurement Data

Below are the results of the qualitative analysis of these interviews, taking into account both the benefits and challenges related to the implementation of artificial intelligence in the daily work of Agenza:

- Application of artificial intelligence in project work - the perspective of the Project Manager

Employee 1 – acting as a Project Manager in project teams with a variable composition, uses artificial intelligence, mainly ChatGPT, to support administrative and office tasks. This tool helps in preparing contracts, powers of attorney, official correspondence and other formal documents. A significant advantage is the ability to perform other duties simultaneously – while AI generates the content of documents, the Project Manager can conduct telephone calls or coordinate the work of teams. Employee 1 notes, however, that despite the significant time savings, each content prepared by AI requires verification and possible correction. ChatGPT therefore acts as a tool that speeds up work, and does not replace decision-making and an analytical approach. In addition, the Project Manager uses AI to organize data and structure it in tables, but the substantive analysis remains his responsibility.

- The role of artificial intelligence in marketing and social media

Employee 2 – a marketing and social media specialist uses ChatGPT mainly as a source of inspiration when planning content. However, he emphasizes that each action in the area of digital marketing must be tailored to a specific client and their target group, which requires a deep knowledge of their needs. The marketing team he works for sees a problem with content generated by artificial intelligence – it is often ‘visible’ in the sense of a specific style, which means that recipients may feel a lack of authentic brand engagement. Therefore, in their approach, AI plays the role of an auxiliary tool, but does not replace the content and strategies created by employed specialists.

- Artificial intelligence in the graphic design process

Employee 3 – the lead designer emphasizes that his conceptual and implementation work remains fully original. Artificial intelligence serves him mainly as support in the research phase and in searching for inspiration and trend analysis. He does not use generative AI to create graphics or designs, but only treats it as a tool enabling access to a wide database of visual references, which speeds up the creative process.

A similar approach is taken by Employee 4 – a photographer, who also takes all the photographs and processes them manually. However, he uses graphic programs equipped with functions supported by artificial intelligence, which automate certain time-consuming aspects of editing, such as improving exposure, retouching or adapting photos to specific formats. He points out that the ability to capture the right moment and composition remains key in photography, which is a human competence unattainable for artificial intelligence.

- Artificial Intelligence in Film Production

Employee 5 – a filmmaker, similarly to Employee 4 in the area of photography, uses AI mainly for supporting processes, such as noise reduction in recordings and improving post-production. His creative process – from recording to editing – remains fully original, and artificial intelligence only automates certain repetitive, tedious activities. He also uses AI capabilities for research, inspiration and analysis of trends in the film industry, but artistic decisions remain in the hands of humans.

4. RESULTS

Based on the interviews conducted, several key aspects related to the use of AI in the branding and marketing industry by Agenza can be identified. The main opportunities for using artificial intelligence in the company's operations are:

- time saving – artificial intelligence speeds up administrative work and some aspects of post-production in photography and film,
- support in research and trend analysis – artificial intelligence enables quick access to a wide database of information,
- data structuring – ChatGPT helps organize information, which is useful, for example, in project summaries,
- automation of tedious tasks – in photo editing and film editing, artificial intelligence supports the performance of repetitive tasks.

Agenza employees also point to the risks resulting from the use of artificial intelligence in their work. These include:

- the need to verify content generated by AI – artificial intelligence does not always generate correct or consistent content, which requires human control,
- lack of authenticity in marketing communication – content generated by AI may seem mechanical and deviate from personalized strategies,
- dependence on technology – excessive reliance on artificial intelligence in creative processes can weaken the originality and individuality of creators.

The analysis of interviews conducted among Agenza employees shows that artificial intelligence is a tool that significantly affects the efficiency of work in the branding and marketing industry. In most cases, it serves a supporting function, not a replacement for human competences. Practitioners use artificial intelligence to automate repetitive processes, inspiration and research, while strategic and creative decisions remain in their hands. Despite the numerous benefits, users also point to the need for critical analysis of the results of AI and maintaining authenticity in marketing and creative activities. Artificial intelligence, used with caution, can provide significant support for specialists, but it does not replace human experience, intuition and creativity, education – humans still remains the key subject of the creative and decision-making process.

5. DISCUSSION

Marketing practitioners unanimously indicate that the use of AI in marketing activities will constantly grow. In marketing trends for 2025, they indicate the following aspects related to the use of artificial intelligence in marketing activities (Trendy marketingowe, 2025)**:**

- AI dominance in creating video marketing content,
- hyper-personalization – the use of artificial intelligence to create extremely precise messages,
- the use of artificial intelligence will increase the role of audio communication,

- personalized versions of artificial intelligence tools for data analysis will be tailored to a specific company,
- changes in search engines and positioning – bypassing traditional search engines in favour of video-based platforms,
- the growing importance of artificial intelligence in e-commerce (e.g. virtual models, employee training conducted by AI),
- more advanced algorithms for automatic adaptation of advertising materials to recipient groups in real time.

The same experts add, however, that despite the growing importance of artificial intelligence, it is human creativity that is key to creating unique and engaging content for customers (Trendy marketingowe, 2025).

As can be see, artificial intelligence is becoming an inseparable element of marketing activities in the future, and the role of tools offered by AI is growing, as indicated by expert opinions.

Referring to the aim of the study, which assumed the assessment of the use of artificial intelligence in branding and marketing activities in the functioning of the Agenza company from Gryfice, it should be noted first of all that it is a tool necessary to conduct such activities today, in order to meet the requirements of at least maintaining, if not increasing the level of competitiveness of the dynamic organization on the marketing market. Agenza, as a company with an established market position, but at the same time developing and innovative in its industry, follows new market trends, including supporting itself with artificial intelligence tools in the execution of orders. Specializing in comprehensive brand and product introduction to the market, it offers comprehensive branding services, website creation and advertising campaign planning, and all proposed solutions are based on market analysis, which effectively responds to the needs of customers and consumers. Due to the huge competition on the market, Agenza operates holistically, offering a range of activities at the same time, such as: branding and logo design, designing, creating and managing a website, designing and systematically conducting marketing campaigns in social media, preparing and distributing advertising photography, and if necessary, effective rebranding, as well as market consultations, marketing research and brand audits, cooperation with influencers, as well as R&D and patent services. As shown in interviews conducted with Agenza employees, artificial intelligence tools are used in all stages and aspects of the company's activity. Employees particularly emphasize the great importance and simplification of work thanks to artificial intelligence in the case of tedious and routine activities, but at the same time they perform the final process of creating a finished product independently, without using it. This confirms the opinions of marketing experts, quoted earlier, who unequivocally claim that artificial intelligence helps, but does not replace ‘ordinary’ human thinking and its creativity in creating unique features of products and services. Artificial intelligence can therefore be an inspiration, an idea for action. However, the ultimately created product and service offered to the buyer, which are to attract the consumer's interest for a longer time, should have ‘human’ features, which is not entirely possible only with the use of tools offered by artificial intelligence.

However, it must be remembered that artificial intelligence has permanently entered everyday life, in all market entities, including companies and households. Operating in the age of the constant development of AI, both manufacturers, sellers and consumers are not able to eliminate the influence of artificial intelligence solutions and tools from their daily decisions, which are partly consciously made based on the use of AI, but some of these decisions are made completely unconsciously. Consumer experiences enriched with AI will provide them with interactive ways of interacting with products and brands, as well as sellers and manufacturers. On the other hand, it can be expected that in the case of companies, AI will lead to improved product personalization, so that in real time, such products will be offered that will fully respond to user preferences. In addition, algorithms based on artificial intelligence improve marketing, providing personalized experiences to potential customers. By analysing user data, artificial intelligence will adapt content, ads and recommendations, creating a more engaging and personalized customer experience.

Experts predict that the near future of AI in marketing, over the next five years, will be shaped by major advances in automation, personalization, and decision-making. The most frequently indicated future actions are (Meliana, 2025):

- the growing importance of AI in automating routine tasks,

- AI will deliver highly personalized customer experiences (e.g. product recommendations, targeted advertising) and increase customer engagement and satisfaction,
- ethical issues will be raised to ensure responsible use of AI, protecting consumer rights and data privacy,
- AI will automate many routine tasks, but will also create new opportunities to act in roles requiring strategic and creative thinking,
- AI will go beyond traditional analytics, deep learning algorithms will be used to predict customer needs, preferences and future behaviour with great accuracy,
- AI tools will generate highly engaging and tailored content in various formats (text, images, videos),
- new AI technologies will ensure greater precision and efficiency of advertising,
- new AI models will be able to understand and interpret human emotions more accurately,
- AI will lead to hyper-personalization,
- increased integration of artificial intelligence (AI) with augmented reality (AR).

6. CONCLUSION

Artificial intelligence is a field that is currently still developing and constantly evolving. The enormous dynamics of this field's development provide many new opportunities for various fields, including marketing. It facilitates everyday work, brings many conveniences and opens up new, practically previously unknown possibilities. In marketing, it is used to explore customer knowledge, create new, more complete and better content, helps in segmenting recipients, product marketing, improving e-mail marketing or advertising.

It should be added, however, that the rapid development of artificial intelligence does not mean the end of marketing, which has so far been implemented by marketers and which was based on their intuition and creativity. The efficiency and effectiveness of using artificial intelligence is visible in proposing content and advertising, or analysing quantitative data on consumer behaviour. It significantly facilitates and speeds up the performance of tasks, which helps save time in companies. However, artificial intelligence does not have the ability to interpret results, creativity, or enter the meanders of the human mind and understand the context of situations. The use of AI in marketing is not a way to replace human work and thinking, but rather a tool supporting the soft skills of employees, such as intuition or empathy. The near future in branding and marketing activities using artificial intelligence therefore means the ability to effectively use modern technologies and the tools they offer by humans, along with their combination with their creativity, ingenuity, intuition and feelings.

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THE IMPACT OF TECHNOLOGICAL INNOVATION AND DIGITAL TRANSFORMATION ON THE FUNCTIONING OF MODERN ENTERPRISES

Małgorzata Tarczyńska-Łuniewska[a], Grațiela-Georgiana Noja[b], Alexandra-Mădălina Țăran[c], Piotr Niemcewicz[d*], Jelena Stankevičienė[e]

[a] *University of Szczecin, Institute of Economy and Finance, Poland,*
[b] *West University of Timisoara, Faculty of Economics and Business Administration, Romania*
[c] *West University of Timisoara, Faculty of Economics and Business Administration, Romania,*
[d] *University of Szczecin, Institute of Management, Poland,*
[e] *Vilnius University, Faculty of Economics and Business Administration, Lithuania*

ABSTRACT

Purpose: *The study aims to assess the impact of technological innovation and digital transformation on enterprise performance and the evolution of their business models.*

Need for the study: *As digitalization and technological advancement reshape business landscapes, companies must innovate to remain competitive and efficient. However, further research is required to assess the effects of these transformations on business performance and models.*

Methodology: *Based on European data from 2017–2024, the analysis combines a literature review with empirical methods – robust regression and network analysis (GGM).*

Findings: *The results indicate that digitization and technological investments significantly improve companies' operational efficiency and financial performance.*

Practical Implications: *Furthermore, digital transformation facilitates the adaptation of business models to changing market conditions, increasing the flexibility and competitiveness of companies.*

Keywords: technological innovation; business investment; business models; digital transformation; performance; econometric modelling

Jel codes: O32; Q55; L25

1. INTRODUCTION

The modern economy is becoming increasingly digital and technological, significantly impacting business models and company performance (Bresciani et al., 2021; Nambisan et al., 2022). Cloud computing, artificial intelligence, the Internet of Things, and big data increase operational efficiency but require adaptation to new management methods (Martinez-Caro et al., 2020; Leão & Silva, 2021).

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Despite a growing body of research, the literature continues to focus mainly on short-term and sectoral analyses, neglecting the broader perspective and long-term effects of digital transformation (Medhioub & Boujelbene, 2024; Chen et al., 2024; Verhoef et al., 2021).

This study fills this gap by analyzing the impact of technological innovation and digitalization on companies' operational and financial performance and the evolution of their business models. It covers companies of different sizes and industries and European regional diversity between 2017 and 2024.

The key research questions concern the impact of digitalization and technological investments on company performance, the relationship between the business environment and business model transformation and identifying key drivers of this change.

Advanced analytical methods were used—Huber's iterative regression and Gaussian graphical models (Pirtea et al., 2021; Canestrino et al., 2024; Strazzullo, 2024; Dahani et al., 2024)—which allowed us to capture complex, nonlinear relationships.

The results confirm the positive impact of digitalization on business performance and the modification of business models towards greater flexibility and adaptability.

2. LITERATURE REVIEW

2.1. Key theories of innovation and digital transformation

The theoretical foundations of innovation research date back to Schumpeter, who was the first to draw attention to the role of internal resources in creating innovation (Croitoru, 2012; Shughart, 2008). Schmookler's alternative model focuses on demand as the driver of innovation (Schmookler, 1976), while Rogers (2019) points to the diffusion process as the final stage of innovation. Factors influencing the adoption of new solutions include the characteristics of the innovation itself, the characteristics of innovators, and the environmental context (Wejnert, 2002). According to the Oslo Manual, innovations should be measurable and assessable (OECD & Eurostat, 2018).

The literature also refers to disruptive innovation, i.e., a new technology or business model that is initially ignored by market leaders but ultimately changes the rules of the game (Christensen et al., 2018). Companies, especially SMEs, often find it challenging to adapt to digital transformation due to limited resources, lack of digital strategies, and low external pressure (Salamaga, 2020; Del Do et al., 2023). Despite the tools available, many companies do not fully exploit the potential of digital technologies, fearing risk and complexity (Pirtea et al., 2014; Roblek et al., 2021).

The digital orientation concept emphasizes treating digital transformation as a strategic direction rather than merely implementing technology. It comprises elements such as openness to digitization, data management, solutions personalization, implementation persistence, and employee engagement (Bouncken et al., 2018; Nadkarni & Prügl, 2021). Successful transformation also requires a change in organizational culture and new digital leadership.

2.2. Business models in the age of digitisation.

Digital transformation is affecting business models, changing entire industries – from music (Spotify) to transportation (Uber) to tourism (Airbnb). Technologies such as artificial intelligence, the Internet of Things, and blockchain enable value creation in new forms and accelerate adaptation to market changes (Zare & Persaud, 2024). Platform and subscription models provide flexibility, scalability, and revenue stability (Lindström et al., 2024; Taipale-Erävala et al., 2021).

Research points to the need to integrate business models with operational processes and the importance of organizational structures that enable rapid decision-making (Lara Machado et al., 2023; Tejano, 2024). A digital strategy based on platform collaboration contributes to co-creating value and adapting the offering to changing customer needs (Qiao & Liu, 2024; Struwe & Slepniov, 2023). Business models are becoming increasingly open, involving users in content creation and innovation (Franke et al., 2013; Massa & Tucci, 2017).

2.3. The impact of technology on business performance.

The impact of innovation on companies' financial results is not always direct – customers or competitors often reap profits. Strategic decisions regarding integrating activities and cooperation with other entities are important here (Teece, 1986). Digital technologies such as artificial intelligence, cloud computing,

and predictive analytics enable process optimization and increased innovation (Lenka et al., 2017; Appio et al., 2021).

However, there is still a lack of long-term analyses of the impact of digital transformation on financial performance and sustainable development (Billi & Bernardo, 2025). Research on enterprises' cultural and structural context is also insufficient (Nadkarni & Prügl, 2021). In developing countries, the impact of digitalization on economic development and the implementation of green technologies is significant (Sharma et al., 2024; Baffour Gyau et al., 2025).

The digital transformation is also affecting global patterns of value creation, especially in energy-intensive industries such as photovoltaics (Yongzhang, 2025). The importance of data-driven strategies, the development of platform ecosystems, and flexible business models is emphasized (Fogoroș et al., 2020).

3. DATA AND METHODOLOGY

3.1. Dataset and Indicators: Technological Innovation and Firm Performance in the EU-27

This study uses a panel data set from the European Innovation Scoreboard (EIS) covering 27 EU Member States from 2017 to 2024. The data set includes trends in innovation, digitization, and business performance, collected from various national and sectoral sources. The indicators are grouped into five dimensions to assess the multidimensional impact of technological innovation on the performance of enterprises in different industries and sizes in the EU context, thereby increasing the generalizability of the results.

The analysis covers the following variables:

1. Business performance: business investment (FIRM_INV), employment in innovative firms (EMPL_INNOV_FIRM), impact on sales (SALES_IMP), sales of innovations new to the market (SALES_NEW_MKT), resource efficiency (RES_PROD).
2. Digitization: overall level of digitization (DIGITAL), broadband penetration (BROAD), percentage of people with digital skills above a basic level (DIGITAL_SKILLS), ICT usage (USE_ICT).
3. Technology: share of medium- and high-tech exports (EXP_HT_PROD), development of environmental technologies (ENV_TECH).
4. Innovation: PCT patent applications (PCT_PATENT), innovation index (INNOV_INDEX), percentage of innovators (INNOVATORS), innovation expenditure per employee (INNOV_EXP), business expenditure on research and development as a percentage of GDP (RD_EXP_B).
5. Environmental sustainability: overall environmental sustainability indicator (ENVIRON_SUST).

This structure provides a solid basis for analyzing the links between digital transformation, innovation capacity, and business performance in the European Union.

Selected descriptive statistics were chosen to understand the structure of the analyzed phenomenon. The indicators examined are characterized by high variability, which manifests in high standard deviations from arithmetic means. Indicators related to digitization, innovation, and financial performance of enterprises show significant diversity, indicating a varying degree of adaptation of enterprises to the digital transformation. The scale of differences in indicator levels (min-max) and the analysis of distribution asymmetry indicate varying progress in technology, innovation, and operational efficiency. However, most enterprises are in the implementation phase, suggesting uneven development of digitization and innovation.

In addition, we used graphical representation and data mapping methods to rank the EU Member States and map the level of selected indicators representative of the dimensions we analyzed, using a colour background method at the EU level with STATA 18, which converts numerical data into interactive maps with regional breakdowns.

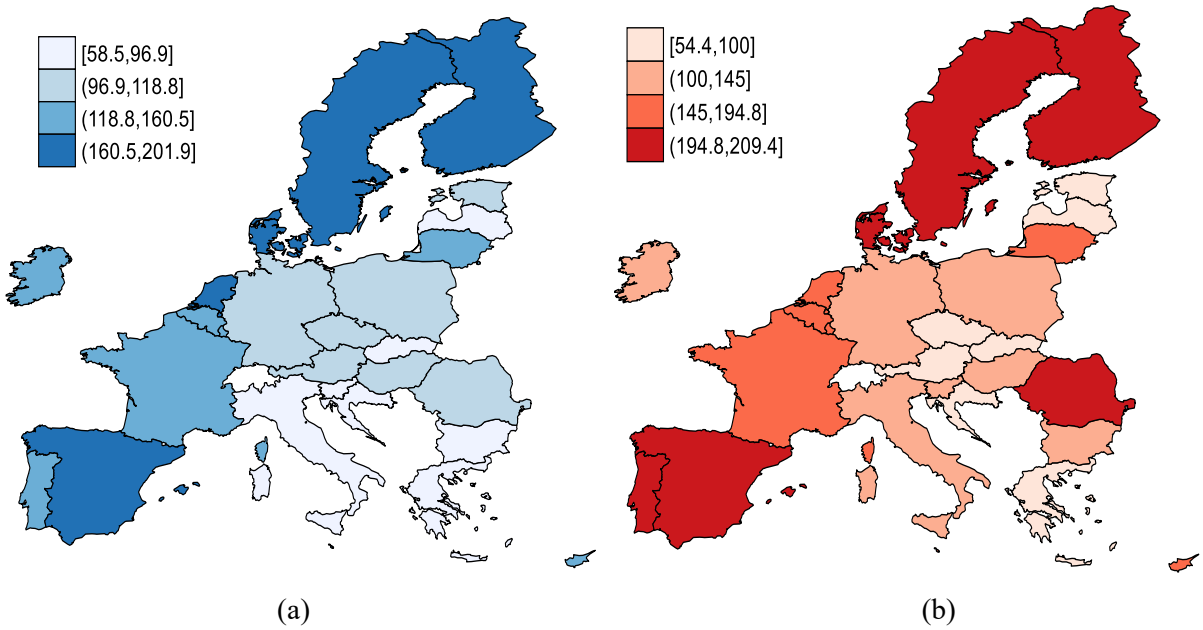


Figure 1. (a) Digitalization dimension and (b) Broadband penetration, respectively
Source: authors' research in Stata 18.

The results of the analysis of selected digitization indicators in EU countries in 2024 are presented in Figure 1. In terms of digitization, the highest level of digital technology development in 2024 was recorded in the Scandinavian countries (Sweden, Finland, Denmark), as well as in the Netherlands and Spain. Finland, Sweden, Denmark, Portugal, Spain, and Romania recorded the highest broadband penetration rates. The percentage of people with digital skills above the basic level is highest in Finland, Denmark, the Netherlands, Ireland, and Spain, and lower in Germany. Regarding information technology use, Germany, Sweden, Finland, Denmark, the Netherlands, and Belgium stand out.

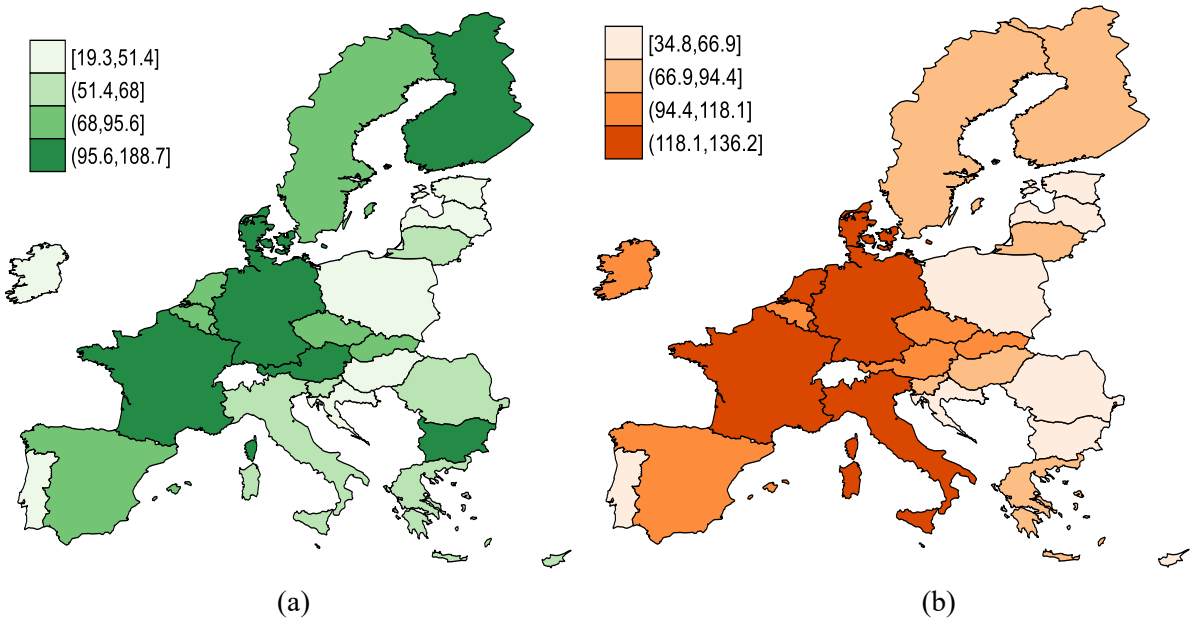


Figure 2. (a) Environment-related technologies and (b) Environmental sustainability at the EU-27 level, 2024
Source: authors' research in Stata 18.

In the EU, Finland, Germany, France, Austria, and Bulgaria will have the highest level of environmental protection technology in 2024. Italy, France, Germany, Belgium, Malta, and Denmark have achieved the highest environmental sustainability (environ_sust) and reduced their negative environmental impact.

There are significant differences between EU-27 countries in terms of digitization, the use of information technology in businesses, and environmental technologies. Only a few countries show a high level of implementation in these areas. In terms of business performance, innovation implementation, and investment, there are signs of ongoing adjustment processes, but there is no significant increase in intensity over time. These processes are relatively stable in some countries, such as France, Romania, and Slovakia. However, from an overall perspective, a positive change in direction is visible.

An important stage of the study in achieving the set goal was the analysis of the relationships between indicators describing digital technologies, innovation, financial indicators of enterprises, and the business environment. In this regard, correlation indicators were used in the study. The results indicate generally positive relationships between these indicators. In particular, some of them, such as investment in innovation and expenditure on research and development, show a robust correlation, suggesting that these areas are closely linked. Although the correlations are less intense, other indicators also point to a positive impact of digital transformation and innovation on companies' financial performance. The correlation results suggest that digitization and innovation processes positively impact companies, although these relationships may vary across sectors and countries.

3.2. Methodology.

Two advanced econometric techniques were used to analyze the impact of technological innovation and digitization on investments and business performance in sustainable development: robust regression models (RREG) and network analysis based on Gaussian graphical models (GGM). Econometric modelling was performed using STATA18 software.

In the first stage, robust regression was used to ensure reliable estimates of coefficients in the presence of outliers. Robust regression allows for the estimation of stable results by reducing the influence of extreme values using Huber weights and iterations.

The robust regression models are presented in the following form:

Model 1 (FIRM_INV): $FIRM\_INV = \alpha_0 + \alpha_1 DIGITAL + \alpha_2 BROAD + \alpha_3 INNOVATORS + \alpha_4 INNOV\_EXP + \alpha_5 PCT\_PATENT + \alpha_6 EXP\_HT\_PROD + \alpha_7 ENV\_TECH + \alpha_8 DIGITAL\_SKILLS + \alpha_9 ENVIRON\_SUST + \alpha_{10} EMPL\_INNOV\_FIRM + \alpha_{11} USE\_ICT + \alpha_{12} RD\_EXP\_B + \theta_i + \varepsilon$ (1)

Model 2 (SALES_IMP): $SALES\_IMP = \alpha_0 + \alpha_1 DIGITAL + \alpha_2 BROAD + \alpha_3 INNOVATORS + \alpha_4 INNOV\_EXP + \alpha_5 PCT\_PATENT + \alpha_6 EXP\_HT\_PROD + \alpha_7 ENV\_TECH + \alpha_8 DIGITAL\_SKILLS + \alpha_9 ENVIRON\_SUST + \alpha_{10} EMPL\_INNOV\_FIRM + \alpha_{11} USE\_ICT + \alpha_{12} RD\_EXP\_B + \theta_i + \varepsilon$ (2)

Model 3 (RES_PROD): $RES\_PROD = \alpha_0 + \alpha_1 DIGITAL + \alpha_2 BROAD + \alpha_3 INNOVATORS + \alpha_4 INNOV\_EXP + \alpha_5 PCT\_PATENT + \alpha_6 EXP\_HT\_PROD + \alpha_7 ENV\_TECH + \alpha_8 DIGITAL\_SKILLS + \alpha_9 ENVIRON\_SUST + \alpha_{10} EMPL\_INNOV\_FIRM + \alpha_{11} USE\_ICT + \alpha_{12} RD\_EXP\_B + \theta_i + \varepsilon$ (3)

Model 4 (SALES_NEW_MKT): $SALES\_NEW\_MKT = \alpha_0 + \alpha_1 DIGITAL + \alpha_2 BROAD + \alpha_3 INNOVATORS + \alpha_4 INNOV\_EXP + \alpha_5 PCT\_PATENT + \alpha_6 EXP\_HT\_PROD + \alpha_7 ENV\_TECH + \alpha_8 DIGITAL\_SKILLS + \alpha_9 ENVIRON\_SUST + \alpha_{10} EMPL\_INNOV\_FIRM + \alpha_{11} USE\_ICT + \alpha_{12} RD\_EXP\_B + \theta_i + \varepsilon$ (4)

In the next stage, quantile regression allowed variables to impact different points of the dependent variable distribution (e.g., the 25th, 50th, 75th, and 90th percentiles). This allows for capturing the heterogeneity and asymmetry of the data and the impact on the performance of companies in different groups, from those performing below average to those achieving the highest results.

To obtain more accurate results and understand the relationships between variables, Gaussian graph (GGM) models were also used, which allow for the modelling of conditional relationships between variables. GGM models enable the study of direct and indirect effects between variables, minimizing the risk of false correlations and supporting inference in multidimensional environments. GGMs generate a graph in which nodes represent variables, and the edges reflect their relationships. The thickness and colour of the edges indicate the strength of these links, allowing for a better understanding of the complex interactions between variables related to digitalization, innovation, and sustainable development.

All these econometric techniques support a comprehensive assessment of the impact of technological innovation and digitalization on business performance in the context of sustainable development. They enable both general conclusions and a detailed analysis of the distribution of these effects across different groups of companies.

4. RESULTS AND DISCUSSION

4.1. Results of the Robust Regression (RREG) models.

Table 1 presents the results obtained using the robust regression (RREG) technique. These estimates provide robust and consistent estimates for four econometric models (Models 1, 2, 3, and 4) with many important implications.

Table 1. Results of the robust regression models with Huber and biweight iterations

	(1)	(2)	(3)	(4)
	FIRM_INV	**SALES_IMP**	**RES_PROD**	**SALES_NEW_MKT**
DIGITAL	–9.971	–13.19	2.456	–93.91***
	(7.999)	(9.717)	(15.90)	(27.76)
BROAD	4.889	6.543	–1.307	46.64***
	(3.986)	(4.842)	(7.924)	(13.84)
INNOVATORS	0.00194	0.0328	–0.0678	0.121
	(0.0200)	(0.0243)	(0.0397)	(0.0693)
INNOV_EXP	0.521***	0.260***	–0.0498	0.579***
	(0.0241)	(0.0292)	(0.0478)	(0.0835)
PCT_PATENT	–0.172***	0.0618	0.297**	–0.615***
	(0.0481)	(0.0584)	(0.0957)	(0.167)
EXP_HT_PROD	0.0908*	0.478***	–0.816***	0.358**
	(0.0363)	(0.0441)	(0.0721)	(0.126)
ENV_TECH	0.110***	–0.0737**	–1.252***	–0.0760
	(0.0200)	(0.0242)	(0.0397)	(0.0692)
DIGITAL_SKILLS	5.032	6.641	–1.451	47.46***
	(4.016)	(4.878)	(7.983)	(13.94)
ENVIRON_SUST	–0.173***	0.0155	3.279***	–0.113
	(0.0361)	(0.0438)	(0.0717)	(0.125)
EMPL_INNOV_FIRM	0.0645**	–0.0116	–0.139**	0.0877
	(0.0243)	(0.0296)	(0.0484)	(0.0845)
USE_ICT	–0.0151	0.0803*	0.0381	–0.196*
	(0.0261)	(0.0317)	(0.0519)	(0.0907)
RD_EXP_B	0.276***	–0.206***	–0.104	–0.0611
	(0.0320)	(0.0389)	(0.0637)	(0.111)
_cons	30.92***	27.08***	8.000	56.76***
	(3.780)	(4.591)	(7.514)	(13.12)
N	216	216	216	216
R^2	0.944	0.741	0.945	0.438

Note: „Standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$"

Source: authors' research in Stata 18.

Model 1 (FIRM_INV – business investment) indicates that the most favourable impact on business investment is exerted by expenditure on innovation per employee, development of environmental

technologies (ENV_TECH), and expenditure on research and development in the business sector (RD_EXP_B). Investments in environmental technologies and research and development stimulate innovation processes and improve the efficiency and competitiveness of enterprises, supporting long-term growth and sustainable development. At the same time, patent applications (PCT_PATENT) and issues related to sustainable development (ENVIRON_SUST) harm business investment.

Model 2 (SALES_IMP – impact of sales) shows that expenditure on innovation per employee (INNOV_EXP) and exports of medium- and high-tech products (EXP_HT_PROD) have a positive impact on a company's financial results. Investments in innovation and advanced technologies increase the ability of companies to compete in international markets, which translates into increased sales. In turn, developing environmental technologies and expenditure on research and development harm the sales of innovative products.

Model 3 (RES_PROD—Resource efficiency) indicates that sustainable development (ENVIRON_SUST) and patent applications (PCT_PATENT) have a positive impact on resource efficiency, increasing companies' competitiveness and improving process efficiency. On the other hand, exports of medium—and high-tech products and environmental innovations harm resource efficiency.

Model 4 (SALES_NEW_MKT – Sales of new products on the market) shows that digitization and exports of medium- and high-tech products positively impact sales of innovative products. On the other hand, R&D expenditure per employee harms sales of new products.

The results indicate that innovation expenditure, environmental technology development, and high-tech exports are crucial for firm performance, although different variables affect different aspects of economic activity. Despite its importance, digitization shows mixed effects, especially in the context of new product market entry.

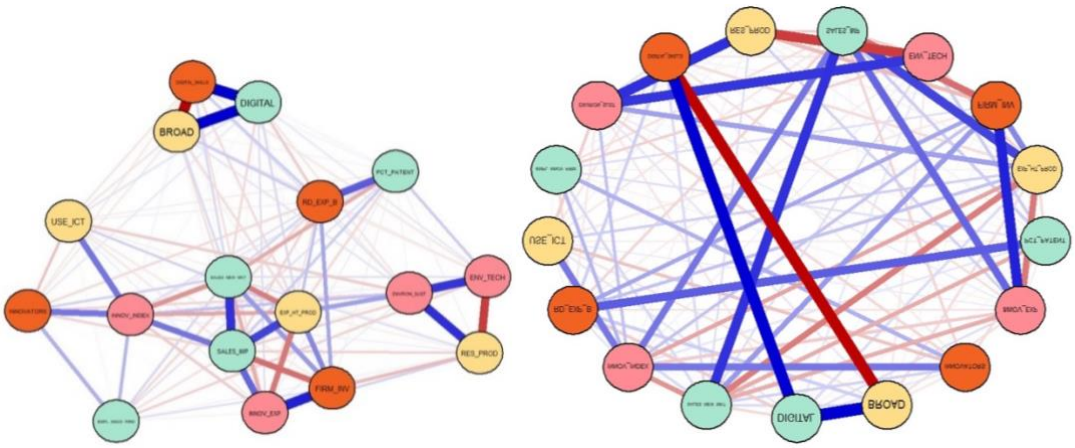
Analyses using quantile regression models were also conducted to ensure the accuracy of robust regression estimates (RREG). The results indicate that innovation expenditure (INNOV_EXP) and research and development expenditure (RD_EXP_B) have a stable positive impact on business investment (FIRM_INV) and sales of new products (SALES_NEW_MKT) across different quantiles. In contrast, patent applications (PCT_PATENT) and sustainable development (ENVIRON_SUST) have a more differentiated impact. Digital skills (DIGITAL_SKILLS) positively impact sales in higher quantiles, while sustainable development positively impacts research and development in lower quantiles.

The results highlight that innovation and digitalization improve business performance and carry risks, such as cybersecurity threats and labour market restructuring. Some variables, such as patent applications and sustainable development, may negatively impact investment, indicating the need for a strategic balance between investment and risk management.

4.2. Results of the Gaussian Graphical Models (GGMs).

An analysis was conducted using Gaussian graphical models (GGM) for EU member states in 2017–2024, applying the extended Bayesian information criterion (EBICglasso) and partial correlation (PCOR). The results of the graphical presentation of these models are shown in Figures 3a and 3b.

The models reveal strong positive correlations between business investment (FIRM_INV), digitization (DIGITAL), and innovation (INNOV_INDEX). These investments are crucial for realizing the potential of digitization and innovation. In addition, significant links were found between innovation expenditure (INNOV_EXP), research and development (RD_EXP_B), and sustainable development (ENV_SUST), highlighting the importance of green technologies in achieving sustainable development goals. Negative relationships have also been identified, suggesting that investments in fundamental innovation may conflict with environmental technologies, pointing to the need for a strategic approach to resource allocation.



(a) (b)

Figure 3. Gaussian Graphical Models (GGMs) estimated through (a) Extended Bayesian Information Criterion (EBICglasso) and (b) partial correlation (PCOR)
Source: author's research in RStudio.

5. CONCLUSION

The study analyzed the impact of technological innovation and digital transformation on business performance, focusing on the EU-27 countries between 2017 and 2024. It integrated technological innovation, digital transformation, and business performance using robust econometric models such as Huber's iterative regression and Gaussian graphical models. Key findings indicate that digital transformation and technological innovation positively impact business performance, although there are differences between countries. The analysis highlights the need to tailor policies to these differences, especially between companies of different sizes and sectors. Implementing integrated analytics to automate processes is recommended for large industrial companies, while the service sector should focus on digital customer service channels and AI-based service personalization. SMEs should prioritize the development of digital skills and seek technology support programs.

Despite the challenges, especially for SMEs facing resource constraints, the overall direction of digital transformation is positive. The study highlights the importance of flexible strategic management structures and the need for sector-specific support, especially for SMEs. The study results also reveal significant differences between companies (and the countries analyzed) regarding digital technology adoption, innovation, and financial performance. In addition, many companies are still in the process of transformation in this area.

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28th European Conference on Artificial Intelligence (ECAI 2025)

THE ROLE OF ARTIFICIAL INTELLIGENCE AND ICT IN VETERINARY BUSINESS: A LITERATURE REVIEW

Karolina Beyer[a], Edyta Skarzyńska[b], Kesra Nermend[c]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *Warsaw University of Life Sciences, Management Institute, Warsaw, Poland*
[c] *Maritime University of Szczecin, Szczecin, Poland*

ABSTRACT

Purpose: *The integration of artificial intelligence (AI) and ICT technologies in veterinary units offers new opportunities for diagnostics, remote monitoring, and practice management. The aim of this article is to conduct a systematic literature review to analyze the applications, challenges, and future prospects of artificial intelligence (AI) and information and communication technologies (ICT) in veterinary industry Ipsum is simply dummy text of the printing and typesetting industry.*

Need for the study: *Despite AI's growing role in veterinary care, challenges such as algorithmic bias, regulatory concerns, and limited research on long-term impacts persist. Additionally, the adoption of AI in practice management remains underexplored, despite its potential to improve efficiency, automate workflows, and optimize resource allocation. A systematic review of existing literature is necessary to address these gaps.*

Methodology: *This study conducts a systematic literature review of AI applications in veterinary medicine using Scopus, Web of Science, and Google Scholar. The analysis explores key themes, including diagnostics, telemedicine, data management, business efficiency, and regulatory challenges.*

Findings: *AI enhances diagnostic accuracy, workflow automation, and predictive analytics, improving clinical decision-making and patient outcomes. In veterinary practice management, AI-driven automation optimizes scheduling, inventory control, and client communication. However, barriers such as technological resistance and regulatory uncertainty hinder widespread adoption. Emerging trends include interdisciplinary collaboration, blockchain for data security, and AI training in veterinary curricula.*

Practical Implications: *AI adoption can transform veterinary practice management by enhancing efficiency, reducing administrative burdens, and improving profitability. Future research should explore long-term impacts, standardization, and client acceptance to ensure responsible and effective AI implementation in veterinary medicine. By addressing these challenges, AI and digital technologies can significantly advance both veterinary care and practice management, leading to improved patient outcomes and business performance.*

Keywords: AI in Veterinary medicine; Digital Transformation; Veterinary Business; Veterinary Management; Artificial Intelligence; ICT in Veterinary Practice

Jel codes: M10; M15; O33

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1. INTRODUCTION

In today's rapidly evolving technological landscape, the emergence of new ICT tools, including artificial intelligence (AI), and the growing socio-economic demands create new challenges for businesses. The success of modern enterprises increasingly depends on the implementation of innovative solutions. Gaining a competitive advantage has become both a crucial and challenging task, and AI, along with cutting-edge technological advancements, offers businesses new opportunities for growth and efficiency improvements. Veterinary clinics also have the potential to benefit from these modern solutions—not only in terms of medical imaging and high-quality healthcare services but also in the modernization of business processes.

Artificial Intelligence (AI) has become ubiquitous, impacting various sectors of society and raising significant ethical and societal implications. The emergence of AI technology has led to a wide-ranging influence on industry, society, and sustainable development (Tomczyk et al., 2024; Dwivedi et al., 2021; Vinuesa et al., 2020). As AI research progresses, there is a consensus that its impact on society will likely increase, necessitating the validation and verification of AI behavior to overcome potential hazards (Bandi et al., 2023; Sovrano et al., 2022, Tomczyk et al., 2024).

The need for the introduction of AI and ICT solutions has been confirmed by research conducted among veterinary clinic clients in Poland (Beyer, 2023a). One of the key findings indicated that implementing technological innovations and understanding customer expectations are crucial for the success of veterinary practices and should be a priority for clinic owners. Innovations are key for veterinary practices to meet the growing expectations of customers and adapt to the dynamically changing market. The implementation of modern technologies, such as telemedicine and information management systems, can significantly improve the quality of services provided by veterinary clinics.

The level of satisfaction among pet owners with veterinary services varies. Many individuals using the services of smaller practices express reasonable concerns about the quality of service, which serves as an indicator for clinics regarding areas that need improvement. Additionally, many pet owners prefer digital interactions with clinics, such as the ability to schedule appointments online and access e-prescriptions. Implementing such solutions can increase the efficiency of managing veterinary practices and enhance relationships with clients (Beyer, 2023a).

There are several barriers faced by veterinary clinics that want to implement innovations. These include limited financial resources, employee resistance to change, and a lack of knowledge about modern technologies. Veterinary clinics should adopt a data-driven approach to effectively manage health information about animals and make better clinical decisions (Beyer, 2023b).

Furthermore, the growing demand for veterinary diagnostic imaging has created a need for advanced tools, such as AI, to assist general practitioners in analyzing medical images and improving diagnostic accuracy (Burti et al., 2024). Beyond veterinary applications, AI has also become an essential tool in public health, where it is widely used for disease diagnosis, risk assessment, outbreak prediction, and the development of health policies and strategic planning (Guitian et al., 2023). By enabling the rapid processing and interpretation of large volumes of medical data, AI enhances both the speed and precision of diagnostics, allowing veterinarians to make more informed clinical decisions and optimize treatment strategies. In addition to improving efficiency, AI-driven technologies contribute to the early detection of diseases, facilitating timely interventions that can significantly improve patient outcomes. The integration of AI into various aspects of veterinary practice, including imaging, predictive analytics, and treatment planning, is paving the way for more personalized and data-driven approaches to animal healthcare. As research and technological advancements continue to evolve, AI is expected to play an increasingly central role in transforming veterinary medicine by enhancing diagnostic capabilities, streamlining workflows, and ultimately improving the quality of care provided to animals (Sharun et al., 2024).

Modern IT solutions enhance veterinary services and research, focusing on process automation, big data processing, management efficiency, and cybersecurity (Dyndyn, 2024). The application of artificial intelligence has significantly transformed various industries, including healthcare, playing a crucial role in enhancing clinical examination, diagnosis, and treatment for both humans and animals. The integration of AI in veterinary medicine has opened doors to accurate and efficient care, benefiting both animals and their owners. AI-powered sensors and devices can monitor vital signs and behaviors of animals in real-time, allowing early detection of potential health issues (Basima et al. 2024).

Due to the immense potential of AI in the veterinary industry, we propose the following research questions:

1. What are the key areas of application for artificial intelligence and new technologies in veterinary medicine?
2. What are the main challenges and limitations associated with the implementation of digital technologies in veterinary practice?
3. What trends dominate the scientific literature on the use of AI in veterinary medicine?
4. Are there research gaps in the field of digitalization and innovation in the veterinary sector?

The aim of this article is to conduct a systematic literature review to analyze the applications, challenges, and future prospects of artificial intelligence (AI) and information and communication technologies (ICT) in veterinary industry.

To achieve the aim of this article and answer the research questions, a systematic literature review was conducted, using the Scopus, Web of Science (WoS), and Google Scholar databases to identify relevant and up-to-date publications on AI and ICT technologies used in veterinary practices.

2. METHODOLOGY

2.1. Research questions

To answer the research questions posed in this paper, we designed an original testing procedure. In the first step, we selected three databases for analysis: Scopus, Web of Science (WoS), and Google Scholar. These databases are among the most prominent search engines and metadata repositories for academic publications.

For the selection of relevant literature, in the second step, we formulated ten questions that served as key search terms:

1. What are the main applications of artificial intelligence and ICT technologies in veterinary medicine?
2. How can AI and ICT improve the diagnosis of animal diseases?
3. What are the biggest challenges in implementing AI in veterinary practice?
4. Which AI technologies are currently the most used in the diagnosis and treatment of animals?
5. How does artificial intelligence impact the efficiency and precision of treatment in veterinary medicine?
6. What are the potential risks and limitations associated with the use of AI in veterinary practices?
7. What benefits does digital transformation bring to veterinarians and pet owners?
8. How can smart technologies support real-time animal health monitoring?
9. What are the prospects for AI and ICT development in veterinary medicine over the next ten years?
10. What ethical and legal aspects should be considered when implementing artificial intelligence in veterinary medicine?

In the third step, we conducted a literature search based on these ten AI-focused themes. The authors reviewed each article for accuracy, quality, uniqueness, and qualified uniqueness. Accuracy was assessed by analyzing the titles and abstracts to determine whether the article was relevant to the research questions. Uniqueness was evaluated by checking whether an article retrieved from one database also appeared in the search results of another. Qualified uniqueness was determined by verifying whether a high-quality article found in one database was absent from the results of another.

2.2. The Process of Literature Selection in the Systematic Review

Artificial intelligence is transforming various aspects of life, including medical practice, with an exponential increase in AI-related publications in medicine over the last two decades. Veterinarians will play a crucial role in ensuring the appropriate use of AI and data curation, as their expertise is essential for maintaining high-quality data that meets the profession's needs.

To conduct a systematic literature review, an extensive search for scientific publications was carried out in three key databases: Scopus, Web of Science, and Google Scholar. The analysis included both peer-reviewed articles and other relevant sources that could provide valuable insights into the

application of artificial intelligence (AI) and information and communication technologies (ICT) in veterinary medicine and veterinary business management. As a result of this process, an initial set of 87 publications in Scopus, 64 in Web of Science, and 134 in Google Scholar was identified, forming a broad pool of potential sources.

To enhance the comprehensiveness of the review, additional sources were examined. The bibliographies of previously selected articles were reviewed, leading to the identification of 11 additional potentially valuable publications. Furthermore, the tables of contents of key industry journals were scanned, resulting in 9 additional relevant sources. This approach ensured that the review covered the broadest possible range of available studies, including both indexed sources in well-established databases and those that might have been overlooked by conventional search methods.

After collecting all available publications, duplicate removal was performed. Since some sources appeared multiple times across different databases, the final number of unique sources was 123 articles after eliminating redundancies. The next step involved analyzing the titles and abstracts to assess their relevance to the research questions. At this stage, 75 publications were excluded, as their topics deviated from the core focus of the review or did not provide sufficient scientific value.

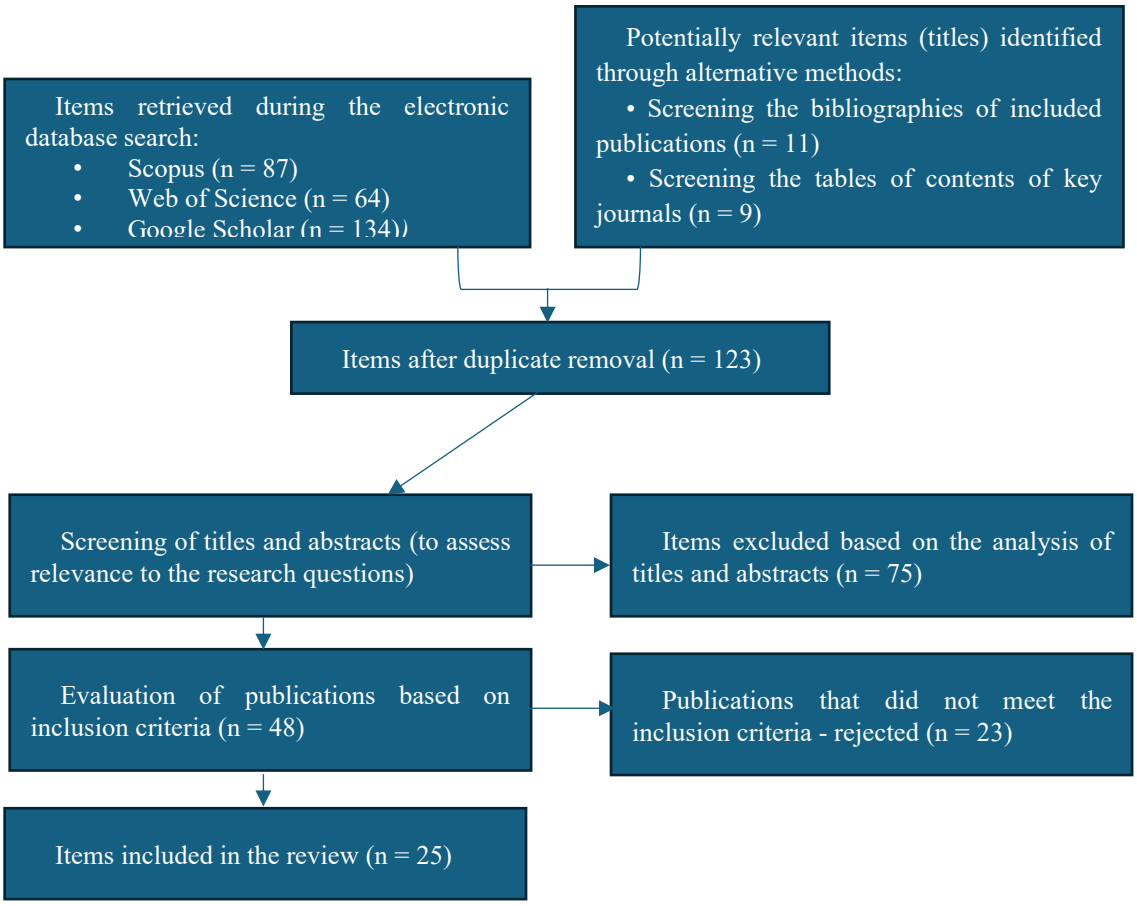


Figure 1. Flow diagram of searched and selected literature
Source: own elaboration (using the methodology of Mazur and Orłowska, 2018).

In the next phase, a thorough evaluation of the remaining 48 articles was conducted to determine whether they met the inclusion criteria. The primary factors considered included the relevance of the content to AI and ICT in veterinary management, the research methodology, and the significance of the findings for further exploration of the topic. Based on this analysis, 23 publications were rejected, as

they either failed to meet methodological or substantive requirements or did not directly address the business-oriented application of emerging technologies in veterinary medicine.

Ultimately, 25 publications were included in the systematic review, as they best addressed the research questions and provided valuable insights into the role of AI and ICT in veterinary practice management. The literature selection process was illustrated through a flowchart that visualizes the sequential steps of searching, eliminating, and finalizing the selection of sources (Figure 1). By applying a rigorous selection process, the most relevant publications were obtained, forming a solid foundation for further analysis and conclusions regarding the impact of new technologies on the development and efficiency of veterinary business management.

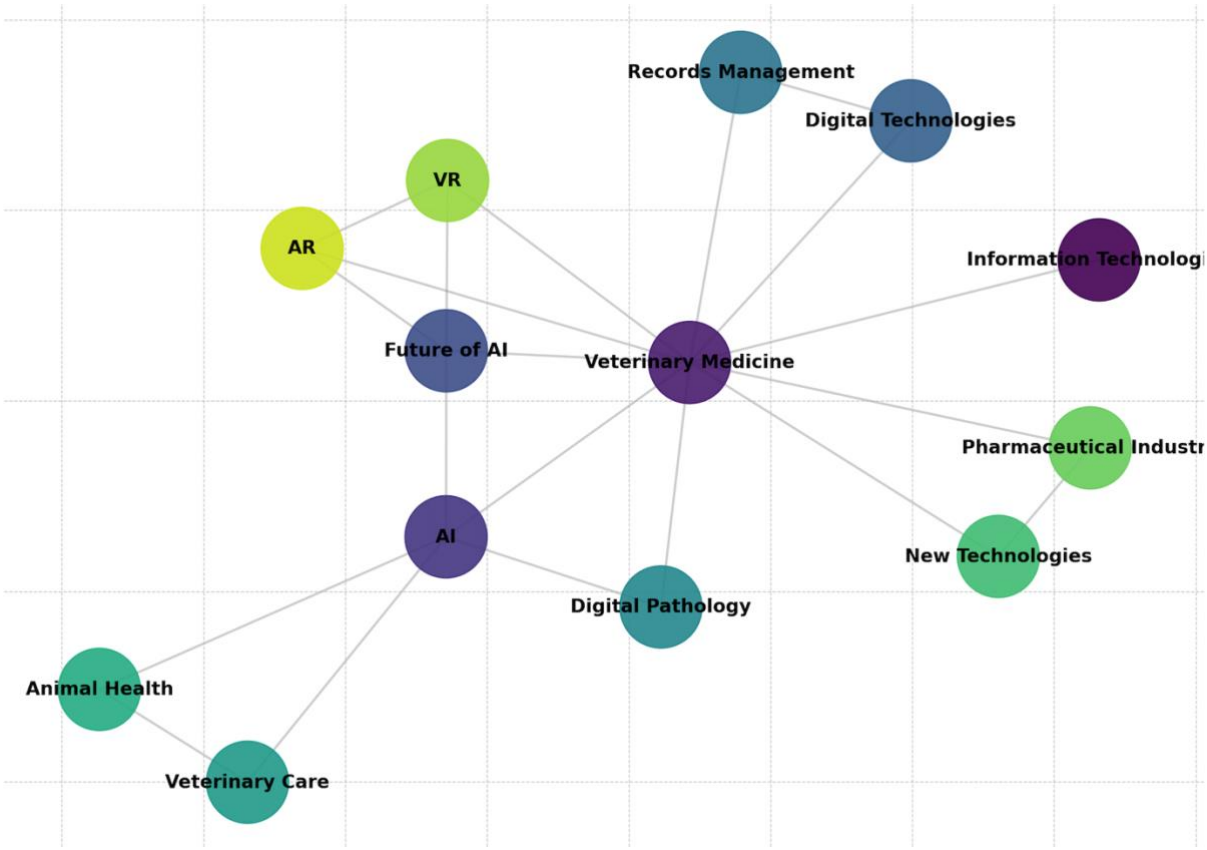


Figure 2. Most related categories
Source: own elaboration.

The Figure 2 presents a network map of key technological and thematic areas related to veterinary medicine. The central node, 'Veterinary Medicine' connects to various emerging technologies and domains, illustrating their relevance to the field.

Artificial Intelligence and its subcategories, such as 'Future of AI' and 'Digital Pathology', highlight the growing role of machine learning and automation in diagnostics and treatment. Augmented Reality (AR) and Virtual Reality (VR) are linked to veterinary advancements, suggesting their potential use in training and medical procedures.

Additionally, the diagram emphasizes the importance of 'Digital Technologies', 'Records Management', and 'Information Technology' in modernizing veterinary practices. The inclusion of 'Animal Health', 'Veterinary Care' and 'Pharmaceutical Industry' further illustrates the integration of innovation into animal healthcare.

This visualization underscores the interdisciplinary nature of veterinary medicine and its intersection with technological progress.

Based on the systematic literature review, selected texts were analyzed in relation to the four research questions outlined in the introduction. The results of the inductive-deductive analysis of the literature are presented in the following sections of the article.

3. RESULTS AND DISCUSSION

The integration of artificial intelligence and emerging technologies in veterinary medicine has led to significant advancements across various domains. Based on the analysis of multiple studies, four key areas have been identified, corresponding to the research questions outlined in the introduction of this article: (1) major applications of AI and digital technologies in veterinary practice; (2) challenges and limitations associated with their implementation; (3) prevailing trends in scientific literature, and (4) research gaps that require further exploration.

3.1. Major applications of AI and digital technologies in veterinary practice

The application of AI and new technologies in veterinary medicine is expanding rapidly, bringing significant advancements across various domains. One of the most notable areas is diagnostics and imaging, where AI-powered methodologies, particularly deep learning algorithms and convolutional neural networks, have demonstrated high efficacy in analyzing medical images. These technologies assist veterinarians in diagnosing conditions across various anatomical systems, including the musculoskeletal, nervous, and abdominal regions (Basran, Appleby, 2022; Sharun et al., 2024; Arfat, et al. 2024; Min, 2023; Pereira, et al., 2023). By enhancing both accuracy and efficiency, AI-driven diagnostic tools enable quicker and more precise treatment decisions, ultimately improving patient outcomes (Dundyn, 2024; Appleby, Basran, 2022; Amaral, et al. 2024).

Another key advancement is in telemedicine and remote monitoring, which facilitates remote consultations and real-time health tracking of animals, particularly through wearable devices (Dundyn, 2024; Beyer, 2023b; Kozioł-Nadolna, 2024). These innovations have proven especially beneficial for managing chronic diseases and post-surgical recovery, ensuring continuous care without the need for frequent in-person visits. As telemedicine adoption grows, it offers veterinarians and pet owners more flexible and accessible healthcare solutions (NAVC, 2021; Convertus, 2021a, 2021b).

In addition to clinical applications, AI plays a crucial role in data management and practice automation. Cloud-based platforms and digital databases can transform veterinary clinic operations by streamlining patient record management, automating administrative tasks, and supporting data-driven decision-making (Beyer, 2023b; Dundyn, 2024). These improvements not only enhance workflow efficiency but also contribute to better service quality and client satisfaction.

Furthermore, AI is increasingly utilized in bioinformatics and predictive analytics, enabling the processing of large datasets to identify health trends and predict medical outcomes. This approach enhances preventive care strategies by leveraging data-driven insights to anticipate potential health issues before they become critical (Dundyn, 2024). As AI continues to evolve, its role in diagnostics, patient management, and predictive analytics will further redefine veterinary medicine, improving both clinical and operational efficiency.

3.2. Challenges and Limitations in the Implementation of Digital Technologies in Veterinary Practice

Despite the potential benefits, several challenges and limitations hinder the widespread adoption of AI and digital solutions in veterinary medicine. One of the primary concerns is algorithmic bias and accuracy, as AI-based diagnostic tools may produce skewed results if trained on non-representative datasets. This can lead to disparities in veterinary care, affecting the reliability of automated diagnostic processes (Sharun et al., 2024; Bouhali, et al. 2022). Ensuring diversity in training data is essential to mitigate these risks and improve the overall performance of AI-driven solutions.

Another significant challenge lies in regulatory and ethical considerations, as the integration of AI in veterinary practice raises complex issues related to data privacy, intellectual property rights, and the responsible use of technology in clinical settings. The lack of clear guidelines makes it difficult for veterinarians to navigate legal and ethical concerns when incorporating AI into their workflows (Sharun

et al. 2024; Burti, et al., 2024). Without well-defined regulations, the adoption of AI remains inconsistent, potentially leading to unintended consequences in veterinary decision-making.

Additionally, resistance to change within the veterinary community poses a considerable obstacle to digital transformation. Many professionals express concerns about reduced human interaction and an over-reliance on automated systems, fearing that technology may diminish the role of veterinary expertise. This reluctance to embrace AI-driven innovations can slow down adoption rates and limit the benefits these technologies offer. However, increasing awareness, providing education on AI applications, and fostering transparent communication about its supportive rather than replacement role in veterinary care could help overcome these barriers (Kour et al. 2022; Muftić, Fejzić, 2024; AlZubi, 2023; Aghapour, Bockstahler, 2022). Addressing these challenges is crucial to ensuring the responsible and effective implementation of AI in veterinary medicine.

3.3. Dominant Trends in the Scientific Literature on AI in Veterinary Medicine

Recent scientific literature reveals several key trends in the application of AI and digital technologies in veterinary medicine. One of the most prominent developments is interdisciplinary collaboration, as research increasingly emphasizes the importance of cooperation between veterinarians, data scientists, and technology developers. These partnerships play a crucial role in addressing unique challenges within veterinary practice and fostering technological innovation tailored to the field (Sharun, et al., 2024). By integrating expertise from multiple disciplines, AI-driven solutions can be more effectively designed and implemented to meet the specific needs of veterinary professionals.

Another significant trend is the growing emphasis on education and training in AI, as there is a broad consensus on the necessity of incorporating AI-related coursework into veterinary curricula. Proper training ensures that veterinarians can effectively utilize digital tools in clinical practice, enhancing their ability to integrate AI-driven diagnostics, data management, and telemedicine solutions into daily operations. Without adequate training, the potential benefits of AI in veterinary medicine may remain underutilized (Basran, Appleby, 2022; Dyndyn, 2024; Burti et al., 2024; Vet Futurist, 2019; El Idrissi, et al., 2021).

Furthermore, emerging technologies continue to gain attention in veterinary research, with studies highlighting the potential applications of blockchain for securing patient data and the Internet of Things (IoT) for continuous health monitoring (Dundyn, 2024; Sharun, et al. 2024; Pico-Valencia, Holgado-Terriza, 2025). These innovations offer new possibilities for improving data security, streamlining patient record management, and enabling real-time tracking of animal health. As these technologies continue to evolve, their integration into veterinary practice is expected to further enhance efficiency, security, and patient outcomes (Waltham, 2022).

3.4. Research Gaps in Digitalization and Innovation in the Veterinary Sector

Despite significant advancements, several research gaps remain in the digital transformation of veterinary practice. One of the most pressing issues is the lack of standardization in AI frameworks and guidelines specifically tailored to veterinary applications (Sharun et al., 2024). The absence of uniform protocols limits the ability to conduct comparative studies and hinders the widespread adoption of AI-driven solutions in veterinary medicine. Further research is required to establish best practices that ensure consistency, reliability, and effectiveness in AI deployment.

Another critical gap is the limited understanding of the long-term impacts of AI adoption in veterinary practice. While current studies primarily focus on the immediate benefits of AI, such as improved diagnostic accuracy and workflow efficiency, little is known about its long-term effects on veterinary business operations and patient care. There is a need for longitudinal studies that assess the sustainability, cost-effectiveness, and overall impact of AI integration over time (Appleby, Basran, 2022; Kozioł-Nadolna, 2022).

Additionally, client acceptance and trust in AI-driven veterinary care remain underexplored. The role of pet owners in adopting AI solutions has largely been overlooked, despite their influence on the success of digital innovations in veterinary practice. Understanding client perceptions, concerns, and expectations regarding AI technologies is crucial for ensuring their acceptance and effective implementation. More research is needed to explore factors that build trust in AI applications and encourage broader adoption among veterinary clients (Beyer, 2023a).

Addressing these research gaps is essential for ensuring the responsible and effective integration of AI and digital technologies in veterinary medicine, ultimately benefiting both professionals and pet owners.

The integration of AI and digital technologies in veterinary medicine holds immense potential to enhance diagnostics, improve clinic management, and optimize patient outcomes. However, challenges such as algorithmic biases, regulatory complexities, and cultural resistance must be addressed. Additionally, bridging existing research gaps—particularly in standardization, long-term impact assessment, and client trust—will be crucial in harnessing the full potential of AI-driven veterinary innovation. Future studies should focus on developing comprehensive frameworks for responsible AI implementation while ensuring that veterinary professionals are adequately trained to leverage these advancements effectively.

4. CONCLUSION, LIMITATIONS, AND FURTHER RESEARCH.

The integration of artificial intelligence and digital technologies into veterinary medicine presents transformative opportunities for diagnostics, telemedicine, data management, and predictive analytics. AI-driven imaging solutions enhance diagnostic accuracy, while remote monitoring and automated practice management improve efficiency and accessibility of veterinary care. Additionally, interdisciplinary collaborations and advancements in emerging technologies, such as blockchain and IoT, indicate a growing trend toward digitalization in the sector. However, despite these advancements, several challenges remain, including algorithmic biases, regulatory concerns, and resistance to change among veterinary professionals. Addressing these issues through education, standardized practices, and ethical guidelines will be crucial for the responsible and effective implementation of AI in veterinary practice.

Innovation in animal healthcare practices is essential to meet the evolving needs of the veterinary industry. The adoption of new technologies and digitalization improves the accuracy of diagnosis and treatment, enhances operational efficiency, and optimizes the overall client experience. Veterinary practices that successfully integrate these innovations not only can improve the quality of care provided to animals but also increase their resilience and competitiveness in the market. In particular, AI-driven solutions for practice management—such as electronic medical records, telemedicine, and automated systems—allow clinics to streamline workflows and focus more on personalized and complex cases. Additionally, tools such as mobile applications enhance communication between veterinarians and pet owners by providing convenient access to medical records, appointment scheduling, and real-time health updates. As the veterinary sector continues to shift toward virtual service delivery, the optimization of digital client experiences will play a critical role in maintaining customer satisfaction and engagement.

This study has certain limitations that must be acknowledged. First, the current analysis is based on existing literature, which primarily focuses on the immediate benefits of AI implementation rather than long-term impacts on veterinary care. Additionally, the lack of standardized methodologies and datasets in veterinary AI applications poses challenges in comparing findings across different studies. Furthermore, while regulatory and ethical considerations are highlighted, the evolving nature of AI policies means that future legal frameworks may significantly influence the adoption and effectiveness of these technologies. Finally, client perspectives on AI adoption remain underexplored, limiting a comprehensive understanding of how pet owners perceive and trust AI-driven veterinary solutions.

Future research should focus on several key areas to bridge the identified gaps. First, longitudinal studies are needed to assess the long-term impacts of AI on veterinary efficiency, diagnostic accuracy, and patient outcomes. Second, efforts should be made to develop standardized protocols and best practices for AI applications in veterinary medicine, ensuring consistency and reliability. Third, further exploration into client acceptance of AI-based veterinary services would provide valuable insights into potential barriers to adoption. Additionally, interdisciplinary research involving veterinarians, data scientists, and regulatory bodies should be encouraged to create ethical and regulatory frameworks that support responsible AI integration. Lastly, emerging technologies such as blockchain for secure patient data management and IoT for real-time health monitoring should be investigated further to maximize their potential in veterinary practice.

As technology continues to drive change in the veterinary industry, adaptability will be a key determinant of success. Those veterinary professionals who quickly embrace new technologies and align with evolving client expectations will build future-proofed, resilient businesses capable of responding to industry challenges. The ability to integrate AI and digital solutions into everyday operations will become a defining trend in veterinary practice management. The optimization of digital services, including telemedicine and mobile-friendly platforms, will not only enhance veterinary care but also strengthen the digital presence and reputation of veterinary clinics through online engagement and client feedback.

The systematic literature review conducted in this study highlights a significant research gap, particularly in the use of AI and digital technologies for business optimization in veterinary practice. While much of the existing research focuses on clinical applications, there is a pressing need for studies exploring how AI can enhance financial management, operational efficiency, and strategic decision-making in veterinary clinics. This article contributes to filling that gap and provides a foundation for further theoretical and empirical research. The findings may be valuable not only to researchers but also to veterinary practitioners and business owners seeking to implement AI-driven innovations in their facilities.

By addressing these research gaps and challenges, AI and digital innovations can be more effectively integrated into veterinary medicine, ultimately improving both clinical outcomes and business efficiency, ensuring that veterinary practices remain competitive and capable of delivering high-quality care in an increasingly digitalized world

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EMERGING TRENDS AND FUTURE DIRECTIONS OF AI IN AUDITING: INSIGHTS FROM A BIBLIOMETRIC PERSPECTIVE

Katarzyna Renik[a], Kamila Łuczak[b], Hang Zhou[c]

[a] *University of Economics in Katowice, Katowice, Poland*
[b] *Wroclaw University of Economics and Business, Wroclaw, Poland*
[c] *SGH Warsaw School of Economics, Warsaw, Poland*

ABSTRACT

Purpose: *The article aims to summarize current research trends and identify potential research directions for artificial intelligence (AI) in auditing.*

Need for the study: *Previous studies using bibliometric methods exploring AI directly in auditing were not identified. Instead, the articles simultaneously focused on accounting and auditing, AI, and other new technologies. It indicates the research gap that this article will fill.*

Methodology: *The article presents an overview of published articles about AI in auditing based on a critical literature review and a comprehensive bibliometric analysis utilizing two different tools - VOSviewer and Bibliometrix - to map the current research and monitor the development of key themes over time.*

Findings: *This review analyzes the current state of the literature, summarizes the most productive authors, countries, and journals, and maps the research directions on AI in auditing. The study highlights prevalent themes such as algorithmic fairness and ethics. Despite threats and challenges for auditors, AI provides many benefits in auditing procedures by automating many time-consuming and expensive tasks, replacing humans in analytical tasks, providing risk detection, and decreasing human errors. Therefore, auditors can focus on unautomated processes and ensure their profession will be irreplaceable.*

Practical Implications: *Our study contributes to the current literature by highlighting key themes specific to previous research. For researchers, the article provides a roadmap for future outstanding scientific work, but also helps auditors understand the role of AI in their profession and the challenges that await them.*

Keywords: Audit; Profession; Artificial Intelligence (AI); Automation; Auditing Processes; Bibliometric Analysis

Jel codes: M42; O33

1. INTRODUCTION

Artificial Intelligence (AI) dominated the scientific and practical community worldwide, including the auditing area. Over 3,3% (22700 publications) of all documents from the Scopus database represent

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articles connected with AI published in the Business, Management, and Accounting areas. This interest in AI has been rapidly growing.

Since companies launched significant tools, e.g., ChatGPT (OpenAI, 2023), AI has become more discussed in many fields. AI is occupied by publication topics that interest authors in marketing (Allal-Chérif et al., 2024; Hoyer et al., 2020), banking (Ashta & Herrmann, 2021; Munkhdalai et al., 2019), government (Androutsopoulou et al., 2019; Goralski & Tan, 2020), education (Ziemba et al., 2023; Chiu, 2024), sustainability (Saheb et al, 2022; Saleh et al., 2024; Chomiak-Orsa et al., 2024), in economic general (Bickley et al., 2022), but also in accounting and auditing (Zemankova, 2019a, b; McGee, 2023), and many other areas (Fan et al., 2022; Jackson et al., 2024).

Identified studies using bibliometric analysis in the AI field have been conducted on accounting and finance (Gambir & Bhattacharjee, 2021), human resources development (Hamouche et al., 2023), accounting (Bunget & Lungu, 2023), accounting and auditing (Agusti & Orta-Perez, 2023). Yazan et al. (2024) published an article in the auditing field focused on information and communication technology (ICT), AI, and blockchain. Pizzi et al. (2021) examined digital transformation in auditing. However, that issue has not been addressed in the research related to AI and auditing. Due to the increasing appearance of publications in this area, mainly empirical, there is a possibility of delivering new results that influence scientists' and practitioners' insights.

AI and its wide range of applications have generated a large body of research for researchers, which makes it challenging to understand the entire field coherently. Previous studies provided a wide range of research methods, including systematic literature review, interviews, case studies, and statistical methods based on questionnaires in AI usage in the accounting and auditing field. However, very few use bibliometric analysis as a significant method. Bibliometric analysis addresses these concerns by systematically mapping the content of a research area. Unlike literature reviews, bibliometric analysis uses quantitative methods to identify research trends, relevant publications, thematic clusters, networks, and citations. That approach allows for a broad and reliable examination of current trends and potential future research directions in this area. To ensure the transparency of the study, two science mapping applications were used to confirm the consistency of the obtained results.

Our research aims to synthesize current trends through a comprehensive overview of the current state of knowledge based on the literature. Additionally, this study uses bibliometric analysis to indicate emerging future research directions of AI in the auditing profession. It presents a comprehensive overview of the current state of knowledge based on literature and potential research gaps for the future. To achieve the research objective, two questions were posed:

1. What is the current stage of the literature, and what are the main topics in AI in the auditing area?
2. What are the recommendations for professionals and future research directions in AI in the auditing profession for scientists?

To provide the answers to research questions, bibliometric analysis and content analysis of current literature have been applied. The first question is covered by literature, the second by the VOSviewer map, and the remaining four by maps from RStudio.

Contributions from this article would be impactful and substantive for researchers because they would determine the road in future research, fill the research gap, and develop studies of AI in auditing. Considering the beneficial effects on auditors, the paper can support them in understanding the potential role of AI and the improvements, challenges, or risks this technology can bring.

The paper is structured as follows. The first section introduces. Section 2 presents the theoretical background based on the previous literature review. In contrast, Section 3 discusses the study's methodology. Section 4 reports the research findings of the bibliometric analysis. Section 5 provides a discussion, indicates future potential research directions, and presents limitations. The last section concludes the study.

2. LITERATURE REVIEW

The impact of digital transformation and the development of cutting-edge technologies on auditing and auditors has already been addressed in the literature (Kokina & Davenport, 2017; Zhang et al., 2022; Mohamed et al., 2023; Dennis, 2024).

AI technologies have demonstrated impressive abilities in analyzing data and recognizing patterns, possibly improving audit procedures' efficiency and accuracy. AI brings benefits and opportunities to enhance and facilitate those used in various fields, and causes various threats associated with inappropriate usage. AI capabilities facilitate and improve audit tasks: internal control evaluation, risk assessment, analytical review procedures, classification, materiality assessments, decisions regarding the going concern principle, and bankruptcy prediction. It increases efficiency and reduces the probability of human error during audit procedures. It positively influences time-consuming and rules-based tasks (Zemankova, 2019b).

However, AI adoption into the auditing profession might cause threats for audit firms and challenges for auditors, such as a lack of appropriate training, changes in the range of duties (Zemankova, 2019a), and the risk of getting out of control (Sutaria, 2020). Implementing AI requires many requirements and sacrifices from auditors and the challenges they face (Nujiten et al., 2015). Therefore, the best solution to adopt AI is to consider the pros and cons and familiarize yourself with the benefits and risks of AI implementation.

In recent years, considering works on the use of AI in auditing, authors have also presented various types of studies. In examining related papers, we focused on analyzing papers where authors used bibliometric analysis.

Yazan et al. (2024), based on publications from the Web of Science (WoS) database, analyzed the impact of ICT on auditing trends, including AI and blockchain. In the study, the authors highlight four clusters related to ICT and auditing - the determinants of independence and audit quality in an ICT environment, the challenges of applying blockchain technology in the auditing and accounting practices, the use of AI to analyze accounting data, and the impact of ICT on auditor performance in the future.

Another study examined the impact of digital transformation on internal audits (Pizzi et al., 2021). The main findings of their research focused on how companies adapt to the risks and opportunities of digital transformation, where internal auditors play a significant role. Authors identify research areas: continuous auditing, data analytics, fraud detection, and technological innovation. An essential limitation of this study was excluding the conference proceedings from the publications analyzed. They point to the ethics of AI and the evolution of the auditor’s role as further research.

Furthermore, Agustí & Orta-Pérez (2023) investigated the impact of big data and AI on accounting and auditing. The paper identifies key authors, journals, or the most cited articles. Further research indicates conducting a meta-analysis on the use of AI and big data in auditing and accounting, and identifying the impact of AI and big data on fraud detection. The study used publications only from the WoS database.

Lamboglia et al. (2021) mapped the conceptual structure of knowledge that connects ICT to auditing to understand this research stream better. In the results, the authors indicate a growing research interest in the theme, pointing to three main topics: the adoption of continuous auditing and continuous tracking in the auditing profession, the use of software tools in the auditing profession, and the connections between information systems and auditing.

Regarding the above research, it can be concluded that the studies exploring AI directly in the auditing profession were not identified. Instead, the articles explore accounting and auditing, AI, and other new technologies. Therefore, the authors indicate the research gap in this field. Furthermore, by analyzing selected publications that used the bibliometric analysis method, the authors identified the highlighted limitations, using only the WoS database. It poses a research gap in the topic area and in using the Scopus database as a source in bibliometric analysis. This identified research gap will be filled in this article.

3. METHODOLOGY

The above considerations are based on a critical literature review of AI adoption in audits, examining aspects affecting audit procedures, processes, and auditors as a character, profession, and professional society. The theoretical background provides an introduction based on a critical literature review for further bibliometric analysis and contributes to interesting insights for auditors and researchers. This wide range of applied research methods ensures a comprehensive investigation of this field.

Bibliometric analysis is a complex method that implements numerous diverse analyses with mapping software tools (Guler et al., 2016). Bibliometric analysis using different diagrams and tables has recently become widely applied. This analysis allows researchers to map literature and create links between keywords, authors, or journals. It also helps them identify research gaps in existing literature. This method contributes valuable insights for researchers and practitioners in the future. Furthermore, researchers use multiple methodological approaches to apply visual material. Grossi et al. (2023) also claim that the visual approach will be more exploited in research. An initial review of the Scopus database indicated an enormous number of documents in the AI area. The study was conducted according to a prepared procedure (Fig. 1).

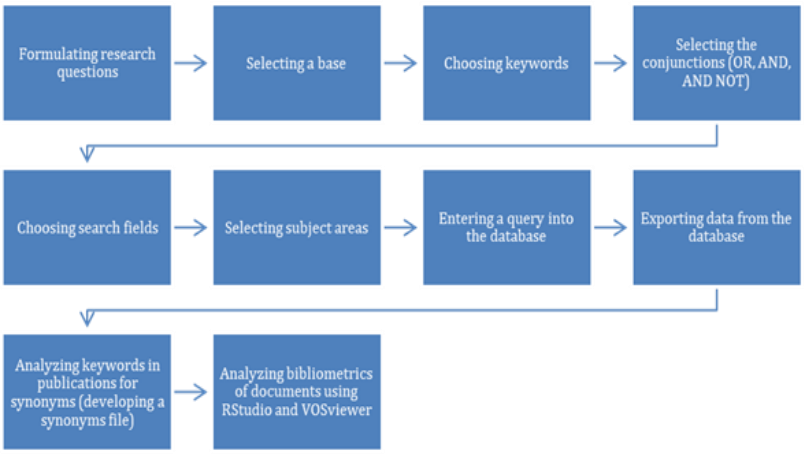


Figure 1. Protocol of the research
Source: own elaboration.

This study focuses on findings based on the Scopus database search. The Scopus database was chosen because of its wide range of available documents and the largest database of peer-reviewed literature abstracts and citations. Compared with the WoS database, Scopus covers a broader range of Core Collections, including its main citation indexes (Martín-Martín et al., 2021). The WoS was searched, and results confirmed that adopting this database for analysis will not significantly affect the results obtained and will not increase the potential of this research. Therefore, the authors decided to reject the WoS database. In addition, other authors conducting bibliometric analysis on the impact of ICT on auditing used WoS (Yazan et al., 2024; Agustí & Orta-Pérez, 2023), so we wanted to expand the set of publications searched.

The search criteria have been established to provide transparent and replicable research of suitable articles to analyze (Table 1).

The relevant literature was systematically searched in Scopus, and the search query string included ‘audit’, ‘AI’, ‘deep learning’, ‘neural network’, ‘machine learning’, and ‘data mining’. The logical relationship between the keywords (OR, AND, AND NOT) was specified to improve the search precision. The subject areas were also applied to focus our investigation on AI's impact on auditing. From the search and bibliometric analysis, the authors excluded keywords regarding ‘accounting’ and ‘internal auditing’, focusing on external auditing. It is motivated by the fact that it differs from internal auditing in terms of role, scope, methodologies, and practices (Pramukti, 2024). Keywords related to ‘internal auditing’ were excluded from the literature search process to maintain the study's clarity and relevance.

Using the keyword ‘audit*’ in the search query string resulted in the Scopus databases’ inclusion of the word ‘auditory’ related to medical issues rather than the directly researched topic of external auditing. This term is most often used in the context of auditory sensing, which is irrelevant to auditing and the use of AI in this area. When preparing the collection of publications, we decided to exclude, among other terms, the word ‘auditory’. To eliminate other publications unrelated to the topic of this article, we excluded the concrete keywords ‘health*’, ‘medic*’, and ‘hearing’. With this limitation, we

wanted to make sure that only publications that were, in fact, related to the topic examined were included in the analysis. Due to the appearance of a substantial number of medical articles, mostly related to auditory, vision, and hearing, the authors decided to modify the query string and apply the criteria of the subject area (Computer Science, Decision Sciences, Social Sciences, Business, Management and Accounting, Economics, Econometrics and Finance, Multidisciplinary).

Table 1. Research searching data

Database	Scopus
Search fields	Article title, Abstract & Keywords
Query string	("audit*" AND NOT "auditory") AND ("artificial intelligence" OR "AI") AND ("deep learning" OR "neural network" OR "machine learning" OR "data mining") AND NOT ("health*") AND NOT ("medic*") AND NOT ("hearing")
Subject areas	Computer Science, Decision Sciences, Social Sciences, Business, Management and Accounting, Economics, Econometrics and Finance, Multidisciplinary
Number of documents	378
Date of the search	13.11.2023
Tools	Bibliometrix (a package for the R statistical programming language) and VOSviewer

Source: own elaboration.

After applying the exclusion and inclusion criteria, the results showed 378 documents. The documents were retrieved on 13.11.2023 from Scopus databases, covering the entire available period, namely from 1994 to 2023.

Data were used in Bibliometrix and VOSviewer applications to provide various bibliometric analyses. Subsequently, results from the database were used in RStudio and VOSviewer applications to conduct a wide range of bibliometric analyses. Eck and Waltman designed the VOSviewer application to analyze and visualize citation networks of scientific documents. It represents graphical bibliometric maps and enables a straightforward manner to interpret them. Conversely, the article also uses the R package to create bibliometric maps based on data retrieved from the Scopus database (Aria & Cuccurullo, 2017).

4. RESULTS

Due to the features of various types of tools, we decided to launch two of them. The article can distinguish types of tools and maps for bibliometric analysis (Table 2).

Table 2. Types of map analysis regarding the tools used

VOSviewer	• authors' keywords co-occurrences analysis • cluster analysis
Bibliometrix (R application)	• authors' production over time • country scientific production • three fields plot (authors, keywords, journals) • historical direct citation network

Source: own elaboration.

Selected articles provide analysis of authors' keywords co-occurrences, clusters, authors' production over time, most productive countries, three fields plot (authors, keywords, journals), and historical direct citation network by using open-source software of VOSviewer and BibliometrixR application (Radha & Arumugam, 2021).

It allows one to understand the impact of AI on auditing, including the conceptual structure and thematic trends. Furthermore, visual representations (e.g., network maps and bibliometric plots) help identify potential research gaps and future research directions.

4.1. Bibliometric analysis with VOSviewer

To analyze the keywords in the collected document database, it was first necessary to standardize by creating a so-called thesaurus file containing the individual keywords' synonyms. Next, the minimum number of keyword occurrences was set to 4. Of the 1,034 keywords, only 35 met this criterion (Fig. 2).

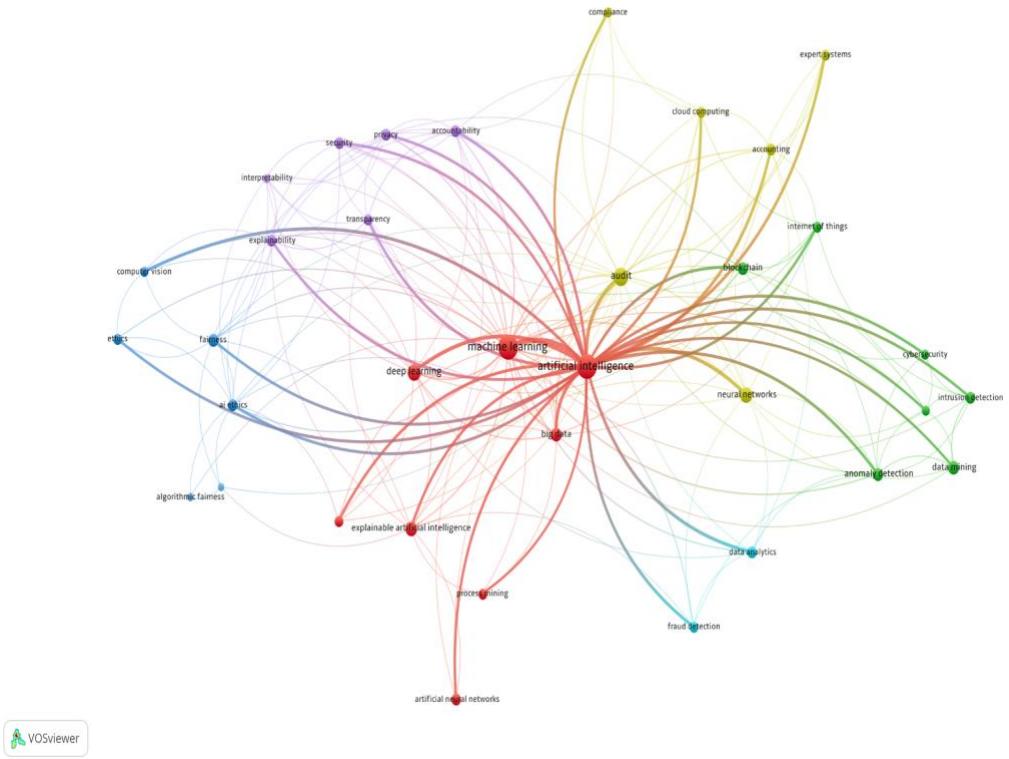


Figure 2. Authors' keywords co-occurrences analysis
Source: analysis performed using VOSViewer (van Eck, N. J. & Waltman, 2010).

The keywords identified placed themselves in six clusters (Table 3). The red cluster contained words that relate to AI and associated areas. The most frequent keyword in this cluster and the entire database is 'artificial intelligence'. The green cluster includes words related to discovering information in data sets, including information security, or detecting various anomalies. 'Data mining' is the most frequently occurring keyword for this cluster. The blue cluster contains words related to ethics, fairness, or bias. 'Fairness' is the most commonly repeated word in this cluster. In the yellow cluster, the most frequent word is 'audit'. In addition, other words related to audit are 'accounting' and 'compliance'. In the purple cluster, a set of words could be issued to look at in the context of using AI to transform specific processes - the most frequent word is 'accountability'. The turquoise cluster has only two keywords: 'data analytics' and 'fraud detection'.

Except for 'artificial intelligence' and 'audit', the most common keywords in the VOSviewer map from each cluster are 'big data', 'deep learning', 'explainable artificial intelligence', 'anomaly detection', 'blockchain', 'data mining', 'intrusion detection', 'fairness', 'neural networks', 'accountability', and 'data analytics'. The least frequent keywords are 'algorithms', 'cybersecurity', 'information security', 'algorithmic fairness', 'bias', 'computer vision', 'cloud computing', 'compliance', 'expert systems interpretability', and 'fraud detection'.

Table 3. Clusters of keywords

No.	Colors	Authors' keywords	Occurrences
Cluster #1	*red*	*algorithms*	*5*
		artificial intelligence	*106*
		artificial neural networks	*8*
		big data	*12*
		deep learning	*25*
		explainable artificial intelligence	*16*
		machine learning	*105*
		process mining	*6*
Cluster #2	*green*	*anomaly detection*	*11*
		blockchain	*10*
		cybersecurity	*4*
		data mining	*13*
		information security	*4*
		internet of things	*6*
		intrusion detection	*8*
Cluster #3	*blue*	*ai ethics*	*8*
		algorithmic fairness	*4*
		bias	*4*
		computer vision	*4*
		ethics	*6*
		fairness	*9*
Cluster #4	*yellow*	*accounting*	*7*
		audit	*39*
		cloud computing	*5*
		compliance	*4*
		expert systems	*5*
		neural networks	*20*
Cluster #5	*purple*	***accountability***	*8*
		explainability	*7*
		interpretability	*5*
		privacy	*7*
		security	*7*
		transparency	*6*
Cluster #6	*turquoise*	***data analytics***	*7*
		fraud detection	*5*

Source: analysis performed using VOSViewer (van Eck, N. J. & Waltman, 2010).

Cluster 3 (blue) is worth highlighting. Among the numerous keywords relating directly to technology, the database has an entire cluster dedicated to ethical aspects. Among the authors, all aspects related to the ethics of the use of AI are of interest, considering factors related to fairness, as well as AI ethics, discrimination, or bias in this technology. When wishing to implement tools powered by AI-based algorithms, it is necessary to ensure algorithmic fairness to generate results without bias or favoring selected groups.

4.2. Bibliometric analysis with R

Quantitative research in bibliometrics and scientometrics analysis is also based on Bibliometrix using the R application (Aria & Cuccurullo, 2017). They claim that quantitative evaluation of publication and citation data is mainly used to evaluate growth, maturity, leading authors, conceptual and intellectual

maps, and trends of a scientific community. First, we presented the authors' production over time, including the number of publications and the total number of citations per year (Fig. 3).

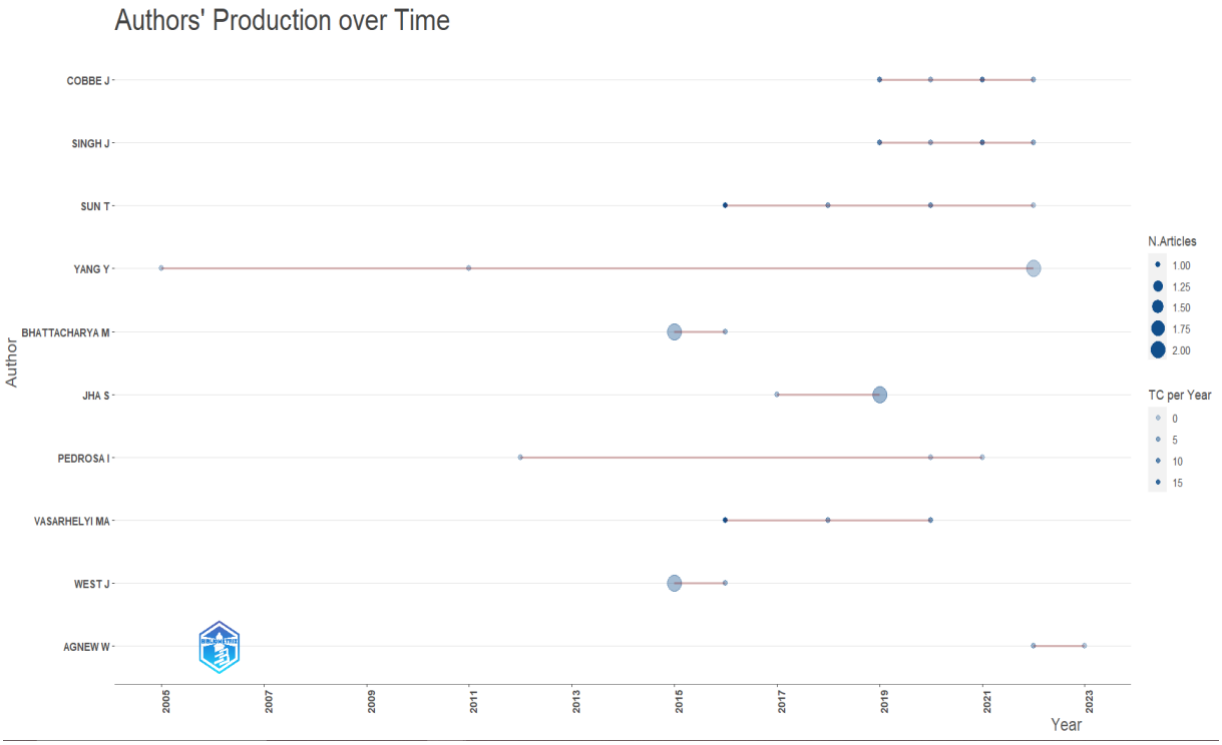


Figure 3. Authors' production over time
Source: analysis performed using R and the bibliometrix library (Aria & Cuccurullo, 2017).

The figure shows the ten most relevant authors in the context of these variables. The size and color of the circles in the diagram are important - the larger the circle, the greater the number of publications, and the darker the color, the greater the number of citations each year. Over the years, three authors - Jennifer Cobbe, Jatinder Singh, and Ting Sun - have produced the most significant number of publications at 4.

An analysis of bibliometric data of publications indicated that Jennifer Cobbe from the University of Cambridge co-worked with, among others, Jatinder Singh, also affiliated with the University of Cambridge, publishing articles on automating decision-making (Cobbe et al., 2021), monitoring misuse for responsible AI (Javadi et al., 2020), intelligent systems (Williams et al., 2022), or decision provenance (Singh et al., 2019). In contrast, Ting Sun of The College of New Jersey's articles have addressed topics related to machine learning in accounting and auditing (Cho et al., 2020; Hu & Sun, 2022), AI in auditing (Issa et al., 2016), and the use of data analytics in auditing through deep learning (Sun & Vasarhelyi, 2018).

The following map indicates the countries' scientific production (Fig. 4).

The authors' appearances determine the number of papers according to national affiliations. The saturation of the color also makes a difference – in the case of countries marked in grey, this means that they have no publications. In contrast, blue means that authors from these countries have produced papers in our database. Meanwhile, the darker the blue, the more publications have been created by authors from the country under review. The diagram shows that the most significant number of publications in the area we are examining comes from the United States. This is followed by countries such as India, China, and the United Kingdom. It is worth pointing out that the United States and the United Kingdom were also ranked highly in other audit and technology research conducted using bibliometric analysis. Canada was also indicated, with few publications in our database (Lamboglia et al., 2021).

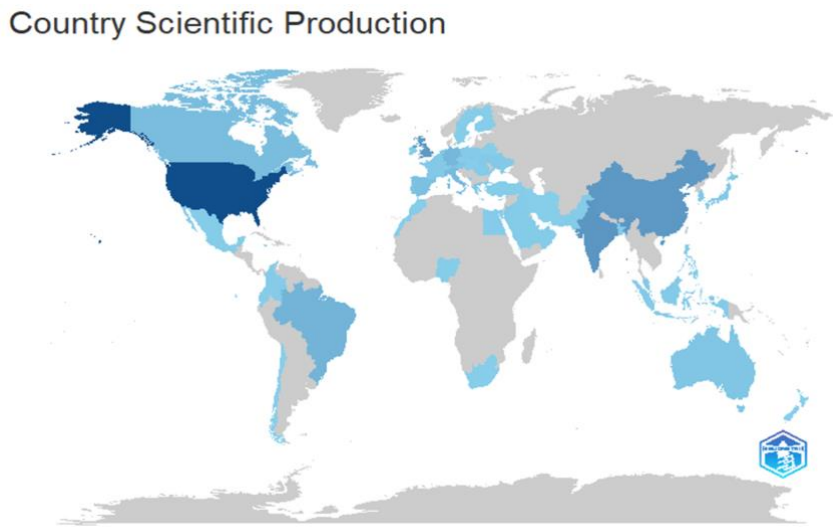


Figure 4. Country scientific production
Source: analysis performed using R and the bibliometrix library (Aria & Cuccurullo, 2017).

It should also be noted that the most cited publications in our collection (as of 15.03.2025) are by authors from Germany and the United Kingdom (Gorwa et al., 2020) with 445 citations, the United States (Raji et al., 2020; Raji & Buolamwini, 2019) with 439 citations and 329 citations, the Netherlands and Germany (Rozinat & Van Der Aalst, 2006) with 229 citations. Notably, the most cited articles did not include publications by authors affiliated with India or China, which are at the forefront regarding the number of publications.

Using a Sankey diagram, the Three Fields Plot displays the main elements of three fields (authors, keywords, journals) and their relationship (Fig. 5).

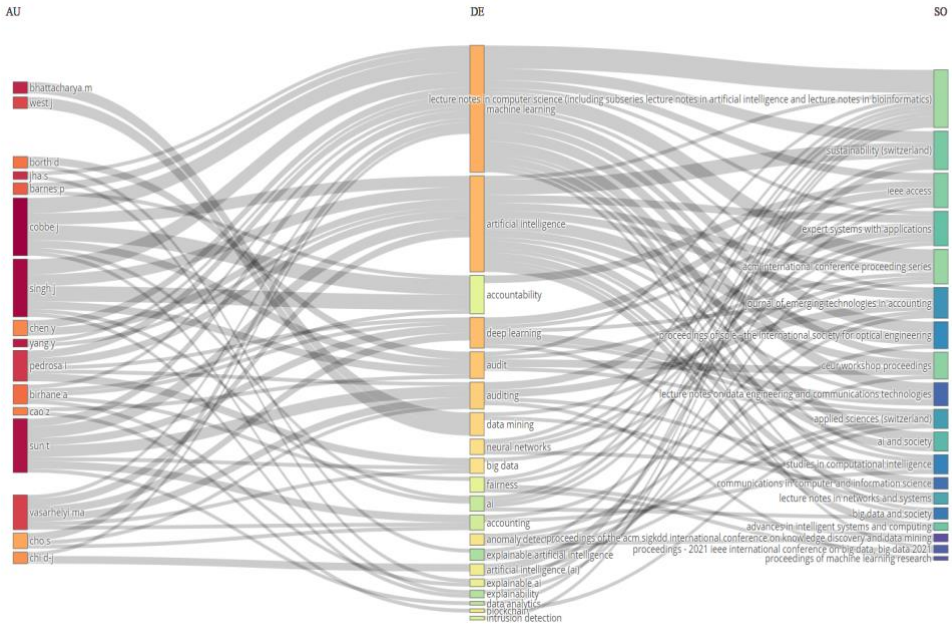


Figure 5. Three Fields Plot (authors, keywords, journals)
Source: analysis performed using R and the bibliometrix library (Aria & Cuccurullo, 2017).

The height is proportional to how often an author, keyword, or journal appears in the collaboration. The line width between nodes is proportional to the number of connections. The keyword with the highest number of links is ‘machine learning’, and most publications including this term appeared in the

journal Lecture Notes in Computer Science (including Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Then we have the word 'artificial intelligence', which appeared most frequently in the journal Sustainability. The third keyword is 'accountability', which appears in the journal IEEE Access. To extend this analysis, it is worth highlighting that the most significant number of articles comes from the journal Lecture Notes in Computer Science (including Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics). Then, there is the ACM International Conference Proceeding Series, followed by CEUR Workshop Proceedings.

The last analysis addressed the historical direct citation network (Fig. 6).

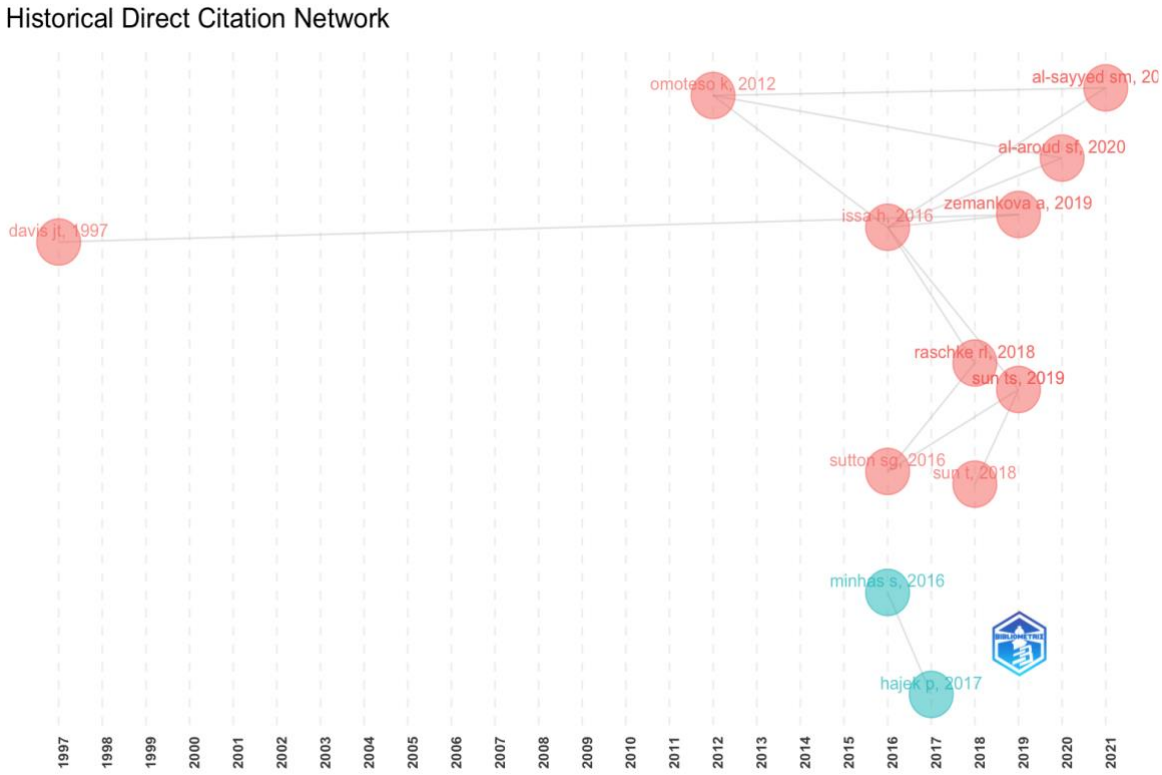


Figure 6. Historical direct citation network
Source: analysis performed using R and the bibliometrix library (Aria & Cuccurullo, 2017).

It is a chronological network of the most relevant direct citations from a publications collection. The network created a plot with the 12 most productive articles. Based on the presented network, it can be concluded that the article 'Supporting a complex audit judgment task: An expert network approach' by Jefferson T. Davis, Anne P. Massey, and Ronald ER Lovell II from 1997 inspired the authors to further work in this area (Davis et al., 1997). Based on the figure, it would seem that it was only 15 years later that the first articles in the area of this study appeared that cited this publication. However, when analyzing the citations of this paper, it turned out that it also has other citations as early as 2000, which relate to, for example, the use of neural networks in auditing.

Bibliometrix and VOSviewer enable a wide range of analyses, including identifying the most productive countries, authors, annual scientific production, and average article citations per year. In summary, they provided valuable insights that will facilitate scientific research across all fields. A trend related to advanced AI techniques stands out in the analyzed clusters, including machine learning or anomaly detection, with ethical and security considerations. Research gaps should be searched for in the context of explainability, data security, and integration of unit processes with the latest technologies, such as blockchain or Internet of Things (IoT).

5. DISCUSSION

A critical analysis of the literature allowed us to analyze the current state of the literature on the use of AI in auditing. Various algorithms are currently used to plan audits and accelerate and automate document reviews (Zemankova, 2019a). In addition, AI can assist auditors in ensuring that audit evidence and documentation standards are fulfilled (Zhang et al., 2022). It facilitates many audit processes and minimizes analytical procedures, which helps auditors focus on different tasks requiring human intervention.

As research has shown, ethical aspects in the use of AI are very important to auditors, especially the fairness of these algorithms and not favoring groups or individuals. In formulating practical tips from the analysis, it is essential to note the auditors' fears of job loss due to the development of AI. Companies should ensure that technology helps them perform tasks rather than replace people. Proper communication and presentation of the benefits of AI can encourage employees to use it. It is also worth educating auditors on the ethical use of AI. However, auditors do not have to be concerned that AI will replace them. Their professional judgment will still be needed.

Despite the challenges that AI brings for auditors, including learning how to work with AI technology, there might be more benefits. For example, AI minimizes time-consuming tasks and human errors, provides risk detection, and, more importantly, auditors can focus on relationships with clients and interpret the results of investigation data. Comparison of the benefits and threats resulting from AI applications can lead to the conclusion that the authors believe AI adoption in audit firms is unavoidable.

Based on the literature, auditors should focus on preparing for AI usage and gaining more knowledge about this technology because AI is rapidly involved in auditing. Training in this area should ensure they use AI appropriately and effectively, minimizing risks, errors, and time-consuming tasks. Those changes can allow us to focus on professional judgment, analytical tasks, ethical issues, and relationships with clients.

Bibliometric analysis can be a sufficient tool not only for researchers but also for auditors. Topics related to machine learning, data mining, data analytics, fairness, and AI accountability are not utterly unknown to auditors. However, AI in auditing has not been fully explored, especially in algorithms, cybersecurity, biases, and computer vision. It should evolve since it can influence compliance, explainability, interpretability, privacy, and fraud detection in auditors' practice.

Scientists and practitioners claim that new technologies such as blockchain or AI will not replace auditors (Ziemba et al., 2025). Nevertheless, auditors should pay more attention to developing their knowledge and, more importantly, skills in the AI area.

Through the bibliometric analysis using VOSviewer and the R application, we provided scientists with various analyses considering the transformation of auditing processes using AI. Besides a critical literature review, bibliometric analysis also answers the research questions.

Most keywords in the VOSviewer map present the main topics examined by researchers in previous studies. They mainly examined issues related to Big Data, anomaly detection, blockchain, data mining, intrusion detection, fairness, neural networks, accountability, and data analytics. It also presents the least frequent keywords that indicate potential research gaps to fill and suggest research directions for scientists in the future. In future research, scientists should pay more attention to informatics and ethical aspects involving algorithms, cybersecurity, information security, algorithmic fairness, bias, computer vision, cloud computing, compliance, expert systems interpretability, and fraud detection. A wide range of research methods should investigate these topics, including empirical and conceptual research in different disciplines and countries.

Regarding the above, auditors should focus on ICT and ethical issues related to AI usage and be aware of the consequences of its implementation. Despite the great benefits that AI can bring to business processes, ethics must be considered first. Munoko et al. (2020) explored ethics into three levels (individual auditor, audit firm, and profession/society) and recommended investigating the ethical implications of using this emerging technology.

Future research directions in this field could explore various aspects of integrating AI technologies into auditing processes. Such as ethical considerations in AI auditing and research methodologies to identify and mitigate biases in AI models to ensure fair and unbiased audit outcomes. Moreover, respond to the question 'How to enhance the explainability of AI-driven auditing models?'. This is crucial for

gaining trust in AI-based audit decisions, especially in regulated industries where transparency is essential. It would also be worth extending the bibliometric analysis to other databases, e.g., WoS.

Furthermore, future research should focus primarily on empirical studies examining auditors' opinions regarding AI adoption in auditing. Scientists should also analyze and compare those results with the literature on benefits and threats and industry reports provided by the Big Four Companies. This study should give a broad overview of the advantages and disadvantages of AI implementation in audit firms and insights for professionals.

It is crucial to interpret the results with caution due to the limitations. The initial issue we faced was the large number of articles originating from the medical field. To address this, we developed a query that excluded keywords such as 'health', 'medic*', and 'hearing'. It is caused by narrowing the subject area to Computer Science, Decision Sciences, Social Sciences, Business, Management and Accounting, Economics, Econometrics and Finance, and Multidisciplinary. Despite our efforts, some documents from the medical field remained. The second issue is that some papers focus on operational or internal audits rather than financial audits, which is our area of interest. It is acknowledged that there may be some limitations in using only the Scopus database, as specific high-impact journals may only be included in WoS. Future research could combine multiple databases (e.g., Scopus, WoS) for a more comprehensive analysis to further validate this study's findings.

6. CONCLUSION

As a new technology, AI facilitates and enhances many professions, and auditing is no exception. Our research aimed to synthesize current trends in literature and indicate emerging research directions of AI in the auditing profession by using bibliometric analysis.

Auditors might face many challenges in gaining new knowledge about AI to face threats like losing their jobs. Moreover, threats like security risks and the risk of losing control arising from AI will bring reputation or financial losses to auditing organizations. Despite these drawbacks, AI facilitates auditing procedures by automating time-consuming and costly processes, reducing human errors, and processing analytics data. AI usage in auditing should be explored in terms of algorithms, cybersecurity, biases, and computer vision. Learning about AI regarding compliance, explainability, interpretability, privacy, and fraud detection is essential. Auditors should focus on gaining knowledge and skills in these areas to fully and effectively benefit from AI, since it will not fully replace auditors and their professional judgment, but complement and enrich audits.

The results show that many areas have been addressed but not fully explored. Key findings and trends have emerged based on the extensive bibliometric analysis using VOSviewer and the R application. The bibliometric analysis revealed prevalent ethical themes, including algorithmic fairness and bias. It is worth considering the USA when searching for researchers to collaborate with because the most significant publications come from there. While looking for researchers to collaborate with, it is worth considering the United Kingdom, as two of the three authors with the most publications are affiliated with the University of Cambridge. When searching for a journal or conference to publish or present an article that combines AI and auditing, researchers should consider Lecture Notes in Computer Science and conferences organized by the Association for Computing Machinery (ACM).

Researchers in their previous studies mainly examined topics related to informatics aspects of AI in auditing, i.e., big data, anomaly detection, blockchain, data mining, intrusion detection, fairness, neural networks, accountability, and data analytics. Therefore, this article recommends potential research directions. In their future studies, scientists should focus on topics directly connected with the auditors' profession, i.e., cybersecurity, bias, transparency, fraud detection, and ethics of AI in auditing. They should use various methods and investigate auditors' opinions in those areas.

We believe this article will provide a roadmap for researchers, introducing them to authors who have contributed to the study area's development, helping them select a journal to publish their paper in, and inspiring them for future research. This article can also inspire practitioners as auditors and accountants to consider the beneficial effects on their professions and support them in understanding the potential role of AI to consider implementing this technology in their audit companies and start training their staff to understand how AI works, and how to deal with challenges they will have to face. While the role of

AI is growing by the day, it is essential to understand how utilizing it in the day-to-day activities of auditors will affect the execution of their tasks.

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ARTIFICIAL INTELLIGENCE IN THE FOOD SERVICE INDUSTRY

Katarzyna Brzychcy[a], Oksana Zamora[b]

[a] *University of Szczecin, Institute of Management, Poland*
[b] *Sumy State University, Institute of Business, Economics and Management, Ukraine*

ABSTRACT

Purpose: *The purpose of the article is to present the position of representatives of the food service industry regarding the use of artificial intelligence (AI) in their workplace. In addition, it indicates the potential difficulties and barriers associated with the implementation of artificial intelligence, as well as possible solutions to these disadvantages.*

Need for the study: *In order to effectively introduce AI technology in the gastronomy, it is necessary to know the opinions of its representatives. It is crucial to identify areas of application of AI e.g. in kitchens. It is worth learning about the dificulties that representatives of the gastronomy perceive, which may contribute to the failure of AI in food service. Addressing the issue stems from the need to look at the phenomenon of AI from the perspective of practitioners and people working in the food service industry.*

Methodology: *The survey was conducted by the interview method using an interview questionnaire.*

Findings: *The results explored the opinions representatives of the gastronomy, on the possibility of using AI in their workplace. The results indicated areas where AI can benefit and be applied. Concerns about AI and the level of readiness for its implementation were also indicated.*

Practical Implications*: The issues raised helped to stimulate respondents' reflections on the possibilities and benefits of applied AI in their organisation. Sources of resistance to AI and opportunities to prevent them were also identified. It was indicated how employees can be prepared for the introduction of AI in the organisation.*

Keywords: Artificial Intelligence, Knowledge, Human Resources Management, Gastronomy, Individual interview

Jel codes: M10, B 40, O3

1. INTRODUCTION

Artificial intelligence is of interest not only to scientists but to the general public. With reports of more and more new uses of artificial intelligence and the successes achieved through it, it is beginning to make its way into everyday life. Emerging solutions based on artificial intelligence make it easier to function at home, but also reduce costs and improve efficiency at work.

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Artificial intelligence has become an area of scientific exploration in various scientific disciplines. As a consequence of the research efforts undertaken, a large number of articles have been published addressing the topic of artificial intelligence. Unfortunately, few items focus on the food service industry among this rich scientific output. To date, no comprehensive pattern has been presented to show the validity of applying innovative solutions using artificial intelligence to entities in the food service industry. Moreover, the studies that have been conducted have mainly focused on large entities that are often leaders in their industry. The research problem addressed by the authors is the issue of the use of artificial intelligence in the operations of food service enterprises. The use of artificial intelligence is controversial, so the purpose of this study is to diagnose the knowledge and opinions of employees in the food service industry regarding the introduction of artificial intelligence in their workplace. In view of the value that artificial intelligence brings, based on the results obtained from the study, recommendations have been made that are likely to make their implementation contribute to the adoption of artificial intelligence-based systems and technologies by micro, small and medium-sized enterprises as well. With the widespread use of artificial intelligence, it has become an area of scientific exploration in various scientific disciplines.

This article presents an example of the application of artificial intelligence in the educational process, involving its use in educating students and graduates of catering schools in the field of human resources management. The proposed example is a good practice that was successfully used in the project entitled "Methodology of teaching human resources management for current and futurecatering employees", No. 2023-1-PL01-KA220-VET-000167215, implemented as part of the ERASMUS plus programme.

2. LITERATURE REVIEW

The term "artificial intelligence" is widely used by both practitioners and theorists working on the subject. Despite the fact that the term "artificial intelligence" was used more than 70 years ago, defining the concept is not simple or obvious. The creator of the term, John McCarthy, made the first attempt to define artificial intelligence. He assumed that artificial intelligence is "the construction of machines whose operation can be said to be similar to human manifestations of intelligence" (J. Grzegorczyk, 2019). Analysing this definition, it can be assumed that any computer program that performs actions that require any feature of human intelligence can be referred to as an artificial intelligence system. In doing so, it is assumed that it does not matter what kind of program performs the activities in question or how it performs them, but what matters is that it performs them at all. Thus, following this line of thinking, it can be assumed that artificial intelligence includes intelligent actions, but this intelligence does not have to match human intelligence. The Dictionary of Polish Language defines artificial intelligence as a machine that simulates human thinking, as a distinguishing feature of artificial intelligence (Dictionary of Polish Language, 2024). English-language dictionaries define it similarly: "Artificial intelligence is a type of computer technology that deals with making machines act in an intelligent way, similar to the way the human mind works" (Collins Dictionary, 2025), the capability of a machine to imitate intelligent human behaviour (Merriam-Webster, 2025). In contrast, the PWN Encyclopedia defines it as a field of science that deals with the study of the mechanisms of human intelligence and the modelling and construction of systems that are capable of supporting or replacing intelligent human actions (PWN Encyklopedia, 2024).

In the literature, you can find many definitions that refer to artificial intelligence as a field of science: artificial intelligence is a field of science that deals with efficient solution of non-algorithmizable problems based on knowledge models (W. Duch, 1997), artificial intelligence is a field of research that attempts to imitate human intelligence in a machine. The field of artificial intelligence includes knowledge base systems, expert systems, image recognition, automatic learning, natural language understanding, robotics and others (R. Kurzweil, 1999), it is the science of actions that would cause machines to perform functions that humans currently perform better. (E. Rich, K. Knight, 1990), a field of science that attempts to explain and mimic intelligent behaviour using computational methods (R. J. Schalkof, 1990). For the purposes of this article, however, the key definitions are those that introduce the practical aspect of the use of artificial intelligence, which is the definition that artificial intelligence

is understood as a technical solution (implicitly a computer program) that performs such activities that are usually the domain of humans, particularly those activities that require the use of human intellect. Artificial intelligence is a machine that behaves like a human; it is, however, a machine that thinks. The cited definition is close to the definition of the original artificial intelligence, which has already been cited above, and pointed out as one of the first in history, formulated in the works of John McCarthy. (J. Mccarthy, M.L. Minsky, N. Rochester, C.E. Shannon, 1955). The authors of the so-called Turing test (A. Turing, 1950) have a similar approach - a machine is intelligent when the response of artificial intelligence and the response of a human are difficult to distinguish. The cited definitions are rather social (humanistic) in nature. Analysing their (definitions) assumptions, it should be said that they put on an equal footing or imply a great similarity between the actions of humans and machines. Judgments in each case are subjective in nature, here too. It is difficult to objectively assess the way a machine and a human operate - everyone can assess the degree of similarity in a different way. In addition, humans are learning and problem-solving beings; not every machine has such functions, so those without learning and problem-solving properties should not carry the name of artificial intelligence, and the definitions cited, however, suggest this. Such a general and liberal definition of artificial intelligence seems simple to understand. As has already been shown, defining the concept of artificial intelligence is complicated. This is certainly due, among other things, to the lack of a uniform and scientifically accepted definition (Nilsson, 2009; Monett, Lewis, 2018). Summarising the definitions quoted here, it can be said that their essence is:

- automating actions that resemble human intelligence,
- explaining and exploiting intelligent behaviour through computation,
- systems that think and behave like humans in a deliberate manner,
- researching and creating models of intelligent human behaviour through various scientific disciplines, and creating computer programs that emulate these behaviours.

Reviewing the literature over the years, as well as observing the technological progress, it is necessary to take the position that artificial intelligence is a field that has been developing for many years, with the participation of specialists from various fields, such as computer science, cognitive science, psychology, linguistics and statistics (S. Pokrivcakova, 1019). However, not only is the scientific dimension important here. Artificial intelligence meets the needs and expectations of working people, practitioners, and professionals in various industries.

Artificial intelligence has also found its place in the food service industry. There are not many studies in this area; usually, they are not strictly about gastronomy, but about cuisine, promotion, health and forecasting related to gastronomy (H. Türkoğlu, G. Yilmaz 2022). Gastronomy is related to the culinary arts, so the introduction of artificial intelligence into the kitchen opens up the process of culinary transformation, which may involve various concerns (Zoran, 2019). However, despite this, conducted analyses of the possibility of using artificial intelligence (Zoran, 2025), ethical issues related to artificial intelligence (Bale, Dhumale, Beri, Lourens, Varma, Kumar, Sanamdikar, Savadatti 2023), or legal issues (Krausova, 2019) are the subject of discourse. Referring to the practical sphere of the use of artificial intelligence, reviewing various sources, one can encounter many proposals for the use of artificial intelligence in the food service industry.

3. METHODOLOGY

3.1. Participants

Entities from Gdansk were selected for the study because the city receives a great number of tourists every year, in 2023 – 4.1 million tourists (Tourist Traffic in Gdansk, 2024), while Gdansk Airport served more than 6.7 million passengers in 2024, almost 14 percent more than in 2023 (R. Pietrzak, 2024). Due to such a large number of tourists and, as the data indicate, their number increasing year by year, it was decided to conduct the research specifically in Gdansk, in January-February 2025.

The study involved 10 people working in the food service industry in Gdansk, Poland. They were people in the positions of chefs or owners of catering outlets. Five representatives of so-called “small catering” outlets, i.e. quick service bars where one can order and buy ready-made (pre-prepared) or quickly prepared snacks, such as burgers, tortillas, hot dogs, pasta, casseroles or sandwiches, were invited to participate in the study. These were mainly the owners of these outlets. The remaining five

respondents were chefs located in hotel establishments (small and medium-sized businesses). The respondents were mostly male - 9 men and one woman (W-2) and had at least five years of experience in the food service industry. Participants were eager to participate in the study. A drop in engagement occurred when asked about the implementation of artificial intelligence in their organisations. This question caused difficulties for the respondents.

3.2. Research Protocol and Stimuli

The research was conducted at the workplace of the study participants.
Analysing the proposed solutions and based on the review of the definitions of artificial intelligence, five questions were constructed:

1. What is your understanding of the term “artificial intelligence”?
2. In what activities is artificial intelligence used by you at work?
3. What opportunities do you see for the use of artificial intelligence in your work in the future?
4. What barriers do you see to the introduction of artificial intelligence at your work?
5. What should be done so that artificial intelligence could be used in your work?

In the questions, it was intentional not to formulate the questions at a high level of generality of asking about the food service industry, but to focus on the workplace and the duties performed by the respondents.

Each interview lasted about 30 minutes and was conducted individually, after the respondents' working hours. Those taking part in the survey were rather eager to answer, and two of them showed great interest in the topic of artificial intelligence. Questions were asked in the same order for each interview.

3.3. Research Apparatus

The surveys were conducted at the participants’ workplaces, which allowed for more authentic and contextual responses. Conducting interviews in the natural work environment of the respondents was intended to minimize the influence of external factors and ensure that the participants felt comfortable and free to share their experiences and thoughts about artificial intelligence. Analyzing the proposed solutions and based on a review of the definitions of AI, five key questions were constructed to explore the understanding of the concept and its application in the context of the respondents’ work. These questions were carefully selected to elicit specific and practical answers that would be relevant to the study group. They are as follows:

1. How do you understand the term “artificial intelligence”?

This question was intended to explore how respondents defined artificial intelligence in the context of their work. There were differences in the understanding of the term in the responses, which may indicate varying levels of knowledge about the technology and its applications.

2. In what activities do you use artificial intelligence at work?

This question was intended to identify specific examples of how respondents use artificial intelligence in their daily work. The answers could cover various aspects, such as process automation, data analysis or the use of decision support tools.

3. What opportunities do you see for using artificial intelligence in your work in the future?

This question aimed to explore the respondents' perspectives on the development of artificial intelligence technologies in their industries. Participants could indicate potential benefits such as increased efficiency, improved quality of services or better personalization of the offer for customers.
4. What barriers do you see to the introduction of artificial intelligence in your work?

This question aimed to identify obstacles that may hinder the implementation of artificial intelligence in the workplace. The answers could include issues such as lack of resources, resistance to change or insufficient knowledge of the technology.

4. What should be done to use artificial intelligence in your work?

This question aimed to explore what actions can be taken to facilitate the implementation of artificial intelligence in the daily duties of the respondents. Participants could indicate the need for training,

investment in technology or changes in the organization of work. I deliberately avoided formulating questions at a high level of generality, focusing on the specifics of the workplace and the duties performed by the respondents. This selection was aimed at obtaining more practical and useful answers that would be applicable to the realities of their daily work. Each interview lasted about 30 minutes and was conducted individually, after the respondents' working hours, which allowed for a free conversation without the pressure of time and professional obligations. The participants of the study were quite eager to answer, which indicates their interest in the topic. Two people in particular showed a strong interest in the topic of artificial intelligence, which could lead to more detailed and engaging discussions. The questions were asked in the same order in each interview, which ensured the consistency and comparability of the collected data, allowing for later analysis of the answers in the context of general trends and differences in the perception of artificial intelligence by the participants.

3.4. Analysis of Measurement Data

The first question, "What is your understanding of the term 'artificial intelligence'?" was answered by all respondents, but it can be concluded from the answers obtained that the respondents do not have specific knowledge of artificial intelligence; their answers are usually characterised by a high degree of generality:

- it's a machine that relieves humans of their work (W-4),
- it's such systems that help with work (W-5),
- it's a Thermomix-type device that, if someone can't cook, tells him step by step what he should do (W-8),
- it's such a device that has features of artificial intelligence (W-9, W-10).

The most precise answer was given by two respondents:

- such a technology that allows a machine to demonstrate human reasoning and capabilities, suchas autonomous decision-making (W-1),
- are high-level developed systems, processes that a machine uses that are similar to what human intelligence does. You can say that it uses the properties and characteristics of a human being (W-3).

In the interview, it turned out that one of them graduated from a technical college (W-1) and another is interested in artificial intelligence as a hobby, with his son playing computer games where artificial intelligence is used (W-3).

Other respondents said that:

- it is difficult to explain what this artificial intelligence is (W-2),
- don't know exactly (W-6),
- hard to say (W-7).

After the responses, it can be concluded that the knowledge of artificial intelligence among representatives of the food service industry varies greatly. Indeed, technical education and interests allow "on their own" to seek information about artificial intelligence. However, as the survey shows, most people do not know what artificial intelligence is or have little knowledge of it.

It should be emphasized that these statements are not extensive. Rather, they cited "definitions" of artificial intelligence, which are commonly referred to in catchphrases in casual conversations.

Another question asked was about the use of artificial intelligence: In what activities is artificial intelligence used by you at work? The answers received were surprising, as they caused difficulties for most of the respondents. They could not identify tools that function with artificial intelligence; moreover, they did not think further about the answers:

- I do not use artificial intelligence at work (W-2, W-6, W-7),
- I have no need to use artificial intelligence in cooking (W-4),
- I don't use it, but I have young people at work, and sometimes they slip me a recipe from artificial intelligence and want us to try it out. Sometimes I agree, and then they tell the customers that it's an artificial intelligence recipe – we have fun (W-5).

It should be noted here that the respondent was a representative of a small catering business.

Respondents who gave a definition of artificial intelligence were also able to point out examples of devices they use that could be equipped with artificial intelligence:

- It seems to me that some substitute for artificial intelligence is in the mixer, as it separates cakes on its own, and the tilting pan, which regulates the heat on its own, adjusting to the baking level of the product (W-3).
- I sometimes use artificial intelligence on a trial basis when creating a list of products to buy. I then upload the menu and recipes to the computer - artificial intelligence, no Chat GPT and try it out. It works out nicely, but I always still check to make sure it's all right. It's definitely faster, but I wouldn't be able to trust it so completely. After all, it's artificial intelligence and you have to remember that it's just a machine (W-1).

The presented positions confirm the lack of knowledge about the possibilities created by artificial intelligence. Using artificial intelligence not only creates new development opportunities but also allows for faster work. The claim that there is no need to use artificial intelligence at work presents an attitude that is closed to new solutions, as well as does not allow for the acceleration of methods of performing tasks. Artificial intelligence offers various solutions that can inspire and increase their effectiveness.

Three respondents tried to identify the devices they use, but were unsure of their statements:

- In our kitchen, we would rather not have any such machine with artificial intelligence, but I saw in the lobby of the hotel a riding robot that helped with cleaning. He did everything himself and washed and wiped and frothed, and when he had too much or got tired, he went down to his corner. Such an attraction for guests, by the way, for us too (W-9)
- We have a modern kitchen and we have machines that do various things, but it's hard for me to say whether they have artificial intelligence or rather not (W-8)
- I don't know what artificial intelligence really is, so I don't know which of the equipment we own can have such an artificial intelligence module encoded into it. It seems to me that they are ordinary robots with higher technology, that they have artificial intelligence, rather not (W-10)

The answers obtained show that awareness of the use of tools equipped with artificial intelligence is not high. Although it was not verified whether artificial intelligence is actually used in the respondents' workplaces, this was not the purpose of the survey. However, based on the answers given, it can be assumed that for some respondents, they are accompanied by concerns about artificial intelligence. The response to the question asked suggested surprise. It should be assumed that if the respondents cannot describe what artificial intelligence is, it will also be difficult for them to identify tools that use artificial intelligence. But when asked the question about the tools used at work, it was suggested by the complexity of the device or the functions it has. As the results of the survey showed, one person consciously uses artificial intelligence, but it is on the basis of playing and "trying" artificial intelligence.

The third most important question: "What opportunities do you see for using artificial intelligence in your work in the future?" required additional explanation. For some respondents, it was necessary to ask a supporting question: "What could artificial intelligence help you with? What activities could it perform for you?" The answers obtained were as follows:

- It would be good if she prepared nice descriptions of dishes that are posted on the website handled social media (W-2).
- I would like her to offer menus tailored to specific requirements and instructions for employees to make them (W-4).
- At work, we have problems with waiters, maybe he could serve customers, distribute dishes and clean up tables (W-5).
- For me, he could support us in terms of running the warehouse, determining what needs to be bought, and what needs to be used up so that it doesn't go to waste. It could be such a control over the warehouse of products (W-1).
- Sometimes it is the case that when a customer is waiting for an order, he is impatient, maybe such a robot could talk to the customer, occupy his time (W-3).
- For me, artificial intelligence could help in customer service, in taking orders, maybe not in making payments, because I would have concerns and maybe customers too, but in serving the customer and waiting so patiently for what he decides (W-6).
- Maybe analysing employees' working hours and their schedules. This poses difficulties because they change frequently. Maybe artificial intelligence would embrace this subject (W-7).

- paperwork, administrative issues, reminding people to pay their taxes (W-8).
- I would like such a robot that would replace a kitchen helper, that could peel potatoes, cut up sausage, etc. (W-9).
- I wouldn't let artificial intelligence into the kitchen, nor would I send it to get groceries, but maybe a conversation with a customer, I don't know (W-10).

The responses obtained indicate what problems the respondents are facing. What's interesting is that they rather seek artificial intelligence support outside the kitchen. They prefer to bring artificial intelligence into administrative or customer relations issues. This may be due to the fact that the products created in the kitchen are the most important element indicating the quality of the services and dishes offered. It is the customers who judge the taste, preparation and aesthetics of the dishes. If the quality of the dishes offered dropped, customers might not return. Hence, there are concerns of introducing artificial intelligence into the kitchen. The second important point from the point of view of the owner of a catering entity is customer service. Here, they are more ready to entrust this task to a robot. Customers can sometimes be difficult, and waiters can be impatient, while a well-programmed robot can serve customers to a high degree of quality.

The next question asked about the difficulties of introducing artificial intelligence at work: "What barriers do you perceive to introducing artificial intelligence at your workplace?" None of the interview participants had difficulties with such a question:

- Convincing superiors to introduce artificial intelligence is certainly a challenge, but also convincing employees to use it would be difficult. Training and a rather long process of adaptation, getting employees used to it and becoming friends would be necessary. Not everyone is enthusiastic about the idea of introducing artificial intelligence (W-3).
- The introduction of devices, robots with artificial intelligence, seems to be quite expensive, but the use of artificial intelligence in administrative management, scheduling, maybe reserving space in a restaurant would be useful, given my own adventures with artificial intelligence and attempts made to use it would certainly improve work. This is my position, of course, and I'm open to innovation, but I don't know how it would be with employees. There is always resistance when we want to introduce new equipment or new technology. Employees see it as a change, and no one likes changes (W-1).

Other respondents themselves showed resistance to introducing tools using artificial intelligence into their work:

- Human beings can't be replaced by anything. Why introduce some solutions that will have to be supervised anyway (W-2).
- It is not a good idea to introduce artificial intelligence to work in the kitchen. If such a step is taken, people may lose their jobs, besides, how will the machine taste the cooked food? Not likely, no. (W-4).
- The barrier is certainly finances; it must be an expensive venture. (W-6).
- We have a small catering business, and we are unlikely to need artificial intelligence. Barriers? Probably cash, money with them, there are always more or less problems, still not enough (W-10).
- There are always financial barriers, especially in an uncertain market, you have to look at different issues. If it turns out that we are an outlier in terms of artificial intelligence, you will have to look for solutions to put it to work. I think it is still a long way in the future before we have to think about what and how with this artificial intelligence (W-8).
- The problem will be the employees, the lack of competence in the use of artificial intelligence, besides, I don't think there are legal regulations on the use of artificial intelligence. Maybe it's better not to get ahead of the game, because you'll miss something, and there will be a problem (W-9).
- I myself don't quite know what this artificial intelligence is, everyone says it promotes development and efficiency. Hmm... maybe if someone could tell me what and how more, help me implement solutions, then there would be no problem, and well, the cost, maybe some funding? (W-7).

The only optimistic, even carefree position seems to be that of one respondent:

- For the willing, nothing is difficult. Since my guys are already out there digging into artificial intelligence and (W-5).

The indicated barriers seem obvious. The concerns presented vary in nature and are certainly mostly related to financial issues, but also the barriers suggested by the respondents are a lack of knowledge about artificial intelligence, a lack of regulation, as well as employee resistance. Knowledge and resistance are categories that require effort but are surmountable.

It should be noted that the answers obtained were formulated at a high level of generality. None of the respondents provided specific data, information, or details. All of them answered in a way that suggested little knowledge about artificial intelligence. This means that the answers given could only have been overheard in casual conversations. The respondents themselves did not reach for information that would be credible, based on their own experiences or scientific research. Lack of knowledge means that the respondents may feel insecure about a given topic. Contact with a stranger very often arouses uncertainty and fear. What is more, it is more difficult for employees to convince their superiors of new solutions than it is for an employer (leader) to convince employees of their arguments. Therefore, it seems important to convince entrepreneurs, leaders, and employers who could introduce artificial intelligence to their organizations.

The last question from the prepared questionnaire of questions was: “What should be done so that artificial intelligence could be used in your work?” This question made the respondents smile. The answers were as follows:

- Preparing a plan, a project on the application of artificial intelligence, determining in what areas it would be applied, such as a business plan for artificial intelligence in our restaurant (W-1).
- Convincing me and my employees of the appropriateness of applying artificial intelligence to us (W-2).
- Consulting on the use of artificial intelligence and developing a scenario for introducing it inthe company, well and costs (W-3).
- Showing the tangible benefits of its application, what pays off and what doesn't (W-4).
- Maybe funding for the introduction of artificial intelligence, but also conducting an expert analysis of our business and pointing out the risks associated with the introduction of artificial intelligence. But I think I need to think about introducing artificial intelligence into our work anyway (W-5).
- Looking at other organisations, how they use artificial intelligence, what costs they incur, and what risks they have. There's more and more talk about it, I mean this artificial intelligence, maybe it would surprise us, and I think I'd rather be prepared, but I have concerns about what will happen if something goes wrong (W-6).
- I think I'm getting closer and closer to the decision that we need to look at artificial intelligence and consider its presence with us (W-7).
- I don't know, I'll think about it in a while (W-8).
- Hard to say. I haven't thought about artificial intelligence in or out of the kitchen yet. Certainly, these machines that we have probably somehow use artificial intelligence, then I don't need to introduce... (W-9).
- I would not like to make any declarations. I will certainly look into the subject in the near future (W-10).

Analysing the responses obtained, it can be assumed that the respondents recognise the need to pay attention to artificial intelligence and think about introducing it in their organisation. Certainly, from the statements, there are concerns about the application of artificial intelligence. The respondents themselves suggest solutions that would make them feel “familiar” with the tool, which is used in various industries.

4. RESULTS

The research conducted using the individual interview method was a pilot study, and its purpose was to find out the knowledge of artificial intelligence and its use among representatives of the food service industry.

The results obtained show that knowledge of artificial intelligence, as well as its current use it in the industry, is not high. Respondents had difficulty defining what artificial intelligence is, as well as having doubts about the use of artificial intelligence in their organisations. They struggled but were able to indicate how it could be used in their work and in their organisation. It is optimistic that despite pointing out the barriers that could occur in the introduction of artificial intelligence in their organisation, at the same time, they are able to suggest forms of bridging them. In general, it can be assumed that despite little knowledge of artificial intelligence, the respondents are aware of the need to draw attention to the fact that artificial intelligence exists and that it brings certain benefits. In addition, respondents indicated concerns about the introduction of artificial intelligence in their organisations.

To sum up the research, the following conclusions can be drawn:

1. Lack of use of artificial intelligence at work. Respondents clearly indicate that they do not use artificial intelligence in their work. This may suggest several things: Low awareness of technology: Respondents may be unaware of available artificial intelligence tools that could improve their work. Traditional nature of the industry: Catering is a sector that often relies on traditional methods of cooking and customer service, which may limit the willingness to introduce new technologies. Fear of novelty: Fear of change and uncertainty about the effectiveness of artificial intelligence in the catering context are also possible factors.

2. Cautious approach to artificial intelligence. The respondent uses artificial intelligence to create shopping lists and recipes, but at the same time emphasizes that he always verifies the results. This shows: Critical thinking: Respondents realize that AI is a tool that can bring benefits, but it is not able to work flawlessly. This approach can be a healthy balance between using technology and maintaining control over processes. Experience-based trust: Respondents note that AI speeds up processes, which can be beneficial in the context of catering work, but at the same time requires active supervision. 3. Interactive use of artificial intelligence. The responses indicate an interesting aspect of using artificial intelligence – interaction between employees. The younger generation introduces recipes from artificial intelligence, which may suggest: Creativity and innovation: Experimenting with recipes together creates an atmosphere of openness to new ideas, which can be beneficial for team development. Team integration: These activities can foster building relationships within the team, which is important in the catering industry, where cooperation is key.

4. Examples of technology as artificial intelligence. Respondents point to specific kitchen appliances that can be seen as forms of artificial intelligence. This highlights: Practical understanding: Respondents connect the concept of artificial intelligence with everyday tools, which may indicate their practical approach to technology. They realize that many devices in their environment have functions of automation and autonomous operation. Educational opportunities: There is potential for education on how technology can support everyday tasks, which could encourage greater use of artificial intelligence in the workplace.

5. Perception of artificial intelligence as a tool. Overall, respondents perceive artificial intelligence as a tool that supports, rather than replaces, human creativity. This indicates: Human skills as key: In the catering industry, culinary skills and creativity are irreplaceable. Artificial intelligence can support, but cannot replace, the passion and knowledge of chefs. Trust and customer relationships: Respondents recognize that customer relationships and personalization of service are key in the catering industry, which may limit their willingness to use artificial intelligence in customer interactions. Summary The analysis of the responses indicates a variety of approaches to artificial intelligence in the context of catering work. Respondents are cautious and critical of technology, emphasizing the importance of human skills. However, there is potential for further education and exploration of the possibilities that artificial intelligence brings, especially in terms of automating processes and facilitating everyday tasks. The introduction of artificial intelligence in a thoughtful manner could contribute to increased work efficiency and innovation in the catering industry.

5. DISCUSSION

Reflection on the obtained research results shows that in smaller organisations, the concept of artificial intelligence is a known concept, but it has a rather pejorative character. Such a statement results from the resistance to introducing artificial intelligence to micro and small organisations. Interestingly, one can assume that the interview was conducted in a "relaxed atmosphere" until the respondents were

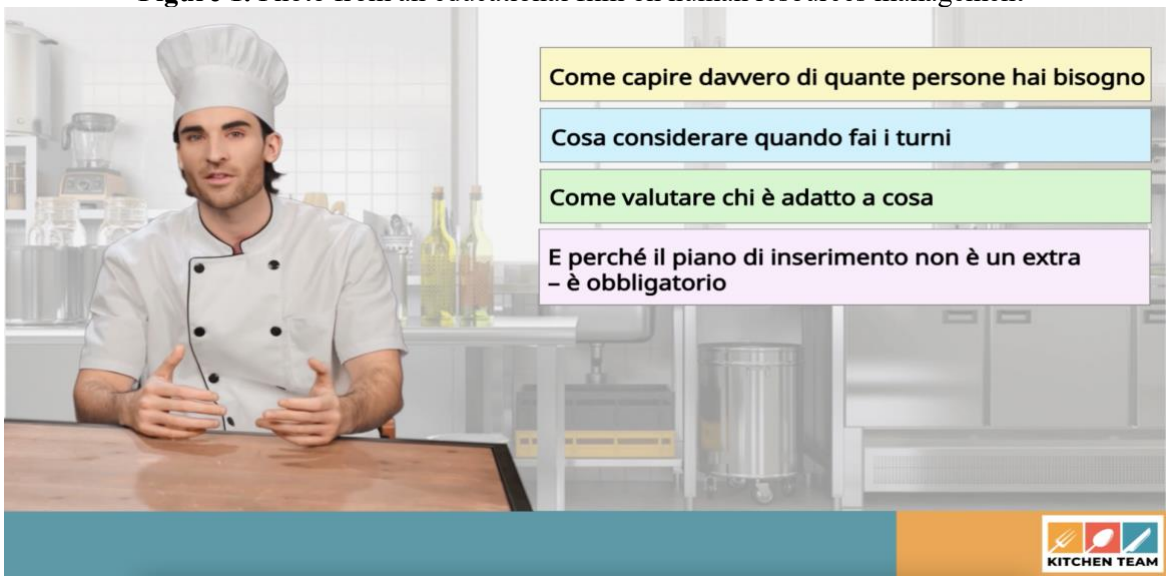
confronted with the claim that artificial intelligence could be used in their workplace. The question arises: Where does the resistance in this area come from? The obtained research results may suggest that the lack of sufficient knowledge about artificial intelligence and awareness that it is not an abstract creation, but is present on the market, may cause the interest in artificial intelligence to increase. What is more, it can become a real tool in the organisation and cooperate with the employees present there.

Another aspect that may also affect the degree of use of artificial intelligence, moreover, familiarisation with information materials related to artificial intelligence, is the position on the pejorative nature of the term ‘artificial intelligence’. In order to avoid bad associations, it seems right to consider introducing a new term that would replace the term "artificial intelligence". It seems that this term should be characterised by accessibility in its understanding. Therefore, it may be worth proposing the term ‘modern technology’, ‘complex IT systems’. Such an approach gives employees information about the need to learn how to use devices, new systems, and does not "threaten" their workplace.

Returning to educational issues, it is worth discussing the sources of reliable knowledge about artificial intelligence. What entities and institutions should play such a role, and how to prepare people who will talk about artificial intelligence? It is obvious that artificial intelligence educators among entrepreneurs will be sales representatives of entities that will have services or products based on artificial intelligence to offer. Here, therefore, an important role is that, in addition to the substantive preparation of sales representatives in the scope of the functioning of artificial intelligence in the offered production or service, they have knowledge about what artificial intelligence is and what its significance is in contemporary reality and what benefits it provides and risks it creates. Such an approach can start the process of broad education of all entrepreneurs, not only in the catering industry.

It is worth getting acquainted with examples of good practices that were used in the process of developing methods and academic materials for graduates of catering schools in the field of management as part of the project “Methodology of teaching management for future catering employees”, No. 2023-1-PL01-KA220-VET-000167215, which is covered by the ERASMUS plus program. The project's objectives included developing educational materials on human resources management, including topics such as employee selection, team building, task delegation, conflict resolution, and motivation. The materials developed included a curriculum, lesson plans, knowledge assessments, and educational videos discussing specific topics. Sample images from the videos are presented below.

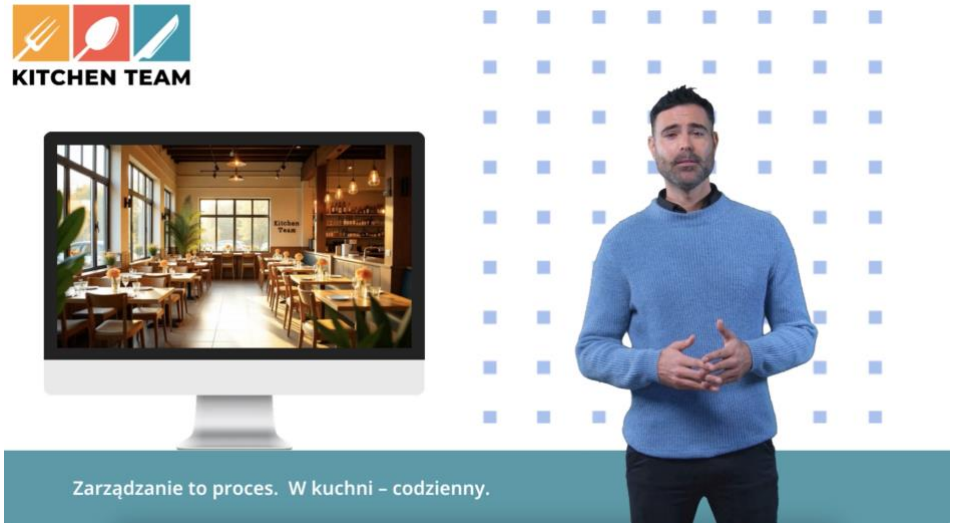
Figure 1. Photo from an educational film on human resources management



Source: “Methodology of teaching human resources management for current and future catering employees”, No. 2023-1-PL01-KA220-VET-000167215.

All educational videos were created using artificial intelligence. As you can see from the photos presented, AI helps create a friendly learning environment and inspire trust. The characters presenting educational content evoke sympathy, but above all, credibility.

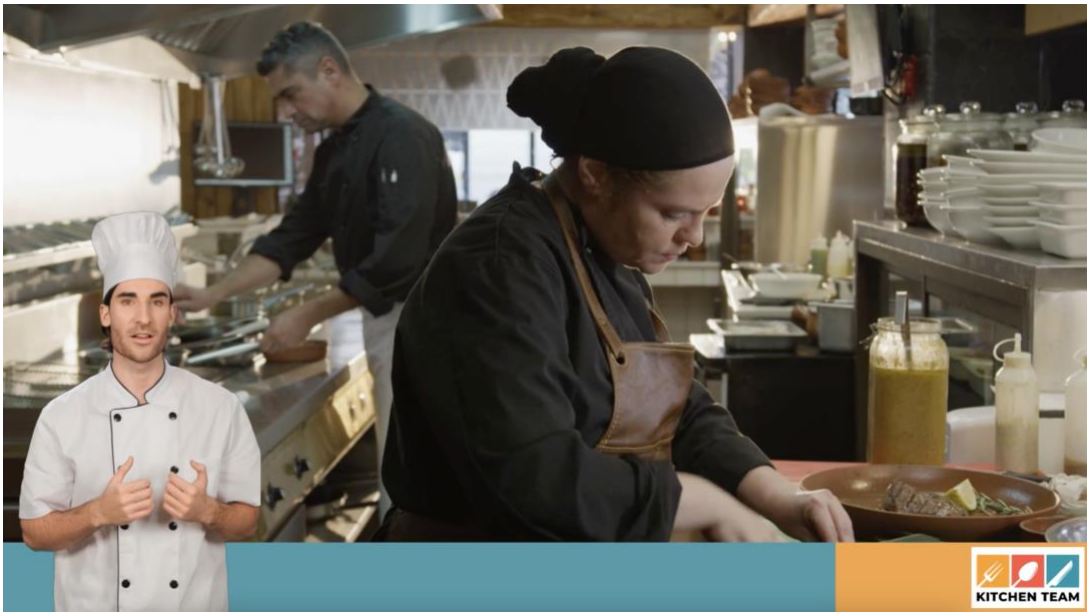
Figure 2. Photo from an educational film on human resources management



Source: "Methodology of teaching human resources management for current and future catering employees", No. 2023-1-PL01-KA220-VET-000167215.

Additionally, artificial intelligence allows for the creation of various characters, depending on needs, and suggests solutions that are effective in the learning process. Above all, it allows for the language to be adapted to the audience. In addition to using industry-specific terminology, it also employs slang appropriate for the age of the audience. The narrator's attire and the selection of backgrounds and scenes in educational videos create the impression that the audience is in a familiar, familiar environment, which encourages them to engage with the educational content.

Figure 3. Photo from an educational film on human resources management



Source: "Methodology of teaching human resources management for current and future catering employees", No. 2023-1-PL01-KA220-VET-000167215.

The solution proposed in the project creates additional opportunities for students and employees in the food service industry to become familiar with artificial intelligence. Preparing educators and teachers to impart knowledge and use AI-based educational materials requires them to acquire skills in this area.

By using such materials, teachers disseminate knowledge about how to use AI tools and the benefits of its application among their students.

In the context of further research explorations, when taking on issues of artificial intelligence, one would have to consider the scale of the phenomenon and the anonymity of the research. In the case of the interview method used, the respondents were confronted with the interviewer. Perhaps if the research had been carried out using the diagnostic survey method and with the survey questionnaire tool, the respondents would have felt more at ease. To a certain extent, the questions regarding knowledge of artificial intelligence were in the nature of control questions. This could have made the respondents uncomfortable. Which, in turn, could have shown a desire to "please" the respondent, or caused concerns about the correctness of behaviour and getting a negative evaluation in the eyes of the interviewer. In the case of an anonymous survey, the respondents, when left alone with the survey questionnaire, would have a kind of freedom and space to answer the questions therein. The length of time they have to think about each question, as well as the lack of control over what answers they mark in each question, certainly provides an opportunity for reliable answers. Conducting research by means of a diagnostic survey would provide an opportunity to verify the statements made during the interview. In addition, it would be valuable to have statements from people working in a wider range of positions. This would provide a cross-sectional view of the representatives of the catering industry on the use of artificial intelligence in their work. In addition, the survey could show the opinion of individual professional groups of the catering industry on the use of artificial intelligence in their daily work. However, it should be emphasised that the research conducted, the results of which are presented in this article, represents a preliminary understanding of the issue of artificial intelligence in the catering industry. The results obtained, as presented earlier, show concern and resistance.

In turn, the survey research carried out and the results obtained may show a deepening of the resistance phenomenon. In this situation, it may be worrying because an artificial intelligence tool can be compared to other tools, such as a computer or a mobile phone. Both, at the time of their introduction and widespread use, inspired fear and uncertainty. In the case of mobile phones, users quickly became convinced of their usefulness and ease of use. However, it should be emphasised that mobile phones are a "better" version of landline phones, which are still used in offices today. Familiarity and relevance of telephones was and is widespread. It was different with computers. They were a new tool and were introduced into offices quite quickly. Mature people found it difficult to learn how to use a computer, and there were also negative emotions about having to transfer data collected on paper into computer databases. Support for the introduction of computers into workplaces was provided by staff training. These were often cyclical in nature. Over time, there was also technical support in the form of a hired IT specialist or an external company helping employees to improve their computer, digital skills. Certainly, the educational process, which was gradually introduced in primary and secondary schools, contributed to the 'familiarisation' of people with computers.

So, building on good practice, it may be worth considering the possibility of supporting, or rather taming, more people, not just those interested in artificial intelligence. As mentioned above, certainly one method to familiarise employees will be to conduct training sessions. A series of two to three meetings should be recommended. Training topics should consist of a section on the pros and cons, benefits and losses of artificial intelligence. This will sensitise and encourage verification of content generated by artificial intelligence. Subsequent sections could be practical and deal with the handling of artificial intelligence and its application. It does not seem right to recommend the creation of a dedicated position for artificial intelligence, especially in entities that do not specialise in this field.

In the context of the recommended measures to disseminate knowledge on artificial intelligence, it is necessary to introduce regulations to control the use of artificial intelligence at work. It is not sufficient to only train and allow employees to use artificial intelligence. It would be appropriate to introduce procedures, rules regarding the use of artificial intelligence for professional purposes. The regulations, which have already been pointed out in terms of the need for them at national level, should also be reflected in regulations at workplace level. Artificial intelligence offers a great number of possibilities for its application, moreover, it has a factor that triggers creative and imaginative thinking, so it can inspire various initiatives, activities, problem solving for humans. With the functioning of artificial intelligence and the experience of its functioning, its users are very quickly becoming convinced that artificial intelligence offers more possibilities than standard, commonly used browsers. This may lead

to some degree of reduction in the use of existing browsers or perhaps even their displacement from the market.

Thus, a revolution of sorts taking place necessitates the introduction of regulations to provide a sense of security, which was also mentioned by respondents.

6. CONCLUSION

Artificial intelligence, depending on the context, can be considered as a phenomenon, a tool, among other things. It can be perceived positively and negatively. It can be presented and discussed in the language of benefits and losses. However, despite this, it is clear that it inspires different environments, industries and scientific disciplines. Artificial intelligence is entering the world of education, business, affecting many industries, including the catering industry, which was considered in this article. Whatever one does not write, one must state with conviction that it is present in human life. It is used by man in various ways. Thus, it is man who is in control of artificial intelligence and not vice versa. This should obviate concerns about the legitimacy of the presence of artificial intelligence. One should not close oneself off to it, pretend that it does not yet apply to an industry, an area of life or play. On the contrary, an attempt should be made to "disenchant" it and familiarise ourselves with it.

Based on the results obtained, it should be recommended to start activities popularising artificial intelligence not only at the academic level, but also at the level of vocational schools, or by reaching specific employees and owners of specific catering entities. Fears about introducing artificial intelligence to catering organisations result precisely from insufficient knowledge. It is important for managers to be able to convince their employees to work with artificial intelligence systems. This can be supported by raising competences in the field of artificial intelligence of both managers and their employees. It is certainly desirable to create a consulting network for the use of artificial intelligence in all industries, not only in the catering industry. In addition, adding national regulations on artificial intelligence and developing ethical principles regarding the use of artificial intelligence would encourage a more bold use of artificial intelligence. The subject of the article has not been exhausted, and the research conducted in the field of artificial intelligence was of a pilot nature and should be conducted systematically.

It is worth adding that the presented example of good practice will be available after the completion of the project "Methodology of teaching human resources management for current and future catering employees", No. 2023-1-PL01-KA220-VET-000167215, which is implemented under the ERASMUS plus program, on the website of the Erasmus + Project Results Platform: https://erasmusplus.org.pl/platforma-rezultatow-projektow-erasmus.

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28th European Conference on Artificial Intelligence (ECAI 2025)

ARTIFICIAL INTELLIGENCE IN THE EMPLOYMENT PROCESS IN HIGH-TECH COMPANIES IN EUROPEAN UNION REGIONS. CURRENT STATE OF KNOWLEDGE AND NEEDS FOR FURTHER RESEARCH

Aneta Sokół[a], Karolina Drela[b], Petr Hlaváček[c], Rafał Czyżycki[d]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *University of Szczecin, Institute of Management, Szczecin, Poland*
[c] *University of Jan Evangelista in Usti nad Labem, Faculty of Social and Economic Studies, Usti nad Labem, Czech Republic*
[d] *University of Szczecin, Institute for Spatial Planning and Social and Economic Geography, Szczecin, Poland*

ABSTRACT

Purpose: *This article aims to consider the cognitive, theoretical-methodological, and empirical issues surrounding the development of the percentage of people employed by high-tech companies and to establish the extent of the impact on the GDP of the countries studied, while also pointing to the significant potential for the positive impact of artificial intelligence.*

Need for the study: *High-tech companies and their development lead to wisdom and create intellectual excellence in the regions where they develop. Artificial intelligence, which enriches the development of these actors with new tools not previously used and allows the acquisition of new digital competencies not previously used, has and will continue to significantly impact these development processes in the near future.*

Methodology: *The empirical part presents the results of a survey conducted on a sample of 242 NUTS 2 regions of the EU. The study uses Pearson's correlation coefficient and presents the evolution of the coefficient value examining the impact of high tech on the development of GDP per capita (t=0) in individual EU regions.*

Findings: *Furthermore, based on the analyses conducted, it can be clearly stated that the percentage of people employed in high-tech areas has a significant statistical impact on the shape of a region's GDP regardless of the time lag. However, detailed analysis shows that the strongest impact of the high-tech indicator on GDP occurs when a two-year lag is taken into account.*

Practical Implications: *The resulting conclusions of the study provide knowledge to regional managers that their development and the development of high-tech companies are interrelated.*

Keywords: artificial intelligence, regional development, high-tech enterprises, employment, EU regions

Jel codes: J01; D8; E2

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1. INTRODUCTION

In recent years, there has been a fundamental change in the approach to the issue of high-tech enterprises in economics, but also in management. As a knowledge- and technology-intensive economic unit that continuously conducts research and development (R&D) and technology transformation, the high-tech enterprise is an important carrier of scientific and technological innovation, a major force for the development of the national high-tech industry and a new force for regional innovation (Zhang, Lv, 2013).

Human creativity is one of the most important sources of socio-economic development, including the emergence of high-tech companies. The sector is one of the most promising economic sectors in many highly developed countries. Its potential encompasses many activities characterised by a high proportion of human labor. There is a close relationship between the number of people employed in high-tech companies and the development of regions. A key issue in this relationship is, first and foremost, the very broad spectrum of impact of these enterprises in both the economic and socio-cultural spheres. For this reason, a special role is seen for demographic and socio-cultural factors as drivers of their development. Hence, both theoreticians and practitioners aim to meet the challenges of achieving such development, also while taking environmental conditions and social aspects into account. Accordingly, the focus of this article is to examine the development of a coefficient examining the impact of the hi-tech index on the development of GDP per capita (t=0) in individual EU regions. Therefore, in order to show a certain scientific area and subject it to analysis, two strands are distinguished in the article. The first, which is cognitive in nature, focuses on a qualitatively comprehensive analysis of the literature on the subject, which has provided a critical analysis and shaped the research framework. On this basis, we believe that research on the development of the percentage of people employed by high-tech companies has made significant progress and evolved. Our conducted research explored concepts related to the employment rate of high-tech enterprises in EU regions. We analyzed aspects available in the literature on the use of different proprietary methods to best estimate the development of the people employed of high-tech enterprises, so that we can constructively conclude what needs to be done in order for it to develop in the best possible way, in order to then generate added value for the development of the regions. The second strand, a study, focused on ongoing research in which we suggest that the percentage of people employed in high-tech enterprises is important for sustainable development at the NUTS2 regional level of European Union countries. In addition, implications for the development of artificial intelligence and its possible forms of impact on employment in high-tech enterprises are indicated.

The purpose of this paper is to consider the cognitive, theoretical-methodological, and empirical issues of the development of the percentage of people employed by high-tech enterprises and to determine the extent of the impact on the GDP of the countries studied. In the first stage, we investigate the extent of the impact of the hi-tech indicator on the development of GDP per capita, taking into account a possible time lag, and an analysis of the development of the Pearson linear correlation coefficient is carried out, taking into account the impact of the hi-tech indicator on the development of GDP of a given region in a given year (t = 0), in the following year (t = 1) and two years later (t = 2). In addition, we conduct time-sensitive research and compare the relationships and changes over ten years (the analysis considers the years 2012–2022). We conduct the research using measurable indicators, considering analytical data from Eurostat. We then analyze the results obtained by engaging in a thematic discussion and commenting on the research, pointing out limitations and suggesting further research directions.

The results of the research are of particular relevance to innovation, as high-tech companies and the creation of the right conditions for this development promote their competitiveness. The identification of guidelines that can change this state of affairs and the research that has been carried out has made it possible to identify areas whose improvement could help them develop more effectively and meet the demands of global competitiveness.

2. LITERATURE REVIEW

In the 21st century, the digital age is changing the way organizations operate, especially in the high-tech (HT – high tech) sector. The high-tech sector includes knowledge-intensive manufacturing (C-HT) and knowledge-intensive services (KIS-HT) industries. It should be noted that the key characteristics of knowledge-intensive organizations are becoming knowledge combined with other elements of the competencies of highly skilled employees (Alvesson, 2009; Sienkiewicz, 2013). It should be emphasized that entities operating within the high-tech sector are expected both to have and to apply state-of-the-art technological solutions in order to increase competitiveness and innovation (Grześ, 2023). Employees are required to have high competencies, which include, in addition to knowledge, also experience, attitudes and behaviors, and other qualities needed to perform specific professional tasks, regardless of how they are acquired (Kocór, 2019).

Roberts and Wolf (2018) believe that high-tech companies are significant to economies as they produce a significant proportion of total output. From a labor force perspective, high-tech industries employ a large number of skilled workers and provide higher wages for all types of workers than other industries (Roberts, Wolf, 2018). Also, Mohelska et al, (2020) emphasize that high-tech sectors and companies are key drivers of economic growth and productivity, and generally provide high value-added and well-paid employment. It can be assumed that the importance of high-tech industries will continue to grow as organizations want to be competitive. At the same time, it is needed for further economic and productivity growth (Horobet, et al. 2020; Alexandra, et al. 2022), so these directions should be further developed and supported (Mohelska et al, 2020).

According to Braja and Gemzik-Salwach (2020), knowledge-intensive and innovation-absorbing industries are seen as key drivers of economic growth and economic competitiveness. On the other hand, developed and competitive economies can create a favorable environment for further adoption of cutting-edge technologies and serve as reservoirs for the most promising technologies, which is why, among other things, employment in high-tech companies will grow.

Labor markets in the EU are showing diversity in terms of working time and the nature of employment relationships. First and foremost, these changes are driven by socio-economic trends, such as the shift to a service-based economy, the increasing participation of women in the labor market and technological developments. In addition, as a consequence of increased global competition, labor markets are responding to workers 'needs for employment adapted to private life and to employers' demands for flexible workloads (Weber, 2020).

Employment in the high-tech economy can be presented in the form of an indicator showing the percentage of people employed in manufacturing and service sectors that are considered high-tech, i.e. knowledge-intensive sectors. In 2022, high-tech sectors across the EU employed 9.8 million people, equivalent to 4.9% of total EU employment, with men accounting for just over two-thirds (67.2%) of the total (Eurostat 2023). Table 1 shows high-tech manufacturing, knowledge-intensive high-tech services and the high-tech economy in the EU (Employment in high-tech economy, 2024).

Knowledge-intensive services currently account for 38.5% of total employment in the EU and this percentage is increasing. It can be noted that in Belgium and Austria, the 'old' EU countries, employment in high-tech manufacturing will remain at the 2022 level in 2035 (no change marked in yellow). Only for 1 'new' EU country – Hungary – will there be a decrease in employment in high-tech manufacturing (the decrease is marked in blue), and for 4 'old' EU countries: Denmark, France, Italy and Luxembourg. The percentage of people employed in knowledge-intensive services will be at the same level for 1 'old' EU country – Ireland and will also fall for only 1 'old' EU country (Luxembourg). In conclusion, the percentage of people employed in the high-tech economy in 2035 will be higher for the 'new' EU countries, will decrease for Luxembourg, and will remain at the same level for Italy as in 2022. In 2035, the average employment in the high-tech economy is estimated to be 8.8%, where the minimum employment will be 4.1% for Greece and the maximum will be 15.4% for Slovenia (Employment in high-tech, 2024).

It is calculated that between 2022 and 2035, the average growth in employment in high-tech occupations will be 21.1%. For Bulgaria, however, this will be a decrease (minimum) of –7.1%, and the highest increase for Malta of 62.6%. It should be added that Malta's index is significantly higher than that of other countries, while Bulgaria's index is below standard compared to other countries (Employment growth, 2022).

Table 1. Employment (Employment in high-tech economy) in high-tech economy in old and new EU countries in 2022 and 2035 in %

Country	High-technology manufacturing		Knowledge-intensive services		Whole high-tech economy	
	2022	2035	2022	2035	2022	2035
Old EU countries „14”						
Belgium	3,3	3,3	2,8	3,0	6,1	6,3
Denmark	4,1	3,8	3,6	4,7	7,8	8,5
Germany	8,1	8,2	3,3	3,5	11,4	11,7
Ireland	3,3	3,4	4,4	4,4	7,7	7,8
Greece	1,2	1,3	2,3	2,8	3,6	4,1
Spain	2,7	3,2	2,9	3,4	5,6	6,6
France	2,3	2,1	4,5	5,1	6,8	7,2
Italy	4,8	4,5	3,0	3,3	7,7	7,7
Luxembourg	1,9	1,7	4,8	4,7	6,7	6,4
Netherlands	2,5	2,6	3,7	4,2	6,2	6,8
Austria	5,5	5,5	3,1	3,8	8,6	9,3
Portugal	2,7	2,9	2,5	3,2	5,2	6,2
Finland	4,7	5,3	4,3	5,0	9,0	10,3
Sweden	4,8	4,9	4,5	4,6	9,4	9,5
Old EU countries „14”	3,7	3,8	3,6	4,0	7,3	7,7
New EU countries „13”						
Bulgaria	4,1	5,3	3,6	4,8	7,7	10,1
Czechia	10,9	10,4	3,5	4,2	14,4	14,6
Estonia	4,3	4,5	4,9	7,5	9,1	11,9
Croatia	3,8	4,2	3,1	4,0	6,8	8,3
Cyprus	0,9	1,0	3,0	3,4	3,9	4,4
Latvia	2,4	3,0	4,0	5,3	6,5	8,3
Lithuania	2,5	3,1	3,0	3,3	5,5	6,4
Hungary	8,1	7,9	3,8	4,3	11,9	12,2
Malta	1,7	1,8	3,9	4,8	5,6	6,6
Poland	5,4	5,5	2,8	3,6	8,2	9,1
Romania	6,1	8,9	2,4	3,2	8,4	12,1
Slovenia	7,7	9,7	3,8	5,7	11,5	15,4
Slovakia	8,0	9,1	3,4	4,0	11,4	13,1
New EU countries „14”	5,1	8,7	3,5	4,5	8,5	10,2
EU 27	5,0	5,1	3,4	3,9	8,4	9,0

Source: own elaboration based on (Skill Projections, 2024).

When considering employment in high-tech occupations, it was estimated at 10% in 2022 and 11.5% in 2035. The minimum employment in high-tech occupations is 5.8% for Greece (6.1% in 2035) and the maximum is 15.6% for Finland (17.8% in 2035). Finland's index is significantly higher than that of other countries – in 2035, in addition to Finland, Sweden will have a high index, while Greece's index is planned to be below standards compared to other countries. Note that employment in high-tech occupations in the EU27 is estimated at 13.9% in 2022 and 15% in 2035. The minimum index will be 0.9% for accommodation and food (1.4% in 2035) and the maximum 53.3% for ICT services (56.1% in 2035) (Employment in high-tech economy, 2024).

It is interesting to note that in many countries, the area around the largest cities, e.g. for Berlin, Budapest, Bucharest, Copenhagen, Helsinki, Madrid, Paris, Prague, Stockholm, or Warsaw, has a much higher share of high-tech employment than in other parts of the country. London (including the area to the west of it, particularly Oxford), for example, is the largest technology center in Europe in terms of employment share. Almost 12% of the working population is employed in the high-tech sector in this area. Prague and Budapest are also major technology centers in Europe. Both cities have a very good environment for technology start-ups and employ more than 10% of the working population. Other cities with a high share of high-tech employment are Stockholm and Helsinki, employing 9.7% of the city's working population (Employment in High-Tech, 2024).

In summary, the number of 'good', high-skilled jobs is increasing in economically developed countries, introducing new technologies. This growth is significantly faster than the growth of low-skilled jobs (Carnoy, 2002). A clear line of demarcation between 'good' and 'inferior' jobs is emerging. Clearly, the introduction of new technologies goes hand in hand with an improvement in the quality of jobs. The experience of developed countries shows that new technologies are forcing on the one hand, and enabling, on the other hand, the development of new, atypical forms of employment. There is an increase in task-oriented and periodic employment contracts, while the share of work provided based on long-term employment contracts and full-time employment is decreasing. Artificial intelligence will be particularly important for the development of high-tech companies, including employment in these entities. It is influencing and modifying not only the organization of work, but also the entire processes involved. AI technologies are determining and increasingly conditioning employment through the automation of work, the creation of new jobs or the transformation of existing occupations, as well as the acquisition of new competences by those employed in this industry. In the last decade, there has therefore been a growing awareness of the implementation of artificial intelligence and its impact on employment. Accordingly, the following initiatives have been adopted to support this development are: European AI Champions, Digital Europe Programme, DigComp Digital Competence Development.

3. METHODOLOGY

The subject of the analysis was all 242 NUTS 2 regions of the European Union, for which data on the development of gross domestic product in individual regions and an indicator describing the percentage of employed in the hi-tech companies of these regions in 2012–2022 were collected based on Eurostat data (access to data: 5.06.2024). The choice of Eurostat data was dictated by their availability in terms of time and region. Currently, there are reports available from other institutions on the implementation of AI in enterprises, but they are not yet comprehensive enough to be analyzed within the scope adopted in the article. Hence, the authors decided to use only Eurostat data, considering these limitations, which may not fully reflect the nuanced impact of AI on productivity, labor markets, and innovation. As data was missing for the high-tech indicator in some regions, a pairwise case elimination procedure was used in the analyses.

In order to determine the impact of the high-tech index on the development of GDP per capita, considering a possible time lag, an analysis of the development of the Pearson's linear correlation coefficient was carried out, considering the impact of the high tech index on the development of GDP of a given region in a given year ($t = 0$), in the following year ($t = 1$) and two years later ($t = 2$).

4. RESULTS

On the basis of the analyses carried out, it can be clearly stated that there is a significant statistical impact of the percentage of people employed in hi-tech fields on the GDP development of a given region regardless of the time lag, but detailed analysis shows that the strongest impact of the hi-tech indicator on GDP occurs when a two-year lag is considered (cf. Table 1). On the other hand, there is practically no difference in the development of relationships between the analyzed indicators when the so-called old (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden) and new (Bulgaria, Croatia, Cyprus, Czechia, Estonia, Hungary, Latvia, Lithuania, Malta, Poland, Romania, Slovakia, Slovenia) EU countries are analyzed separately. For both groups of countries, there is in practice a strong and statistically relationship.

When examining the impact of the high-tech indicator on the development of GDP at the level of each NUTS2 region of the EU separately, it no longer gives such a clear picture and relationship. Depending on the regions and the time shift adopted, the Pearson correlation coefficient takes both positive and negative values, with negative values definitely more frequent in the case of regions of the so-called old EU countries and adding values in the case of the so-called new EU countries. On the other hand, the significance of such a relationship can be said to exist only in the case of some regions (this may also be due to the limited number of data on which the analysis was based, covering only the years 2012–2022). For 165 NUTS2 regions included in the so-called old EU countries (the remaining 13 regions lacked data to carry out analyses in this regard), considering the previously assumed lags of the impact of the hi-tech indicator on the development of GDP, independence can be said to exist in the case of 77 regions. This relationship was present in 4 regions in Austria (with a total of 9 NUTS2 regions), 2 regions in Belgium (11), 25 regions in Germany (38), 3 regions in Denmark (5), 2 regions in Greece (13), 11 regions in Spain (19), 2 regions in Finland (5), 10 regions in France (27), 2 regions in Ireland (2), 8 regions in Italy (21), 3 regions in the Netherlands (12), 3 regions in Portugal (7) and 2 regions in Sweden (8). For the 63 regions in the so-called new EU member states, there was a significant impact of the percentage of people working in high-tech on regional GDP in 28 cases. This was the case for 3 regions in Bulgaria (6), one region in Cyprus (1), 2 regions in the Czech Republic (8), 1 region in Estonia (1), 2 regions in Croatia (4), 2 regions in Hungary (8), 2 regions in Lithuania (2), 1 region in Latvia (1), 8 regions in Poland (17), 4 regions in Romania (8), 1 region in Slovenia (4) and 1 region in Slovakia (2).

Table 2. Development of the Pearson linear correlation coefficient between the rate of people employed in the high-tech sector and GDP per capita in the NUTS2 regions of the EU

	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
						t = 0					
total	0,6028 (1,46E-22)	0,5736 (1,48E-20)	0,596 (1,89E-22)	0,6237 (5,21E-25)	0,5952 (2,20E-22)	0,6163 (1,30E-24)	0,6318 (3,86E-26)	0,6386 (1,02E-26)	0,6756 (1,30E-29)	0,6814 (2,26E-31)	0,6662 (1,35E-29)
A	0,5958 (5,97E-22)	0,5607 (1,30E-19)	0,5771 (7,61E-21)	0,5928 (3,63E-22)	0,5914 (4,77E-22)	0,6031 (2,20E-23)	0,6146 (1,87E-24)	0,6184 (1,05E-24)	0,6692 (6,73E-29)	0,6904 (1,73E-32)	0,6775 (6,51E-31)
B	0,6105 (4,88E-23)	0,5801 (5,34E-21)	0,5999 (1,33E-22)	0,6324 (1,23E-25)	0,5985 (1,77E-22)	0,6226 (5,25E-25)	0,6398 (9,90E-27)	0,648 (1,82E-27)	0,6937 (1,83E-31)	0,6965 (5,70E-33)	0,6857 (1,27E-31)
						t = 1					
total	-	0,6065 (6,90E-23)	0,5839 (2,06E-21)	0,6195 (1,34E-24)	0,6243 (4,55E-25)	0,6091 (1,24E-23)	0,6308 (4,89E-26)	0,6527 (2,44E-28)	0,6479 (1,07E-27)	0,6682 (8,83E-29)	0,6717 (3,15E-30)
A	-	0,5983 (3,63E-22)	0,5756 (1,01E-20)	0,6133 (5,10E-24)	0,6264 (2,89E-25)	0,6094 (1,19E-23)	0,6334 (2,67E-26)	0,6532 (2,15E-28)	0,6495 (7,23E-28)	0,6785 (6,00E-30)	0,6818 (2,00E-31)
B	-	0,6142 (1,39E-23)	0,5908 (5,36E-22)	0,627 (2,50E-25)	0,6312 (9,63E-26)	0,6136 (4,82E-24)	0,6377 (9,62E-27)	0,6599 (3,96E-29)	0,6567 (1,18E-28)	0,6852 (9,79E-31)	0,6873 (4,26E-32)
						t = 2					
total	-	-	0,6168 (8,02E-24)	0,6072 (1,88E-23)	0,6218 (8,00E-25)	0,6372 (2,39E-26)	0,6249 (4,05E-25)	0,6495 (5,51E-28)	0,6625 (2,02E-29)	0,6467 (1,46E-27)	0,6570 (1,43E-27)
A	-	-	0,6095 (3,74E-23)	0,6002 (8,09E-23)	0,6177 (1,99E-24)	0,6413 (9,03E-27)	0,6258 (3,28E-25)	0,6534 (2,05E-28)	0,6613 (2,71E-29)	0,6509 (5,09E-28)	0,6694 (6,42E-29)
B	-	-	0,6244 (1,58E-24)	0,6171 (2,23E-24)	0,6277 (2,13E-25)	0,6448 (3,90E-27)	0,6296 (1,40E-25)	0,6562 (1,01E-28)	0,6694 (3,19E-30)	0,6561 (1,38E-28)	0,6748 (1,57E-29)

*– in parentheses the p-value for the Pearson's linear correlation coefficient significance test is given

Source: own elaboration.

The evolution of the coefficient examining the impact of high tech on GDP per capita (t = 0) by region in the EU is shown in the Fig. 1 below.

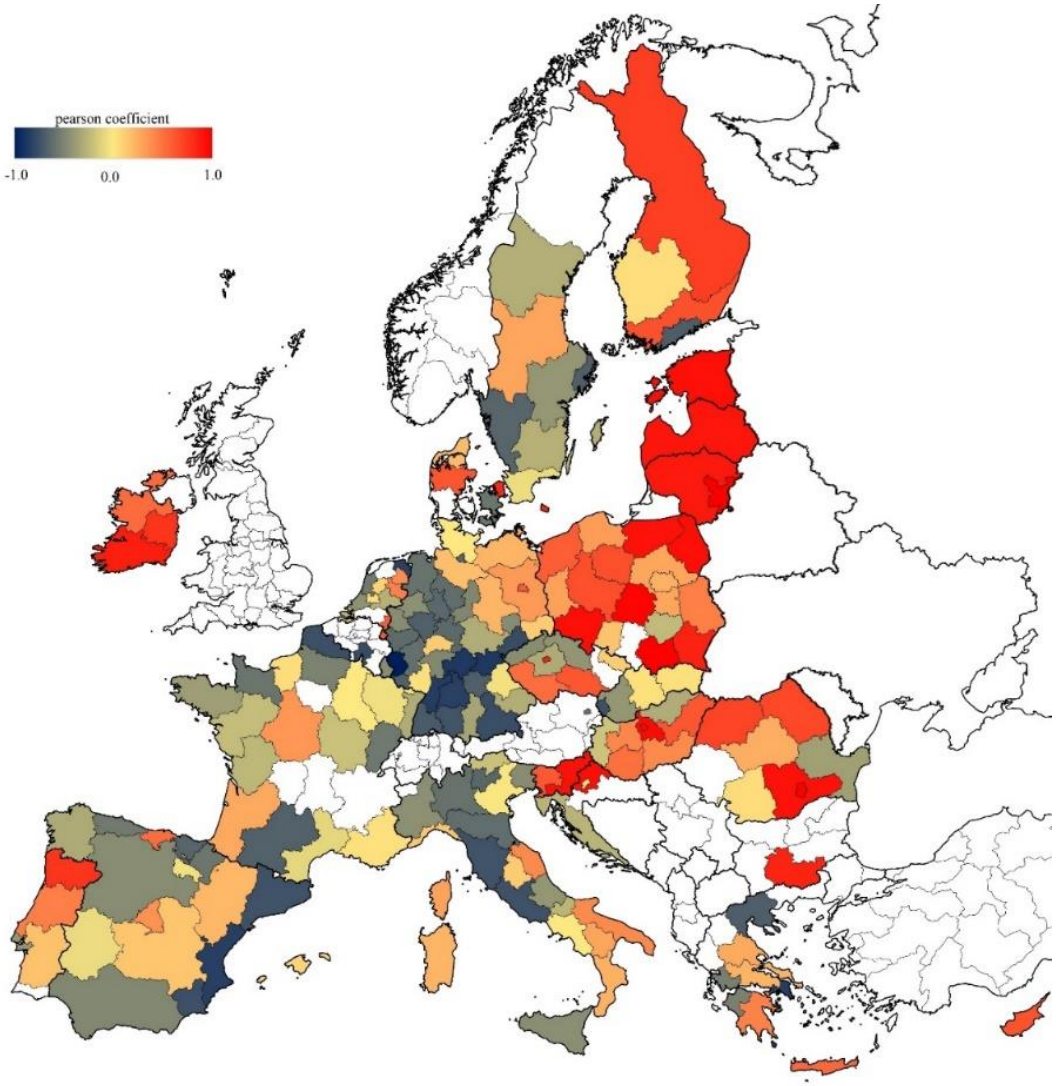


Figure 1. The evolution of the coefficient examining the impact of high tech on GDP per capita (t = 0) by region in the EU
Source: own elaboration.

5. CONCLUSION

The development of high-tech companies and artificial intelligence in the countries of the European Union is associated with opportunities for the development of innovation and, therefore, economic growth. In the near future, the impact of artificial intelligence on the development of these entities will become apparent. For on the one hand, it may lead to job losses as a result of automation and process optimization. On the other hand, however, it creates new jobs, especially in areas related to the development, management, and use of AI technologies. However, this requires adequate preparation of the labor market, investment in education to support employees in adapting to the changing labor market. These changes will require workers to be flexible and to continuously learn about the changes being introduced. Artificial intelligence, as seen above, poses new challenges for such entities, as there is a lack of a qualified workforce in terms of the possibilities of applying artificial intelligence, or competences related to this modern technology.

To gain a more complete understanding of the impact of AI, it is useful to look at additional studies and datasets. Although they do not directly relate to the high-tech industry, they show a trend, the use of AI tools by employees of enterprises in general. By the same token, it is hoped that a similar or even greater trend will be shown by employees of the companies surveyed. By way of comparison, the European Central Bank, for example, examined the impact of AI on labor markets, noting that

occupations with greater exposure to AI technologies saw an increase in the share of employment, especially among younger and skilled workers. The May 2024 European Central Bank survey asked employees in 11 Eurozone countries (Belgium, Germany, Ireland, Greece, Spain, France, Italy, Netherlands, Austria, Portugal, and Finland) whether they used AI at work. Several interesting patterns emerged in the responses. "First, there is a notable age bias. Workers aged 18-34 are twice as likely to use AI in their work (36%) as those aged 55–74 (18%). Second, workers with university educations are also more likely to use AI (30%) than those without (18%). Third, there is a less pronounced but noticeable gender difference, with men more likely to use AI (28%) than women (24%)" (Aldasoro et all, 2024 for: Dias da Silva, Weißler, 2025). In addition, past research provides evidence of AI's significant impact on business growth, which may be related to increased product innovation (e.g., in the form of patents, trademarks or product portfolio updates), consistent with the fact that AI reduces product development costs (McElheran et al., 2024; Wouter et al., 2024). This can have a significant impact on the development of high-tech companies, including the employment of workers.

The idea of analyzing the impact of people employed in high-tech companies on GDP in the countries studied as a research category is a popular one. Additionally, considering the impact of artificial intelligence on these processes is becoming a research challenge for the coming years. This inspires researchers to identify further research areas and contribute to the development of this topic. The proposed indices adopted for the study were created based on a theoretical review and on the basis of indices proposed in European Union countries.

The practical implications of the index are not limited to an assessment of the EU countries and their regions. Like any study, this one too is not without its limitations. One of them relates to the subjective selection of the data used, despite the fact that it was done with great care and based on available studies, theories and reports. Another limitation is that there is a lack of individual data describing the development of artificial intelligence in the various countries studied.

Following the research, it is suggested that emphasis should be placed on developing compact databases containing information on variables determining the development of artificial intelligence on a regional basis, including for cities. Panel data analysis, cyclicality, and repetitive testing for the developed indicator would enable broader inference, provide more robust results on the impact of artificial intelligence on the percentage of people employed in high-tech companies, and deal with the limitations of the current study.

The conclusions obtained in the study make it possible to indicate that the indices selected for the study have an impact on development in the regions studied. To a large extent, the data obtained confirms the long-standing research contributions of various authors on these research aspects. Thus, an important determinant for the development of regions favoring the development of high-tech enterprises and employment in these entities is also the development of artificial intelligence. Although this statement represents a hypothetical assumption as yet unconfirmed many times by various researchers, it seems very valid for the inference in the presented study. Furthermore, on the basis of the analyses conducted, it can be clearly stated that there is a significant statistical impact of the percentage of people employed in hi-tech areas on the shape of a region's GDP regardless of the time lag, but detailed analysis shows that the strongest impact of the high-tech indicator on GDP occurs when a two-year lag is considered. In contrast, there is virtually no difference in the development of the relationship between the analyzed indicators when the so-called old and new EU countries are analyzed separately. For both groups of countries, there is in practice a strong and statistically relationship.

Therefore, with a view to the development of high-tech companies and employment in them, including the impact of artificial intelligence on these entities, regional as well as national authorities should pay particular attention to the aspects mentioned above, as they are important elements in the direction of development. Attention to the development of these key aspects leads not only to the economic development of these regions but also to the improvement of the lives of the inhabitants of a given territorial area. These guidelines and the research that has been carried out make it possible to identify areas whose improvement could lead to more effective development, not only in the scope presented in the article, but also to meeting the demands of global competitiveness.

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EMPLOYEE DIGNITY AS A KEY VALUE IN MANAGEMENT PRACTICES IN THE AGE OF ARTIFICIAL INTELLIGENCE

Marta Młokosiewicz[a], Agnieszka Piasecka[b]

[a]*University of Szczecin, Institute of Management, Szczecin, Poland*
[b]*Maria Curie-Sklodowska University, Institute of Management and Quality Sciences, Lublin, Poland*

ABSTRACT

Purpose: *The aim of the study was to examine the possibility of using the concept of dignity-based management in so-called intelligent management and to develop recommendations for managers using AI systems in the human resources management process based on dignity-based management practices.*

Need for the study*: Based on a literature review carried out for the purposes of the study, there was a clear lack of publications that would strictly relate to the issue of using the concept of dignity-based management in so-called intelligent management, based on the implementation of AI technology into management processes. Moreover, European Union documents encourage stakeholders to formulate ethical guidelines for entities implementing AI technology, including management processes.*

Methodology*: The study was prepared on the basis of a critical review of current European Union regulations concerning the ethical aspects of the use of artificial intelligence tools and an analysis of the literature on intelligent management and dignity-based management.*

Findings*: The issue of employee dignity was not sufficiently addressed in the analysed European Union regulations on the implementation of AI into management processes; dignity-based management practices can contribute to a more effective implementation of the human in command principle.*

Practical Implications: *A set of recommendations for managers using AI systems in the human resources management process based on dignified management practices has been developed.*

Keywords: Dignity Management Practices; Employee Dignity; Artificial Intelligence; Ethics; Intelligent Management; European Union

Jel codes: M12

1.INTRODUCTION

The global and intensive development of artificial intelligence (AI) is increasingly affecting the functioning of companies in various areas of the economy. The term artificial intelligence refers to systems that display intelligent behaviour by analysing their environment and taking action – to a certain degree autonomously – to achieve specific goals (European Commission [EC], 2018, pt 1). The integration of artificial intelligence into human resource management practices is a process that has

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already been initiated, although it is difficult to determine the pace and depth of the resulting changes. One area of this process is reflected in the predicted growth of the global AI HR market by 35.26% from $3.89 billion in 2022 to $17.61 billion by 2027[1].

The European strategy *Artificial Intelligence for Europe* states: 'the way we approach AI will determine the kind of world we live in' (EC, 2018, pt 1). As mentioned in this document, the European Union should become a world-class centre for artificial intelligence and ensure that AI is human-centred and trustworthy (EC, 2018). This approach is based on anticipating the effects of the transformation associated with artificial intelligence and focusing on investing in the development of knowledge and human skills necessary for mastery of new technologies. The basis of this so-called inclusive approach to AI is to put people at the centre, to ensure their safety and the possibility of exercising their fundamental rights. Also, with regard to the labour market, it has been assumed that 'ensuring that workers can adapt and access new opportunities will be a prerequisite for people to accept AI' (EC, 2018, pt 3.2).

Operating in the volatile, uncertain, complex and ambiguous environment of the VUCA world, organisations find themselves in a difficult position defined by the need to balance the opportunities for progress offered by AI technology with the risk of dehumanisation that its implementation entails (Fioravante, R., & Vaccaro A., 2024). They recognise a number of beneficial opportunities to use artificial intelligence to optimise their decisions, but these changes – on a par with the industrial revolution – raise a number of ethical questions, particularly regarding the protection of human dignity in the workplace. Metaphysical questions about the nature of humans and the status of machines pose a significant challenge to the development of AI (Stahl, 2021). The ethical dilemmas arising from the rapid progress and widespread use of artificial intelligence point to the need to create legal and ethical standards that could limit the potential negative consequences of AI development, such as the lack of algorithm transparency, the risk of discrimination or problems with accountability (Kosiak, 2023). In the context of managing modern organisations, the issue of using AI systems, especially in relation to human resource management (HRM), undoubtedly requires reflection and discussion.

This study is part of the ethical discourse on the use of artificial intelligence in human resource management and fills a research gap by emphasising the importance of employee dignity as a key value in this process. They were prepared on the basis of a critical analysis of current regulations at the European Union level and literature on the ethical (and especially dignity-related) aspects of management using AI tools. The aim of the thesis was to examine the possibility of using the concept of dignity-based management in intelligent management and to develop recommendations for managers using AI systems in the process of human resource management based on dignity-based management practices.

2.ETHICAL FRAMEWORK FOR THE DEVELOPMENT OF ARTIFICIAL INTELLIGENCE - OVERVIEW OF SELECTED EUROPEAN UNION REGULATIONS

Trustworthy AI should create a safe and innovation-friendly environment for users, developers and implementers. The process of building trust in AI in the European Union is to be served by the following three - interrelated - legal initiatives (European Approach to AI, 18.02.2025):

- a European legal framework for artificial intelligence – to protect fundamental rights and address the security risks inherent in artificial intelligence systems,
- a cvil liability framework – adapting liability rules to the digital age and artificial intelligence,
- a review of sectoral safety legislation (e.g. Machinery Regulation, General Product Safety Directive).

Europe's comprehensive regulation of artificial intelligence is the *AI Act* (2024). It entered into force on August 1, 2024, and will become fully applicable from 2 August 2026. The regulation creates a legal framework "in particular for the development, marketing, commissioning and use of artificial intelligence systems (....) in the Union, in accordance with the values of the Union, with a view to promoting the dissemination of human-centred and trustworthy artificial intelligence while ensuring a

[1] The Global Artificial Intelligence in HR Market Will Grow to USD 17.61 Billion by 2027, at a CAGR of 35.26% - ResearchAndMarkets.com | Business Wire 31.03.2022

high level of protection of health, safety, fundamental rights as enshrined in the Charter of Fundamental Rights of the European Union (...), including democracy, the rule of law and the protection of the environment, protection against harmful effects of AI systems in the Union, and the promotion of innovation" (AI Act, 2024, pt 1).

Among other things, it identifies different levels of risk for AI systems, depending on how the use of AI may affect risks to health, safety or the realisation of fundamental rights. High risk AI systems were considered to be those that may pose a high risk of harm to health, safety or fundamental rights, which include labour rights. It was noted that both the severity of the potential harm and the likelihood of the harm occurring should be taken into account when assessing these systems (AI Act, 2024, pt 48, 52). The *AI Act* notes that the use of artificial intelligence systems in the areas of employment, employee management and access to self-employment may affect the future job prospects of these individuals, their livelihoods and the extent to which their employment rights are realised (in particular in relation to recruitment and selection of candidates, decision-making affecting the terms and conditions of the employment relationship, decisions on promotion and termination of the contractual employment relationship, for personalised assignment of tasks based on individual behaviour, personality traits or character and for monitoring or evaluating individuals in employment relationships). These systems should therefore be classified as high-risk systems, as should AI systems that recognise emotions or make inferences about emotions in workplaces, or biometric categorisation to infer certain legally protected characteristics (AI Act, 2024, pt 57)[2] .

The *AI Act* also identifies artificial intelligence systems that do not significantly affect the outcome of the decision-making process, whether carried out by humans or by automated means, and do not lead to a significant risk of harm. These systems should meet the following conditions (AI Act, 2024, pt 53):

1. Performing narrowly defined procedural tasks (e.g. a system that transforms unstructured data into structured data, or categorises incoming documents).
2. Performing tasks aimed at improving the results of an already completed action carried out by a human being (e.g. linguistic proofreading of previously prepared documents).
3. Performing tasks to detect decision-making patterns or deviations from patterns of previously made decisions (the AI system is used here after human assessment).
4. Performing only preparatory tasks.

The *AI Act* imposes a requirement for transparency in the operation of AI systems. Providers of this technology, those using it (including employers) and those affected by it (including employees) should be equipped with the necessary competencies – enabling them to make informed decisions in relation to AI systems, to use the technology appropriately and to interpret the results of its operation adequately, while ensuring that fundamental rights, health and safety are protected and that they exercise control over these systems (including understanding how decisions made using AI will affect specific individuals) (AI Act, 2024, pt 20).

The *AI Act* discussed above takes into account the previously published ethical principles for AI systems. The stakeholder consultation on the draft ethics guidelines for trustworthy AI was an important step towards a European approach to AI. The first draft of the guidelines (Ethics Guidelines for Trustworthy AI) was published in December 2018. It contained practical guidance for developers, users and implementers of AI to ensure the trustworthiness of the AI technology used. *The Guidelines* were revised and published in April 2019 (High-Level Expert Group on Artificial Intelligence [AI HLEG], 2019).

According to *the Guidelines* trustworthy AI should be (AI HLEG, 2019, pt 15):

- lawful – i.e. ensuring respect for laws and regulations,
- ethical – to ensure that ethical principles and values are respected,
- robust – both from a technical and social point of view, as AI systems can cause unintended harm even when used in good faith.

Each of these three characteristics is necessary but not sufficient on its own to achieve trustworthy artificial intelligence, so their complementarity is assumed. The basis for trustworthy artificial

[2] In Poland, regulations on banned artificial intelligence systems are already in force as of 2.02.2025, and the deadline for all regulations related to AI Act adaptations to national legislation is 2.08.2025; New law to support AI development in Poland, https://www.gov.pl/web/cyfryzacja/nowe-prawo-ma-wspomoc-rozwoj-ai-w-polsce (16.10.2024)

intelligence - aimed at improving individual and collective wellbeing - is to ensure its compliance with four ethical principles based on fundamental rights: These principles have been formulated as ethical imperatives, compliance with which should ensure the trustworthy development, implementation and use of artificial intelligence systems (AI HLEG, 2019, pt 16, 47, 48).

The key requirements for AI systems to ensure their reliability are defined in the form of a detailed checklist. These are as follows (European Commission [EC], 2019):

1. Human agency and oversight human agency and oversight – Artificial intelligence systems should be created, developed and used as tools to serve people, enable them to make informed decisions, support their fundamental rights, be subject to their control and oversight, ensure respect for human dignity and autonomy.
2. Technical Robustness and safety – Artificial intelligence systems must be resilient and secure; this means that they should be safe, providing a contingency plan in case of problems, as well as being accurate, reliable and reproducible, thus guaranteeing that unintentional damage or attempts at unlawful use by third parties are also minimised and prevented.
3. Privacy and data governance – in addition to ensuring full respect for privacy and data protection, appropriate data management mechanisms must also be in place, taking into account data quality and integrity and ensuring legitimised access to data.
4. Transparency Transparency – AI systems and their decisions should be explained in a way that is tailored to stakeholders, should ensure that people are aware that they are interacting with an AI system, and that they are informed of the capabilities and limitations of such a system, and that those affected by AI are informed of their rights.
5. Diversity, non-discrimination and fairness diversity, non-discrimination and fairness – in support of diversity, AI systems should be accessible to all, regardless of any disability, and engage relevant stakeholders across the lifecycle; they should be designed to avoid unfair bias that generates negative outcomes such as marginalisation of vulnerable groups, increased prejudice and discrimination.
6. Societal and environmental – AI systems should benefit society as a whole, including future generations; they are to be sustainable and environmentally friendly, including consideration of other living beings, and their social and societal impact should be carefully considered.
7. Accountability accountability – mechanisms should be put in place to ensure responsibility and accountability for AI systems and their outcomes; auditing of these systems is key as it enables evaluation of algorithms, data and design processes, especially in critical applications; adequate an accessible redress should be ensured.

Further to the European strategy for artificial intelligence, *Artificial Intelligence for Europe* (EC, 2018), a *White Paper on Artificial Intelligence - A European approach to excellence and trust* (European Commission, [EC], 2020) was produced. In it, the European Commission stressed the importance of promoting the development and deployment of artificial intelligence based on European values. The *White Paper on AI* refers to the seven key ethical requirements for artificial intelligence systems listed in the *Ethics Guideline for Trustworthy AI*.

The European Economic and Social Committee (EESC) has an important role in shaping an ethical environment for the operation of AI. On 31.08.2017, the EESC published the document *Opinion of the European Economic* and *Social Committee 'Artificial intelligence: the impact of artificial intelligence on the (digital) single market, production, consumption, employment and society' (Own-initiative opinion)* (European Economic and Social Committee [EESC], 2017). Recognising both the benefits and the possible negative consequences of artificial intelligence, the EESC then committed to monitoring the development of AI from a technical, ethical and social point of view and taking into account security issues, by engaging all stakeholders in a social debate on these topics. The Committee identified 11 areas where AI currently poses societal challenges. From the perspective of employment and human functioning in the workplace, these include ethics, security, privacy, transparency and explainability, work, education and skills, (in)equality and inclusion, and legal and regulatory frameworks. Important recommendations made in this regard by the EESC in *its Opinion* (EESC, 2017, pt 1, 1.1–1.14) include the following:

- the need to adopt *a human-in-command* approach to AI, taking into account the responsible, safe and socially useful development of AI technologies on the assumption that humans are able to maintain control over machines at all times,

- a call for the development of a code of ethics covering the development, deployment and use of artificial intelligence so that artificial intelligence systems throughout the operational process respect the principles of human dignity, integrity, freedom, privacy, cultural and gender diversity and fundamental human rights,
- the need to develop standardisation procedures to verify, validate and control AI systems against standards of safety, transparency, understandability and explainability of AI operation, as well as taking ethical values into account,
- the need to jointly identify (at EU level, national governments and social partners) which sectors of the labour market, to what extent and in what timeframe artificial intelligence will impact, and to seek solutions to mitigate the effects on employment, the nature of work, social systems and (in)equality,
- the need for stakeholders to jointly commit to and co-create complementary AI systems in the workplace, e.g. human-machine teams, whereby AI complements and enhances human work; the paper also emphasises the need to invest in , education, formal and informal training that gives employees the opportunity to work with AI and, in particular, to develop skills that AI will not or cannot take over.

In its *Opinion* on Artificial Intelligence, the EESC also mentions risks in the ethical dimension related to the development of AI, concerning personal integrity, autonomy, dignity, independence, equality, security, freedom of choice, i.e. related to respect for fundamental human norms, values and rights (EESC, 2017).

Concluding the considerations undertaken in this part of the study, it is worth emphasising that the development of artificial intelligence should take place within an ethical framework - based on respect for fundamental human rights, norms and values embedded in European culture. Due to a certain unpredictability as to the future problems that the development of artificial intelligence may raise and the various ethical aspects that may play a significant role in shaping the ethical environment for the design and use of AI systems, it should be recognised that the existing provisions are not a closed set of regulations, and stakeholders have the possibility to supplement and clarify them.

3.INTELLIGENT MANAGEMENT - THE NATURE, OPPORTUNITIES AND RISKS OF AI-BASED MANAGEMENT

Today's organisations are operating in an era of digital transformation. New opportunities have opened up for them related to the use of artificial intelligence to improve management processes. On the other hand, however, in order to fully exploit the potential of organisational human resources, managers should rely on the natural, human intelligence of employees. The combination of natural and artificial intelligence in business management thus appears as an answer to the challenges of today (Odrekhivskyi, Pshyk-Kovalska, Zhezhukha, Ivanochko, 2022). In this view, intelligent management practices / intelligent management can be understood as the integration of advanced information, analytical and automation technologies (including artificial intelligence systems) with a reliance on the intelligence of the organisation's human resources, in order to manage organisational resources and processes more effectively. This is also the definition adopted for the purposes of this study.

AI research and development is expected to lead to the automation of intelligent behaviours such as reasoning, information gathering, planning, learning, communicating, manipulating, signalling and even creating and perceiving (EESC, 2017). AI systems are designed to operate with varying levels of autonomy, meaning that they are to some extent independent of human involvement and capable of operating without human intervention (AI Act, 2024, pt (12)). However, there is no doubt that in an Industry 4.0 or 5.0 environment, despite the intensive development of AI, people remain an organisation's most valuable resource.

According to the *Opinion* on Artificial Intelligence by the European Economic and Social Committee (EESC, 2017), AI will undoubtedly affect the volume of employment (the amount of work available) and the type and nature of many jobs, and thus also social security systems, although no one can predict to what extent and over what time period this will happen. What is known is that the impact will extend to all sectors of the economy, to both manual and white-collar workers, to the low-skilled as well as to the medium- and high-skilled. Referring to these predictions, the expert committee stressed

the importance of involving managers and professionals in particular in collaborative processes with artificial intelligence, so that their control over the process of change in this area of organisational functioning is preserved. Similarly, Trunk, Birkel and Hartmann (2020) highlight the issue of manager responsibility for using AI in decision-making. These researchers argue that AI can assist humans in predictive analysis, data collection and interpretation, but should not replace them, especially at higher levels of the organisational hierarchy. A similar classification of AI tools that can be applied to human resource management practices is given by Sucipto (2024). According to this author, these tools can include:

1. Recruitment tools based on artificial intelligence; these use AI algorithms to screen CVs, conduct interviews and identify the best job candidates.
2. Artificial intelligence-based performance management tools; these use artificial intelligence algorithms to analyse employee performance data and provide insights into areas for improvement.
3. AI-based learning and development tools; these use artificial intelligence algorithms to personalise learning and development programmes for employees based on their individual needs and preferences.
4. Artificial intelligence-based employee engagement tools; these use artificial intelligence algorithms to analyse employee opinions and sentiment, identify areas for improvement and generate recommendations for improving employee engagement.
5. Artificial intelligence-based workforce planning tools; these tools use AI algorithms to analyse workforce competencies and provide insights into future workforce needs, including skills gaps and talent shortages.

Research findings (Alasmri, Basahel, 2022; Trunk, Birkel, Hartmann, 2020, Sucipto, 2024) confirm that the incorporation of smart technologies brings a number of important benefits in the area of people management, including improved individual performance, overall company effectiveness, positive changes in organisational culture, increased efficiency in processes and decision-making. AI can also optimise the allocation of human resources and increase employee productivity. Moreover, AI technology can benefit HRM in the following transaction areas (Rodgers, 2020):

- Time pressure decisions: the cost of unhurried decisions is high (speed being essential).
- Accuracy: the cost of wrong decision choices is minimised.
- Allocation of resources: the data size is too large for manual analysis or traditional algorithms.
- Decisions where prediction accuracy is more important than explanation or clarification.
- Provision of information where regulatory requirements are slight.

Regardless of the area of application of AI in the management of organisations, however, it is important to remember that managers play a fundamental role in the application, supervision and control of artificial intelligence systems and must therefore consciously act to balance the development of AI with responsible management (Berente, Recker & Santhanam, 2021).

The *White Paper on Artificial Intelligence - A European approach to excellence and trust* (European Commission, [EC], 2020) points out – in addition to the undoubted benefits of AI due to increased product and process safety - the potential harms generated by AI, which may involve different types of risks. These included material damage (to the safety and health of individuals, including loss of life, damage to property), as well as immaterial damage (loss of privacy, restriction of the right to freedom of expression, violation of human dignity, discrimination related, for example, to access to employment). In contrast, the European Economic and Social Committee paper *Artificial Intelligence: the impact of artificial intelligence on the (digital) single market, production, consumption, employment and society* (EESC, 2017) expressed concerns about the disappearance of jobs as AI takes over existing work activities, predicting that with further development of AI, only low-paid mini-jobs will be available on the labour market for an increasing number of flex workers. Attention was also drawn to the potential risk of depletion of the activities performed by workers and the associated loss of key skills. Existing contemporary examples of defining and distributing work without human involvement, by means of algorithms, are shaping the nature and conditions of work. Artificial intelligence systems offer more and more possibilities for tracking and monitoring employees. Their uncontrolled development could therefore pose a real threat to the autonomy and privacy of employees.

Key issues of concern in the use of AI systems relate to data security and the confidentiality of employee and organisational information. Equally important is the impact of AI on the psychological

realm of employees and team dynamics. It is therefore important that HR personnel have the right skills to enable them to use AI appropriately (Sucipto, 2024).

To some extent, the risks that apply to the use of AI systems in management practices stem from the characteristics of AI and concern its autonomy, learning and opacity. In terms of autonomy, concerns relate to the accountability and control of AI; in terms of learning, the fact that modern algorithms work on large data sets and are superior to the skills of humans in this area can raise problems in interpreting the results; in terms of opacity, the complexity of AI raises complications with AI oversight and ethics (Berente, Recker, & Santhanam, 2021). It can be assumed that organisations are afraid of incorporating AI into their workplace for three reasons: employee detachment from decision-making, human understanding and perception of AI processes, and the impact of AI interpretation of datasets (Rodgers, Murray, Stefanidis, Degbey, & Tarba, 2023).

In the *White Paper on Artificial Intelligence* (EC, 2020), the main risks arising from the use of AI were identified in the area of laws protecting fundamental rights, including laws on the protection of personal data and privacy and non-discrimination, as well as issues related to security (such as cyber-security, the use of AI in bad faith) and liability. In relation to workplaces, for example, violations of fundamental rights such as the right to freedom of expression, respect for workers' dignity, the right not to be discriminated against on the grounds of sex, race, ethnicity, religion or belief, disability, age or sexual orientation, the protection of personal data and private life, or the right to seek redress through the courts and due process were pointed out. It has been pointed out that such risks may be caused by the improper design of artificial intelligence systems (also in relation to human surveillance). Furthermore, the data used by these systems may not be corrected for possible biases (e.g. the system is trained using only or mainly male data, which may lead to suboptimal results for women). Artificial intelligence could also be used by employers – in violation of legislation – to track and analyse employee behaviour. On the other hand, the *Opinion* on Artificial Intelligence (EESC, 2017) points out that AI is developed in a homogeneous environment of predominantly young, white males, thus inscribing (consciously or not) cultural and gender differences, not least because AI systems learn from learning data. Theoretically, the data may therefore be ‘loaded’ with biases.

No less significant danger from the use of artificial intelligence systems is the so-called dark side of AI. It is primarily related to a lack of trust in AI and power asymmetry (Grewal et al., 2021). It also includes manipulation of intelligent algorithms, biases or errors in the interpretation of results. The dark side is mainly driven by political, legal and institutional aspects (Valle-Cruz, García-Contreras, Gil-Garcia, 2024). In addition, the high utility of AI provides a temptation for managers to use AI for their own purposes. Abuses may occur here, with consequences that are detrimental to the organisation.

4.FROM EMPLOYEE DIGNITY TO INTELLIGENT DIGNITY-BASED MANAGEMENT

The answer to the discussed challenges of using AI tools in organisational practices is ethical leadership. An ethical leader is true to certain values in his/her behaviour and actions for employees and the organisation, and is people-oriented but impartial in decision-making (Sharma, Agrawal, & Khandelwal, 2019). Top characteristics of ethical leaders include: integrity, empathy, accountability, transparency, fairness, vision, trustworthy, resilience, respect (Kandasamy, 2024). Ethical leaders communicate the importance of ethical standards and enforce compliance by subordinates (Brown and Treviño, 2006; Uddin, 2023). Ethical leadership is needed in the complex environment of artificial intelligence to ensure that decision-making processes are not only in line with ethics, but also with societal expectations. This type of leadership in the age of digitalisation should be considered morally necessary and strategically beneficial (Kandasamy, 2024), as even the best algorithm cannot replace human moral judgement and operating within a defined h of ethical principles and premises (Kosiak, 2023). It has also been pointed out that in order to manage effectively in the age of digitalisation, it is necessary to combine technical competence with emotional intelligence, as leaders who use both emotional intelligence and AI experience higher employee satisfaction, improved team performance and better organisational outcomes (Vivek, & Krupskyi, 2024; Sposato, 2024).

The development of management practices based on ethical standards is a sign of the drive to shape artificial intelligence systems that operate with dignity in accordance with moral principles and human rights. Unfortunately, the process of formulating ethical standards may not be fully effective. Firstly,

there is no guarantee that the standards developed will be respected by organisations. Secondly, the pace of development in the field of artificial intelligence is far higher than the pace of lawmaking and regulation, so there is a risk that newly adopted rules will be outdated in the face of evolving AI (Kosiak, 2023). These conditions mean that the burden of responsibility for shaping human/employee-machine collaboration will fall on leaders. Their personal moral formation will determine the ethical status of the course of processes of implementing AI systems into the management of organisations. In this situation, it seems important to pay attention to the benefits for the organisation of forming managerial attitudes with regard to the concept of employee dignity, which has been described in the literature as so-called dignity management.

Dignity is a characteristic intrinsic to a person's actions and is one of their most essential values (Fontrodona and Melé, 2022, p. 182). Caring for the dignity of another person means recognising their subjectivity - their identity and difference, seeing them as an integral human being who can express themselves and is entitled to be accepted (Hicks, 2016). A sense of dignity manifests itself in self-respect and respect for others, in trust, in dialogue, in being able to express one's opinion, in experiencing being a subject at work. Satisfying the need for dignity, as a strong need to feel self-worth and to be proud of oneself, determines people's behaviour, also in the workplace (Blikle, 2018). Employees' sense of dignity depends on their self-esteem, on the one hand, and on respect for their autonomy in their relationships with others, on the other. Favourable conditions for respecting dignity are created by developing a culture of honesty in the organisation, treating co-workers as trustworthy individuals with the potential for autonomy, and expressing recognition that confirms the value of their work (Gruszczyńska-Malec and Hoffmann 2011; Sypniewska, 2019, p. 104; Zawadzki, 2018, p. 173). This fosters employees' experience of personal fulfilment, a sense of agency and meaningfulness at work, which is reflected in their stronger identification with the company, the high quality and productivity of their work, and therefore the efficiency of the organisation (Ahmed, Liang, Anjum, Durrani, 2023; Haarjärvi, Laari-Salmela, 2022; Pirson, Piedmont, Nagy, Hicks, 2023; Sypniewska, 2016). The concept of dignity management refers to an employee's sense of dignity (Kosewski, 2012; Blikle, 2018; Ambroziak, Kosewski, 2012). Managing with reference to dignity means combining the ability to dignitarily motivate employees with such an organisation and structuring of the work process that gives employees the opportunity to realise the values they value (which lie deep in human nature – such as honesty, fairness, reliability, solidarity, loyalty, responsibility, professionalism, etc.), which gives them a sense of inner satisfaction and thus creates dignitarian employee self-control (Kosewski, 2012). In this sense, dignitary management practices contribute to the creation of a working environment in which intrinsic motivation determines the commitment of employees (Młokosiewicz, 2023), who are aware of their role in the organisation and the importance of the actions they take. Dignity management is thus subjective management and management by values. The manager builds relationships with colleagues based on trust. Research confirms that the ability to build relationships in organisations, also understood as the ability to deal with people, is determined by the behaviour of leaders, as (Maxwell, 2007, pp. 177–178):

- admitting mistakes and accepting their consequences,
- not placing the blame on others,
- the ability to deal with diverse types of people, with different personality profiles,
- outstanding interpersonal relations skills and sensitivity and tact in dealing with people,
- peace, confidence and stability of moods.

The subjective approach to management also involves taking into account the diversity of attitudes resulting from the individual characteristics of employees. It presupposes flexibility in responding to the behaviour and attitudes of employees, according to their individual needs – differently towards employees who value freedom of action, freedom, independence, the possibility of co-determination, differently towards those who are motivated by directiveness, firmness and clear rules and regulations, and still differently in situations where subordinates need psychological support, understanding, care or a good word (Haman, 2015, pp. 229–230).

By contrast, through values, leadership manifests itself in such attributes of managers as (Taczkowska-Olszewska, Oręziak, Wielec, 2021, pp. 128):

- supportive, fostering the emergence of subordinates' self-esteem, stimulating creativity and the sharing of ideas,

- facilitating interaction by creating a climate for cooperation,
- generating enthusiasm for working for the organisation through the skilful formulation of objectives (either independently or as a team) and creating a climate of enthusiasm around their achievement,
- facilitating activities through the use of organisational solutions that increase access to means of achieving goals and creating conditions for the team's emotional involvement in work.

Based on a review of the literature on various aspects of dignity management, it was concluded that the issue of employee dignity is closely related to the implementation of the *human-in-command* principle, which – in accordance with the assumptions regarding *trustworhy AI* – should ensure the improvement of individual and collective well-being, also in the organisational dimension. The concept of dignity-based management is consistent with this principle and the assumptions of *trustworthy AI* in relation to the concept of autonomy, subjectivity, and integrity of the human being – the employee, as well as by referring to the assumption of providing employees with a sense of agency and meaning in their work (which is achieved through dignity-based motivation with reference to valued values) as a condition for the organisation's efficiency. This concept could therefore be used in so-called intelligent management, based on the implementation of AI technology into management processes. Dignity management practices - reinforcing the importance of employee dignity - could contribute to a more effective implementation of the *human in command* principle.

A review of European Union regulations on ethical issues related to the design and implementation of artificial intelligence systems has noted that the issue of employee dignity has not been sufficiently emphasised, which would mean that the recommendations for entities implementing artificial intelligence systems could be expanded in this regard. Therefore, both general and more specific recommendations based on dignity management practices for managers using AI systems in the human resources management process are proposed below. Their application promotes the shaping of employee well-being in intelligent management conditions. The general recommendations are as follows:

- ensuring that intelligent dignity management is included in the company's strategy, codes of ethics and internal regulations,
- ensuring that a dignity approach (thinking and acting) to management using AI systems is developed and maintained, which should be reflected in daily intelligent dignity management practices,
- emphasising the tension between operational efficiency and ethical responsibility in the age of AI-supported management, taking into account the dignity aspect; recognising that employee/human dignity is a fundamental ethical value that takes precedence over optimisation and efficiency; All decisions regarding the design, implementation and application of AI systems in HRM should be evaluated in terms of their impact on the dignity of employees,
- regular evaluation and updating of guidelines for the ethical use of AI in HRM, taking into account employee dignity, based on experiences with their implementation and changing technological (dynamic development of AI) and social realities.

Table 1 shows the specific requirements for *intelligent dignity-based management* practices, thus defining the essence of these practices as arising from the use of the concept of dignity-based management in so-called intelligent management, based on the implementation of AI technology into management processes. These can serve as recommendations for managers. Seven dimensions of dignity-based practices have been defined and recommendations have been assigned to them to ensure that the implementation and use of artificial intelligence in human resource management will respect employee dignity as a key ethical value (see Table 1).

Table 1. Intelligent management practices – recommendations for managers

Dimensions of dignity management practices	**Requirements for intelligent management practices (using AI systems)**
Respect for the values inherent in human nature	• definition of clear rules of responsibility for decisions made using AI concerning employees

	• taking into account human intuition and empathy in the context of managers' implementation and use of AI systems, especially in situations related to respect for human/employee dignity • the way in which AI technology is used should support the dignified motivation of employees, combining AI tools with a work organisation that enables the realisation of values they hold dear (honesty, fairness, reliability, etc.)
Respect for autonomy	• guaranteeing privacy, data protection and secure data management mechanisms by defining the principles of protecting the privacy and personal data of employees in the context of data collection, processing and use by AI systems • ensuring that the adopted data protection principles comply with the law in terms of what data is collected, for what purpose and how it is secured • clearly specifying in which areas and to what extent decisions made by AI require verification and approval by a human being in order to protect the autonomy of employees
Recognition of subjectivity (integrity)	• taking into account the leading role of the human/employee over AI by exercising control and supervision over the AI systems used • managers ensuring that employees experience being the subject of their work and not just part of an automated process • co-creating AI systems with the participation of employees, which can contribute to better consideration of their perspective and dignity • informing and consulting employees on the implementation and functioning of AI systems in the organisation to the extent that they are key to them, in order to better adapt these systems to their needs and ensure that they feel empowered • looking for AI applications where AI supports and improves human work instead of replacing him (augmented intelligence) • ensuring the development of those employee skills that AI will not or cannot take over (e.g. creativity, empathy, ability to cooperate) • raising awareness among HR specialists, managers and employees of the ethical aspects of using AI in management practices, including issues related to employee dignity • informing employees about their rights regarding interaction with AI, protecting fundamental human/employee rights, including ensuring health and safety
Respect for diversity and difference	• designing and implementing solutions aimed at mitigating the effects of implementing AI systems in terms of employment, the nature of the work performed by employees, possible inequalities in employee teams resulting from different levels of competence related to AI systems • use of systems that exclude unfair bias, prejudice and discrimination – design and implement AI systems in HRM in a way that prevents the reproduction or reinforcement of existing biases and discrimination • monitoring the input data and results of AI operations for potential manifestations of bias and correcting this data to avoid perpetuating existing inequalities
Creating conditions for expression of opinion, dialogue	• organising formal and informal training courses enabling employees to acquire competences in the field of cooperation with AI (knowledge of technology, correct interpretation of results) • ensuring adequate appeal mechanisms for employees in the event of AI decision-making • ensuring transparency of AI systems – informing about interaction with the AI system, about the possibilities and limitations of this system, about the possible impact of decisions made with the help of AI on specific employees

	• ensuring that AI systems are monitored and audited, and that there is an adequate and accessible redress system in place in case of damage caused by the operation of these systems
Fulfilling the need for self-esteem	• counteracting the risk of dehumanisation by using AI systems as tools to support decision-making processes, rather than replacing leaders in key (high-risk) decision-making processes for the recognition of employee subjectivity, concerning such aspects as employment and working conditions, promotions, dismissals • applying methods of conduct that emphasise the identity and distinctiveness of employees, preventing them from being treated solely as input data or algorithm results
Creating relationships based on trust	• recognising the requirement for *trustworthy AI* as an integral part of an organisational culture based on mutual respect, integrity and trust, and incorporating it into the organisation's ethical principles • choosing AI tools that strengthen positive relationships between employees and between employees and the employer, rather than weakening them

Source: own research based on the literature used and EU documents analysed.

The analysis carried out certainly does not exhaust the subject of building *trustworthy AI* in the context of management practices. One of the limitations of research is the research method used. Although a critical literature review has many advantages (by synthesising the results of many studies, it helps to understand complex phenomena and propose new model approaches), it is based on a subjective selection of sources, which can cause bias in the presentation of views. Furthermore, the review reflects the state of knowledge/legal solutions at a given moment, and with regard to AI, there is a growing interest in this topic, also in the field of legislation. Nevertheless, the considerations made partially fill the identified gap and thus may constitute an introduction to further research in this area, including planning of empirical studies.

5.CONCLUSION

Based on a critical review of selected regulations and literature on the ethical aspects of human resource management in the context of the use of AI tools, it must be concluded that the issue of ethics and the formulation of ethical standards with regard to AI systems in HRM appears to be a fundamental issue for contemporary organisations.

On the one hand, artificial intelligence has a positive impact on HRM practices and decision-making in this area. On the other hand, it brings certain challenges and risks. For managers, the important question is not whether to use AI tools (because the answer to this is obvious), but how to design, implement and use them in order to maximise the possible benefits (creating a technologically advanced work environment) while preventing possible risks. It is therefore important to develop and adopt solutions that enable the safe use of intelligent technologies (creating an ethically responsible work environment).

At the international level, but also at the level of individual companies, attempts are being made to formulate principles, guidelines and standards aimed at reducing the risks associated with the use of AI in management practice. However, it should be remembered that creating trustworthy artificial intelligence requires – in addition to ensuring that the system itself is trustworthy – a holistic and systemic approach that includes the credibility of all entities and processes that make up the socio-technical context of the system's operation throughout its life cycle (AI HLEG, 2019, pt 6). From the perspective of individual organisations, the creation of systems that their users can trust depends on how these organisations deal with the ethical dilemmas of AI and the moral competence of managers. Their ethical credibility, reflected in intelligent dignity management practices (subject to ongoing self-assessment), can help ensure that employees retain sufficient autonomy and control over machines and lead them to feel fulfilled and satisfied with their work.

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28th European Conference on Artificial Intelligence (ECAI 2025)

FOSTERING EMPLOYEE EFFECTIVENESS THROUGH INTELLIGENT MANAGEMENT – THEORETICAL FRAMEWORK

"I think what makes AI different from other technologies is that it's going to bring humans and machines closer together. AI is sometimes incorrectly framed as machines replacing humans. It's not about machines replacing humans, but machines augmenting humans."
Robin Bordoli, Authentic Ventures

Anna Pluta[a], Justyna M. Bugaj[b]

[a] *University of Szczecin, Institute of Management, Poland*
[b] *Krakow University of Economics, College of Management and Quality Sciences, Poland*

ABSTRACT

Purpose: *This study explores the relationship between employees' effectiveness (EE) and intelligent management (InMan), focusing on how modern technologies, particularly AI, influence workplace performance. It examines whether InMan can enhance EE, and identifies key factors shaping workplace design in this context.*

Need for the Study: *The increasing integration of AI and InMan systems in organizations raises questions about their impact on employees' effectiveness. While existing research highlights AI's benefits in various business areas, direct studies addressing its influence on EE are missing. This study fills this gap by analyzing how InMan can support or challenge employees' ability to do their tasks efficiently while maintaining work comfort.*

Methodology: *A critical literature review was conducted using the snowball method to select and analyze specialized academic sources. Additionally, international and national reports on EE and InMan were reviewed to identify relevant trends, challenges, and opportunities. The analysis was structured within a holistic framework, considering four employee activity spheres: physical, mental, emotional, and spiritual.*

Findings: *The study finds that InMan has the potential to enhance EE by optimizing decision-making, resource allocation, and process efficiency. However, its effectiveness depends on integrating AI with human competencies to balance high productivity and employee well-being. Key EE-related factors must be considered in workplace design using InMan.*

Practical Implications: *Organizations should adopt a holistic approach when implementing InMan, ensuring technological advancements align with employees' competencies and well-being. Practical recommendations include designing AI-driven workplaces, fostering productivity without compromising employee comfort. The findings highlight the importance of combining human expertise with AI to achieve sustainable organizational performance.*

Keywords: employee effectiveness, employee, effectiveness, intelligent management, holistic theory, individual capabilities, artificial intelligence

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1. INTRODUCTION

The use of modern technologies in the workplace is increasing yearly (Morawski, Jagoda & Jędrzejczyk, 2024). Forecasts indicate that AI will become increasingly important for employees, taking over their duties (Schneider, 2021) and not just supporting management processes (intelligent management – InMan). These modern technologies will undoubtedly bring many benefits and problems for employers. From improving the organization's performance in individual areas of activity, e.g., in management (Odrekhivskyi, Pshyk-Kovalska, Zhezhukha & Ivanochko, 2022), marketing (Bharathi, Manjunath, Hemantha & Praveen, 2024; Davenport, Guha, Grewal & Bressgott, 2019), or supporting HR processes (Balsmeier, 2019; Gîrlovan, Horobeț, Boțoroga, Belaşcu & Lucian, 2024; Henkel, Bromuri, Iren & Urovi, 2020; Kaplan & Haenlein, 2019) to individual workplace customization (Arslan, Cooper, Khan, Golgeci & Ali 2022; Li, Li & Chan, 2019; Zirar, Ali, & Islam, 2023) and intelligent programs to control work safety (Kaur, Gabrijelčič & Klobučar, 2023; Selenko, Bankins, Shoss, Warburton & Restubog, 2022). It is a driving force for developing people, organizations, and economies (OECD, 2024), evolving rapidly (Dignum, 2017). However, will it increase employees' effectiveness (EE)? There are currently hardly any direct scientific publications presenting research results on this topic. Some information can be found in reports from international and national organizations and consulting firms presenting the latest information on employees' effectiveness (EE) and intelligent management (InMan) in organizations.

EE, or the ability of employees to effectively achieve goals and tasks, is analyzed here according to a holistic approach (Pluta & Rudawska, 2016), in which each employee has a set of unique competencies. They testify to their effectiveness, which, in turn, can be characterized by considering four spheres of activity (physical, mental, emotional, and spiritual). We believe they are all important in combining EE (manifested in expected and high productivity and effectiveness at work) with work comfort (good working atmosphere, work without overload and overwork, work without stress). InMan, on the other hand, is understood as the use of advanced technologies, including AI, to make decisions, optimize processes and improve the efficiency of organizations. InMan integrates information technology, analytical technology, and automation to manage resources and processes in organizations more effectively.

Therefore, the study aims to present the relationship between EE and InMan. The following research questions were posed:

(RQ1) How can EE be fostered through InMan?

(RQ2) Which EE-related factors form the basis for workplace design using InMan?

The first part of the study is a theoretical introduction to the issues discussed. It uses a critical analysis of specialized literature selected thematically by the snowball method. On this basis, criteria were developed for selecting and analyzing the content of international and Polish reports on the relationship between EE and InMen. A summary of the analyzed reports is then presented. This description is the basis for the practical and theoretical recommendations considering a holistic approach to understanding EE (Pluta, 2018; Pluta & Rudawska, 2016; Schwartz, 2020).

2. FROM ARTIFICIAL INTELLIGENCE TO INTELLIGENT MANAGEMENT

Artificial intelligence (AI) is a broad field of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence' (Sarker, 2022, p. 157). However, it is not a phenomenon, but rather "AI as the frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems" (Berente, Gu, Recker, Santanam, 2021, p. 1434). The value of this way of thinking is that AI is not limited to a thing, a set of technologies, a program, or an algorithm but is understood as a concept that evolves from phenomena (Berente et al., 2021) present in the workplace. This allows AI to be used to optimize work (Selenko et al., 2022; Zirar et al., 2023; Kaur et al., 2023) but also to analyze more precisely the concerns and risks associated with the increasing use of AI by employees (WEF, 2025). AI is a key element transforming the professional activities of employees – it simplifies and eliminates some tasks (routine, monotonous), shortens the time of their implementation (Zirar et al., 2023), improves decision-making processes by providing access to information (fast, pre-analysed), as well as improving working conditions and increasing comfort (Kajtaniak, Socha & Wróblewski, 2024; Korgul, Witczak & Święcicki, 2024).

InMan refers to integrating advanced technologies and methodologies to enhance decision-making and operational efficiency across various domains. This concept encompasses using artificial intelligence, data analytics, and system modeling to optimize processes and improve outcomes in business and other sectors. So, it can be defined as applying artificial intelligence, machine learning, and data-driven insights to manage complex systems, processes, and resources effectively. It involves integrating human expertise with automated systems to achieve superior outcomes. The core principles of InMan include (Odrekhivskyi et al., 2022):

- Data-Driven Decision-Making: Leveraging real-time data and analytics to inform decisions, ensuring accuracy and timeliness.
- Automation and AI Integration: Utilising AI and machine learning algorithms to automate routine tasks, predict trends, and optimize operations.
- Human-Machine Collaboration: Combining human intelligence with machine capabilities to enhance problem-solving and innovation.
- Predictive and Preventive Capabilities: Anticipating potential issues and proactively mitigating risks.

In addition to the above, the impact of InMan in the workplace has numerous adverse effects that are only just emerging and are still being researched. Most researchers point to work overload (Selenko et al., 2022), resulting in professional burnout (Riegel & VanHusen, 2024) or technostress (La Torre, De Leonardis & Chiappetta, 2020). Current employees perform their professional duties under constant pressure – of tasks and time (Pluta, 2018). On the one hand, this results from the cult of work, which obliges them to work long hours (Benson, 2022; Welsh, 2013). It is socially accepted and additionally rewarded, one of the most pressing problems facing entrepreneurs (Schulte, 2024). Employees feel increasingly overworked, frustrated, and burnt out (La Torre et al., 2020; Mental Health UK, 2025, p. 5; Riegel & VanHusen, 2024). It leads to dissatisfaction with work and life. They feel guilty about neglecting their professional and non-professional duties. It hurts their health, leading to a decline in their commitment to work, encourages them to make mistakes and is a reason for them to leave their job (Schwartz, 2007). As a result, EE decreases, and employee frustration and burnout increase (e.g., Chan, Clarke & Cebrian, 2024; Mental Health UK, 2025; Mindgram, 2021).

3. HOLISTIC THEORY AND EMPLOYEE EFFECTIVENESS

The human capital resources (HCR) theory (Ray, Essman, Nyberg, Ployhart & Hale, 2023) indicates that a person has individual capabilities (knowledge, skills, abilities, and other characteristics – KSAOs) (Ployhart & Moliterno, 2011). They determine a person's effectiveness at work, engagement (Bugaj & Chałupczak, 2020; Henkel et al., 2020), and creativity. They can be treated as human capital, i.e., 'individual or unit-level capacities based on individual KSAOs that are accessible for unit-relevant purposes' (Ployhart, Nyberg, Reilly & Maltarich, 2014). This approach allows for a better look at employees and their capabilities. However, such a broad understanding of individual effectiveness does not fully allow for identifying factors influencing performance in the process of current changes at work. Of course, employee competencies (knowledge, skills, attitude) are important but insufficient to answer the question of where individual effectiveness arises.

It is also necessary to consider resilience factors, which are responsible for the ability to perform various professional activities that translate into the efficiency of employees and the organization's results (Schwartz, 2020). The basis for this are theories based on energy perspectives (Quinn, Spreitzer & Lama, 2012), which allow a more detailed look at the factors shaping individual effectiveness as parts of the human body, including its physicality – that is, the ability to work that requires the use of force, but also its activation sphere. Three aspects can be distinguished within the activation part: mental (Lykken, 2005; Mayer & Gavin, 2005) – allowing one to think about the problem and look for a solution; emotional (Collins, 2004) – providing the initiative to act, enthusiasm and a sense of trust, as well as spiritual (Ashar & Lane-Maher, 2004; Fisher, 2011) – guiding a person and referring to the essence of their existence and higher moral qualities. In turn, it allows us to look at the individual effectiveness of an employee according to the holistic paradigm (Covey, 2012; Covey, 2005). It is a four-dimensional being composed of the following aspects: physical (body), mental (mind), emotional (heart), and spiritual (principles, values). A deficit in just one of these areas can already threaten EE and adversely

affect the activities undertaken by the individual (Pluta, 2018; Pluta, Rudawska, 2016). The characteristics of individual effectiveness understood in this way are shown in the table 1.

Table 1. Holistic understanding of shaping individual effectiveness

Category of analysis	Characteristics	Examples
Physical	Influences human activity or lack thereof; its level depends on the health, resilience, and resistance of the human body, its physical condition	Physical condition Health Physical resistance
Mental	Determines the ability to focus on a task and perception, as well as the ability to solve problems and learn and be creative	Concentration Memory and learning Problem-solving Creativity
Emotional	Reflects the strength of emotions and their sign (positive or negative), which is the basis for establishing and maintaining relationships with others, motivation, and well-being	Attitude and mobilization Well-being Satisfaction Self-control
Spiritual	Being a moral compass of a person – a set of ingrained values that shape self-awareness and the inner sense of purpose in life	Self-esteem Sense of self-efficacy Meaning of life Ethical standards, values

Source: own study based on (Pluta, 2018, p. 111; Pluta, Rudawska, 2016, p. 300).

A holistic approach to individual effectiveness provides a deeper understanding of how the use of InMan in an organization impacts employees' work. It is important not only to identify and reinforce positive effects but also to recognize and mitigate negative consequences. Furthermore, organizations should take proactive steps to slow down the decline of individual capabilities, which act as a resilience factor but are inherently limited and require replenishment (Sayre, Chi, & Grandey, 2025). This process involves not only buffering actions to minimize strain but also renewal initiatives to restore the capabilities depleted in the course of work. The development of EE will also be enhanced by the alignment of employee values with organizational values (Siwińska-Olszówka & Bugaj, 2024). This relationship positively impacts every aspect of the employee's performance.

To achieve this balance, organizations should implement HR practices that promote the regeneration of capabilities and foster a work environment that supports employee well-being (Petrou, Demerouti &, Häfner, 2015; Salanova, Bakker & Llorens, 2006). At the same time, employees can take individual initiatives to recover their energy on a daily basis, ensuring sustained effectiveness in the long run (Kujanpää & Olafsen, 2024). By integrating both organizational and individual efforts, EE will gradually improve, contributing to a healthier and more productive work environment.

4. CRITERIA FOR ANALYZING THE RELATIONSHIP BETWEEN EMPLOYEES' EFFECTIVENESS AND INTELLIGENT MANAGEMENT

A practical problem concerning the relationship between EE and InMan inspired our research. Employers in social media signaled it, as did expert opinions, reports and industry conferences (grey literature). Therefore, the research work plan consisted of 4 stages. In the first stage, a pilot literature review was carried out on 12 February 2025 in the SCOPUS database using the keywords 'employee's effectiveness' and 'intelligent management,' resulting in 5 loosely related texts related to the scope of the search. Then, the search was expanded to include 'artificial intelligence' OR AI, and the number increased to 9 texts. After analyzing the abstracts and content of the searches, it was concluded that the data source should be changed, and in the second stage of the research, reports from international and Polish organizations and consulting firms were used, the content of which concerned EE and the use of AI or InMan in the workplace. The exclusion criterion was also the year of publication, with a cut-off date after COVID-19. These activities were conducted on 26.02.2025 (Table 2).

Table 2. Reports analyzed

No.	Report name	Prepared by
1.	Future of Jobs Report 2025, January 2025	World Economic Forum (WEF)
2.	Using AI in The Workplace Opportunities, Risks And Policy Responses, OECD Artificial Intelligence Papers, March 2024	International organization with worldwide reach – OECD.
3.	The impact of AI on the workplace: Main findings from the OECD AI surveys of employers and workers', OECD Social, Employment and Migration Working Papers, March 2023	International organization with worldwide reach – OECD.
4.	AI at work. Why there is more to it than task automation, 2024	International organization focusing on EU issues – CEPS Explainers
5.	Artificial Intelligence at Work: The Shifting Landscape of Future Skills and the Future of Work, 2024	Diversity Institute and Environics Institute for Survey Research commissioned by the Government of Canada
6.	Work Trend Index Annual Report, AI at Work Is Here. Now Comes the Hard Part, May 2024	Edelman Data & Intelligence on behalf of Microsoft and LinkedIn
7.	Raport płacowy (Payroll Report), 2025	Hays Poland
8	Rynek pracy, edukacja, kompetencje. Aktualne trendy i wyniki badań (Job market, education, competences. Current trends and research results), January 2025	Polska Agencja Rozwoju Przedsiębiorczości (The Polish Agency for Enterprise Development, PARP)
9	Workmonitor: nowy standard miejsca pracy (Workmonitor: The New Standard for the Workplace), 2025	Randstad
10.	AI na polskim rynku pracy (AI on the Polish labor market), Warsaw 2024	Polish Economic Institute
11.	Rynek pracy a rewolucja cyfrowa. Wpływ AI i nowych technologii (The labour market and the digital revolution. The impact of AI and new technologies), June 2024	Polityka Insight
12.	Gotowi na sztuczną inteligencję. Oczekiwania polskich konsumentów i firm (Ready for artificial intelligence. Expectations of Polish consumers and companies), October 2024	PwC Polska (Poland)
13.	Zastosowanie sztucznej inteligencji w procesie pracy (Application of artificial intelligence in the work process), December 2024	ProVision Solutions Jakub Wróblewski commissioned by the Regional Labour Market Observatory in Łódź
14.	HR TECH changer, 2023	Polish HR Forum

Source: own elaboration.

In the third stage of the research, criteria for analyzing reports were identified after a critical review of the scientific literature concerning EE, AI, and InMan separately. They are presented in Table 3. It includes main and additional criteria, each briefly characterized. In the fourth stage of the research, the analyzed reports were summarized, and practical and theoretical recommendations were prepared.

Table 3. Criteria used to analyze reports on InMan in the workplace

No.	Criteria		Characteristics
	Main	**Additional**	
1.	InMan possibilities and scope of application task	Automation tasks	Elimination of human intervention in time-consuming or monotonous
		Process automation	Use of software and technology to carry out business processes and functions
		Areas of application of InMan in the organization	Identification of areas in the organization where AI can be applied
		Impact of AI on increasing efficiency in the workplace	Assessment of the operational efficiency of the organization, work teams, or employees
		Level of digitization of the organization	Assessment of the level of use of various digital technologies (including AI) in the organization
2.	Readiness to implement InMan in the organization	Barriers to the implementation of AI in the workplace	Identification of factors hindering the use of InMan in the organization
		Use of experts when implementing InMan in the organization	Evaluation of the solutions adopted in the process of implementing AI in the workplace
3.	Impact of InMan on employment and the labor market	Availability of jobs in organizations using AI	Evaluation of whether AI creates or eliminates jobs
		The type of impact of AI on employment in the organization	Estimating the support or replacement of a given activity leading to the performance of tasks or the profession itself by AI
		The impact of AI on the professional structure of employees	Assessing which professions AI eliminates and which it creates
		Acquiring new competencies (knowledge and skills)	Examining competence needs and their changes
4.	InMan's impact on the business aspects of an organization	Impact on the organization's efficiency and productivity	The possibility of financial savings, increased revenue, and reduced costs through the implementation of InMan in the workplace
		Achieving a competitive advantage	The value that distinguishes an organization from its competitors and indicates its position in the market
5.	Impact of InMan on work and	Economic sectors using AI and InMan	Identification of economic sectors using AI and InMan
		Change in the nature of work and tasks	Performed transformations in activities and tasks performed at the workplace
		Identification of work forms	Indication of the form of work used: stationary, remote, hybrid

	working conditions	Reduction of working hours	Change in the timing of activities and tasks
		Changes in relationships between employees	Understanding of each other's needs and possibilities in a workplace using InMan
		Fears about AI in the workplace	Fear of being replaced by AI in the workplace
		Exposure to InMan in the workplace	Assessment of the impact of InMan depending on demographic characteristics, education, place of residence, etc.
6.	Social, ethical, and legal issues of using InMan	Ethics of AI use in the workplace	Compliance with existing ethical and moral standards in InMan-using workplaces
		Legal compliance	Assessment of the legality of AI implementation and use in the workplace, reliability, and transparency of InMan solutions

Source: own elaboration.

The criteria presented in Table 2 can be used to develop a research model and to prepare a tool to examine the relationship between EE and InMan. They are described at a high level of generality and require further elaboration in analyzing a specific case of an employer and its employees. In addition, they draw attention to the complexity of this relationship, which can be different in each organization and, therefore, requires several research tools (mixed methods) to complement the information obtained.

5. CONCLUSIONS FROM THE ANALYZED REPORTS

All reports selected for analysis focus on issues identified as analysis criteria, although to varying degrees. Among the main conclusions from international reports published after the COVID-19 pandemic are:

- visible progress in the use of AI in the workplace:
  - the most popular application of AI is the automation of work processes (Korgul et.al., 2024; HR TECH changer, 2023; Lane, Williams & Broecke, 2023; PwC, 2024),
  - employers are increasingly using various applications to support the cognitive abilities of employees (Cukier, Saiphoo & Parkin, 2024) and to facilitate the execution of tasks and improve work coordination (Nurski, 2024),
  - the possibility of using AI in the workplace for various tasks is emphasized - both routine ones and the ones enabling innovation (PwC, 2024; Work Trend Index Annual Report, 2024),
  - the application of AI to enhance the employees' professional roles (Randstad, 2025),
  - the impact of AI on every profession and sector of the economy is indicated (OECD, 2024), and its key role in the organization's operations until 2030 is emphasized (Ivanova, Budzewski & Sienkiewicz, 2025; WEF, 2025);
- employers' readiness to implement InMan in organizations:
  - the possibility of using AI in the workplace (WEF, 2025) and the enthusiasm of employees is emphasized (Work Trend Index Annual Report, 2024), but also the concerns of organizations, especially Polish ones (Cichy, Czapluk, Kiebzak & Kieroński, 2024; Kajtaniak et al., 2024; PwC, 2024),
  - the obstacles and barriers to the implementation of InMan are indicated, e.g., the high costs of this technology (Lane et al., 2023; Kajtaniak et al., 2024), lack of appropriate employee skills, and discrimination against them (Cukier et al., 2024; Hays, 2025; OECD, 2024; PwC, 2024), or insufficient government regulations and compliance (Lane et al., 2023; PwC, 2024) and fears of job losses (Hays, 2025; Ivanova et al., 2025; Korgul et al., 2024; Nurski, 2024; OECD, 2024; PwC, 2024; WEF, 2025);
- InMan's multi-faceted impact on the labor market and employment:

  - an improvement, but also a deterioration of the situation of employees in the labor market is indicated (Kajtaniak et al., 2024), which is the result of the perceived elimination of jobs (Cichy et al., 2024; Hays, 2025; Lane et al., 2023;) and the professions that carry it out (Kajtaniak et al., 2024; Korgul et al., 2024;),
  - a change in the nature of work is indicated (Kajtaniak et al., 2024; Nurski, 2024), which affects the change in the competence needs of specialists and the skills of employees (Hays, 2025; Ivanova et al., 2025; Korgul et al., 2024; Lane et al., 2023), which emphasizes the importance of training and consultation with employees (OECD, 2024), initiating self-learning by employees in the use of InMan (Cukier et al., 2024);
- strong relationship of InMan with the organization's areas of activity:
  - the potential of AI for business transformation and the possibility of achieving productivity growth in all functions of the organization is indicated (Cichy et al., 2024; Work Trend Index Annual Report, 2024) especially in finance, engineering and manufacturing, marketing and sales, life sciences, as well as telecommunications (Hays, 2025),
  - it is emphasized that new technologies, including InMan, can support new ways of achieving organizational goals that increase productivity (Korgul et al., 2024; Lane et al., 2023; Nurski, 2024; OECD, 2024) and creativity (Hays, 2025; Ivanova et al., 2025),
  - it is mentioned that unequal access to the use of InMan in organizations contributes to their more significant competitive advantage (HR TECH changer, 2023; Kajtaniak et al., 2024; Korgul et al., 2024; OECD, 2024; PwC, 2024; Work Trend Index Annual Report, 2024);
- the significant connection between InMan and work and working conditions:
  - one of the OECD reports (Lane et al., 2023) examines these issues in detail, analyzing the perception of the impact of AI in the workplace from the point of view of employers and employees,
  - a change in the nature of work is perceived (reorganization of tasks, automation of tasks, creation of new tasks), which changes the competence needs of employees (Cichy et al., 2024; Hays, 2025; Kajtaniak et al., 2024), but also leads to an acceleration of the pace of work (Lane et al., 2023), which forces the redesign of work organization (Korgul et al., 2024; Nurski, 2024) and affects the productivity and creativity of employees (Cukier et al., 2024; Hays, 2025; Ivanova et al., 2025; Work Trend Index Annual Report, 2024), as well as relationships in the workplace (Lane et al., 2023),
  - attention is drawn to AI's benefits in the workplace but also to the risk of losing autonomy, agency, and even dignity and depriving employees of rest (OECD, 2024);
- linking the social, ethical, and legal areas of InMan application in organizations:
  - it is pointed out that trust and inclusiveness in the organization must be built for AI to contribute to the positive and sustainable activities of the organization, as well as to the innovation, productivity, and well-being of employees (Lane et al., 2023; OECD, 2024; PwC, 2024),
  - attention is drawn to algorithmic human resource management (AHRM), which can lead to discrimination against employees in an organization if there is no adequate control over the algorithms (Cukier et al., 2024; Korgul et al., 2024) and it also raises concerns about legal and ethical consequences (Hays, 2025),
  - the need for responsible implementation of AI in the workplace is also mentioned. One possibility is the renegotiation of contracts between employers and employees in connection with the introduction of AI (Work Trend Index Annual Report, 2024), as well as attention to data security and ethics (Cichy et al., 2024; Korgul et al., 2024).

The most in-depth description of the use of InMan in an organization is contained in an OECD report (2024). For example, employers use the application in the recruitment process (searching CVs) to build and maintain customer interactions, monitor work (assign tasks and control their execution), or plan and provide employee training. On the other hand, employees are using AI in more and more tasks and are realizing that this is changing their work (depending on complexity, diversity, and speed) and forcing them to constantly update and improve their knowledge and skills. It is confirmed by another OECD report (Lane et al., 2023), which shows that managers and employees are positive about InMan in the

workplace, although they also have concerns. As a result, they emphasize the need for constant monitoring of the effects and use of InMan.

6. RESEARCH FINDINGS AND RECOMMENDATIONS

Table 4 summaries the consequences of implementing InMan in organizations, which positively and negatively affect EE. However, InMan itself is neither good nor bad. Depending on how it is used, it can maximize the positive effects of employee support and minimize the negative ones. It can also become a remedy for the omnipresent burnout in the workplace. For this to be possible, it is necessary to consider a broad EE perspective.

Table 4. Positive and negative effects of InMann for holistically understood shaping of individual effectiveness

Potential category	Positive effects	Negative effects
Physical	• can lead to a reduction in the physical strain on employees through the automation of repetitive tasks • better organization of work and information flow can reduce physical fatigue associated with chaos and lack of clarity • it can have a positive effect on physical health by balancing work and life, e.g., through the possibility of remote working	• replacing human labor can lead to reduced physical activity and poorer fitness and health • working with modern technologies is conducive to health problems (eyes, spine, etc.) • remote working makes it difficult to interact with others, which can reinforce feelings of isolation
Mental	• automation of routine tasks allows to focus on analytical and problem-solving activities, as well as tasks requiring creativity • supports data-driven decision-making through access to advanced analytical tools • better work organization facilitates concentration and cognitive activities	• ai in the workplace can weaken the ability to think critically and solve problems, as well as creativity • it causes information overload, which makes it difficult to make decisions
Emotional	• clear work rules influence the work climate and relationships between employees • stress is reduced, which has a positive effect on emotions • better time management can lead to a reduction in burnout	• competing with ai can cause anxiety, frustration, and, as a result, stress and burnout • using ai at work can generate conflicts within the team
Spiritual	• it creates opportunities for development, which affects the sense of meaning in life and work • it allows time for social activities (volunteering), which supports a sense of fulfillment and self-realization	• ai in the workplace can be a source of existential crisis • it lowers morale and makes it easier to respect pathological behavior

Source: own elaboration.

The EE described it can indeed be fostered, thanks to InMan, through a holistic approach to each employee, i.e., from a physical, mental, emotional, and spiritual perspective. It promotes a better match between the workplace and the employee. Awareness of this approach is important among organizational decision-makers and employees. It increases the chance of preparing ways to implement

InMan tailored to the organization's current needs and supports building a culture of productivity and well-being (Schulte, 2024). However, this requires comprehensive management measures in each organization (especially when designing workplaces), divided into four categories:

- physical health protection:
  - ensuring ergonomic workstations and opportunities to rest during tasks,
  - o promoting a healthy lifestyle in the organization (healthy eating, physical activity, etc.),
  - facilitating access to healthcare (access to doctors but also preventive programs);
- mental health protection:
  - clear definition of tasks and roles of employees,
  - investment in the development of employee competencies enabling the use of AI in the workplace,
  - psychological support and training in stress management;
- emotional development of employees:
  - promotion of harmony between employees' professional and private lives,
  - promoting a sense of community in the organization, which integrates employees and improves their relationships, but also has a positive impact on their work,
  - training on building relationships with others, but also on relaxation;
- spiritual support for employees:
  - identifying the goals and purpose of AI-based work,
  - caring about the values of employees and taking them into account when determining the values of the organization,
  - funding training and workshops that develop employees outside of work.

Of course, implementing such a broad program of measures to support employees in the workplace requires constant monitoring and the adaptation of specific solutions to current needs. Therefore, it is necessary to collect feedback from employees and, on this basis, make decisions to improve this support.

7. CONCLUSIONS

The novelty of the presented approach is the combination of EE and InMan. In theory, the presented impact criteria, derived from scientific and specialist literature analysis, should be verified in empirical research on large groups of employees and specific examples of organizations using InMan. Studies using surveys and/or interviews could provide tangible evidence of how InMan impacts EE in specific organizational settings. Paying attention to industry-specific applications of AI in the workplace and conducting sectoral analyses would help identify similarities and differences in the implementation of modern technologies, as well as their concrete effects.

It is particularly important to examine how AI adoption and InMan implementation influence highly automated production environments compared to creative industries or sectors focused on healthcare and education. Understanding these nuances will enable the development of more targeted practical recommendations on the effective integration of modern technologies.

It will be a source of good practices for employers considering the comprehensive use of InMan systems to improve processes and resources. At the same time, it is worth assessing whether and to what extent the proposed recommendations improve EE and prevent or limit the phenomenon of burnout visible in organizations, as reported in recent reports (Chan et al., 2024; Mental Health UK, 2025 Mindgram, 2021). It is worth focusing on the current and long-term effects of such activities. Both require a different research approach. The long-term effects of InMan employee collaboration, in particular, can affect not only the increase or decrease in an organization's productivity, risk management, and organizational resilience but also the change in the organization's competitive position using InMan. From the employee's perspective, it is essential to examine how to reduce resistance to the implementation of and collaboration with InMan while also preventing the loss of individual capabilities. Ultimately, this raises the key question: how can organizations better support employees during implementation to ensure that workplace changes do not negatively impact them, and, as a result, do not lead to a decline in their performance (EE).

Although the presented discussion applies a holistic framework to assess EE–including its physical, mental, emotional, and spiritual dimensions–it does not provide specific information on the quantitative measurement of how these factors interact with InMan. The proposed relationship remains purely conceptual and requires empirical research as well as statistical analysis to validate its assumptions. Such studies would strengthen the theoretical findings and offer practical recommendations that better align with the current needs of organizations.

Future research should focus on developing a model for employee collaboration with AI in the workplace. It is crucial to acknowledge that AI has the potential for continuous operation and process optimization, whereas humans have inherent physical and cognitive limitations. To ensure long-term employee effectiveness, organizations must address the working conditions and human-AI collaboration dynamics. Implementing InMan in organizations should account for human needs and proactively address potential long-term consequences.

Therefore, studies using a holistic framework to assess EE in AI-driven workplaces should be long-term. This would allow for a deeper understanding of how AI impacts the workforce and whether the benefits of AI implementation outweigh its potential drawbacks over time. Naturally, these considerations should incorporate not only social perspectives but also ethical and legal dimensions to ensure responsible and sustainable AI integration.

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IMPACT OF ARTIFICIAL INTELLIGENCE ON CUSTOMER EXPERIENCE MANAGEMENT

Anna Szwajlik[a]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*

ABSTRACT

Purpose: *The digital technology revolution has greatly changed how companies interact with their customers, which is directly related to the company's probability and durability. As a result, companies are constantly looking for new ways to improve customer experiences and engagement to remain competitive. One technology that has proven particularly effective in this area is artificial intelligence (AI).*

Need for the study: *Companies can use AI-based technologies such as machine learning, natural language processing, and predictive analytics to analyze customer data and learn more about consumer preferences, routines, and behaviors. This data can be used to personalize marketing initiatives and offers, improve customer service, and increase revenue.*

Methodology: *The article is theoretical in nature and presents previously published research on the contribution of artificial intelligence to customer experience management.*

Findings: *The article presents the possibilities of using Big Data at different stages of the customer journey. Possible implications for customer experience management are also indicated.*

Practical Implications: *The analyses and indications contained in the article can be a valuable guideline for practitioners in the context of using artificial intelligence in collecting and processing customer-related information during the purchase decision-making process. At the same time, it confirms for those managers who have already undertaken the effort of designing and managing customer experiences that they can streamline this process thanks to artificial intelligence*.

Keywords: Customer Experience Management, purchase decision-making process, Big Data, Artificial Intelligence, AI Marketing, Customer Experience.

Jel codes: M31; C8; M3

1. INTRODUCTION

In today's world, the emergence of artificial intelligence has caused a revolutionary change in customer experiences. Companies, by analyzing numerous data resources, aim to improve customer journeys, from the moment of purchase to the moment of product use, making the entire process convenient, satisfying, and efficient. Due to growing competition, customer satisfaction has become the highest

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priority for companies; hence companies strive to capture the voice of customers to increase customer satisfaction by using artificial intelligence.

Artificial intelligence can enhance both productivity and economic growth. It can create new products and services, markets, and industries, as well as increase the effectiveness and quality of decision-making procedures. The consumer experience is becoming increasingly difficult to understand. Customers express their requirements, desires, attitudes, and perspectives through several channels, including searches, comments, blogs, tweets, "likes," videos, and dialogues (Court, Elzinga, Mulder, and Vetvik, 2009). This endless flow of user-selected content is growing in terms of volume, speed, variety, and authenticity.

Artificial intelligence is an information technology that teaches computers to understand and emulate human communication and behaviors. It's a collection of several technologies capable of performing tasks that require human intelligence. When applied to standard commercial processes, they can learn, act, and perform tasks with intelligence similar to humans. Artificial intelligence optimizes the data analysis process, providing timely and on-demand insights, and improving user satisfaction and conversion rates without marketer assistance. MIT Technology Review states that artificial intelligence simply refers to "machines that can learn, reason, and act autonomously" (Baro, 2019). Artificial intelligence consists of techniques such as machine learning, deep learning, data mining, and natural language processing. Through these techniques, AI applications can train their models, analyze new information, and deliver highly accurate results (Copeland, 2020).

AI-based applications help customers and decision-makers in an extended customer journey full of possibilities, suggestions, and solutions. Personalized recommendations will save consumers' valuable time. Traditional retail will give way to AI-based marketing and personalized commerce. The customer funnel increases day by day, and satisfied customers seem to find what they want; user-friendly environments and interfaces, customer-oriented tools, and personalized suggestions and forecasts through various media and channels. More than ever, daily interactions require the use of AI tools, otherwise the amount of data generated will be unmanageable.

The integration of artificial intelligence into data management along the customer journey not only enhances operational effectiveness and decision quality but also fully embodies the principles of Intelligent Management, which leverages the synergy of technology and knowledge to create organizational value in conditions of uncertainty and market volatility.

Customers express their needs, desires, and opinions through a variety of channels on the digital platform, including searches, comments, blogs, tweets, likes, videos, and personal conversations (Court et al., 2009). As a result, consumer data is more readily available than ever before in terms of quantity, speed, variety, and accuracy. AI can be used to transform such data flow into valuable customer information (Kietzmann, 2018). These statistics form the basis for choices made by marketers when they determine their marketing strategy and predict revenues. AI applications are considered a necessity on which brands should focus their future efforts. Otherwise, brands will offer consumers less relevant and time-consuming choices. Customers will be dissatisfied with the experience gained during the entire purchasing procedure (Novoseltseva, 2020). In this article, the subject of interest will primarily be the use of AI Marketing and Big Data in customer experience management.

2. LITERATURE REVIEW

2.1. AI Marketing

Before artificial intelligence appeared, digital marketing existed and still affects the consumer journey. Digital or internet marketing is defined as marketing products or services using information technology through digital channels, such as search engines, social media, email, and other websites, to connect with current and potential customers. Digital marketing has changed the way brands and companies use technology for marketing, employing techniques such as search engine optimization, search marketing, content marketing, chatbots, etc. (Sankaran, 2020).

After the application of artificial intelligence in marketing science, a new term appeared, called "AI marketing." Forbes magazine presents AI Marketing, describing it as "a method of using technology to improve the customer journey." AI Marketing can be defined as the process of using artificial intelligence as a tool to automate procedures such as data collection, data analysis, and data processing,

giving decision-makers the ability to strengthen decision-making processes and transform them into improved consumer-focused decision-making mechanisms (Kowatsch, Maass, 2010).

AI Marketing consists of three main pillars: Big Data, machine learning, and personalized marketing services (Smartboost, 2020). Currently, most companies use AI techniques such as advanced analytics and machine learning, trying to create patterns that they will use to design marketing strategies. The presence of AI has generated new opportunities for companies, especially in the digital marketing and e-commerce sectors. AI will transform the marketing scenery, improving most marketing sections. Advanced Big Data analytics tools, sophisticated machine learning algorithms, large stored data records, and intelligent agents lead to unprecedented technological progress along with user satisfaction and multi-level implications across the marketing industry.

Traditional approaches to collecting customer experience data were primarily based on surveys, interviews, and focus groups. These methods, while still valuable, have significant limitations—they are time-consuming, costly, and often provide only a fragmentary picture of customer experiences. Additionally, they often suffer from low response rates and may be biased by the subjective opinions of respondents. Currently, AI can be used as a tool to collect predictive data from consumers by examining a wide range of consumer data, including social media activity, purchase history, and browsing history (Katawetawaraks, Cheng, 2013). AI algorithms and machine learning allow for predicting future consumer behaviors, including purchase propensity, churn probability, and product affinity. This technology can be used to solve problems, business and organizational performance, customer loyalty, advertising and marketing promotions, and product recommendations (Gochhait et al., 2019). These include modifying voice and tone, focusing on the topic, taking proactive steps, and continuous learning and development. AI systems enable real-time feedback collection to determine how customers feel at a given moment. This means that the artificial intelligence system can learn from each customer interaction, which will result in improved customer experience.

AI has changed or brought marketing and sales functions closer to consumers, offering advertising, personalization, sales forecasting, lead evaluation, and market research capabilities (Kietzmann, 2018). AI innovation provides marketers with all data collected from multiple sources, including social platforms, browsing history, and purchasing behaviors, allowing them to create effective campaigns. It also improves ad positioning, continuous content production, and tailored customer experiences through email newsletters, suggestions, and behavior tracking. Sales forecasting involves using techniques such as data mining, trend identification, demand generation, automatic lead scoring, tailored sales, and real-time information dissemination to support sales force needs. It analyzes competitor activities, notes market changes, and determines customer attitudes toward companies based on social media, reviews, and similar materials. Consumer behaviors are also examined in detail, covering their behaviors, consumer segmentation, and signs of churn. Customers are grouped in different ways, applying behavioral and preference segmentation, enabling the development of appropriate market strategies that respond to different segments (Devenport, 2020). Artificial intelligence also recognizes paths leading to customer churn, allowing companies to correct factors that may lead to customer departure. The positive impact of artificial intelligence on sales and marketing includes optimized return on investment, improved customer satisfaction, utilization of large datasets, and improved efficiency and productivity. Direct sales and selected advertisements increase the likelihood of action and work more effectively than general advertising.

Many data scientists and market researchers have studied the impact of using artificial intelligence (AI) in marketing in several countries. In 2018, a customer experience futurist, Blake Morgan, examined three aspects in which AI positively affects the customer experience. First, he states that many customers like to talk to a virtual assistant during or after the purchase process. Second, the use of personalized services for the customer has proven effective when customers decide which products to buy. Third, AI gives the company insight into customers, enabling companies to plan strategies appropriately (Morgan, 2018). On the other hand, a study conducted by InMoment (2018) highlights that 75% of customers are afraid of personalized ads. Many customers who value personal experiences may feel like someone is ‘watching’ them through the Internet, which can result in a more negative reaction. Moreover, Mannino et al. (2015) demonstrated the risk associated with the use of AI in business during their research. “If machines become faster, more reliable, and cheaper than humans in many areas of work, it will likely lead to disruption of the labor market on a scale unseen since the industrial revolution.”

Legget (2017) used quantitative data from "Forrester's 2016 global state of AI online survey" to highlight the fact that customer service is one of the leading areas of investment and implementation of AI systems. Legget states that currently many organizations increasingly use AI to enhance personalized customer experience. For example, half of consumers already engage in automated conversations with intelligent assistants such as Siri, Cortana, and Alexa. He states that "AI will delight customers by making these conversations natural and effective, predicting needs based on context, preferences, and previous inquiries; providing advice, solutions, alerts, and offers; and becoming smarter over time."

When it comes to after-sales services, many intelligent companies transform such services into a competitive advantage, using automated conversations, case classifications (automatic classification of phone calls into separate categories), process automation, and proactive actions. In addition, he used quantitative data to show that more personalized customer service leads to higher purchases, as 69% of U.S. customers shop at companies that offer high customer service.

According to Jeffs (2018), a company that is ready to provide services at the highest level should use artificial intelligence to solve problems that have the greatest impact on customer experiences. These strategies should be low-risk but very satisfying:

1. Using chatbots or other automation technologies to free up customer waiting time, as well as reduce pressure on employees.
2. Using customer data to predict which aspects of the company are most likely to affect the customer and allowing salespeople to focus on this aspect.
3. Using customer data to advertise relevant promotions based on their needs, which allows for greater customer satisfaction. Dahlhoff et al. (2018) used an example of the application of artificial intelligence in drones as a delivery method. The results were promising for researchers, as almost 40% of consumers would consider a drone as a delivery method, taking the customer experience to a new level.

Debecker (2016), demonstrates the need for chatbots. "With chatbots, data, and machine learning join forces to extend the always-open arm of the customer service team and use data to customize the experience," the authors state. They state that 51% of customers believe that a company should be open to 24/7 support. By using intelligent chatbots, companies can offer customers human-like support 24 hours a day, 7 days a week. Such technological strategies will provide customers with smarter experiences.

While several studies, such as IBM, Forbes, and Gartner, suggest that "by 2020, 85% of all customer interactions will be handled without human involvement," Moore (2018, p. 104) emphasized that today's customer service representatives will move to tasks that bots are unable to perform. For example, serving special customers may be a task for a real person.

Klein et al. (2017) conducted a study among leading retail directors to examine the impact of AI technology on the transformation of customer engagement. Using quantitative data, the authors suggest that "AI-based customer service is the new reality of the retail seller. Shopping doesn't wait for retailers to catch up, they simply transfer their loyalty to a competitor with a better experience." They used Zendesk (2018) to highlight that 87% of brands need to put more effort into providing a consistent experience. Although AI doesn't solve all problems, there is no shortage of AI's positive impact on delivering a consistent customer experience.

Klein et al. (2017) continued to study the impact of delivering a good customer experience on the company. Research has shown that 86% of adults will spend more on a product if they are loyal to the brand, over 70% of shoppers would share their shopping experience with other shoppers if it was positive, and 43% of adults will buy "a supposedly inferior product if they had 'satisfactory' experiences with that brand." The three outcomes show that delivering an excellent customer experience will increase sales, create loyal customers, and expand the company's customer base through word-of-mouth marketing. In other words, a high-quality customer service experience "can create a huge competitive advantage."

The Voice of the Enterprise (VotE): Customer Experience & Commerce, Digital Maturity 2023 study indicates that GenAI is the strongest driver of planned investments in CX use cases. The results also show that 35% of respondents are adopting new GenAI tools to scale sales, marketing, and customer service activities, such as conversational interfaces and guided summaries. Other frequently cited use cases for GenAI tools include creating engagement flows to reach customers through their preferred communication channel (33%) and intelligent process automation to streamline operations across the

company (32%). For companies to effectively compete in this changing environment, they must capture, analyze, understand, and act on information; they must also recognize patterns, understand ideas, plan, predict, solve problems, identify actions, and make decisions on a large scale. When implementation reaches a critical phase, enterprise-wide data and process automation help ensure that all stakeholders can deliver relevant business outcomes.

Although many studies highlight the positive impact of using AI on customer experiences, Bentley et al. (2018) mentioned the threat that machines will become superintelligent and will not have control, stating that "the entire human race (will) struggle for survival," before we begin to realize it. As a result, this evokes fear in many customers, deterring them from wanting to experience such technology during their shopping journey. On the other hand, Bentley et al. (2018) conducted an in-depth literature review to show that AI—like any other aspect of technology—develops slowly and under difficult conditions. "It's not easy to become wise"—the authors mention. Moreover, Mannino et al. (2015) emphasize that care should be taken to ensure that the advantages of using AI outweigh the disadvantages.

2.1. Big Data as a Key Element of AI Marketing

As digital platforms become 'smarter' and more widely used by retailers, and consumers use digital devices instead of visiting brick-and-mortar stores, digital marketing applications become important and efficient. Users worldwide are constantly connected to digital platforms, generating a huge amount of data every day called big data. Big Data refers to analytical methods and tools that companies use to compile information from their global internet interactions with customers. Due to its large volume, speed, and variety, big data stands out from other historical materials collected via the Internet (Chaffey, Ellis-Chadwick, 2019). Both organized and unstructured huge amounts of data can be managed by AI. Examples of structured conventional datasets include demographic information, transaction history, and online browsing patterns. AI can analyze these datasets because it can perform complex calculations and obtain accurate results in real-time (Kietzmann, 2018).

Although unstructured data constitute the majority of consumer information collected daily, they are more complex and require processing to provide results that cannot be seen in spreadsheets (Sponder, Khan, 2018). Artificial intelligence uses two types of input data:

Structured data: This data is common, standardized datasets, such as purchase history, basic consumer data, or website browsing habits. AI uses huge amounts of this type of structured data to perform complex calculations that typically generate results immediately.

Unstructured data: Almost 80% of the 2.5 billion gigabytes of daily data generated by users is unstructured and includes written texts, spoken words, and images, Rizkallah (2017). The ability of artificial intelligence (AI) to quickly evaluate huge amounts of this type of data distinguishes it from traditional computer systems. Unstructured input data is pre-processed by artificial intelligence to prepare it for additional calculations or element creation.

By applying AI, companies can move from a reactive to a proactive CX data management model. Instead of analyzing historical data and responding to problems that have already occurred, organizations can use predictive algorithms to predict future customer behaviors, identify potential problems before they occur, and adjust customer experiences in real time. This proactive model is crucial in today's rapidly changing business environment, where customer expectations evolve at an unprecedented speed, and companies must be ready to adapt quickly to remain competitive.

Intelligent AI-based systems break through these limitations, enabling continuous, automatic data collection from multiple customer touchpoints with the brand. Unlike traditional methods, which often operate in reactive mode (collecting data after the fact), AI solutions allow for real-time information gathering, enabling an immediate response to changing customer needs and behaviors.

Big data analytics refers to the collection, analysis, and delivery of potential correlations or causal relationships between certain variables or attributes to reveal patterns and hidden information that will help decision-makers make more precise, affordable, promising, and responsible decisions. Nevertheless, big data analysis relies on predictive analytics using machine learning and data mining, known as advanced artificial intelligence algorithms [6]. Artificial intelligence (AI) provides marketing science with the ability to efficiently handle large amounts of daily generated data and overcome the human inability to process this data using outdated methods, providing highly accurate results. Brands must record and study the consumer journey to predict consumer behaviors. Knowing the next moves of consumers, marketers can make more efficient decisions through automated 'intelligent' procedures

and platforms. The true potential of artificial intelligence is revealed in the results of large datasets, machine learning, and data mining applications in companies. As mentioned earlier, because marketers managed to model, find patterns, and manipulate data on an unprecedented scale, it gave them an advantage in eliminating errors, and narrowing target groups.

Regarding prediction, machine learning, and deep learning, along with data mining and result extraction, give decision-makers a significant advantage in pre-defining and accurately predicting potential consumer needs, trends, and purchases. Artificial intelligence algorithms train their models for self-improvement by processing huge amounts of data. Because machine learning can handle large amounts of data strings, they certainly can partially 'understand' the human world in terms of choices and needs. However, while many brands rebuild their foundations on innovation and artificial intelligence, many of them must cope with the increasing amount of data, which can improve their understanding of customers (Gochhait, 2019).

Companies using artificial intelligence applications on social media platforms collect significant amounts of data from their customers regarding their preferences. Whether companies use social media analytics to segment their audience and measure the impact of their products or services, AI goes a step further, using AI algorithms. Social listening, sentiment analysis, text mining, and behavioral data are stored and processed to provide a new set of customer behavior patterns (Gochhait, 2019).

Big data analytics is the process of examining large and varied datasets (big data) to discover hidden patterns, unknown correlations, market trends, customer preferences, and other useful information that can help organizations make more informed business decisions. Chen (2014) refers to big data as a constantly growing flood of data in terms of volume, variety, speed, and complexity, which is generated in today's digital ecosystem. Big data is generated around customers based on their online shopping behaviors, website clicks, social media activity logs, connected smart devices, geolocation attributes, etc. Advanced analytics solutions for big data provide new approaches to solving some key marketing mandates and delivering impressive results. (Sagiroglu et al. 1998). These solutions can transform traditional marketing roles and improve how core marketing functions are performed. Marketers collect data generated from various customer touchpoints live to present a complete picture of each customer's behavior. Analyzing this large amount of data in motion allows marketers to fine-tune customer segmentation models and apply insights to develop customer engagement strategies and increase customer value. Many big data applications show enormous potential for driving marketing impact in the customer management domain. Marketing analytics involves collecting and processing information about a specific market to facilitate decisions on where to spend the budget to get more value. In market analytics, three factors come to mind, namely, who the customer is, what they buy, and how purchases change over time (Hauser 2007). Descriptive analytics aims to present or 'summarize' facts and figures in an understandable format to inform or prepare data for further analysis (EMC Education Service, 2015). It uses two basic techniques, namely data aggregation and data mining, to report past events. It presents past data in an easy-to-digest format for the benefit of a wide audience. Descriptive analytics helps describe and present data in a format that can be easily understood by a wide range of business readers. As data-driven companies continue to use descriptive analysis results to optimize their supply chains and increase their decision-making capabilities, data analysis will move away from predictive analysis towards prescriptive analysis or rather towards a combination of predictions, simulations, and optimizations. Customer behavior modeling identifies behaviors among customer groups to predict how similar customers will behave in similar circumstances.

Customer behavior models are typically based on customer data mining, and each model is designed to answer one question at one point in time (Tadajewski 2009, Sheth 1985, Fullerton 2013). A large amount of data is a key resource to process and analyze for knowledge extraction, which enables support for cost savings and decision-making. Data mining is a collection of tools and techniques that can be applied to processed data to explore hidden knowledge or patterns in the data. This hidden knowledge provides decision-support personnel with support in making sensitive decisions. The main purpose of the data mining process is to extract information from a dataset and transform it into an understandable structure for further use (Fayyad et al. 1996).

2.3. Using Big Data in Customer Experience Management

Customer experience management involves recognizing all the reactions that customers exhibit in the purchase process, and then developing the right set of indicators to create value for customers (Berry et al., 2002, 2006). This requires understanding the customer's path—from the expectations the customer had before the experience occurred, to the evaluations they are likely to make after it is completed. The central theme of CX management is the identification and improvement of the customer experience at all touchpoints through the development of processes and employees (Klausa, 2015). The goal of customer experience management is to optimize interactions from the customer's perspective and, as a result, build their loyalty (Rouse, 2010). Customer experience management encompasses the customer's experiences before, during, and after purchase, taking into account the emotional and functional dimensions of product quality and the customer's social context (Klaus and Maklan, 2012).

This allows AI to acquire data and make predictions based on a set of stages. These stages include consideration, evaluation, purchase, and post-purchase behavior. At the moment when marketers or advertisers realize that consumers have begun their consumption journey, the consideration stage refers to the strategy of reaching consumers with advertisements. Marketers use AI tools to determine needs and recommend solutions that are likely to be received by audiences as personalized recommendations that will meet their current needs [8, 66]. The evaluation stage allows marketers to use AI tools to process images, voice, emotions, and natural language in real time to generate content that will tip the scales and convince customers that this is the best choice for them. The shopping phase identifies what consumers are ready to buy depending on the season and dynamically adjusts the price, along with brand authority, customer service, and assurance reinforcements. The last stage concerns consumers who evaluate the outcome of their purchase decision. The evaluation calculates satisfaction with the shopping experience, satisfaction with product acquisition, the possibility of repurchase, or even impact on others. Post-purchase also includes the performance of marketers by assessing the level of effectiveness they provide in identifying and responding to the needs of potential customers [8]. However, there is a certain group of recipients who ultimately make a purchase. Due to certain key elements, customers are encouraged to make a transaction. After the purchase, the post-purchase phase determines the loyalty of buyers and potential re-engagement. The consumer journey seems to be a more repetitive journey consisting of four stages: the initial decision-making process, evaluation of potential purchase options, conversion, and engagement.

AI throughout the customer shopping journey brings many benefits for organizations (CXPA, 2018):

- At the awareness stage, predictive analytics (a subdomain of AI) identifies interesting aspects for the customer and suggests recommendations regarding products or services.
- In the consideration phase, AI can help sites integrate huge data, allowing customers to gain knowledge and compare related products.
- In the purchase process, AI learns about the customer's unique purchase pattern by examining data patterns and provides recommendations accordingly.
- In the support phase, AI can also examine customer behavior and track any signs of dissatisfaction to take appropriate action towards a specific customer. Such strategies provide highly personalized customer service.

Artificial intelligence (AI) can analyze huge amounts of customer data, including demographics, purchase history, browsing behaviors, and social media activity. This data can then be used to create customer profiles that can be used to deliver personalized experiences. Companies can use AI-based recommendation engines to recommend products or services to which customers may be attracted based on their previous purchases and browsing activities.

Similarly, natural language processing (NLP) is a tool through which artificial intelligence can improve customer experiences and engagement. NLP can analyze customer reactions and opinions to provide companies with valuable insights into the requirements and preferences of their buyers by understanding customer sentiments, most companies can make progress in their products and services to better meet customer requirements and increase satisfaction. Similarly, voice assistants are new methods of AI tools that can increase customer engagement and actions by providing customers with a more spontaneous and appropriate way to perform duties such as ordering products or services, making payments, and accessing information. Compatible AI-based visual search tools can enrich customer experiences and engagement by providing customers with a more instinctive and convenient approach

to finding products based on images, making it easier and faster to find what they are looking for. We can understand that artificial intelligence can be a powerful tool for enhancing customer experiences and engagement in digital transformation.

According to Kotler et al. (2017), companies should realize that the first stage of the customer path is awareness of needs. According to Batra and Keller (2016), needs lead to categories, not brands. As a result, it may be difficult to remember the requirements and goals of everyone. Artificial intelligence can understand the requirements and desires of customers when they communicate online. With artificial intelligence, marketers will be able to create more accurate customer profiles in real time. Customer online behaviors, such as status updates on social media, online shopping, comments, and posts, create their digital footprints, which machine learning then uses to automatically update customer profiles. Artificial intelligence can help companies provide more personalized, efficient, and engaging customer experiences. However, it is important to balance the use of AI with human touchpoints to ensure that customers still feel valued and heard. Companies must clearly define the use of AI and ensure that customers understand how their data is used.

3. DISCUSSION

In conclusion, despite the fact that algorithms surpass human capabilities, they are nothing more than a tool, and it is humans who invented them. Artificial intelligence is growing, but it still requires more effort to become 'intelligent.'

Nevertheless, artificial intelligence is expected to eventually completely revolutionize the way transactions are conducted. Brands, decision-makers, researchers, and consumers shape, willingly or not, a new AI landscape. Daily use of smartphones, competition, research, and the need for better solutions train AI algorithms. The author hopes that "the proper use of artificial intelligence for the benefit of consumer behaviors" will motivate consumers, decision-makers, and policymakers to rationally use the technological means currently available to decision-makers, in order to preserve the human right to autonomy, dignity, and independence.

Artificial intelligence deals with creating intelligent machines that can think and act like humans. It provides exceptional capabilities for a wide range of industries. Each listed industry is either terrified or fascinated by the advent of AI. AI creates intelligent machines and devices that can think and react like humans. This technology has been called the 'next step' of the industrial revolution. Artificial intelligence and machine learning are believed to be solutions to most of today's problems.

The evolution of artificial intelligence has brought new value to consumers and decision-makers. Artificial intelligence affects consumer behavior through process automation, making them consumer-oriented and easier to use. Despite the advantages, artificial intelligence due to data processing for segmentation, targeting, and recommendations is considered a threat to free will and consumer autonomy. Consumer autonomy in making decisions for them and making their own choices seems to affect their well-being. Consumers believe that freedom of choice is essential to their lives. Free will strengthens people's belief that they make decisions proving their existence and independence. The contribution of artificial intelligence to consumer autonomy must aim to serve people. Autonomous choices must be balanced, act according to certain principles and boundaries, and most importantly, must be based on self-determined choices.

There are certain factors that affect consumer autonomy in choosing the best option for them through the unexplained desire to choose, even if the selection procedure requires no effort. Consumers not only feel hedonism during the purchase procedure and the desire to choose, but also significantly consider autonomous choice important. Finally, we realize that artificial intelligence is a fast-moving train that is developing in our homes and workplaces. It will eventually take over every device we use and become an inevitable part of our lives. All of us, including the creators of this technology, should ensure that it serves only to comfort people, not to replace them.

4. CONCLUSION

As organizations want to scale personalized experiences in real-time throughout the customer journey, they will have to accelerate basic improvements to harness the potential of artificial intelligence agents,

i.e., the structure in which agents powered by artificial intelligence are deployed to analyze data, make decisions, and take actions without human intervention. Evaluating enterprise processes, moving to cloud environments, utilizing data and content, and implementing strategies for artificial intelligence and machine learning—all contribute to optimized Customer Experience. As companies invest in new technologies to become data-oriented in the experience economy, understanding and benchmarking digital maturity is essential for progress on this path. A transition to a modern architecture is required, consisting of process automation throughout the enterprise, to enable all stakeholders to achieve business results. The goal is to effectively use digital tools to transform work, ensuring that data and insights connect people with information and processes that ultimately lead to better Customer Experience.

Although research reflects a significant improvement in overall digital maturity among Customer Experience respondents since 2019, still only about 20% of respondent companies deliver optimized Customer Experience (Edelman, 2023). As companies invest in new technologies to become data-oriented in the experience economy, benchmarking and understanding digital maturity is key. For companies to effectively compete in this changing environment, they must capture, analyze, understand, and act on information; they must also recognize patterns, understand ideas, plan, predict, solve problems, identify actions, and make decisions on a large scale. When implementation reaches a critical phase, enterprise-wide data and process automation help ensure that all stakeholders can perform essential business results. Additionally, the use of artificial intelligence in call centers and other after-sales services will shorten customer waiting times, thus improving their experiences. Finally, the thematic analysis of interviews shows that not all companies in Palestine can fully adopt artificial intelligence technology due to high costs and lack of skills in Palestinian society.

The consumer decision journey has transformed into an extremely complicated procedure that has already laid the groundwork for a new overall marketing strategy adopted by companies. Companies are currently being reorganized, trying to adapt to new, demanding circumstances. They must embed new "intelligent" ways of monitoring consumer habits, optimizing brand effectiveness, and marketing transformation efficiency on multiple scales to be able to handle the amount of personalized data generated daily efficiently. The application of artificial intelligence in consumer data will help brands analyze their customers, manage the funnel, optimize advertising campaigns, increase user satisfaction, providing personalized solutions and product recommendations.

The consumer journey examines and identifies customer needs. AI enables decision-makers to quickly understand current and future consumer needs and direct marketing campaigns to them. Data from website users, online stores, internet portals, social media, and applications contribute to identifying, analyzing, and directing user behaviors and user intentions. By targeting consumers, Artificial Intelligence manages to track and observe consumers at certain stages of interaction during their decision journey.

Artificial intelligence in marketing is the best technique for predicting customers and improving the customer path through the integration of customer data. Advances in artificial intelligence provide companies with more meaningful ways to do this.

This technology can help develop more effective marketing strategies, improve the customer path, and change the way companies attract, nurture, and convert potential customers. Marketers use artificial intelligence to separate customers into key groups, segmenting them based on specific niches. Machine-generated content and automated personalization of the customer path are regulated by AI content production. AI-based content curation allows us to engage visitors better and stay up to date with their thoughts, offering relevant materials and added value while presenting industry knowledge. It can be used for various purposes, including customizing messages and creating better suggestions for consumers.

The use of Artificial Intelligence can help marketers generate authentic content for sharing and distribution on social media. Copywriters and social media analysts can create targeted social media content faster. Social media tools using AI can generate patterns of content creation and selection based on data from previous posts and determine what colors, keywords, and hashtags they will use to increase user engagement. In addition, AI social media tools can predict which posts will increase reach, clicks, shares, conversions, or brand awareness in the future. Marketers can monitor, analyze audiences, generate content, and reach their customers on multiple social media channels, using powerful platforms to handle multiple ads from multiple social media channel accounts in one place.

Referring to predictions and insights, 'intelligent' social media tools surpass basic social media business services, offering a range of advanced services. Artificial intelligence can easily identify which channels will have the greatest reach and which audience groups will be most susceptible. These services include content selection, user profile segmentation, audience targeting, increasing market share, detecting consumer trends, and optimal social media scheduling (André et al., 2019).

In addition to organic social media posts, there are also paid posts that are powered because artificial intelligence knows how to automatically generate ads aimed at increasing views, click performance, conversion optimization, and user engagement. The features mentioned, including targeting, ad effectiveness, and creativity, can help achieve paid results that exceed expectations. Referring to ads, artificial intelligence can analyze PPC ads on various platforms and offer recommendations for maximum efficiency. These new features can help marketing experts reduce customer churn by monitoring behaviors, observing consumer discussions, and what they are looking for. Customer experiences (CX) and technology investments are set for significant transformation. Generative artificial intelligence (GenAI) is expected to significantly change the way organizations allocate resources and plan their technological strategies. This trend is complemented by a growing emphasis on digital maturity and data strategies, as companies strive to use data to increase customer engagement and operational efficiency effectively. The balance between personalization and privacy will also be crucial as companies navigate consumer expectations for tailored experiences while complying with rigorous data protection regulations.

Contemporary approaches to organizational management increasingly rely on the concept of Intelligent Management, which integrates information technologies, data analytics, and advanced algorithms to support more effective managerial decision-making. In this context, the use of artificial intelligence in the analysis and processing of data related to the Customer Journey constitutes a fundamental component of this concept. First and foremost, AI enables real-time personalization of customer experiences through dynamic analysis of behavioral and transactional data. This allows for the customization of offerings, communication, and interaction channels according to individual preferences and needs, aligning with the principles of data-driven management. Moreover, AI supports operational optimization by automating analytical processes, customer segmentation, and behavioral prediction. The result is increased efficiency in marketing and sales activities, as well as more accurate resource allocation. Another key aspect is the predictive capability of AI algorithms, which, based on historical and real-time data, can forecast customer behavior, identify churn risks, and estimate customer lifetime value. This knowledge facilitates proactive decision-making, which is a central feature of intelligent management. AI also contributes to the integration of data from multiple customer touchpoints, ensuring informational consistency and enabling a holistic view of the customer relationship. Such integration is essential for conducting comprehensive analyses and developing strategies based on a complete understanding of customer experience. Finally, AI systems possess the ability to learn and adapt, which supports the continuous improvement of managerial decisions. Intelligent management assumes flexibility and the capacity to respond to dynamic environmental changes—characteristics that are inherently supported by machine learning algorithms.

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CONCEPT OF AN AI-BASED SYSTEM FOR ENHANCING THE ACCESSIBILITY OF HOSPITAL WEBSITES

Izabela Rejer[a], Ewa Krok[b]

[a] *Faculty of Computer Science and Information Technology, West Pomeranian University of Technology in Szczecin, Poland*
[b] *Institute of Management, University of Szczecin, Szczecin, Poland*

ABSTRACT

Purpose: *The purpose of the paper is to present the concept of an AI-based system that automates the process of verifying and repairing accessibility errors on hospital websites. The system aims to ensure compliance with international WCAG standards and improve websites usability for individuals with various dysfunctions.*

Need for the study: *With the growing number of people with disabilities and the increasing role of the Internet as a source of information, website accessibility has become a key challenge in today's digital space. Hospital websites present a particularly critical challenge, as they serve as official platforms offering access to health information, medical services, and effective communication with facilities.*

Methodology: *The authors described the concept of a system in which artificial intelligence iteratively identifies and fixes accessibility problems to support web administrators creating and managing the hospital's website. Advanced technologies like convolutional neural networks, transformers, and models that combine natural language processing with computer vision are included.*

Findings: *The proposed system has the potential to significantly improve the accessibility of hospital websites, eliminating barriers affecting people with disabilities.*

Practical Implications: *The automation of accessibility processes using artificial intelligence not only saves time and reduces human errors but also counteracts social exclusion and increases inclusivity. The concept presented in the paper is a step toward full automation of accessibility enhancement, while supporting healthcare institutions in managing their websites in accordance with regulations and social responsibility.*

Keywords: digital accessibility, WCAG standard, hospital websites, artificial intelligence, machine learning, automation

Jel codes: L86, M15; O3; I18; C61

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1.INTRODUCTION

With the rapidly growing number of people with disabilities and the ever-increasing role of the Internet as a significant source of information, web accessibility has become one of the key challenges of today's digital space.

Hospital websites, as official platforms of health units, serve a particularly important function, offering access to medical information, appointment registration and communication with facilities. Their role becomes even more important, given that more and more people seek health information online. In the context of existing legislation in most countries, such as laws governing digital accessibility, hospitals are obliged to ensure that their websites comply with international accessibility standards, such as WCAG (Web Content Accessibility Guidelines).

Despite these regulations and growing public awareness, research indicates that many hospital websites still do not meet accessibility requirements. These barriers mainly affect people with disabilities, for whom properly designed pages may be the only way to obtain necessary information. Against the backdrop of intense technological development, artificial intelligence can play a key role in automating and assisting the process of bringing websites into compliance with accessibility requirements, ensuring WCAG compliance and improving the user experience.

Ensuring the digital accessibility of websites is not only a matter of compliance but also a strategic element of management and marketing. Accessible websites increase the trust of citizens (in this case, patients), improve the institution's image, and enable better communication with diverse groups, counteracting social exclusion. They exemplify a modern approach to facility management that combines technology with social responsibility.

Traditional methods of improving accessibility, based on manual changes by website administrators, can be time-consuming, costly, and error-prone. In addition, the dynamically changing content of websites, as well as their expansion, requires constant review and updating, which poses additional challenges.

The purpose of this article is to propose a concept for a system that automates the process of validating and fixing digital accessibility errors on hospital websites. The proposed solution facilitates the efficient validation and adjustment of web pages to accessibility standards, while ensuring regular updates in response to evolving user needs. The article presents the concept of a closed-loop system operation, wherein the system iteratively modifies a page until no further changes are identified by the *Accessibility Validators* and *User Experience (UX) Evaluation Modules*. By leveraging artificial intelligence, the system can identify and fix issues that are difficult for traditional tools to detect, such as mislabeled images, illegible text, or navigation problems in dynamic elements.

The rationale for such a system stems from ensuring that hospital websites are fully accessible to a wide range of users, including people with disabilities, and the need for effective and efficient management of websites that often require updates and corrections. Using artificial intelligence to automatically analyze and improve accessibility saves significant time, reduces human error and ensures consistency with legal requirements, ultimately improving the quality of hospital services.

The system concept proposed in the article has been designed with the specific requirements arising from the nature of the information on hospital websites. Thus, the system considers the need to tag medical-specific elements such as medical images (e.g., X-rays, CT or MRI images) and medical diagrams, which often require a specific type of alternative descriptions. Moreover, the system is able to generate precise, contextual descriptions of these images, enabling patients with visual impairments to fully understand the visual content on the website. In addition, the system takes into account the fact that hospital websites often contain complex medical texts that may be incomprehensible to the layperson and therefore it is equipped with features to simplify texts, translate complex medical terminology into more accessible language, and adjust the level of difficulty of the content according to the potential user's needs and preferences.

2. LITERATURE REVIEW

Research is gaining increasing attention on web accessibility. Electronic media permeate almost every aspect of our lives, so ensuring equal access to information obtained through these channels is fundamental to inclusivity and social inclusion. Research in this area not only identifies barriers but also shows how to minimize exclusion, redress inequalities, and create a more equitable digital space for everyone.

In reviewing the literature in this area, initial reference was made to the eGovernment Benchmark 2023 Insight Report commissioned by the European Commission (Report of the EC, 2023). Although the analysis does not deal directly with hospital websites, but with the progress in the digitization of public services in Europe, the study is worth citing. The study covered 27 EU member states, plus countries such as Iceland, Norway, Switzerland, Albania, Montenegro, North Macedonia, Serbia and Turkey. It is a comprehensive study that, in addition to assessing digital public services in four key dimensions: User-Centricity, Transparency, Key Enablers and Cross-Border Services, it also identifies the most common errors found on the 15,000 e-government websites analyzed for digital accessibility. Many of these deficiencies can also be found on hospital websites, making this analysis relevant to the article's issue. Using the Axe tool (a browser extension), websites were evaluated against 8 of the 50 WCAG 2.1 criteria. The results indicated that the majority (82%) of public sector websites violate one or more of the 8 WCAG 2.1 criteria examined, which, of course, does not mean that the remaining 18% are compliant with accessibility requirements (as this would require checking all 50 success criteria). The most problems were revealed in terms of criteria related to:

Contrast (Minimum) (WCAG 1.4.3) – this is a criterion from the AA level; providing adequate contrast helps people with visual impairment, daltonism or elderly users to read text on the screen more easily; low contrast makes it difficult or even impossible to access information.

Link Purpose (In Context) (WCAG 2.4.4) – this is also an AA-level criterion and is concerned with ensuring that the purpose of each link can be determined from its content or related context. The content of the link should clearly inform the user of its purpose. Understandability of links is important for all users, but especially for those using assistive technologies such as screen readers. Such people can move between links on a page and hear only the link's content. Unclear links make it difficult for them to navigate and understand the website.

Parsing (WCAG 4.1.1) is an A-level criterion, which means it is one of the basic accessibility requirements. It refers to the correctness of a website's code, i.e. the correctness of HTML and CSS syntax, to ensure its compatibility with supporting technologies such as screen readers. Errors in the code can result in supporting tools not being able to correctly interpret the content of the website.

Non-text Content (WCAG 1.1.1) – is one of the fundamental requirements at Level A. This criterion focuses on providing text alternatives for all non-text elements (e.g., images – verbal description, videos – transcription, icons and buttons – labels) on a website.

According to the report, many websites of state institutions in Europe do not meet accessibility standards, which poses a challenge for some 60 million Europeans with various limitations. The document underscores the need to constantly strive to bring websites aligned with WCAG guidelines to ensure equal opportunities in accessing public services.

The following are the results of previous studies focused on the accessibility of medical institutions' websites. The growing number of publications in this area reflects the importance of e-health in providing services and medical information to patients. Selected results of studies conducted in the last few years are included, which gives a picture of the accessibility of healthcare entities' websites and their compliance with the recommended WCAG standards.

Kaur et al. (2017) assessed the accessibility, usability and security of hospital websites in metropolitan cities in India. They found that many websites had accessibility problems, and full compliance with WCAG guidelines was low. In addition, the websites of the hospitals surveyed neglected performance and quality criteria and, according to the researchers, needed many improvements to meet people's expectations and motivate them to use digital media for health-related information. Most websites lacked multilingual features, making it difficult to understand the content. Due to the CMS used (which was not updated regularly and had vulnerabilities), security also remained low.

Kuzma et al. (2017) conducted a study of international scope. Using the Tawdis tool, they analyzed 160 hospital websites in 16 countries on four continents. In all countries, they revealed a high prevalence of problems with meeting the WCAG standard, with Asian hospital websites having the highest incidence. Only two hospital websites included in the survey were fully compliant with Level A of the WCAG guidelines. The survey found that hospitals are not doing an adequate job of complying with accessibility standards and government regulations, thus depriving people with disabilities of the opportunity to fully use their websites.

Saghaeiannejad-Isfahani et al. (2019) presented similar findings after analyzing the websites of Iranian hospitals. They concluded that none of them were in the desired state. The researchers suggested that this was due to a lack of consultation with experts, a failure to follow design rules, and a lack of content management and website monitoring.

Sik-Lanyi and Orbán-Mihálykó (2019) tested the accessibility of nearly 100 health websites in nine European countries: the N-WE-EU group, which includes countries such as Germany, Switzerland, Sweden, Austria, Finland, and the V4 group, which included the Czech Republic, Hungary, Poland and Slovakia. They used AChecker and Nibbler tools for testing, as well as information obtained through interviews with website users. In their conclusions, they highlighted the most serious accessibility problems of the tested websites. The vast majority of them did not meet accessibility guidelines. According to the researchers, the errors were largely repetitive, common and easily avoidable. They mainly concerned criteria related to non-text content, contrast and text resizing. In many cases, the criterion related to correct structure, information and relationships between elements on the website, so that supporting technologies could interpret them correctly, was also not met. Interestingly, the researchers found no differences between the results of the N-W-EU and V4 countries. However, the GDP and GNI of the N-W-EU countries are significantly higher than those of the V4 countries.

Hospital websites in Saudi Arabia have also been examined for accessibility. Analyses using the AChecker tool were conducted by Alhadreti (2021). He focused on the websites of the top-rated 10 public and 10 private hospitals in Saudi Arabia. He found that only 20% of them fully complied WCAG 2.0. He found no significant difference in accessibility compliance between public and private hospital websites. The most commonly observed accessibility errors were in information structure, non-text content, labels and instructions, headings and keyboard access. The results show that most hospitals pay minimal attention to the accessibility of the content and structure of the information provided, which in the case of Saudi Arabia may be due to the country's failure to establish accessibility regulations and guidelines.

Against the background of previous studies, the evaluation of 91 infectious disease hospital websites in Poland was quite positive. According to the study's authors (Król & Zdonek, 2021), most of the websites appeared to be of satisfactory quality, but the results indicated strong variation among the websites in terms of search engine optimization, mobile-friendliness, and the needs of people at risk of digital exclusion.

Alajarmeh (2022) analyzed the public health websites of 24 different countries. The vast majority of them had many critical accessibility barriers, especially with regard to perceived information and handling of interface elements. At the A level, only five websites (from Italy, the UK, China, the Netherlands, and Brazil) and at the AA and AAA levels, only three websites (i.e., those belonging to Italy, the UK, and China) fully complied with the WCAG 2.1 standard.

An interesting study was conducted by Jonsson et al. (2023). They were interested in how healthcare providers in Sweden used accessibility claims on their websites. None of the providers fully addressed the requirements for accessibility statements, which means they did not meet the law's goal of providing accessible medical information and eHealth services. There was little or no progress between the first and most recently published accessibility statements.

Finally, the results of a study from Turkey and Malaysia. Macakoğlu and Peker (2023) examined the accessibility of 58 university hospital websites in Turkey. As in other countries, they revealed a low level of compliance with the WCAG 2.0 guidelines, with most of them not even meeting the minimum requirements for compliance level A. Almost all of the websites had broken links, and one-third had mobile device access problems.

Sarantis et al. (2024), in turn, surveyed the websites of 107 public and private hospitals in Malaysia against various criteria defined by the Health Sector Website Assessment Index (HSWAI). Most websites scored satisfactorily on the technology criterion and performed reasonably well in providing

essential content but showed significant deficiencies in accessibility and community interaction. Compliance with the WCAG 2.0 standard at the AAA level for no website exceeded 16.8%, and for the weakest website, it was 0.9%.

A literature review identified significant deficiencies in the digital accessibility of websites, including those of hospitals, and the most common errors that limit their functionality. Before presenting the author's concept of a system using artificial intelligence to automate the work of ensuring the digital accessibility of hospital websites, the tools and methods currently used for this purpose were discussed.

3. TESTING DIGITAL ACCESSIBILITY OF WEBSITES

Automated tests are one of the most widely used tools in the process of checking the digital accessibility of websites. Although they cannot detect all errors and problems, they are worth using because of their speed and efficiency. They are helpful not only for accessibility auditors but also for the daily work of developers, designers, and testers. This is because they can be used at all stages of website maintenance, i.e. website creation, maintenance, evaluation and improvement.

The tools currently available differ in several key aspects (Colantonio, 2024; Pracownia Dostępności Cyfrowej LepszyWeb.pl, 2025):

The scope of tests: some of them analyze only single subpages (single web pages), while others can examine multiple pages or even entire websites at once (groups of web pages or websites).

Compliance: digital accessibility assessment tools can be used to test compliance with various WCAG levels (A, AA, AAA) or other standards (e.g., US Section 508 and ADA, French RGAA, Australian DDA, Canadian ACA or Italian Stanca).

Complexity: some tools have a very limited, specialized scope of operation and focus on one or a few functions (e.g., checking the correctness of headings, contrast or link accessibility). Others are more extensive, covering many aspects at once and combining multiple functionalities to offer a comprehensive approach to accessibility analysis, handling other formats in addition to HTML content, checking, for example, PDF documents or office application documents.

Users: tools of this type are created with different audiences in mind, on the one hand, some tools can be used by any 'average' Internet user, on the other hand, there are tools aimed at specialists (designers, programmers, content developers) that can be integrated with advanced software development systems and applications.

The level of detail in the results: tools can visually (by outlining, icon, comment) mark problematic areas on the page that need accessibility improvements, which enables analysis of the inconvenience in context and helps understand the relative importance of each problem. Other tools can generate simple reports that present synthetic results of the tests performed, based on a preset checklist, or more advanced and detailed reports that include, for example, paths to errors in HTML code and statistics on the problems detected.

Method of use: the tools can be available online via a website (online tools, online checkers), as extensions to authoring tools (authoring tool plugin), in the form of extensions to web browsers (browser plugin), in the form of web applications (desktop application) or mobile applications (mobile application) running under a specific operating system, but also as hosted services, regularly checking the website and providing reports.

Cost: you can find free and paid tools offered under commercial licenses.

The market has various automated digital accessibility testing tools that can filter by multiple criteria (W3C WAI, 2025; Colantonio, 2024). These include tools such as WAVE, AChecker, Free Website Accessibility Checker, Achecks, AccessibilityChecker, Utilitia, Tanaguru, and Lighthouse, allowing for multi-faceted accessibility assessment. Other tools evaluate selected accessibility elements, such as contrast (Color Contrast, ColorSafe, Contrast Checker) or markup correctness (HTML Validator, CSS Validator, Total Validator).

It's worth mentioning that because different tools often lead to slightly different results, there is an ongoing effort to unify the principles of accessibility testing (ACT, 2019). Documenting how accessibility requirements are tested will make accessibility testing transparent and test results repeatable. The Accessibility Conformance Testing rule format defines requirements for describing these descriptions.

It is also important to realize that even the most sophisticated accessibility testing tools available today cannot assess compliance of all aspects with the WCAG guidelines. Thus, the results of only an automatically performed assessment are mostly incomplete and require human judgment. The proposal presented in the article to incorporate AI into accessibility testing is intended to ease the auditor's burden and speed up adapting the website to the set criteria, ultimately without human involvement.

4. GENERAL SYSTEM FRAMEWORK

The system proposed in this article for automatization of the process of improving the accessibility of hospital websites consists of six main modules: *Accessibility Validators Module*, *User Experience (UX) Evaluation Module*, *Problem Classification Module*, *Automatic Repair Module, AI Repair Module*, and *Web Admin Module*. The connections between modules are illustrated in Figure 1, and their primary tasks are outlined in Table 1.

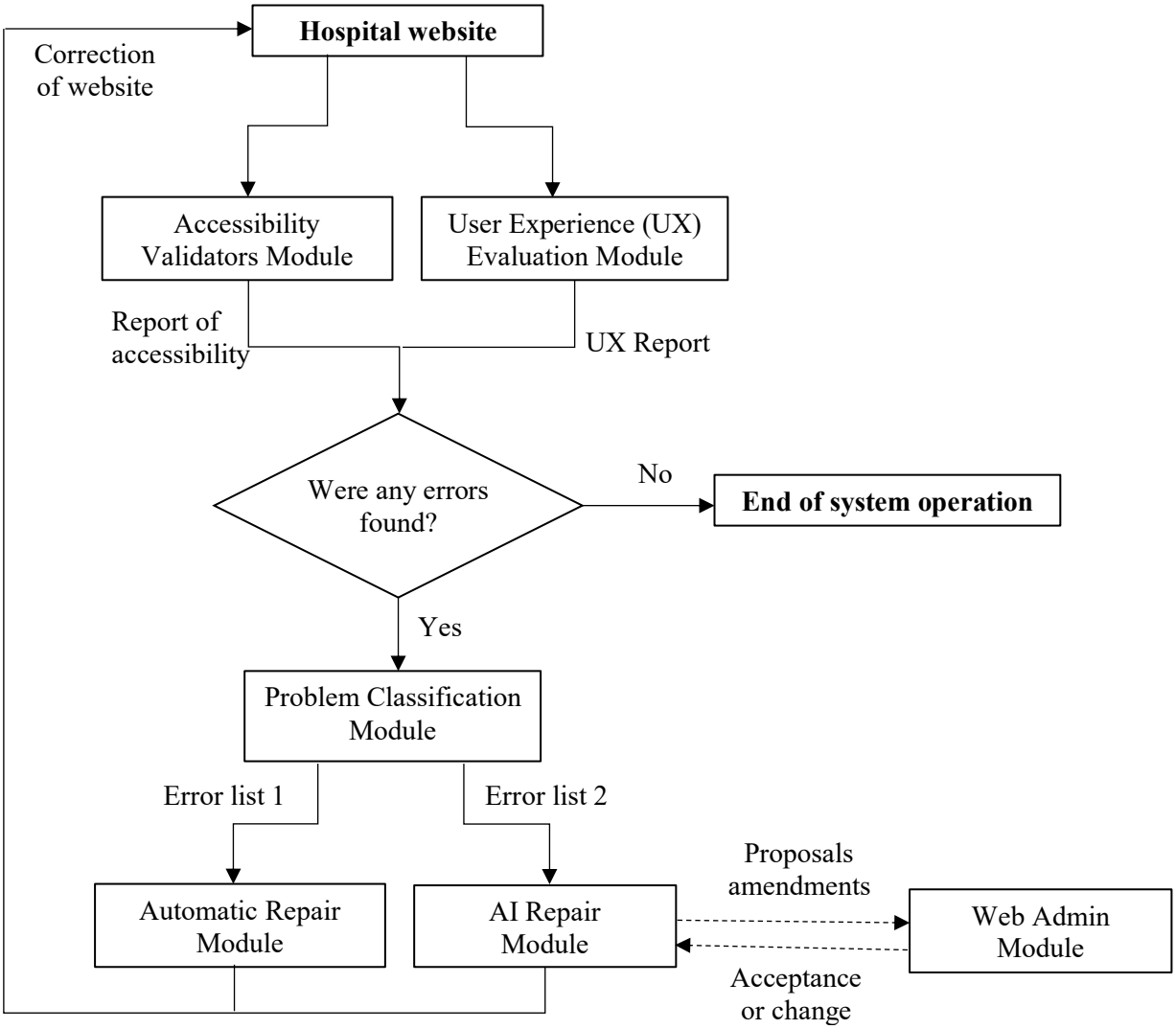


Figure 1. System architecture
Source: own elaboration.

The first stage of the system's operation involves conducting an accessibility audit of the website using a selection of the wide range of validators available, as discussed in the previous section. These tools generate reports that include a list of detected problems, such as a lack of alternate text for images, insufficient colour contrast, lack of visible markup for interactive elements, or incorrect navigation

order. Also of particular concern for hospital websites are issues related to compatibility with assistive technologies, as well as ensuring that urgent messages are correctly labelled, such as in emergency situations.

A module that performs user experience (UX) evaluation is launched in parallel. This module works fully automatically and does not require user interaction, as its task is to simulate typical user paths using built-in artificial intelligence models. The system analyzes typical scenarios, including navigation through the structure of medical departments and interaction with dynamic content, such as test results. The analysis results in a second report identifying potential user difficulties, such as insufficient highlighting of active links, keyboarding errors or non-intuitive information hierarchy.

Both reports are then processed in the *Problem Classification Module*, which divides errors into two categories. The first includes standard problems that can be fixed using rules stored in the expert system's database. This group includes, for example, improper header structure, lack of proper labels for form fields and incorrect use of ARIA attributes. The second category includes non-standard problems that require artificial intelligence models. Examples include issues that require visual interpretation, such as generating descriptions for unsigned images or dynamically adjusting interface colours to meet contrast requirements.

Table 1. Tasks of each module of the system

Module name	Module task
Accessibility Validators Module	The module audits the website using tools dedicated to this purpose, detecting accessibility errors.
User Experience (UX) Evaluation Module	The module automatically analyzes user interactions, evaluating the user experience without human intervention.
Problem Classification Module	The module analyzes reports and divides errors into two categories: those that can be repaired automatically and those that require AI.
Automatic Repair Module	The module fixes standard accessibility errors with an expert system.
AI Repair Module	The module uses machine learning algorithms to generate solutions to more complex problems.
Web Admin Module	The module allows developers to monitor patches and accept changes generated by AI.

Source: own elaboration.

After the problems are classified, two lists of errors are generated. The first list, containing standard errors, is passed to the *Automatic Repair Module*, which makes corrections directly to the page code based on the expert system's rules. The system can, for example, automatically add missing 'aria-label' labels to buttons or correct the hierarchy of headings, providing a logical structure to the document. The second list, containing custom problems, goes to the *AI Repair Module*. Depending on the system settings, adjustments generated by this module can be automatically implemented or passed to developers for verification. An example of the operation of this part of the system could be a generative AI model, which analyzes image content and creates alternative descriptions in natural language, helping to meet WCAG requirements for multimedia.

Once the repair process is complete, the *Accessibility Validators* and *UX Evaluation Modules* are restarted to verify the effectiveness of the corrections made and to detect any new errors introduced by changes in the code. The system terminates if the reports provided by both modules show no further errors.

The presented concept makes it possible to significantly improve the accessibility of hospital websites, minimize barriers for people with disabilities, and ensure regulatory compliance. The system can act both as a tool to assist developers and as a fully automated platform for maintaining website accessibility.

4.1Accessibility validators module

The *Accessibility Validators Module* analyses a hospital's website for compliance with current accessibility standards. Most countries adopt WCAG (as of October 2023, W3C recommends version 2.2) as the baseline digital accessibility standard, the implementation and requirements of which are sometimes modified depending on local regulations and needs. The main task of the *Accessibility*

Validators Module is to detect technical problems that may impede the browsing of the website by people with disabilities, seniors or hospital patients using assistive technologies. For this purpose, validator tools present on the market can be used as mentioned earlier in this article. It is best to select them so that they complement each other in terms of functions and provide a comprehensive testing set, i.e. they identify both contrast or keyboard operation problems, detect HTML and CSS code errors, and allow evaluation of the semantic structure of the website, pointing out errors in headers, forms or multimedia. Other criteria, such as the scope of tests, compliance with standards, and the cost of implementation will also dictate the selection. Decisions on these issues should be made at the hospital's *Web Admin Module* level.

The module performs a holistic website analysis, identifying various categories of problems. The most common errors are those related to multimedia, including the absence of alternate text for images, which is important in the case of images informing about medical procedures, navigation pictograms or doctors' photos. For audio and video materials, the system checks for the presence of transcriptions and subtitles, which is particularly important for deaf people. Dynamic interface elements, such as system messages, are also analyzed and should be appropriately tagged in the code using ARIA technology.

Another important area of analysis is the problems related to navigation and user interaction. The system evaluates whether all key website functions are accessible via the keyboard, which is crucial for those who do not use a mouse. Navigational order is also checked so that users can logically move between website elements, such as registration forms. The correctness and accessibility of links are also verified, including whether they all work, are correctly described, and lead to the right places.

The analysis also covers readability and contrast problems. The system detects insufficient contrast between text and background, making reading difficult for people with poor eyesight. It also verifies that the website allows the font to be enlarged to at least 200% without losing functionality, which is crucial for the elderly and visually impaired.

Forms and patient registration systems are also important and should be intuitive and comply with accessibility standards. The module analyzes whether each form field has an appropriate label, whether interactive elements such as buttons are clearly marked, and whether error messages are clear and legible. It also checks whether fields can be auto completed, making it easier for users to enter data.

In addition to static page elements, the system also evaluates dynamic content, including notifications and changing interactive content. Key messages, such as information about changes in doctors' appointment times or test dates, must be appropriately marked in the code so assistive technologies can read them. The structure of headings on the website should be logical and organized, allowing easy navigation for those using screen readers.

After the analysis, the system generates a report summarizing the errors detected. The report includes detailed descriptions of the problems along with their location in the website code, as well as recommendations for fixing them, such as adding missing alternative texts, improving the structure of headings, or increasing text contrast. This report is then passed to the *Problem Classification Module*, which performs further analysis and evaluates which errors can be fixed automatically and which require developer intervention.

4.2 User Experience (UX) evaluation module

The *UX Evaluation Module* focuses on identifying problems that may hinder patients' and medical staff's interaction with the hospital's website. Its operation is based on using artificial intelligence methods to automatically simulate the user's interaction with the website and evaluate the clarity, intuitiveness, and efficiency of navigation. The module consists of five submodules, listed in Table 2, along with the type of problems they identify.

The module is based on deep learning models and natural language processing (NLP) techniques (Yang et al., 2018), as well as deep reinforcement learning algorithms (Arulkumaran et al., 2017) that learn from actual patterns of user interaction with a website. Transformer models such as BERT (Devlin et al., 2019) or T5 (Raffel et al., 2020) are used to analyze the structure and organization of content, evaluating readability and the logical arrangement of information on the page. For example, by analyzing button descriptions and form labels, these models can detect unclear wording that may confuse users. In addition, the module uses computer vision techniques, including Faster R-CNN (Ren et al., 2016) and YOLO (Redmon et al., 2016), to visually analyze the layout of elements on a page and assess their compliance with interface ergonomics.

In terms of evaluating navigation and user interaction, the module uses reinforcement learning techniques based on models such as Deep Q-Networks (DQN) (Mnih et al., 2015) or Proximal Policy Optimization (PPO) (Schulman et al., 2017). These algorithms learn by simulating real-world user actions, mapping patients' paths when registering for an appointment, searching for a doctor or reviewing test results. Based on these simulations, the system detects navigational barriers, such as the need to make excessive number of clicks, the lack of an intuitive section layout, or the difficulty in finding key functions such as registering for a doctor.

Table 2. Types of problems identified by each submodule of the *UX Evaluation Module*

Submodule number and task	AI methods	Problem identified
UXS1: analysis of the structure and organization of content	BERT, T5	Unclear wording and illogical information layout make it difficult for users, including people with disabilities, to find the content they need. Examples: The system detects that the "Save" button on the registration form is not clear; An analysis of the website's structure shows that information about the hospital's operating hours is scattered in various sections.
UXS2: analysis of the visual ergonomics of the interface	Faster R-CNN, YOLO	Suboptimal placement of elements on a page makes navigation difficult for people with limited visual perception. Examples: Visual analysis shows that the "Registration" button is low-contrast to the background, which can make it difficult to see. The system detects that key interface elements, such as navigation menus, are not evenly distributed across devices, which can cause problems for users of screen readers.
UXS3: evaluation of navigation and user interaction	DQN, PPO	Non-intuitive user paths lead to frustration and increased time to complete basic tasks. Examples: The system detects that the user must go through five unintuitive steps to sign up for an appointment. The interaction analysis shows that patients often abandon the process of searching for a doctor because relevant information, such as available appointments, is not presented intuitively.
UXS4: evaluation of alternative (alt) descriptions of images	CLIP	Inadequate alternative descriptions for graphics, making accessibility difficult for blind and visually impaired users. Examples: The system detects that an image showing a doctor at work has the description ‘Image1.jpg’. Analysis of the chart with laboratory results indicates that the alternative description does not contain key information about the data presented.
UXS5: analysis and evaluation of content readability	BERT	Overly complicated language that makes it difficult for patients, especially the elderly and those without medical expertise, to understand the content. Examples: The system detects that the medical procedure description uses the term ‘cholecystectomy laparoscopy’ without explanation. analysis of the website's texts indicates that the sentences in the ‘Patients' Rights’ section are too long and contain many interjections, making them difficult to understand.

Source: own elaboration.

An additional functionality of the *UX Evaluation Module* is the analysis of the compatibility of alternative descriptions (alt) with the graphic content of images. Standard accessibility validators only check for the presence of alternative text without assessing its adequacy. To extend this functionality, the system uses artificial intelligence to analyze the content of images and compare them with the assigned description. This process uses the CLIP (Contrastive Language-Image Pretraining) model (Radford et al., 2021), which, due to being trained on image-text pairs, allows for the semantic analysis of image content in relation to text and is ideal for assessing whether the 'alt' description captures the

content of the graphic. The system processes not only photos and images but also charts or diagrams, identifying the key objects and the relationships depicted (with the support offered by the YOLO model). Then, it evaluates whether the description matches this information.

In addition, the system evaluates whether the texts on the hospital's website can be understood by a wide range of users, including the elderly and patients without medical expertise. For this purpose, it uses the NLP (BERT) model to analyze sentence structure, paragraph length and vocabulary complexity. The model evaluates texts based on readability indicators, such as Flesch-Kincaid (Williamson et al., 2010), and then identifies passages that require simplification. In addition, the model detects sentences that are too long and complex, making it difficult to assimilate information quickly.

The final result of the *UX Evaluation Module* is a report containing detected problems and recommendations for their solution. The system can automatically suggest fixes, such as changing descriptions, rearranging elements, adjusting the content of labels or reorganizing the navigational structure to increase interface clarity. This report is then passed on to the *Problem Classification Module*, which determines which problems can be corrected automatically and which require developer intervention. Due to the use of artificial intelligence, the system enables dynamic and precise usability evaluation, adapting to the specific needs of hospital website users and supporting the optimization of their interaction with the system.

4.3 Problem classification module

The *Problem Classification Module* processes reports generated by the *Accessibility Validators* and *User Experience Evaluation* modules. Its main task is to analyze the detected errors, categorize them, and forward the relevant sets of issues to the *Automatic Repair Module* or, if the problem requires more advanced interpretation, to the *AI Repair Module*.

The classification process is based on simple heuristic rules and analysis of typical error categories. The system processes reports sequentially, assigning each detected problem to one of several predefined groups, such as:

Technical errors (e.g., missing alt attribute, incorrect header hierarchy, missing labels in forms) that can be fixed automatically;

Visual problems (e.g., too low contrast, suboptimal placement of interface elements) requiring involvement of the *AI Repair Module*;

Content problems (e.g., unclear instructions, inconsistent nomenclature) also requiring involvement of the *AI Repair Module*.

If a given issue occurs repeatedly in different areas of the website, the system groups it within the same category, enabling more efficient decision-making regarding the repair method. Using simple classification rules, the module works quickly and does not require advanced artificial intelligence algorithms.

4.4 Automatic repair module

The *Automatic Repair Module* is responsible for implementing fixes to the website's code based on previously detected and classified standard errors. Its operation is based on an expert system that uses a knowledge base containing a set of predefined repair rules. Each of these rules describes how to solve a specific problem related to web accessibility based on accepted WCAG standard guidelines and best practices. The knowledge base can be expanded and updated continuously by developers through the *Web Admin Module*, allowing the system to be adapted to new technological challenges and the specifics of hospital websites.

The essential element of the module's operation is to analyze the received list of errors and assign an appropriate repair rule to each problem. These rules take various forms – from simple instructions modifying HTML, CSS or JavaScript code to more complex operations involving the entire document structure. For example, suppose the system detects that the buttons on a page do not have proper markings for screen readers. In that case, it runs a rule with the following content: "For each 'button' element without the 'aria-label' attribute, check the text content, and if it is empty, add a description taken from the visible context (e.g., from the surrounding 'label' or iconography)." Similarly, if the page headers are used in the wrong order, the system applies a rule: "If a 'h2' header is followed by a 'h4' without an intermediate 'h3', change its level to 'h3'." In addition to a set of typical rules that improve page elements, the knowledge base also includes a prioritization mechanism for corrections that

determines the order in which the rules are applied. In addition, the system supports conditional rules that consider a page's specifics. For example, for pages containing patient registration forms, the rules include verifying the presence of field labels and assigning them unique identifiers to ensure compatibility with assistive technologies.

The *Automatic Repair Module* also supports correcting errors related to navigation and interactivity. It can add missing 'tabindex' attributes for elements that should be accessible from the keyboard or remove redundant 'tabindex' values that could disrupt the correct order of transition between elements. For pages containing dynamic components, such as modal windows, the system ensures correct focus when opened and closed (in accordance with WCAG requirements).

For colour contrast problems, the module checks the relationship between the background and text and, if necessary, adjusts the colours to the minimum values specified by accessibility standards. For example, if a button with a light background has white text, the system automatically changes the text colour to a darker one.

The structure of the knowledge base also allows the definition of rules tailored to specific types of content. For example, for tables, the system enforces the use of column headers (‘th’ instead of ‘td’) and the assignment of the ‘scope’ attribute, which helps screen readers interpret the tabular structure correctly. For multimedia embedded on a page without audio and video content control mechanisms, the rules automatically include these mechanisms, allowing the user to pause and adjust the volume.

By using an expert system equipped with a set of rules with multiple levels of detail, the automatic repair module can effectively eliminate the most common accessibility errors, reducing the need for manual programming interventions and speeding up the process of making hospital websites WCAG-compliant.

4.5 AI Repair Module

The purpose of the AI Repair Module is to use advanced artificial intelligence methods to eliminate those errors that cannot be repaired by applying rules, contained in the expert system rule base of the Automatic Repair Module. Examples of such areas include more complex user interactions with website content, such as identifying and adjusting multimedia, understanding the context of texts, and improving the accessibility of dynamic elements that automatic tools may have difficulty interpreting. Like the first of the modules using AI methods, the UX Evaluation Module, the AI Repair Module also consists of several submodules, each designed to address a different type of accessibility problem (Table 3).

The first submodule (AIS1) deals with improving the accessibility of navigational content by automatically generating more relevant headings and precise text on user interface elements. It uses language models (BERT, T5) to analyze the content of page fragments and adjust section names, button labels and navigation menu descriptions to make them more intuitive and understandable to users. This corrects previously detected problems related to unclear names or unintuitive navigation structure. The submodule automatically replaces vague button descriptions, such as changing ‘Save’ to ‘Save patient data’, making it easier for users to understand the function of an item. In the case of headings, the system identifies their context and generates more descriptive versions – e.g., ‘Hospital opening hours’ appears instead of ‘Section 1’, and ‘Patient admission procedures’ instead of ‘Other information’. Navigation menus are also being optimized, with generic or vague terms such as ‘Department 1’ being replaced with more precise names, such as ‘Emergency Department’ or ‘Intensive Care Unit’.

Submodule AIS2 also deals with text analysis, but from a slightly different point of view. Its task is to analyze and simplify larger chunks of text flagged by the *UX Evaluation Module* as containing complex medical terminology that patients may not understand without proper training. This submodule also uses advanced language models, such as BERT or GPT, which, when adequately trained on medical data, can detect complicated terms and complex language constructs in medical texts. These models analyze the content on the hospital's website, identifying words or phrases that may be difficult for people without specialized knowledge to understand. Once difficult passages are detected, the system automatically generates simplified translations or definitions that are more accessible to many users. The generated explanations are aligned with general comprehension standards, eliminating the language barrier and ensuring that patients, even those without medical knowledge, can understand the content more easily.

Submodule three (AIS3) aims to improve the accessibility of visual content on hospital websites. To accomplish this task, the system uses pre-trained convolutional networks (such as EfficientNet (Tan et al., 2019) and ResNet (He et al., 2016)) that are further tuned on medical datasets. This approach makes it possible to accurately recognize elements typical of medical content in charts, diagnostic diagrams or images depicting patients' health conditions. Then, alternative descriptions are generated using the CLIP model, which enables semantic matching of textual content with image content, ensuring high relevance and detail. This submodule is used both to improve alternative texts identified as inadequate for the described content and in cases where such texts are completely absent.

The fourth submodule (AIS4) uses the Swin Transformer model (Liu et al., 2021) to analyze video frames and the VideoBERT model (Sun et al., 2019), also based on the Transformer architecture, to automatically generate a description of the video based on analysis of both video and audio. In addition, in the case of a previously identified lack of video transcription by the *UX Evaluation Module*, the system attaches a transcription generated using an automatic speech recognition package, the Whisper package (Radford et al., 2023), which has high transcription accuracy, even under difficult acoustic conditions such as background noise, different accents or fast speech.

Submodule AIS5 focuses on reducing the steps required to complete key actions, such as registering online, getting information about a medical service, finding a doctor, or downloading test results. It uses DQN and PPO reinforcement learning methods to analyze the sequence of actions that a user must perform, for example, to search for the desired information. Then it recommends their optimization by indicating the shortest path leading to their execution.

The task of the last submodule (AIS6) is to improve the layout of content on the website so that users can find key information more quickly and easily. To this end, it employs heuristic interface analysis algorithms and image processing methods. Heuristic interface analysis, based on the PageRank metric calculated for individual subpages and their sections, allows for determining which elements of the website are most important and should be placed in more prominent positions. At the same time, image processing models, such as Faster R-CNN, analyze the visual structure of the website, detecting potential problems with the layout of elements, such as non-intuitive button placement or excessive density of text. In addition, by analyzing the HTML and CSS structure, the submodule suggests changes to the navigation so that key information is placed in easily accessible locations and minimises content distraction.

Table 3. Submodules of the *AI Repair Module*

Submodule number and task	AI methods	Problem solved
AIS1: improving the accessibility of navigational content	BERT, T5	Overly general or vague wording on user interface navigation elements. Examples: Changing the non-intuitive name of the ‘Save’ button on the registration form to ‘Save patient data’ Adjusting the header of the patient registration information section to match its content, changing from ‘Other information’ to ‘Patient registration information’
AIS2: simplifying and translation of medical terminology	BERT, GPT	Complicated medical terminology that is incomprehensible to a wide range of patients. Examples: The system replaces the term ‘adjuvant radiotherapy’ in the description of patient recommendations with a simplified definition of ‘Treatment with radiation given after surgery to lower the chance of the disease coming back’ The system replaces the study description: ‘A patient with a diagnosis of advanced-stage COPD, accompanied by hypoxemia, requires immediate stabilization of respiratory function and compensation of electrolyte disturbances, especially hypokalemia’ with a simplified version: ‘A patient with advanced lung disease has an excessively low oxygen level in their blood and needs immediate respiratory improvement and potassium equalization’

AIS3: improving the accessibility of visual content	EfficientNet, ResNet, CLIP	Inadequate or missing alternative descriptions for images and visual content. Examples: The system adds a missing alternative description for the chart of laboratory results: 'A graph showing changes in a patient's blood glucose level during treatment' The system replaces the overly general description of the medical diagram 'Medical diagram 1' with a description referring to the contents of the diagram 'Diagram showing the distribution of organs in the human body including the circulatory and respiratory systems'
AIS4: improving video accessibility	Swin Transformer, VideoBERT, Whisper	The lack of alternative descriptions/transcriptions for videos or descriptions/transcriptions are inadequate for the content presented. Examples: Adding a transcription to a video showing a medical procedure; Changing the overly general alternative description 'Medical lecture' to a description that refers to the content presented: 'Lecture on new cancer treatments, discussing chemotherapy and immunotherapy treatment techniques'
AIS5: optimization of user paths	DQN, PPO	Non-intuitive or suboptimal user paths. Examples: The system recommends reducing the number of steps required to sign up for an appointment from five to three, removing two of them that do not provide relevant information; In order to reduce the number of abandonment of the process of searching for a doctor by users, the system proposes to move information about available appointments directly to the search results, which shortens the interaction path.
AIS6: reorganization of information	PageRank Faster R-CNN	Suboptimal distribution of content on the website. Examples: The system suggests moving the hours of operation of the hospital's departments scattered across individual subpages to one central section on the home page or a dedicated subpage; The system proposes changing the order of sections and reducing the number of fields in the registration form, reducing the need to scroll through it and shortening the time of filling it out.

Source: own elaboration.

4.6 WEB MODULE ADMIN

The *Web Admin Module* provides full control over the process of implementing corrections on the hospital website, enabling both the management of automatic repair rules and the approval of changes suggested by artificial intelligence. The administrator can supplement and edit the expert system's knowledge base, which makes customization of the system flexible and precise.

One of the module's key features is the ability to specify the repair mode. That means that the administrator can decide whether the changes suggested by the AI algorithms should only be recommended and require manual approval or whether they should be automatically implemented on the website. In the initial phase of the system's operation, it is recommended to use the patch acceptance mode, as this allows the AI models to continuously learn from the administrator's decisions. Human verification provides the system with feedback on the quality of suggested changes, which allows the algorithms to better adapt to the actual needs of the website's users.

Once the system becomes sufficiently effective, the administrator can switch it to full automation mode, eliminating the need to manually approve each adjustment. In this mode, the artificial intelligence models no longer receive feedback, and the tuning process is stopped. However, if re-optimization of the system's operation is required, it is possible to restore the manual approval mode, which will restart the process of tuning the models based on the administrator's interactions.

With the *Web Admin Module*, patch management becomes flexible and adaptable to the hospital's changing needs. The system allows a gradual transition from supervised implementation of changes to

full automation, while providing comprehensive control over content organization and website navigation.

5.CONCLUSION

Today's hospital websites play a key role in providing patients access to health information, medical services and communication with staff. However, despite technological advances, many hospital websites do not fully meet accessibility requirements, which poses a serious challenge for people with various disabilities. According to current legislation, these websites should be accessible to all users, including those with visual, hearing, motor or cognitive impairments. Inadequate accessibility of websites can lead to difficulties in accessing medical information, negatively affecting the quality of health care and equality of access to services.

Technological advancements and the development of artificial intelligence are creating new opportunities for ensuring web accessibility. While helpful, current tools have limitations – they cannot detect or correct all inconsistencies with the WCAG standard. Moreover, they require human labour and manual testing, which significantly lengthens the process of auditing and correcting websites, making it more expensive.

The concept of the system proposed in the article is based on the use of AI to achieve full automation in ensuring accessibility, while supporting designers and developers from the early stages of website development. By integrating advanced artificial intelligence, computer vision and context-sensitive tools, the system has the potential to significantly increase the widespread accessibility of hospital websites in a short period of time. Nowadays, despite rapid technological advances, there is still no solution that completely eliminates the need for human verification when testing and ensuring website accessibility. The proposed system is a step in this direction, effectively reducing barriers to information access, increasing inclusiveness, ensuring equality and reducing social exclusion.

The growing number of studies and publications in this area, following years of the Web Accessibility Directive, also indicates that these issues are finally receiving more attention and interest, along with the expected increase in awareness.

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UNDERSTANGING THE POTENTIAL OF AI: INSIGHTS FROM POLISH ACCOUNTANTS

Konrad Biercewicz[a], Stanisław Hońko[b]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *University of Szczecin, Institute of Economy and Finance, Department of Accounting, Szczecin, Poland*

ABSTRACT

Purpose: *The increasing integration of artificial intelligence (AI) in accounting raises questions about professionals' willingness to adopt AI tools and the factors influencing this adoption. This study examines key determinants of AI adoption, including openness to technological innovation, professional experience, and perceived control over automation processes.*

Need for the study: *While prior research has explored the benefits and challenges of AI in accounting, there is a need for empirical evidence regarding how demographic and professional factors shape adoption patterns. Understanding these factors is crucial for designing effective training programs and policies that facilitate AI integration while addressing ethical concerns.*

Methodology: *A quantitative research approach was applied, utilizing logistic regression, chi-square tests, and Kruskal-Wallis's analysis to examine the relationships between AI adoption and key variables. The study sample consisted of accounting professionals from various organizational settings.*

Findings: *The results indicate that openness to technological innovation significantly predicts AI adoption, whereas years of experience show a weak inverse relationship with AI acceptance. Ethical considerations and perceived control over automation processes also influence accountants' preferences. Gender differences in AI adoption were observed, though their statistical significance remains marginal.*

Practical Implications: *The findings highlight the need for targeted training programs that enhance technological proficiency and address ethical concerns surrounding AI use in accounting. Organizations and policymakers should develop regulatory frameworks that balance automation benefits with transparency and accountability. Future research should explore the longitudinal effects of AI exposure and investigate the impact of workplace culture and institutional policies on AI adoption.*

Keywords: AI, accountants, automation, accounting profession, digitalization, accounting education

Jel codes: B26; M41; Q56

1. INTRODUCTION

Predictions of the demise of the accounting profession have a long history. More than a hundred years ago, it was predicted that the introduction of calculating machines, and the mechanization of accounting processes would make accountants unemployed. It is also assumed that the mechanization of accounting

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at the beginning of the 20th century led to the separation of the functions of accountants and bookkeepers. In the latter group, the feminization rate increased, due to, among other things, lower wages of women at that time (Wootton, Kammerer 2007). Many years later, Osborne and Frey from Oxford University, in a study of over 700 professions at risk of being replaced by technology, estimated the risk of replacement among "accountants and auditors" at 94% (Osbourne, Frey, 2017). This research influenced media reports, which oversimplified the message that the accounting profession would soon cease to exist. Such reports, often lacking context and depth, have a negative impact on the attractiveness of the accounting profession. Today, in the era of the extraordinary popularity of AI, the topic of replacing accountants with technology has become extremely relevant. Researchers at OpenAI and the University of Pennsylvania (Eloundou et al. 2023), claim that the job of the accountant and auditor is one of the most affected by AI (Cardinaels et al, 2024). This article does not address the issue of replacing accountants with AI. We share the view of many authors, for example (Greenman, Esplin, Johnston & Richards, 2024) or (Hasan 2021), that technology is and will be a tool supporting accountants, not replacing them. We also agree with Leintner et al (2021) that accountants' skills will undergo major changes in the next 10 years due to AI, however, "core" roles and tasks will continue to exist in the future. Some activities will not be performed by humans but by AI, and humans will need to consciously use digital technologies and interact with AI-based technology. The resistance of accountants to being replaced by technology results from the key role that creativity (not to be confused with accounting fraud) and professional judgment play in this profession. The issue of interest to us is to examine how accountants intend to use data prepared by AI. Are they ready for complete automation of the process of recording documents in accounting books? Are they ready to accept minor errors that an inadequately trained AI may make? We decided that the best way to find out the answers would be to conduct a survey among accountants. The invitation to the study was sent by the Accountants Association in Poland (AAP) in cooperation with an innovative IT company implementing AI in accounting. This method of distributing surveys allowed us to reach a group of professionals who are either members of the AAP or are improving their qualifications on certified courses. The article aims to examine the relationship between selected characteristics of accountants and their declared way of working with AI-based tools. To achieve this aim, we formulated the following hypotheses:

H1: Accountants see the potential of AI as a tool to support their work.
H2: Accountants who are open to technology are more likely to use AI.
H3: The longer the seniority, the less willing they are to use AI.
H4: Accountants open to technology can accept AI's minor errors.
H5: The longer the seniority, the greater the lack of confidence in AI-assisted accounting.

These hypotheses form the foundation for our research, providing a structured approach to understanding the relationship between accountants and AI-based tools. In the following sections, we will present the methodology, analysis, and discussion of the findings, which will offer insights into how professionals perceive and adapt to technological advancements in their field.

2. LITERATURE REVIEW

The integration of artificial intelligence (AI) into the accounting profession has generated significant interest and debate among practitioners and scholars alike. A central question concerns how much power accountants are willing to relinquish to AI tools, reflective of their preferences and reluctance to accept varying degrees of automation in their work. This literature review synthesizes findings from recent studies, emphasizing empirical evidence and theoretical interpretations that illustrate the accountant's evolving relationship with AI.

A pivotal study by Mgammal examines the direct relationships between AI awareness, engagement, and the utilization of AI in accounting procedures, revealing that accountants who are knowledgeable and actively engaged with AI are more likely to adopt it in their practices. This awareness facilitates a positive change in accounting processes, aligning with findings from other scholars who argue that institutional knowledge about AI directly correlates with its application in accounting tasks (Mgammal, 2024). Furthermore, Greenman et al. discuss the ethical implications of AI in accounting, highlighting

how understanding AI's transformative potential can prepare stakeholders for a synergistic relationship between human expertise and AI capabilities (Greenman et al., 2024). This suggests that informed accountants may not only integrate AI tools but can also embrace their transformative effects on the profession.

Conversely, there is a concern shared amongst practitioners about the implications of AI for their roles. A study on Nigerian accountants reveals that while AI can automate mundane tasks, it also creates avenues for accountants to transition into more strategic roles, moving beyond traditional bookkeeping functions (Austin, 2022). This duality offers accountants an opportunity to redefine their professional identity while simultaneously raising fears of job displacement, especially when examining the involvement of AI in processes traditionally held by accountants, as noted in a meta-analysis of AI impacts in accounting literature (Rawashdeh, 2025). This highlights a need to understand accountants' preferences for AI tool usage, as they may advocate for AI as an assistant rather than a replacement.

Data privacy and ethical considerations also loom large in conversations about AI within accounting. The findings from Adelakun et al. contextualize this by noting that AI's integration offers significant capabilities for improving accuracy and efficiency but concurrently poses notable ethical challenges that the profession must navigate (Adelakun et al., 2024). Insights from this paper emphasize a growing consensus among accountants regarding their need for oversight and parameters governing AI use to mitigate potential risks associated with bias, transparency, and accountability (Schweitze, 2024). Thus, accountants express a preference for deploying AI tools in a controlled manner that preserves their oversight capabilities while leveraging AI for increased efficiency.

Moreover, recent literature increasingly hints at a threshold of technological proficiency that accountants require to effectively utilize AI tools. Studies conducted in various regions, including a survey of Lebanese Certified Public Accountants (LCPAs), suggest that proficiency with AI applications correlates with improved reliability in financial data, thus enhancing accountants' trust in these technologies (El-Mousawi et al., 2023). This reflects a growing schism where more technologically adept accountants are willing to endorse greater AI adoption, unlike their less tech-savvy colleagues who may perceive AI as a potential threat to their job security and professional relevance (Chen et al., 2023).

The balance between technology and human judgment has emerged as a focal point in understanding accountants' willingness to adopt AI. Research by Chen et al. articulates that while AI may enhance efficiency and accuracy, it necessitates a complementary enhancement of human skills, knowledge, and ethical understanding to guard against pitfalls stemming from over-reliance on automated systems (Chen et al., 2023). This dichotomy stresses the importance of ongoing professional development, which could influence accountants' adaptability and willingness to embrace AI.

Additionally, framing accountants' relationship with AI through the lens of economic opportunity has been particularly insightful. Studies emphasize that AI is not merely a disruptive force but a catalyst for professional growth and expanded career possibilities (Reamer, 2023). For accountants, the evolution of their roles can create more avenues for strategic decision-making, suggesting a gradual acceptance of AI as an ally rather than a competitor. Evidence from multiple sources points to a consensus that AI can liberate accountants from repetitive tasks, allowing them to focus on higher-level strategic functions (Cardinaels et al., 2024; Toli & Manasa, 2024).

In conclusion, while there exists a cautious optimism among accountants regarding AI's role in the profession, concerns regarding ethical implications, job security, and the necessity for balancing human judgment and machine efficiency present barriers to full adoption. Insights from recent studies illustrate the importance of preparing accountants not just through technical training but fostering an ethical, aware mindset that enhances their decision-making capabilities in a landscape increasingly influenced by AI technologies. The evolving relationship promises to redefine professional norms, roles, and the overall landscape of accounting.

As mentioned earlier, accountants have been afraid for decades that technology will take their jobs. There is no doubt that the rapid development of AI-based tools will have a revolutionary impact on this profession, and every revolution causes fear. Even at this stage of technology development, it is possible to draw a balance sheet of opportunities and threats related to the implementation of AI in accounting (Table 1).

Table 1. Balance sheet of opportunities and threats related to the implementation of AI in accounting

Perceived Benefits	Probable Risks
Cost savings and operational efficiencies	Conflict of interest and/or threat to independence (on the part of the external auditor) in case of organization under greater monitoring by AI
Improved productivity	Extinction of conventional jobs/tasks
Improved customer services	Rise of income inequality and wealth inequality
Greater accuracy	At the present level of intelligence in AI applications, the AI system can't update itself in response to changes in laws, regulations, and policies. So, frequent changes may hamper the process
Flexible working style	Greater cost commitment
Process governance	Lack of expertise on the part of the accountants and auditors
Manpower saving	Resistance from the existing workforce
Risk management	
Metadata Analysis	
Moving focus away from repetitive, time-consuming, and rules-based tasks	
Reallocation of saved time and prioritize more complex and value-added tasks	

Source: own elaboration.

Accountants are currently employing artificial intelligence across a diverse range of applications, spanning the identification of high-risk transactions within audit procedures to the execution of accounts payable processing tasks. Consequently, AI is increasingly supplanting human-driven processing and decision-making processes, a trend anticipated to exert a continuing transformative influence on business practices. Despite the nascent stage of AI adoption within the accounting profession, practitioners must comprehend the ramifications inherent in this technological evolution (Cory, Alarcon 2021). It is also worth mentioning literature reviews prepared by other authors, for example, Odonkor et al (2024), Saleeem et al (2023), Hasan (2021), or Moll and Yigitbasioglu (2019).

To verify hypothesis 1, "Accountants perceive the potential of AI as tools supporting their work," a review of studies examining accountants' perceptions of AI was required. The list of publications is presented in Table 2.

It is worth citing selected conclusions from surveys on the perception of AI by accountants. A survey by Holmes and Douglass (2021) found that accounting professionals who use technology do not have significant levels of anxiety about AI. There is evidence that they perceive technological advances to have a positive impact on productivity and increase their chances for promotion and higher salaries. For them, using AI technology is an opportunity for growth. Because technology is changing so rapidly, accounting programs will serve their graduates well by providing not only accounting and data management knowledge but also by nurturing their ability to learn throughout their lives. Hossain et al (2024) reported findings from semi-structured interviews with accounting experts. Topics were divided into five categories related to AI use: efficiency and automation, data accuracy and integrity, fraud detection and security, professional roles and skills, and ethical and regulatory considerations. Participants highlighted significant productivity improvements resulting from implementing automation of repetitive tasks, using AI technologies such as robotic process automation (RPA) and machine learning algorithms to streamline activities such as data entry, invoice processing, and financial reconciliation. The use of blockchain technology was praised for its ability to improve the accuracy and reliability of financial records. The research concludes that AI dramatically improves productivity by automating repetitive tasks such as data entry and invoice processing, freeing up accountants to focus

on more valuable activities. The survey was presented by Bou Reslan, F., & Jabbour Al Maalouf, N. (2024). was conducted among accountants in Lebanon.

Table 2. A compilation of articles on accountants' perceptions of AI in which quantitative research was conducted

Article	Date of publication	Study Setting	Sample Size	Professional Context	Research Focus
Alfares and Şavlı, 2023	2023	Turkey (Istanbul)	155	Certified Public Accountants	Awareness and perception of AI in accounting practices
Bakarich and O'Brien, 2021	2021	Not specified	90	Public accounting professionals	Current AI utilization and perceptions of impact
Banța et al., 2022	2022	Romania	103	Accounting practitioners in multinational companies	Perception of AI benefits and challenges in accounting
Bou Reslan and Jabbour Al Maalouf, 2024	2024	Lebanon	454	Accounting professionals	Impact of AI on efficiency, fraud detection, and skill dynamics
Chouhan et al	2020	India (Rajasthan)	62 companies and 104 respondents	Auditors, Accountants, and Managers of selected companies	Using AI (Accounts Payable, Fixed Assets. General Ledger. Financial Reporting, Payroll)
El-Mousawi et al., 2023	2023	Lebanon	337	Certified Public Accountants	Impact of AI on the accounting and auditing profession
Holmes and Douglass, 2021	2021	USA (Southwest)	107	Public accounting, Industry, Education	AI's impact on the accounting profession and education
Hossain et al., 2024	2024	Global	20-30 Interviews and case studies	Industry experts	Impact of AI and blockchain on accounting
Johnson et al., 2021	2021	USA (Southwest Florida)	34	Accounting professionals (staff to partners)	Interest, knowledge, and usage of AI in the accounting profession

Source: own elaboration.

The findings of the study confirm that implementing AI in accounting significantly increases the efficiency and quality of financial data, as well as positively affects the detection of financial fraud and tax settlements, and changes professional activities and skill requirements in the accounting profession. These results underscore the transformative role of AI in modern accounting practices. Bakarich and O'Brien (2020) reported that both Robotic Process Automation (RPA) and Machine Learning (ML) are not being used extensively by public accountants or their clients. Johnson et al. (2021) found that while the majority of accountants surveyed were interested in and familiar with AI, only a limited number

were currently using it in their practice. Banţa et al. (2022) reported that practitioners recognize the need for skills transformation due to AI integration. The study emphasized that while AI can automate certain tasks, it cannot replace skills involving creativity and professional judgment.

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In conclusion, in light of the cited studies, AI is perceived by accountants mainly as an opportunity and a tool to improve their work. We could not find publications devoted to the modes of cooperation between accountants and AI, including those concerning consent to minor errors made by the automated process of processing accounting data. According to the authors, there is a research gap in this area, which we try to fill with this article.

3. METHODOLOGY

3.1. Participants

The data used in this study was obtained from a survey conducted with individuals working in various sectors, focusing on their attitudes toward and use of artificial intelligence (AI). The survey collected a range of demographic and professional information, as well as data on AI adoption and related behaviors.

This article is devoted to one of the important areas of accountants' relationship with AI, namely their approach to the results of automatically prepared accounting entries and acceptance of minor errors. Some of the responses from an extensive survey were used in the analysis. To further encourage participation, webinars were organized, during which the results of the pilot were presented, and potential respondents were invited to participate in the survey. Responses were collected from a total of 611 participants, divided according to demographic and professional criteria. Women constituted the majority – 80% of the sample, and 19% men. 1% preferred not to disclose their gender. In terms of accounting experience, respondents demonstrated a wide range of expertise. Those with more than 20 years of experience were the largest group, accounting for 34%, followed by those with 1–5 years of experience (18%) and 11–15 years of experience (16%). Participants with 6–10 years of experience

accounted for 15% (87 respondents), while those with 16–20 years of experience accounted for 13%. Early-career professionals, including those with less than a year of experience (3%) or no experience at all (2%), made up a smaller portion of the sample.

We also analyzed the revenues of participants' primary jobs. Organizations with revenues below PLN 1 million were the largest group, accounting for 30% of respondents. Entities with revenues between PLN 1 and PLN 5 million accounted for 16%, while 11% came from organizations generating revenues between PLN 5 and PLN 10 million and over PLN 100 million, respectively. A similar percentage, 11%, came from workplaces with revenues between PLN 10 and PLN 20 million. Entities with revenues between PLN 20 and PLN 50 million accounted for 10%, and 6% were affiliated with organizations earning between PLN 50 and PLN 100 million. Significantly, 5% of respondents chose not to disclose the revenues of their primary workplace. Participants provided information about their roles within their organizations, with this question allowing for multiple responses, which explains why the total number exceeds the number of respondents. Chief accountants were the largest group, with 180 responses, followed by independent accountants, with 155 responses. Accounting office managers were also strongly represented, with 120 responses, while 86 people selected the "other" category. Accounting office employees accounted for 72 responses, while HR/payroll specialists and CFOs contributed 34 and 33 responses, respectively.

The survey, in addition to the metrics, included 14 closed questions (some of the questions allowed for any answer in the "other, what?" section) and 4 open-ended questions. For this study, in addition to the metrics, the answers to the following questions were included in the detailed analysis (table 3).

Table 3. Responses to survey questions analyzed in this study (n = 581)

Question	Answer
Do you like gadgets and technological innovations?	yes, very much: 30,1%; rather yes: 59,2%; rather no: 9,5%; no: 1,1%
Do you use solutions using Artificial Intelligence on your initiative?	yes: 36,2%; no: 48%; I don't know: 15,9%
In what mode would you like to work with solutions using AI?	I would not like to use AI at all: 5,2%; Only suggestions (AI assistance during my work): 15,4%; Automatic accounting by AI, but with my checking everything: 40,3%; Automatic accounting by AI, but with my checking only those decrees that the system indicated as questionable: 33,4%; Full automation: 5,6%
What method of working with AI would be closer to you?	I will accept minor errors if it would save me a lot of time (41,1%); I will verify each automatically posted document to avoid errors (52,4%); Another answer - is the ability to enter any text: 6,5%*

*Selecting the 'other' option allowed for entering any text. Summing up the answers entered in this section, it can be stated that the respondents are in favor of a hybrid approach, where a human actively participates in the process, especially at the beginning, verifying the AI's work and gradually increasing trust as it improves and its effectiveness is confirmed. The key is to maintain control, have the ability to identify and correct errors, and ensure the continuous learning of the AI system.

Source: own elaboration.

3.2. Research Protocol and Stimuli

The survey was conducted using Google Forms. The link to the survey is available in the link. Because the questions were addressed to Polish accountants, the survey was written in Polish. The survey was conducted among Polish accountants between October 2023 and July 2024. The survey, distributed with the support of the Association of Accountants in Poland, a professional organization associating over 26,000 active accountants, aimed to collect various observations. The sampling was random. Any person related to accounting had a chance to take part in the survey. The number of accountants in Poland is estimated at around 400,000. In SurveyMonkey's survey sample calculator, with the population at this level, with a 95% confidence level and a 5% margin of error, the representative sample is 384 people. A 5% higher degree of certainty would require 384 respondents. Unfortunately, we cannot say with certainty that the sample is representative, which is a limitation of the survey's conclusions. Reducing the margin of error to 4% means that a representative research sample is 600 people. Of course, we cannot say with full certainty that the sample is representative. The data collected in the metrics show

that the respondents represented large and small companies from all regions of Poland. The demographic diversity of the respondents corresponds to earlier studies conducted by AAP on samples of several thousand respondents. All these arguments increase the credibility of the obtained studies and indirectly confirm the representativeness of the selected sample. Data collected in the Google Forms form was aggregated in a spreadsheet and then appropriately coded according to the procedure described later in the article. Only the authors had access to the data, and they were not changed in any way.

3.3. Analysis of Measurement Data

The key variables analyzed in this study included:

1. Using of AI adoption: A binary dependent variable indicating whether an individual uses AI in their work. It was coded as 1 for ‘Yes’ and 0 for ‘No’.
2. AI work mode: This variable indicated the level of automation in the respondents' work and was categorized into four groups: ‘Full automation’, ‘Automatic accounting with my supervision’, ‘Verification of selected operations by humans’, and ‘No consent for automation’. The values were mapped numerically from 0 to 3.
3. Liking new technologies: This variable measured the respondent's interest in new technologies, with responses ranging from ‘Not at all’ to ‘Very much’. Values were mapped from 0 to 3.
4. Years of experience: This variable was categorized by the number of years of professional experience, with responses mapped to values from 0 (no experience) to 25 (more than 20 years).
5. Company revenue: This variable represented the revenue of the respondent's company, extracted from textual descriptions. The numerical data were extracted using regular expressions.

The statistical analysis of the data was conducted in several steps to assess the relationships between key variables and their influence on the adoption of AI. The first step involved testing the normality of the data. Since many of the variables did not follow a normal distribution, non-parametric tests were employed for further analysis. The normality of each continuous variable was assessed using the Shapiro-Wilk test, which is commonly used for small sample sizes and tests if the data significantly deviates from a normal distribution.

Once normality was assessed and the non-parametric nature of the data was confirmed, the appropriate statistical tests were selected. The Kruskal-Wallis H test was used to compare the levels of AI adoption across different groups of experience. This non-parametric test is an alternative to the one-way ANOVA and is ideal for comparing medians across multiple independent groups when the assumption of normality is not met.

The Spearman correlation was calculated between openness to technology and AI acceptance, indicating a weak positive relationship between these variables. For the Hypothesis, the Spearman correlation between years of experience and AI acceptance was computed, suggesting no significant relationship between the two. In Hypothesis H5, the Spearman correlation between years of experience and AI work mode was calculated, also indicating no significant relationship.

The Wilcoxon signed-rank test was used to compare related variables. This test is suitable for assessing differences between two paired samples and is often used when the data does not meet the assumptions required for paired t-tests. In this study, it was used to compare AI adoption modes and the participants' interest in new technologies.

To examine the relationship between categorical variables, a chi-square test of independence was applied to investigate whether there was an association between gender and the willingness to adopt AI in the workplace. This test evaluates if two categorical variables are independent or related to each other. Lastly, logistic regression analysis was conducted to model the likelihood of adopting AI, with the dependent variable being the use of AI in the workplace. The regression model included several independent variables, including work mode, interest in new technologies, years of experience, and company revenue. Logistic regression is suitable for binary outcomes, such as the decision to adopt or not adopt AI, and allows for the estimation of the odds of adoption based on predictor variables.

Throughout the analysis, the assumption of normality was a critical factor in determining which statistical tests were used. By applying appropriate non-parametric tests and logistic regression, the analysis aimed to uncover the relationships and factors influencing AI adoption in the workplace.

4. RESULTS

The results of the statistical analyses revealed important insights into the relationships between various factors related to AI usage, automation preferences, and other variables of interest. First, normality tests were conducted on the variables 'automation mode', 'liking of new technologies', 'years of experience', and 'company revenue'. The tests indicated that none of these variables followed a normal distribution, as all p-values were below 0.05. This suggests that the data do not meet the assumptions necessary for parametric tests, and therefore, non-parametric methods were employed for further analysis.

To address potential confusion between overlapping but distinct concepts such as 'AI adoption,' 'AI acceptance,' and 'the likelihood of using AI,' we introduce a set of unique labels used throughout this section and summarized in Table 4.

Table 4. Definitions for AI-related variables

Term	Description
AI Acceptance (AIA)	General attitude toward AI and openness to its use
AI Adoption (AID)	Actual implementation of AI systems in practice
Likelihood of using AI (LUI)	Self-reported probability of future AI use in one's work

Source: own elaboration.

A Kruskal-Wallis's test was performed to compare the levels of automation (AID) across different experience groups. The test resulted in an H-statistic of 9.61 and a p-value of 0.0871, which is above the conventional threshold of 0.05. This outcome leads to the failure to reject the null hypothesis, indicating that there is no statistically significant difference in the level of automation across the various work experience groups.

To further explore relationships between specific variables, the Wilcoxon signed-rank test was applied to compare the levels of automation (AID) with the liking of new technologies. The test produced a t-statistic of 1077.0 and an extraordinarily small p-value of 2.22e-101, which is well below the 0.05 significance level. This strong result suggests that there is a significant difference between these two variables, highlighting the importance of new technology preferences in shaping attitudes toward AI automation.

The analysis of the relationship between various factors influencing AI acceptance (AIA) revealed the following findings. The Spearman correlation between openness to technology and AI acceptance was calculated, yielding a correlation coefficient of 0.0958 with a p-value of 0.0209. This suggests a weak positive relationship between openness to technology and AIA. The Spearman correlation between years of experience and AI acceptance was computed, resulting in a correlation coefficient of 0.0398 with a p-value of 0.3385. This indicates no significant relationship between years of experience and AI acceptance. Similarly, the Spearman correlation between years of experience and AI work mode was also calculated, yielding a correlation coefficient of 0.0398 with a p-value of 0.3385, which suggests no significant relationship between years of experience and AI work mode.

Finally, a chi-squared test was conducted to assess the association between gender and willingness to adopt automation (AID). The test yielded a chi-squared value of 5.10 and a p-value of 0.0782. Although the p-value is slightly above the 0.05 threshold, it is still relatively close, suggesting a potential trend toward a relationship between gender and automation preferences, though it does not reach statistical significance.

Additionally, a logistic regression model was employed to explore factors influencing the LUI (Table 4). The model explained only about 4.3% of the variance in the dependent variable using AI (Pseudo $R^2 = 0.04326$), indicating that other important factors, not included in the model, may be influencing AI adoption. Despite this, the model as a whole was statistically significant (LLR p-value = 6.429e-07), suggesting that the variables included in the model have a meaningful relationship with the likelihood of using AI.

Table 5. Results of logistic regression

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	–1.5056	0.345	–4.366	0.000	–2.181	–0.830
willingness to adopt automation	0.1145	0.123	0.928	0.353	–0.127	0.356
liking of new technologies	0.6540	0.142	4.614	0.000	0.376	0.932
years of experience	–0.0184	0.009	–2.047	0.041	–0.036	–0.001
company revenue	0.0015	0.002	1.008	0.313	–0.001	0.005

Source: own elaboration.

The results showed that liking new technologies and years of experience were significant predictors of AI usage. Specifically, the coefficient for liking new technologies was positive and highly significant ($p < 0.001$), indicating that individuals who like new technologies are more likely to use AI. Conversely, years of experience had a negative coefficient ($p = 0.041$), suggesting that those with more years of experience are less likely to adopt AI. However, willingness to adopt automation and company revenue were not significant predictors in the model, with p-values of 0.353 and 0.313, respectively.

The analyses conducted allow us to conclude that hypotheses H2 (people who are open to technology are more likely to use AI) and H3 (longer job tenure is associated with a lower propensity to use AI) have been confirmed.

The H2 hypothesis is supported by the results of the Wilcoxon test and logistic regression, where the variable "liking of new technologies" had a significant positive coefficient ($p < 0.001$). This means that people who are positive about new technologies are indeed more likely to implement AI in their work.

Hypothesis H3 was also confirmed, as logistic regression showed a significant negative effect of years of experience on the use of AI ($p = 0.041$). This suggests that the greater the seniority, the less likely they are to implement AI, which may be due to attachment to traditional work methods or lack of need for change.

Hypothesis H4 (acceptance of minor AI bugs by those open to technology) received only weak support. The Spearman correlation between openness to technology and acceptance of AI was low ($r = 0.0958$, $p = 0.0209$), suggesting the existence of some relationship, but its strength is low. This could mean that while people who are open to technology are more likely to use AI, they do not necessarily accept its imperfections.

Hypothesis H1 (perception of AI as support at work) was rejected because the variable "willingness to adopt automation" was not a significant predictor of AI use ($p = 0.353$). This indicates that willingness to automate alone does not directly translate into actual AI implementation, which may be due to organizational barriers or lack of access to appropriate tools.

Hypothesis H5 (greater lack of confidence in AI with longer tenure) was also rejected. Spearman's correlation between years of experience and AI mode of operation was non-significant ($r = 0.0398$, $p = 0.3385$), and the Kruskal-Wallis's test showed no significant differences in the level of automation between groups with different seniority ($p = 0.0871$). This means that the length of seniority does not significantly affect the level of trust in AI.

In conclusion, the results indicate that factors such as the liking of new technologies and work experience significantly influence attitudes toward AI automation, while automation preferences and company revenue do not exhibit strong associations with AI usage in this dataset. Specifically, hypotheses H2 and H3 were confirmed, showing that individuals open to technology are more likely to use AI, whereas those with longer work experience are less inclined to adopt it. Hypothesis H4 received only weak support, suggesting a minor link between openness to technology and tolerance for AI errors. In contrast, hypotheses H1 and H5 were rejected due to a lack of significant statistical relationships, indicating that general willingness to automate and work experience do not strongly predict AI adoption or trust in AI-assisted accounting.

5. DISCUSSION

Accountants demonstrate a cautious and sensible approach to using AI tools. Although 95% of respondents intend to use AI in their professional work, only 5.6% would decide on full automation. This means that almost 90% of respondents are not ready to "give power" to AI. The principle of limited trust in technology applies. As many as 40% of surveyed accountants intend to verify every accounting entry prepared initially by AI. This method of cooperation, indicating a low level of trust in technology, can increase the efficiency of accountants' work only to a small extent. Therefore, it is difficult to expect that the benefits related to the use of AI presented in the article (e.g. elimination of routine activities, focus of accountants on advisory and analytical activities) can be observed in the short term. One-third of accountants demonstrate a higher degree of trust in AI because they intend to verify only those accounting entries that are abnormal. At the same time, over 40% of respondents are ready to accept minor AI errors if it allows for greater efficiency of their work. Such a statement is completely different from the stereotype of an accountant, perceived as a person who is overly conscientious and detailed. According to the authors, the key issue is to understand the concept of a 'minor error', which may be perceived differently by accountants as a professional group striving for perfect errorlessness. To sum up, the power over accounting entries will remain in the hands of accountants for a long time. This is due to the wealth of transactions that must be included in accounting, using well-understood creativity and professional judgment. AI is getting better at recording typical transactions, but it has serious problems with nuance. It requires the vast knowledge, experience, and intuition of accountants who will dot the i's and dot the i's.

The findings of this study align with existing literature on the integration of artificial intelligence (AI) in accounting, highlighting both the drivers and barriers to AI adoption among professionals. Prior research has underscored the role of AI awareness and engagement in shaping accountants' willingness to integrate AI into their workflow (Mgammal, 2024). Our results similarly indicate that openness to technological innovations positively correlates with AI adoption, supporting the notion that familiarity with AI fosters confidence in its capabilities. The findings for accountants are consistent with more general research (Kusuma et al, 2024). The weak positive correlation between openness to technology and AI acceptance suggests that individuals who are more receptive to new technologies may be slightly more inclined to accept AI. However, the strength of this relationship is low, indicating that openness to technology alone is not a strong predictor of AI acceptance.

The relationship between experience and AI adoption remains a topic of debate. While some studies suggest that seasoned professionals may resist automation due to entrenched work habits and concerns about job displacement (Cox & Mazumdar, 2022), our findings reveal a statistically significant, albeit weak, inverse relationship between years of experience and AI adoption. This supports previous studies indicating that younger accountants or those with less tenure may be more inclined to embrace AI, seeing it as an opportunity rather than a threat (Austin, 2022). However, our analysis does not provide strong evidence that experience alone is a decisive factor in AI adoption, implying that additional variables such as workplace culture and institutional AI policies may play a role. In contrast, the results do not support a significant relationship between years of experience and AI acceptance, as indicated by the non-significant correlation. This suggests that employees with varying levels of experience do not differ significantly in their willingness to adopt AI. Similarly, the lack of a significant correlation between years of experience and AI work mode implies that work experience does not play a determining role in how AI is integrated into professional tasks. These findings challenge common assumptions that younger or less experienced employees might be more open to AI, highlighting the need for further research on other potential influencing factors, such as organizational culture, training opportunities, or perceived AI benefits.

The ethical and regulatory concerns surrounding AI integration in accounting, as highlighted by Adelakun et al. (2024), are echoed in our results. While AI has the potential to improve efficiency and accuracy, accountants remain cautious about transparency, data security, and accountability. Prior research has demonstrated that accountants tend to favor AI in a controlled capacity, ensuring that human oversight remains a critical component of decision-making processes (Schweitze, 2024). Our findings support this assertion, as AI adoption appears to be more prevalent in environments where accountants retain significant control over automated processes.

Gender-based differences in AI adoption have been previously noted in research, albeit with mixed conclusions. Our chi-square test results suggest that gender may play a role in automation preferences, although the relationship is not strongly significant. This aligns with broader discussions in the literature regarding how demographic factors influence technology adoption, often interacting with other variables such as education, professional specialization, and access to AI-related training (El-Mousawi et al., 2023).

The broader literature also highlights that AI adoption is often contingent upon the level of technological proficiency among accountants. Our findings resonate with those of Chen et al. (2023), who found that accountants with greater exposure to AI tools exhibit higher levels of trust in automation. Conversely, those with limited AI proficiency are more likely to perceive automation as a disruptive force rather than an enhancement to their profession. The results emphasize the necessity of continuous professional development programs to bridge the gap between AI advancements and their practical application in accounting.

Our findings align with existing research suggesting that AI adoption is influenced by a combination of personal attitudes, workplace policies, and institutional support structures. As AI continues to be integrated into various professional domains, including accounting, understanding the nuanced interplay between technological openness, work experience, and organizational readiness becomes increasingly crucial. While openness to technology shows some association with AI acceptance, work experience does not appear to be a key determinant. Future studies could explore additional variables, including attitudes toward automation, industry-specific AI applications, or the role of leadership in fostering AI adoption.

Overall, this study reinforces the evolving nature of AI adoption in accounting, shaped by technological familiarity, experience, and perceived control over automation processes. As AI continues to transform the profession, future research should explore how institutional frameworks, regulatory policies, and education initiatives can facilitate a balanced integration of AI, ensuring both efficiency gains and the retention of ethical, human-driven decision-making.

6. CONCLUSION

This study provides valuable insights into the factors influencing AI adoption among accountants, with a focus on technological familiarity, experience, and perceived control over automation processes. While openness to innovation emerges as a strong predictor of AI adoption, experience appears to play a more complex role, with younger professionals demonstrating greater receptivity to AI tools. Additionally, ethical concerns and regulatory considerations remain central to accountants' perspectives on AI, underscoring the need for frameworks that balance efficiency with transparency and accountability.

However, this study has several limitations. The sample is limited to a specific professional group, which may restrict the generalizability of the findings to other industries. Additionally, while our statistical models identify correlations, they do not establish causal relationships between the examined variables. Future research should consider longitudinal studies to track changes in AI adoption over time and explore causal mechanisms more rigorously. Moreover, qualitative approaches, such as in-depth interviews with accountants, could provide deeper insights into the motivations and barriers behind AI adoption.

Further research should also investigate the role of organizational culture and institutional support in shaping AI adoption patterns. Given the rapid advancements in AI technology, studies should examine how continuous training and education initiatives impact professionals' confidence and willingness to integrate AI into their workflows. Additionally, cross-country comparisons could shed light on how regulatory environments and economic conditions influence AI adoption in accounting.

In conclusion, while AI presents significant opportunities for the accounting profession, its successful integration requires a careful balance between automation and human oversight. Addressing the concerns of professionals through training, regulation, and institutional support will be key to fostering a sustainable and ethical approach to AI adoption in the field.

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THE ROLE OF AI IN BUSINESS MANAGEMENT: BALANCING PRIVATE AND OPEN-SOURCE AI

Roberto Bruni[a], Hanna Soroka-Potrzebna[b], Mohammad Mahoud[c]

[a] *University of Cassino and Southern Lazio, Department of Economics and Law, Cassino, Italy*
[b] *University of Szczecin, Institute of Management, Szczecin, Poland*
[c] *University of Cassino and Southern Lazio, Department of Economics and Law, Cassino, Italy*

ABSTRACT

Purpose: *Create a framework supporting managers in integrating AI into business management decisions.*

Need for the study: *The Artificial Intelligence (AI) discipline is revolutionizing business management via enhanced decision-making procedures, enhanced operational effectiveness, and improved strategic planning. Looking at the openness of their algorithms and data training and handling, AI models are generally categorised into Private and Open-Source models. The aforementioned distinctions significantly affect the functioning of companies in terms of privacy, data security, and competitive standing. Businesses must make a fundamental trade-off between Open-Source AI, that could be limited in data privacy and security, but it presents a lower initial investment, and Private AI, which provides better data control at the expense of increased financial investment.*

Methodology: *Critical analysis of the literature, case studies and practitioner experience.*

Findings: *The research presents limits and opportunities of both Open-Source and private AI, and a framework to support managers in integrating both models in different areas of their operations to optimize benefits.*

Practical Implications: *A structured approach can help managers make informed decisions about adopting AI, balancing cost, security, and scalability*

Keywords: artificial intelligence, open-source AI, private AI, hybrid AI, business management, models

Jel codes: M15; O32; O33

1. INTRODUCTION

Artificial intelligence plays a key role in the modern world, revolutionizing technological, economic and social changes. In business operations, it has established new paradigms in business automation, decision-making, and data-driven analytics (Beverungen, Hess, Köster & Lehrer, 2022; Babina, Fedyk, He & Hodson, 2024). In business management, it has enabled innovation, increased productivity, and improved the accuracy of strategic decisions (Abou-Foul, Ruiz-Alba & Lopez-Tenorio, 2023; Broekhuizen et al., 2023). This is emphasized by business leaders, who almost unanimously (98%) see

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AI as a priority for their organizations (IDC, 2024). In 2025, Megacap technology companies intend to allocate $ 320 billion in the development of artificial intelligence (Subin, 2025). Research conducted by IDC (2024) indicates that enterprise spending on AI will have a cumulative global economic impact of $19.9 trillion by 2030 and will drive 3.5% of global GDP in 2030. It means that AI will impact jobs in every region of the world, in every industry, like contact center operations, translation, accounting, and machinery inspection.

Companies are integrating AI into business management decisions to make them more effective, lower the cost of conducting business, and improve their capacity to interpret large sets of data (Kumar, Ashraf & Nadeem, 2024). This is fueled by technological advancement, improved computing capacity, and the necessity for organizations to adapt to an ever-accelerating digital environment (Mukhopadhyay, Singh & Jain, 2024). Artificial intelligence is being embraced in many fields, such as finance, health, retail, and supply chain management, a clear indication of its versatility and essentiality in contemporary business environments (Pallathadka et al., 2023).

The discourse of artificial intelligence within the business management context is typically based on two broad frameworks: Private AI and Open-Source AI (Tursunbayeva & Gal, 2024). Open-Source AI systems, engineered through the concerted efforts of international communities, provide companies economically viable and scalable solutions (Wang, Li, Du & Wang 2024). Security, compliance, and data privacy concerns are some of the inherent problems with the implementation of Open-Source AI solutions (Bickley, Macintyre & Torgler, 2024). In contrast, even with some limits in algorithm training, Private AI delivers customized, secure, and proprietary artificial intelligence solutions for enterprises that value data privacy and competitive edge (Van Bekkum & Borgesius, 2023). Considerations regarding Open-Source and Private AI emphasize the great importance of developing a framework to support managers in implementing various AI models. In addition, the use of artificial intelligence in business management creates opportunities and challenges that require strategic alignment with organizational goals (Blut, Wünderlich & Brock, 2024). Organizations that can effectively use AI can leverage its potential in predictive analytics, automation, and adaptive learning, thereby improving decision-making and overall performance (Jada & Mayayise, 2023). Moreover, they must consider the cost implications, ethical aspects, and compliance with regulatory requirements of implementing AI (Cristianini, 2024). Some authors (Tursunbayeva & Gal, 2024; Mukhopadhyay et al., 2024; Wang et al., 2024) point to the possibilities of combining Open-Source AI and Private AI to eliminate obstacles and use the advantages of both models. However, none of them indicates what such a hybrid structure would look like, in what areas of operation and why should enterprises use Open-Source AI and in which Private AI, what can be identified as an existing research gap.

This chapter aims to address this gap by explaining the key distinctions between Open-Source AI and Private AI and possibilities of their implementation in various areas of activity. Drawing upon real-case studies and industry observations, this chapter offers an integrated understanding of the evolutionary nature of AI in business management. Chapter will answer two research questions:

1.How business functions could be supported by Open-Source AI or Private AI?

2.Why should companies incorporate Open-Source AI or Private AI in their business functions?

Based on the obtained results, conclusions will be drawn regarding the shaping of the use of individual AI models in the activities of enterprises. Chapter was created based on the analysis of the literature on the subject and the analysis of case studies of companies using artificial intelligence solutions.

2. LITERATURE REVIEW

The scientific justification for adopting AI in business management focuses on how AI-based technology stimulates productivity, optimizes resources, and delivers value to business organizations (Mukhopadhyay et al., 2024). Databases such as Scopus and Web of Science contain hundreds of thousands of articles that address various aspects of AI. The number of publications is growing year by year, covering more and more issues. Research on AI in business management has appeared in almost 6.5 thousand publications over the last 10 years (as presented in Figure 1). In the period January - February 2025, 234 items have already been published, which allows to conclude that the number of studies on this topic will increase.

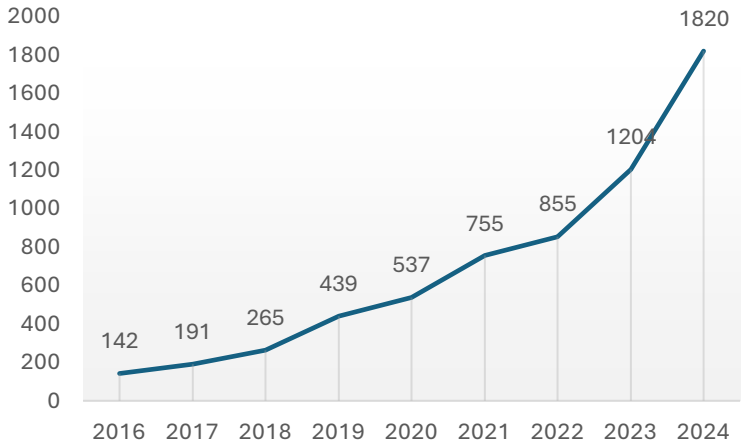


Figure 1. Number of publications on AI in business management, broken down by year
Source: own study based on Scopus, Web of Science.

The bibliometric analysis of the articles made it possible to distinguish six thematic clusters (presented in Fig. 2):
Cluster 1. main keyword categories: information management, blockchain, internet of thing, big data, network security, digital storage, communication system, network security. Looking at the references, the publications concern digital technologies.
Cluster 2. main keyword categories: human, healthcare, economics, quality control, covid-19, pandemic, ai, robotics. Looking at the references, the publications concern health and society.
Cluster 3. main keyword categories: business process, knowledge management, enterprise resource management, business process management, information systems. Looking at the references, the publications concern business management.
Cluster 4. main keyword categories: artificial intelligence, innovation, management, competition, competitive advantage, sustainable development. Looking at the references, the publications concern innovation and development.
Cluster 5. main keyword categories: decision making, learning system, forecasting, analysis, deep learning, risk analysis, business decisions. Looking at the references, the publications concern analysis and decision-making.
Cluster 6. main keyword categories: sales, human resource management, resource allocation, human resource management, marketing, customer experience, customer service. Looking at the references, the publications concern resources and marketing.

Narrowing the literature analysis to Open-Source or Private AI in business management enabled the identification of 307 items, the number of which was reduced to 59 after the analysis of titles and abstracts. The remaining items described the key concepts of Open-Source and Private artificial intelligence models along with an indication of the possibilities of their application in practical examples. Some of them described the development and use of AI in specific regions or countries (Concepcion, et. al., 2019; Ibeneme, et. al., 2021; Camarena, 2022; Turlacu, Chivu, Stoica, Orzan & Herrezeel, 2018; Iwamoto, 2019; Mikalef, Fjørtoft & Torvatn, 2019; Gaur, Maurya & Choubey, 2024; Singh, Sao, Singh & Hinchey, 2023; Abdeldayem, AlDeeb, Sharif & Aldulaimi, 2024), while others focused on industries such as banking (Gustev, 2020; Kadhim & Al Ani, 2023; Singh, et. al., 2023; Nayak, Singh, Baral, Goel & Hota, 2023), construction (Altaie & Dishar, 2024; Marsden, 2019), or healthcare (Kocakoç, 2022; Perdanakusuma, Puspitasari & Saputra, 2020; Cunha, Duarte, Lopes, Guimarães & Santos, 2024).

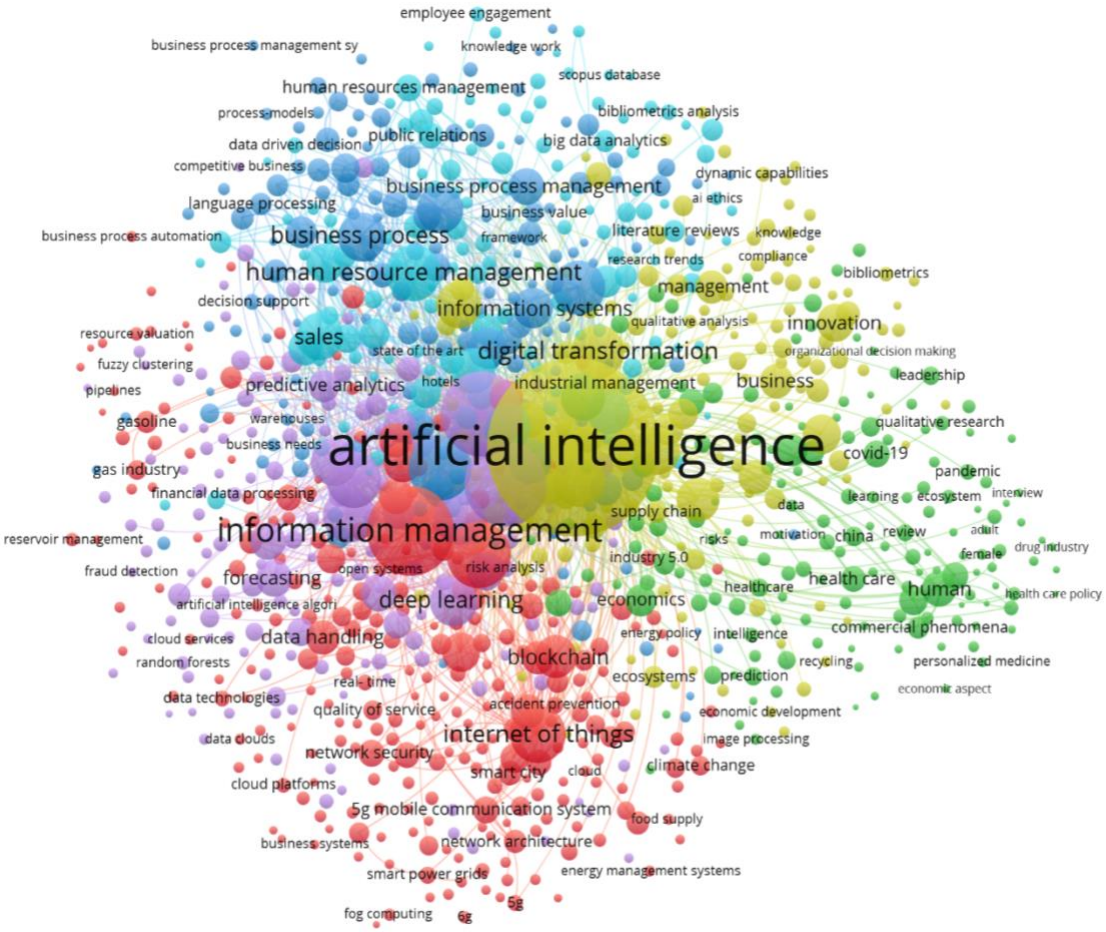


Figure 2. Co-occurance analysis of the keywords in literature
Source: own study based on Scopus, Web of Science.

Most of the analyzed items, however, referred to a specific area of the company's operation in which a specific artificial intelligence solution can be applied. A detailed analysis allowed to distinguish the following functions: accountability (Roberts & Tonna, 2022; Bhavani, 2020), finance (Sanz & Zhu, 2021), marketing (Mittal, Chandel & Nguyen, 2025; Singh & Adhikari, 2023), production management (Khan, Malik & Khan, 2022; Marsden, 2019; Abdeldayem, et. al., 2024), human resources (Gildhiyal & Prasad, 2023; Goel, Sahai, Venaik & Benfadel, 2021; Gomathi, Sabale & Chilamkurti, 2019), research and development (Cooper, 2024; Cooper, 2025), top management decisions (Alshadoodee, Mansoor, Kuba & Gheni, 2022; Joudat & Lighvan, 2021; Rajabion, 2018; Figueiredo, 2024; Altaie & Dishar, 2024; Sträßer & Stolicna, 2023) and procurement (Beheshti, et. al. 2021; Rajakumari, Hamsagsayathri & Shanmugapriya, 2023; Perdanakusuma, et. al., 2020). Among the analyzed items were also those that describe AI models more comprehensively, considering various solutions and possibilities of their implementation (Lang, 2021; Jermsittiparsert, Phongkraphan & Lekhawichit, 2024; Kose & Demirezen, 2024; Khang, Abdullayev, Jadhav, Gupta & Morris, 2023; Singh, Khan, Kumar & Kumar, 2024).

As AI technology advances, more and more organizations are exploring hybrid AI models that leverage the functionalities of both Open-Source and Private AI (Tursunbayeva & Gal, 2024; Pallathadka et al., 2023). The goal of combining AI models is to integrate the scalability and economic benefits of Open-Source AI while providing the security and customized solutions provided by Private AI (Babina et al., 2024). Theoretical insights into integrating both models suggest that organizations can benefit from the strengths inherent in the two by formulating strategic AI adoption plans (Cristianini, 2024).

3. OPEN-SOURCE AI IN BUSINESS MANAGEMENT

Open-source AI is a form accessible to all individuals, although it encompasses a range of approaches – from fully open models with unrestricted access to their code and weights, to partially open models which share certain components and impose restrictions through licenses (Vake, Šinik, Vičič & Tošić, 2025). Open-Source Initiative (OSI), widely regarded as the authority on open-source principles, has introduced a standardized definition aimed at guiding policymakers in regulating AI for consumer protection. According to this new definition, an AI system must be freely usable for any purpose without requiring prior authorization, allow researchers to examine its components, and provide insights into its operational mechanisms. Additionally, it must be modifiable for various applications and shareable, with or without alterations. The framework also sets a transparency benchmark, requiring open disclosure of key elements such as training data, source code, and model weights to ensure accountability in AI development (MIT Technology Review, 2024).

Open-Source AI plays a key role in the digital economy, as evidenced by the fact that over 60% of global websites use open-source servers such as Apache and Nginx (Lifshitz-Assaf & Nagle, 2021). Furthermore, a 2021 EU report emphasizes that the economic benefits of open source far outweigh its costs (Blind, et al., 2021). Open-Source AI platforms are used by many organizations to enable collaborative innovation, speed up software development, and include AI functionality without having to invest large amounts of capital (Broekhuizen, et al., 2023). The most frequently cited benefits of open source include enabling external oversight, accelerating progress, and decentralizing control over potentially transformative technology. As a result, it has a positive impact on most software and AI development processes, determining the direction of technological innovation and facilitating the development of products that are well-adapted to the various needs of users (Seger, et. al., 2023).

Unfortunately, as AI research has progressed, Open-Source has created opportunities for misuse. Their reliance on public datasets and shared learning models puts it at risk of security vulnerabilities, intellectual property infringement, and compliance hazards (Afroogh, Akbari, Malone, Kargar & Alambeigi, 2024). Open-Source increases the risk of model flaws spreading, model modification, and cyberattacks (Seger, et. al., 2023).

Conceptual models for Open-Source AI emphasize the balance between openness and governance with an emphasis on the need for firms to develop robust frameworks for AI implementation (Bickley, et al., 2024). Supporting openness promotes innovation and opportunities for collaboration, but effective governance mechanisms must also be in place to ensure responsible and safe AI development.

4. PRIVATE AI IN BUSINESS MANAGEMENT

Private AI platforms offer organizations customized solutions that provide them with a high degree of control over their data, thereby ensuring security and compliance with regulatory requirements such as GDPR and HIPAA (Van Bekkum & Borgesius, 2023; Rajaguru, 2024). Having this control enables organizations to customize AI applications to fit their particular operational requirements, which results in improved accuracy of analytics and decision-making (Abou-Foul, et al., 2023). Due to rigorous compliance procedures and better data protection mechanisms, it is a preferred solution for organizations operating in fields such as finance, healthcare, and legal services (Blut, et al., 2024).

Institutions tasked with the governance of sensitive data, for example, healthcare organizations and financial institutions, are greatly advantaged by Private AI owing to the possibility of reduced breaches of data and information (Khowaja, Dev, Qureshi, Khuwaja & Foschini, 2022). Private AI also supports governance and administration, enabling companies to fully utilize in-house operations without making any concessions on openness and accountability for AI-driven processes (Afroogh, et al., 2024). One of the most significant benefits of Private AI is that it can provide customized solutions to fit individual business models (Cubric & Li, 2024). In contrast to Open-Source AI, which relies on generalized algorithms developed from openly available datasets, Private AI systems are developed using proprietary datasets and domain-specific algorithms (Tursunbayeva & Gal, 2024).

This personalized strategy provides increased accuracy in intelligence, improves operational efficiency, and allows organizations to stay ahead of their rivals (Broekhuizen, et al., 2023). Private artificial intelligence also assists in strategic decision-making by supporting extensive data analysis, predictive models, and business intelligence activities in accordance with the organization's goals and

position in the market (Babina, et al., 2024). Yet, the use of these technologies is hindered by considerable barriers. The expense associated with developing and sustaining proprietary AI technologies tends to be exorbitantly expensive, involving heavy investment in infrastructure, specialist personnel, and constant maintenance (Trabelsi, 2024). Most small and medium-sized enterprises (SMEs) lack the capacity to devote adequate resources towards Private AI adoption, and hence Open-Source AI or Hybrid AI presents a more realistic alternative (Beverungen, et al., 2022).

In addition, complexity in the management of Private AI systems demands state-of-the-art technical know-how, which may be beyond the means of most companies, thus leading to overdependence on third-party vendors for AI development and maintenance (Jorzik, Klein, Kanbach & Kraus, 2024). One of the traditional case studies of Private AI utilization is in banking, where AI is utilized by banks for fraud detection as well as risk assessment (Rajaguru, 2024). Banks utilize Private AI to examine transaction data, identify anomalies, and block fraudulent transactions in real time while adhering to stringent financial rules (Pallathadka, et al., 2023).

Through the utilization of artificial intelligence-powered security controls, financial institutions are able to safely prevent fraud without undermining data integrity and regulatory compliance (Kumar, et al., 2024). While Private AI is costly, companies operating in highly regulated sectors usually find that the benefits of enhanced security and compliance justify the expenses incurred (Van Bekkum & Borgesius, 2023).

Theoretical discourse on Private AI highlights the necessity to safeguard confidential business information, reduce cybersecurity threats, and maintain adherence to data protection laws (Wang, et al., 2024). However, the resource-demanding and expensive nature of Private AI presents significant challenges for small and medium enterprises (SMEs) in their pursuit of AI-driven solutions (Pallathadka, et al., 2023).

5. OPEN-SOURCE AND PRIVATE AI APPLICATION IN BUSINESS MANAGEMENT

According to the literature analysis presented above and considering the numerous AI tools that can be integrated into business functions, one might imagine that most business activities could be supported in some way by AI systems. Theoretically, everything is possible, but in practice, it can be very complex to understand ‘how’ to integrate these systems and ‘why’. On the basis of such decisions, it is necessary to know the AS-IS of the companies and the skills of the people who work in the company very well in order to understand, on the one hand, the right time to integrate the systems and, on the other, how to train human resources and how to stimulate in them the need to change their work patterns in order to dedicate more time to activities with higher added value.

The first problem to be solved in the application of artificial intelligence in companies is to understand to what level to automate the processes or how to support them through standard or custom AI tools. The first step is to analyze the company organization, its functions and the criticality of the processes. For this reason, the following table can be helpful in understanding how to integrate AI services into business activities according to a logic based on the division of the complexity of the organization into business functions and, further, the complexity of the business functions into processes. The table proposes the ‘how’ and the ‘why’ business activities could be supported by AI systems to increase efficiency or, in some cases, to save time to dedicate to higher-value activities. These considerations can be used when managers will have to further divide the activities of the business functions into processes and, therefore, will have to understand which AI agents to activate for each process and what level of autonomy these AI agents will have to have. Above all, they will have to decide whether the AI agents will have to be supported by Open-source AI or Private AI systems.

Table 1. AI Applications Across Business Functions.

Function	Subcategories	WHY Private AI?	HOW to Use Private AI?	WHY Open-Source AI?	HOW to Use Open-Source AI?	Literature
Accountability	**Risk Management** – This involves the systematic identification, assessment, and prioritization of potential risks—be they financial, operational, or strategic. AI contributes by analyzing vast datasets to predict and mitigate these risks, thereby safeguarding organizational assets and ensuring business continuity	Ensures that sensitive risk-related data is processed securely, maintaining confidentiality and compliance with regulatory standards	Dealing with proprietary risk models or handling data that is subject to strict regulatory oversight	Offers cost-effective tools for general risk assessment, making it accessible for organizations with limited resources	Conducting preliminary risk evaluations that do not involve sensitive or confidential information	Butler & O'Brien (2019), Bhavani (2020), Roberts & Tonna (2022), Addy, et. al. (2024), Dopamu, Adesiyan & Oke, (2024), Dopamu, Adesiyan & Oke, (2024), Laraki, Schaus & Deville (2024), Yafooz & Al-Gumaei (2025)
	Compliance – Ensuring that an organization adheres to relevant laws, regulations, and internal policies. AI automates the monitoring and reporting processes, reducing manual efforts and minimizing the risk of non-compliance	Provides a secure environment for handling regulatory data, ensuring adherence to industry and governmental compliance standards without external exposure	Operating in highly regulated industries such as finance, healthcare, or legal sectors that require stringent compliance measures	Provides readily available compliance monitoring tools that are cost-effective and easy to integrate into existing workflows	Incompliance requirements are standard and do not require high levels of confidentiality	
	Auditing – The systematic examination of financial records and operations to ensure accuracy and integrity. AI enhances auditing by quickly analyzing large volumes of data to detect anomalies and potential fraud	Safeguards financial records and internal auditing processes, minimizing the risk of breaches and unauthorized access	Conducting internal audits for financial integrity and regulatory adherence within large enterprises	Offers scalable auditing tools that can analyze financial data at a lower cost, making it useful for smaller organizations	Organizations require basic auditing solutions without the need for confidential data protection	
Finance	**Fraud Detection** – Identifying and preventing fraudulent activities by analyzing	Provides customized fraud detection systems	Dealing with high-value transactions and critical	Provides accessible fraud detection solutions suitable	Monitoring standard transactions in	Sanz & Zhu, (2021), Jain & Kulkarni (2023),

	transaction patterns and detecting anomalies. AI systems can process vast amounts of data in real-time to flag suspicious behavior	tailored to an organization's specific risks, protecting sensitive financial transactions	financial operations where security breaches can cause severe financial damage	for general financial monitoring	organizations with lower exposure to fraud risks	Yang, et.al. (2024), Kokare, et. al. (2024), Alsaadi et. al. (2024), Chaiwong & Srisai (2024), Lee, Hayes & Maher, (2024)
	Financial Forecasting – Predicting future financial performance based on historical data and market trends. AI enhances accuracy by identifying patterns and correlations that may not be evident through traditional analysis	Customizes financial models based on proprietary data, ensuring accurate and strategic financial forecasting	Financial forecasting needs to be highly specific, confidential, and tailored to a company's market positioning	Offers generic forecasting tools that analyze industry-wide trends	Performing general financial projections that do not require proprietary data	
	Budgeting – Allocating financial resources to various departments and projects. AI automates data collection and analysis, facilitating more accurate and efficient budgeting processes	Ensures confidentiality in financial planning and allows precise budget allocation aligned with company objectives	Budget planning involves sensitive financial strategies and long-term business investments	Provides cost-effective budgeting tools for general financial management	Handling basic budgeting tasks that do not require data security	
Marketing	**Social Media Analytics** – Analyzing social media platforms to understand customer sentiments, engagement, and brand perception. AI processes unstructured data from various platforms to provide actionable insights	Enables organizations to develop advanced, proprietary consumer insights while maintaining control over user data	Targeting niche audiences or creating highly personalized marketing campaigns that require exclusive data	Offers accessible analytics tools for broad social media trend analysis	Analyzing general audience behavior and engagement trends without sensitive data usage	Nikita & Velicheti, (2022), Sharma, Patel & Gupta (2022), Singh & Adhikari (2023), Okeleke, Ajiga, Folorunsho & Ezeigweneme (2024), Fu, Foell, Xu & Hiniker (2024), Hemalatha, Amulya & Lalitha (2024),
	Internal & External Communication – Managing and optimizing communication within the organization and with external stakeholders. AI-powered tools facilitate	Secures internal communications and ensures data privacy within confidential	Managing internal corporate messaging that involves sensitive business information	Provides cost-effective solutions for general customer and public communication	Automating basic customer service responses or general inquiries	

	efficient information dissemination and engagement	company interactions				Mittal, et. al. (2025), Yafooz & Al-Gumaei (2025), AlAfnan (2025)
	Customer Segmentation – AI categorizes customers based on behaviors to improve targeting and personalization	Offers highly accurate and proprietary segmentation models tailored to an organization's specific consumer base	Customer segmentation requires high accuracy and secure customer profiling for strategic targeting	Provides basic segmentation models that are easy to implement	Performing broad customer segmentation that does not require sensitive data	
Production Management	**Supply Chain Optimization** – This involves enhancing the efficiency and effectiveness of the entire supply chain, from raw material procurement to product delivery. AI facilitates real-time tracking, predictive analytics, and automation, leading to reduced costs and improved responsiveness to market demands	Ensures optimal efficiency in production and quality control	Managing proprietary manufacturing processes	Offers low-cost forecasting capabilities	Insights are needed for general production trends	Marsden (2019), Zhang, Muskat & Law (2021), Khan, et. al., (2022), Aminabadi, et. al. (2022), Widder & Nafus (2023), Ma & Wang (2024), Abdeldayem, et. al. (2024), Kagalwala, Radhakrishnan, Mohammed, Kothinti & Kulkarni(2025)
	Quality Control – Ensuring that products meet predefined quality standards through systematic inspection and testing. AI enhances this process by automating inspections, detecting defects, and predicting potential quality issues	Integrates with proprietary production processes, ensuring precise quality control while maintaining trade secrets	Quality control involves sensitive manufacturing processes that differentiate the company from competitors	Offers accessible defect detection models suitable for general production monitoring	Overseeing standard production quality control that does not involve confidential methodologies	
	Demand Forecasting – Predicting future customer demand to optimize inventory and production planning. AI analyzes historical sales data, market trends, and external	Allows organizations to generate highly accurate demand forecasts tailored to their own historical	Demand forecasting is crucial to inventory management and requires proprietary consumer insights	Provides industry-wide demand forecasting tools that analyze macroeconomic trends	Conducting broad market trend analysis that does not require proprietary data	

	factors to provide accurate forecasts	data and market conditions				
Human Resources (HR)	**Talent Acquisition** – The process of identifying, attracting, and hiring skilled individuals to meet organizational needs. AI streamlines this by automating resume screening, matching candidates to roles, and predicting candidate success	Ensures that recruitment data and hiring processes remain confidential while using proprietary candidate assessment models	Managing executive-level hiring or positions that require high-security clearance	Provides cost-effective solutions for automated resume screening and initial candidate filtering	Recruiting for general roles that do not require high levels of confidentiality	Mahatme & Bhoyar (2016), Goel, et. al. (2021), Alsaif & Sabih Aksoy (2023), Thakur, Hinge &Adhegaonkar (2023), Gryncewicz, Zygała & Pilch (2023), Gildhiyal & Prasad (2023), Gomathi, et. al. (2023), Saouabe, Oualla, Mazar & Messadia (2024), Faheem, et. al. (2024), Don-Yehiya, et. al. (2024), Radonjić, Duarte & Pereira (2024)
	Employee Engagement – Fostering a work environment where employees are committed, motivated, and productive. AI assesses engagement levels through sentiment analysis, surveys, and performance metrics	Enables secure analysis of employee feedback, ensuring confidentiality and customized engagement strategies	Managing workforce morale in large enterprises with sensitive internal dynamics	Provides basic tools for assessing employee satisfaction through surveys and analytics	Conducting general employee sentiment analysis without data privacy concerns	
	Workforce Planning – Strategically aligning workforce capabilities with organizational objectives. AI aids by predicting future workforce needs, identifying skill gaps, and optimizing staffing levels	Allows for customized workforce models tailored to company-specific operational needs	Planning for long-term workforce strategy and talent retention	Offers accessible workforce planning tools based on industry-wide trends	Analyzing broad employment trends and general workforce optimization	
Research & Development (R&D)	**AI-driven Innovation** – Leveraging AI to create new products, services, or processes. This includes using machine learning to identify market opportunities and develop innovative solutions	Allows organizations to maintain exclusivity over innovation pipelines and intellectual property	Developing proprietary technologies or disruptive innovations in competitive industries	Provides accessible tools for research collaborations and idea generation	Engaging in open innovation and crowdsourced R&D initiatives	Rane, Choudhary & Rane (2023), Cooper (2024), Govindarajan (2024), Alabi (2024), Cooper (2025), Marion, Yuan &
	Product Development – The process of bringing a new product to market, from	Ensures control over proprietary design data and	Working on high-value product developments	Offers accessible design tools for rapid prototyping	Experimenting with general product iterations	

	ideation to launch. AI assists by optimizing design, predicting market acceptance, and streamlining development processes	customized product optimization	requiring confidentiality	and standard product enhancements	in non-sensitive markets	Moghaddam (2025)
	Competitive Analysis – AI assesses market competitors and industry trends	Provides tailored market intelligence while keeping competitor insights confidential	Strategic market positioning and trade secrets must be protected	Offers general industry trend reports that help businesses stay competitive	Performing broad market research that does not involve confidential business intelligence	
Sales	**Customer Relationship Management (CRM)** – Managing interactions with current and potential customers to improve relationships and drive sales growth. AI automates data entry, analyzes customer behavior, and personalizes communication strategies	Enables secure storage and processing of customer data to maintain exclusive business insights	Handling sensitive customer data that requires compliance with privacy regulations	Provides standard CRM solutions for general customer interactions and engagement tracking	Managing non-sensitive client relationships and lead tracking	Nalini, Radhakrishnan, Yogi, Santhiya & Harivardhini (2021), Singh, et. al. (2023), Ledro, Nosella & Dalla Pozza (2023), Iyelolu, et. al. (2024), Gupta & Agarwal (2024), Ozay, Jahanbakht, Shoomal & Wang (2024), Pattanayak (2021), Raji et. al. (2024), Badmus, Rajput, Arogundade & Williams (2024), Alabi (2024),
	Lead Scoring – AI ranks potential customers based on engagement likelihood	Refines lead-scoring models using internal, proprietary customer engagement data	Optimizing sales pipelines for high-value and strategic customers	Offers scalable lead-scoring algorithms that analyze broad market behavior	Targeting general customer acquisition efforts in non-specialized industries	
	Sales Forecasting – This process involves predicting future sales volumes based on historical data, market trends, and economic indicators. AI enhances accuracy by analyzing vast datasets and identifying patterns that may not be evident through traditional methods	Ensures high accuracy in forecasting using internal financial and operational data	Precise revenue predictions are required for investment and strategic growth	Provides cost-effective sales forecasting tools based on public market data	Conducting broad industry sales projections without proprietary financial insights	

						Acharjee, et. al. (2024)
Logistics	**Inventory Management** – Overseeing the ordering, storage, and use of a company's inventory. AI optimizes stock levels, predicts demand fluctuations, and reduces holding costs	Provides optimized inventory control tailored to specific supply chain needs	Managing large-scale, high-value inventory with complex supply chains	Offers general inventory management tools for small to mid-sized businesses	Handling standard stock management without intricate logistical constraints	Borisova, Taymashanov & Tasueva (2019), Choudhuri (2022), Boute & Udenio (2022), Ping, Zhu, Ling & Niu (2024), Villegas-Ch, Navarro & Sanchez-Viteri(2024), Manaviriyaphap (2024)
	Transportation Optimization – Enhancing the efficiency of transporting goods by selecting optimal routes, modes, and schedules. AI analyzes traffic patterns, fuel costs, and delivery windows to minimize expenses and improve service levels	Ensures proprietary logistics strategies remain confidential and efficient	Dealing with large-scale transportation networks requiring customized optimization	Provides accessible route optimization tools for cost-effective shipping	Improving standard transportation routes without requiring specialized logistics strategies	
	Warehouse Management – AI automates inventory levels and storage logistics	Enables precise warehouse tracking while protecting operational processes	Handling high-value, complex warehousing systems requiring secure management	Provides standard warehouse automation tools for general inventory tracking	Managing straightforward warehouse operations with standard storage needs	
Procurement	**Supplier Selection** – Identifying and choosing suppliers based on criteria such as cost, quality, reliability, and service. AI evaluates supplier performance data and market conditions to inform decisions	Enables advanced supplier evaluation models while ensuring confidentiality	Negotiating high-value contracts with strategic vendors	Provides general supplier assessment tools for broad procurement decisions	Selecting vendors based on publicly available performance metrics	Beheshti, et. al. (2021), Kumar & Kumar, (2023), Rajakumari, et. al. (2023), Yan, et. al. (2024)
	Spend Analysis – Examining procurement data to identify spending patterns and opportunities for cost reduction. AI automates data aggregation	Ensures confidential financial analysis while optimizing procurement budgets	Optimizing procurement costs within large organizations requiring sensitive data protection	Provides general cost-analysis tools for standard expense tracking	Analyzing general spending trends in non-sensitive procurement activities	

	and identifies anomalies or inefficiencies.					
	Contract Analysis – AI reviews legal agreements to highlight key terms and risks	Securely processes and interprets contractual agreements for legal compliance	Handling complex, high-value contracts requiring detailed legal oversight	Provides automated contract review tools for standard agreement analysis	Reviewing basic contracts where confidentiality is not a primary concern	
Top Management within Business Plans	**Strategic Decision-Making** – The process of making long-term decisions that shape the direction of the organization. AI provides data-driven insights, scenario analysis, and risk assessments to support leaders	Offers tailored strategic modeling while securing proprietary decision-making frameworks	High-level strategic planning involves confidential corporate initiatives	Provides accessible decision-making tools using industry-wide trends	Conducting preliminary strategic assessments in a non-sensitive environment	Rajabion, (2018), Joudat & Lighvan (2021), Alshadoodee, et. al. (2022), Eboigbe, Farayola, Olatoye, Nnabugwu & Daraojimba (2023), Alabi (2024), Figueiredo (2024), Badmus, et.al. (2024), Kokare et. al. (2024)
	Market Positioning – AI helps companies adjust strategies based on competitive analysis	Provides exclusive market intelligence and strategic recommendations	Refining market positioning for long-term competitive advantage	Offers general market analysis tools for broad positioning strategies	Gaining industry insights without requiring proprietary market intelligence	
	Performance Monitoring – Tracking and evaluating organizational performance against goals. AI automates data collection, analyzes key performance indicators, and identifies areas for improvement	Ensures confidentiality in business performance metrics and operational assessments	Evaluating company performance in a competitive or highly regulated industry	Provides general performance tracking tools for operational insights	Monitoring standard performance benchmarks in non-sensitive business functions	

Source: own elaboration.

6. CONCLUSION

The analysis of the literature on the subject allow to divide the main research contributions into 6 clusters. This shows that the interest of researchers in the study of AI is certainly very varied and, in particular, 3 clusters – clusters 3, 4 and 6 – are strongly focused on the application of AI in business management, innovation development and marketing of companies. The topic of AI is therefore decisively involving companies and all organizations in search of efficiency and process improvement.

How and why to use AI in business management is one of the complex choices that can be resolved by following an organic sequence that starts from the study of the company's organization, from the analysis of functions and processes, follows the identification of organizational priorities and critical issues and ends with the framing of the organization's skills and the identification of the skills to be acquired, also in light of the AI systems to be integrated.

The research results presented in Table 1 highlight important points that on the one hand allow us to better understand the possibilities of applying AI to business processes and on the other hand show the complexity of integrating these systems into business management. It is advisable to know the company, and try to understand which functions or processes to 'integrate' through AI support. In some cases, therefore, human activity can be replaced, and in others, integrated. Regardless of the technologies used, in organizations the critical elements that involve management in the choices for business management are always the same: the complexity of the processes, the management of information, privacy, the involvement of employees and customers in decisions, the times of implementation of the activities but also the quality of the data to be analyzed and the information obtainable, as well as the training and management of human resources. Managing these critical elements in companies with the support of AI can support the quality of the value proposition, the relationship with the customer and, in general, the opportunity for the company to achieve competitive advantage. Whatever the AI model is applied, to avoid problems and security risks it is essential to implement corporate policies that regulate the use of AI, ensuring that only authorized tools are adopted in business processes by limiting the use of freely adopted open-source tools for specific activities, even marginal ones.

Managers must know which processes require a higher level of human attention and sensitivity and, above all, on which to apply an open-source or a private AI. The adoption of open-source or private systems depends on the specific needs of the company: while open-source AI guarantees scalability and cost-effectiveness, private AI offers greater security and control. A hybrid approach presents itself as an ideal solution, allowing to combine the strengths of both options. This model allows to exploit the advantages of both systems, maintaining flexibility, security and regulatory compliance. There are many aspects still to be studied in this sense, especially trying to understand how to integrate the systems with each other, how open could be the open-source AI should interact with private systems, more closed and limited.

Due to its features, Open-Source AI is the best choice for startups as well as established organizations that intend to implement AI solutions in a cost-effective way. Although they must remember to evaluate carefully in areas that are mission-critical for the business, due to the weaknesses of the solution in terms of data security and regulatory compliance. Private AI, on the other hand, offers greater control, but is associated with high development and maintenance costs. Therefore, it is a solution directed to companies operating in highly regulated sectors, such as finance or healthcare. Often, the cost of Private AI, limits the possibility of its use to only large entities that have advanced technological solutions and high financial resources.

Integrating solutions across the various areas of a company's operations, as presented in Table 1, enables the development of a personalized hybrid model that combines the advantages of both Open-Source AI and Private AI. Managers should use Open-Source AI in processes that do not require data protection, and Private AI in areas that require special confidentiality. This would allow organizations to create a stable and secure environment in which they could develop. This approach promotes more effective AI integration in enterprises, while ensuring data protection, compliance with regulations, and competitive advantage.

As AI technology advances, companies should implement flexible strategies that are adapted to changing trends, industry standards, and technological innovations. While maintaining a balance between innovation, security, and cost optimization.

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INTELLIGENT MANAGEMENT SYSTEMS IN INTERNATIONAL TRADE: AI-DRIVEN TRANSFORMATION OF ORGANIZATIONAL PROCESSES

Joanna Brzyska[a], Monika Ruta-Kujawa[b],

[a] *University of Szczecin, Institute of Economics and Finance, Szczecin, Poland*
[b] *University of Szczecin, Institute of Management, Szczecin, Poland*

ABSTRACT

Purpose: *The purpose of the study is to evaluate how AI-driven intelligent management systems transform operational processes in international trade organizations, with a specific focus on measurable improvements in decision-making efficiency and operational performance.*

Need for the study: *Despite growing AI implementation in supply chain management, significant knowledge gaps exist regarding how these technologies transform organizational processes in international trade. Research lacks comprehensive empirical studies documenting specific process-level transformations and their operational impacts.*

Methodology: *This research combines comparative analysis and multiple case study methodology to examine how artificial intelligence transforms supply chain management processes in international trade. The comparative framework evaluates seven critical management domains with and without AI augmentation, while case studies of Amazon and Maersk provide real-world evidence of implementation approaches and outcomes.*

Findings: *AI-driven supply chain management creates measurable advantages in three critical areas: predictive capabilities replace reactive approaches in demand planning, enabling anticipatory inventory positioning; intelligent logistics systems continuously optimize routing and resource allocation despite disruptions; and new relationship dynamics emerge between supply chain partners, shifting from transactional exchanges toward data-sharing collaborations that enable network-wide optimization.*

Practical Implications: *Organizations should implement intelligent supply chain management by starting with targeted applications before progressing to more advanced implementations. Successful approaches involve progressive capability development, beginning with smaller-scale implementations before scaling to larger operations. Organizations should prioritize implementations in areas showing significant transformation potential: data analysis and forecasting, logistics optimization, and risk management, while establishing appropriate governance measures for compliance and data ethics.*

Keywords: AI; artificial intelligence; intelligent supply chain management; cognitive supply chains; international trade
Jel codes: F10; M11; O32

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1. INTRODUCTION

Supply chain management in international trade is experiencing a fundamental shift as artificial intelligence technologies transform traditional approaches into intelligent systems capable of autonomous operations and predictive optimization. As global trade volumes continue to expand, organizations increasingly recognize that supply chain efficiency and resilience are critical determinants of competitive advantage in international commerce (Toorajipour et al., 2021).

This evolution to intelligent supply chain management (ISCM) responds to mounting challenges of market volatility, geopolitical tensions, and heightened consumer expectations that traditional models struggle to address effectively. While cognitive supply chain adoption accelerates across industries, there remains a significant gap in understanding how these technologies specifically transform operational processes and deliver measurable benefits (Ivanov & Dolgui, 2020).

Despite growing recognition of AI's potential value, current research predominantly focuses on theoretical potential rather than empirical outcomes, with limited systematic process-level analysis of AI implementation effects (Baryannis et al., 2019). Additionally, while numerous studies address technological aspects of AI in supply chains, fewer examine the organizational and operational dimensions of transformation (Dubey et al., 2020).

This research aims to evaluate how AI-driven intelligent management systems transform operational processes in international trade organizations, with a specific focus on measurable improvements in decision-making efficiency and operational performance. By developing a comprehensive comparative framework that systematically assesses transformations across key supply chain processes, the study provides empirical evidence of AI's effects on international trade.

To achieve this purpose, the study employs a mixed-methods approach combining comparative analysis of process capabilities with case study methodology, guided by two primary research questions:

1. How do AI-powered intelligent management systems transform specific supply chain processes compared to traditional approaches?
2. What measurable improvements in operational efficiency, decision quality, and risk management result from these transformations?

The significance of this research lies in its contribution to both theoretical understanding and practical implementation of AI in global supply chains, offering organizations a systematic framework for evaluating and implementing AI-driven transformations in international trade operations.

2. LITERATURE REVIEW

Over the last two decades, research on supply chain management (SCM) has advanced from basic linear models toward integrated, digitally enabled networks that embrace global complexity and dynamic collaboration (Mohsen, 2023; Nayak & Choudhary, 2022). Early writings tended to describe supply chains as discrete sets of sequential processes, with limited attention to the systemic interconnections that stretch across borders and stakeholder communities (Carter & Rogers, 2008; Seuring & Müller, 2008). Subsequently, growing recognition of interdependencies at each stage – from sourcing raw materials to delivering goods to end customers – spurred frameworks stressing coordination, trust, and visibility. The emergence of Industry 4.0 further catalyzed the transition by introducing new information and communication technologies, including sensors, cloud platforms, and robotics (Richey & Davis-Sramek, 2022).

Artificial intelligence plays an essential role in this evolution. It initially appeared as rule-based expert systems and fuzzy logic, helping to automate routine operational tasks (Hartmann & Moeller, 2014). With the rise of big data and powerful computing infrastructure, AI grew more sophisticated, relying on machine learning, deep learning, and advanced predictive models (Mohsen, 2023; Muthuswamy & M. Ali, 2023). These paradigms allowed practitioners to move beyond static or descriptive analytics and embrace predictive and prescriptive functionalities (Wamba & Queiroz, 2020). AI, in effect, started to close the gap between data collection and actionable insights, enabling faster reaction times for disruptions, changes in consumer demand, and emerging opportunities (Pournader et al., 2021).

International supply chains arguably benefit the most from AI-driven insights because of the inherent complexities of cross-border flows (Mohsen, 2023; Pan & Nishant, 2023). Variations in

regulations, cultural practices, and infrastructure can hinder seamless coordination among trading partners. Scholars highlight that AI-based solutions – particularly those integrated with blockchain or the Internet of Things (IoT) – help mitigate some of these complexities by standardizing the exchange of real-time data, automating compliance verifications, and improving operational transparency (Budhwar et al., 2023; G V Radhakrishnan, 2025; Treiblmaier & Garaus, 2023). Indicate how logistics providers have deployed AI-enabled tracking systems that feed data into predictive analytics models, revealing early signals of disruptions like port closures or environmental calamities (Brau et al., 2024; Camargo et al., 2020). Such systems produce granular recommendations for route diversions or dynamic sourcing, effectively reducing lead times and strengthening overall resilience (Cannas et al., 2024; Dey et al., 2024).

Researchers increasingly emphasize the shift from simple decision support systems to intelligent supply chain management. Unlike traditional tools in which humans interpret diagnostic dashboards, ISCM features learning algorithms and autonomous capabilities that enable real-time interventions (Nayak & Choudhary, 2022). Inventory levels, transportation routing, and capacity planning can all be recalibrated by AI routines designed to continuously learn from data on sales forecasts, production constraints, and macroeconomic indicators (Mohsen, 2023). However, the literature shows that successful adoption depends on consistent human oversight for high-stakes decisions such as prioritizing shipments during crises, managing ethical or compliance dilemmas, and balancing productivity with workforce well-being (Dwivedi et al., 2024; G V Radhakrishnan, 2025; Qu & Kim, 2024).

Parallel to advances in AI, the digital transformation of supply chains has spurred widespread adoption of IoT-based systems. IoT sensors on shipping containers, warehouse shelves, and production lines transmit data on temperature, humidity, location, or handling conditions in near real time(G V Radhakrishnan, 2025). Such connectivity is particularly useful in global contexts where products may pass through multiple checkpoints with varying storage requirements, including cold chain logistics for perishable goods (Qu & Kim, 2024). AI analytics then process these data streams to forecast potential issues, detect irregularities, and optimize distribution schedules. For instance, computer vision tools can scan pallets for damage or tampering, automatically prompting re-routing or reordering decisions (Zhang et al., 2024). This automation of detection and response drastically lowers error rates and fosters a proactive, rather than reactive, approach to risk management (Pan & Nishant, 2023).

Blockchain solutions add another dimension by establishing secure, tamper-evident ledgers for each step in the supply chain (Treiblmaier & Garaus, 2023). While blockchain itself is not AI, integrating the two can create intelligent contracts that trigger payments or shipping authorizations when certain sensor conditions are met (Dwivedi et al., 2024; Kshetri, 2023; Richey et al., 2023). This convergence demonstrates how Industry 4.0 technologies collectively reinforce one another, forming a comprehensive digital ecosystem. According to Mohsen (2023), companies that exploit these synergies report lower inventory costs, better demand visibility, and improved customer satisfaction – though the scale of returns varies across industries and regions. Indeed, researchers note the persistent challenges: data sharing across borders often faces regulatory hurdles, uneven telecom infrastructure hinders IoT's effectiveness, and cultural factors may impede technology acceptance (Hendriksen, 2023; Pan & Nishant, 2023).

On the performance side, organizations adopting AI-based systems typically achieve gains in forecasting accuracy, procurement agility, and logistics optimization, but additional empirical research is needed to measure these outcomes systematically (Ozturk, 2024). Randomized trials and large-scale comparative studies remain relatively scarce, yet anecdotal evidence suggests AI's ability to handle large, messy datasets gives it an edge over traditional forecasting or optimization tools (Belu, 2025; Camargo et al., 2020). In practice, managers often rely on hybrid approaches, blending algorithmic recommendations with domain expertise. This synergy preserves human judgment in negotiations with suppliers, strategic decisions about product portfolios, and addressing ethical challenges (Carter & Rogers, 2008; Dwivedi et al., 2024; Seuring & Müller, 2008).

The research in AI-based supply chain management shows strong momentum. The push toward generative AI and large language models suggests new possibilities for analyzing unstructured data – such as social media posts, remote sensing, or weather forecasts – to anticipate disruptions and refine risk models (Brau et al., 2024). Managers can receive proactive alerts, complete with recommended action sequences, resulting in supply chains that respond dynamically to unforeseen shocks (Merlino & Sproģe, 2017; Richey & Davis-Sramek, 2022). Scholars caution, however, that expansion into

generative models also raises ethical and privacy concerns if data usage is insufficiently regulated (Budhwar et al., 2023). Maintaining transparency in algorithmic decision-making can be difficult when models become more sophisticated and opaque (Dwivedi et al., 2024).

In sum, the literature converges on a view that AI has fundamentally altered how global supply chains operate, driving them toward a model of intelligent, collaborative networks. The transformation is incomplete, as organizations still face hurdles around data governance, infrastructure readiness, and social acceptance of automation, especially in cross-border contexts. Nonetheless, mounting evidence indicates that properly implemented AI yields substantial improvements in agility, cost efficiency, and risk mitigation. Future investigations require robust comparative frameworks to evaluate performance and sustainability outcomes across various cultural and regulatory landscapes. The literature suggests ongoing technological integration – linking AI, IoT, blockchain, and advanced analytics – while underscoring the enduring relevance of human oversight in intelligent and ethically sound supply chain ecosystems.

3. METHODOLOGY

3.1. Research Approach and Analytical Framework

This research employs a qualitative case study approach to examine the transformational impact of artificial intelligence on international supply chain management processes. Given the emergent nature of AI applications in global supply chains, case studies provide an appropriate methodological framework to capture the complex, multifaceted changes occurring across organizational processes and capabilities within international trade contexts.

The research design centres on comparative analysis that contrasts conventional supply chain management processes with their AI-enhanced counterparts. This approach enables identification of transformational patterns across specific functional areas including demand forecasting, inventory optimization, logistics management, and regulatory compliance. Rather than attempting broad technological generalizations, the study focuses on process-level transformations to capture nuanced changes in operational capabilities, decision-making frameworks, and organizational outcomes.

Data sources for this research comprise publicly available information including company publications, annual reports, industry analyses, and research reports. A systematic comparative framework has been developed to evaluate supply chain processes with and without AI augmentation, identifying critical operational differences and capability enhancements across the international supply chain spectrum. Supporting evidence is drawn from reports produced by research organizations including McKinsey, Precedence Research, KBV Research, and Polaris Research, OECD, and WTO to establish broader market trends and adoption patterns. However, the core empirical foundation consists of case studies of Amazon and Maersk as exemplars of AI implementation in international supply chains.

The selection of Amazon and Maersk as focal organizations is methodologically significant for several reasons. Both companies represent industry leaders with global operational scale and documented commitment to technological innovation. Historically, both organizations were early adopters of digital transformation, implementing enterprise systems and digital documentation well before industry-wide adoption. This pattern of technological leadership suggests their current AI implementations may foreshadow broader industry trends. Furthermore, these organizations operate in complementary segments of global supply networks – Amazon primarily in e-commerce fulfillment and Maersk in maritime shipping and transportation – providing valuable comparative insights across different supply chain management. Their relative size and market influence also means their technological choices often establish de facto standards that shape subsequent industry adoption patterns. The analytical framework employs process-level comparison to evaluate transformation across standardized dimensions, examining how artificial intelligence supports decision-making and improves performance outcomes.

3.2. Research Limitations

This research methodology faces several significant limitations that warrant explicit acknowledgment. First, quantitative assessment is substantially constrained by data availability limitations. Organizations

typically do not disclose specific performance metrics related to AI implementations in their public reporting, instead using qualitative descriptors of improvement or general statements about enhanced productivity. Annual reports and investor communications describe AI impacts in broad terms of 'improved efficiency' or 'enhanced capabilities' without providing precise measurements of cost savings, productivity improvements, or other quantifiable benefits. This limitation necessitates the case study approach but restricts the ability to make definitive quantitative claims about performance improvements.

Second, measuring AI's specific impact on supply chain processes presents unique methodological challenges beyond typical technology evaluation difficulties. AI systems often function as integrated components within complex organizational ecosystems, making it difficult to isolate their specific contribution from other concurrent technological and process innovations. The 'black box' nature of many machine learning algorithms further complicates assessment, as the relationship between inputs and outputs is not always transparent. Additionally, AI implementations typically evolve continuously as algorithms learn from new data, making point-in-time measurements less meaningful than they might be for static technologies.

Third, the field currently lacks standardized, universally accepted metrics for measuring AI's economic impact on trade and supply chain operations. While potential benefits are widely acknowledged, methodologies for isolating and quantifying AI's specific contribution remain underdeveloped. This measurement challenge reflects both the nascent state of widespread AI implementation and the inherent complexity of separating technological effects from other organizational and market factors in international trade that span multiple regulatory environments, transportation modes, and stakeholders. To demonstrate the development of intelligent supply chain management, changes in the cognitive supply chain market compared to global merchandise and services exports are presented.

Fourth, the case-based approach provides valuable insights into industry-leading implementations but inherently constrains generalizability. Amazon and Maersk's scale, resources, and technological sophistication exceed those of most market participants, potentially limiting the direct applicability of their experiences to smaller organizations or different industry segments. Their ability to invest in proprietary AI development and integration may create implementation pathways that aren't feasible for organizations with more constrained resources or technical capabilities.

Fifth, the cross-sectional nature of the research provides limited insight into the longitudinal evolution of AI capabilities and their impact over time. AI systems continuously learn and adapt, potentially delivering different benefits as they mature and as organizations develop complementary capabilities. This dynamic aspect of AI implementation is difficult to capture through the methodology employed in this study.

Despite these significant limitations, the case study approach represents an appropriate methodological response to the current state of AI implementation in international supply chains management. By focusing on process-level transformations rather than attempting precise quantification of benefits, the research provides valuable insights into how AI is reshaping operational capabilities and strategic positioning within global trade system. The historical pattern of technology diffusion from industry leaders to broader adoption suggests the experiences of Amazon and Maersk may offer meaningful indicators of future industry trajectories, even as implementation approaches are adapted to diverse organizational environments.

4. RESULTS

4.1. Trends in International Trade and Cognitive Supply Chain Market

Analysis of trends in international trade highlights the substantial growth of the cognitive supply chain market. Figure 1 illustrates the relationship between global exports (both merchandise and services) and the cognitive supply chain market from 2017 to 2024. The data reveals that while international trade has experienced moderate growth with some fluctuations – particularly the notable decline during 2020 due to the pandemic – the cognitive supply chain market has demonstrated consistent year-over-year growth (World Trade Organization, 2024). Most significantly, the cognitive supply chain market shows a steeper growth trajectory than general trade volumes, increasing from approximately $5.7 billion in

2019 to $8.6 billion in 2024. This accelerated growth rate suggests increasing integration of AI technologies in global commerce operations and highlights the expanding role of intelligent systems in managing international supply chains.

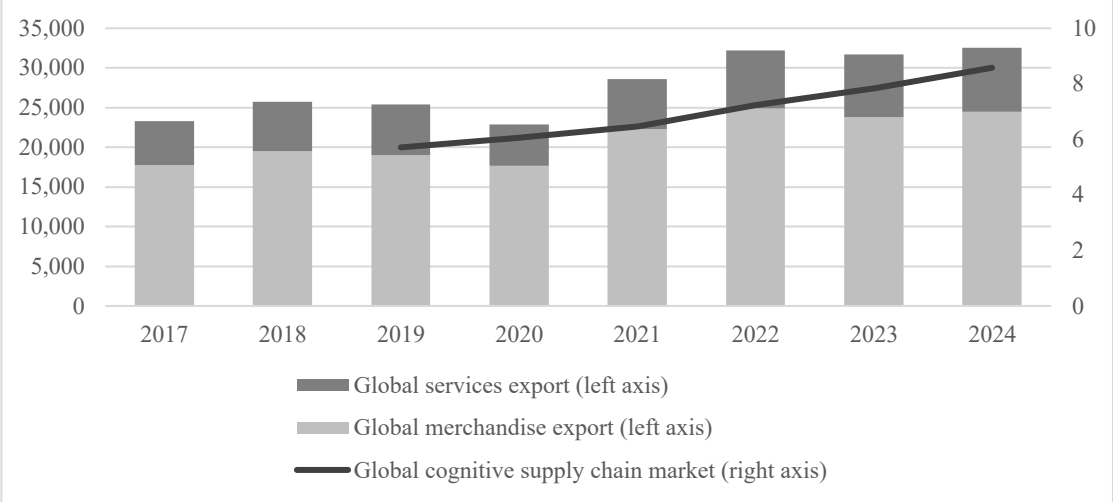


Figure 1. Global exports and cognitive supply chain market (billions of US dollars)
Source: own elaboration based on (Global Cognitive Supply Chain Market Size & Outlook, 2024; *WTO Stats*, 2025).

Future projections for the cognitive supply chain market are highly optimistic. Although specific forecasts differ, market analysis consistently predicts substantial growth. Precedence Research anticipates a 2.6-fold increase between 2024 and 2030, while both KBV Research and Polaris Research project a market size more than doubling within the same period (Artificial Intelligence Market Size, Share, Trends, Industry Analysis Report, 2024; *Cognitive Supply Chain Market Size, Share and Trends 2024 to 2034*, 2025; Global Cognitive Supply Chain Market Size & Outlook, 2024). This strong growth is expected to be driven by the increasing adoption of AI and machine learning, the escalating complexity of global supply chains, and the growing imperative for efficiency and resilience in international trade (Harnessing the Value of Generative AI: Top Use Cases across Sectors, 2024). The integration of cognitive capabilities is becoming essential for organizations aiming to effectively operate in the global marketplace and maintain a competitive advantage.

4.2. AI Implementation in Intelligent Supply Chain Management

While the cognitive supply chain represents a key area of AI application, generative AI is also gaining traction across a multitude of industries and functions. Table 1 illustrates the global adoption of generative AI across industries in 2024, highlighting the diverse applications of this technology. Technology companies demonstrate the highest overall AI adoption at 88%, followed by professional services (80%), advanced industries (79%), and media/telecom (79%). The consumer goods and retail sector shows 68% adoption, while financial services and healthcare register 65% and 63% respectively.

When examining supply chain and inventory management functions specifically, adoption rates are notably lower than in other business areas such as marketing and sales. Advanced industries lead in supply chain AI implementation at 15%, followed closely by consumer goods and retail at 14%. Other sectors show significantly lower adoption rates in supply chain functions: technology (10%), energy and materials (6%), financial services (4%), professional services (4%), media and telecom (3%), and healthcare (2%). This data suggests that despite the potential benefits, actual implementation of AI in supply chain functions lags behind other business areas, indicating substantial room for growth in supply chain AI implementation across industries.

To illustrate the impact of generative AI, the following charts focus on the financial benefits experienced by organizations. Figure 2 shows the percentage of respondents reporting a decrease in costs in their business units due to the generative use of artificial intelligence, while Figure 3 shows an increase in revenue in business units due to gen AI, both charts are for 2024, and segmented by function.

Table 1. Global adoption of generative AI across industries in 2024, by function

Global adoption of generative AI across industries in 2024, by function (%)	Marketing and sales	Service operations	Strategy and corporate finance	Supply chain/inventory management	Manufacturing	Using gen AI in at least 1 function
Technology	55	30	14	10	5	88
Professional services	49	23	14	4	3	80
Advanced industries	48	24	21	15	13	79
Media and telecom	45	37	10	3	3	79
Consumer goods and retail	46	13	7	14	8	68
Financial services	40	26	7	4	0	65
Healthcare, pharma, and medical products	20	14	6	2	5	63
Energy and materials	33	13	5	6	7	59

Source: own elaboration based on (*Statista. Global adoption of generative artificial intelligence (AI)*, 2025).

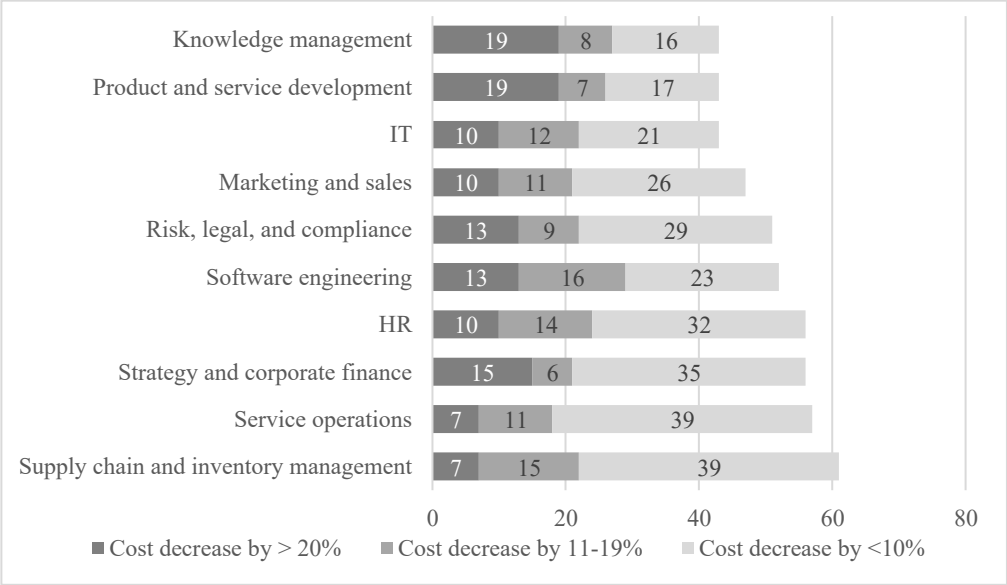


Figure 2. Cost decrease within business units from gen AI use in 2024, by function, % of respondents
Source: based on (Singla et al., 2025).

Supply chain and inventory management functions reported the highest percentage of cost decreases among all surveyed business units, with 61% of respondents confirming this, according to Figure 2. This finding suggests that supply chain applications of AI deliver particularly significant efficiency improvements compared to other functional implementations. Figure 3 complements this data by illustrating revenue increases attributed to AI implementation across business functions, showing how AI technologies contribute to both cost reduction and revenue enhancement in supply chain operations.

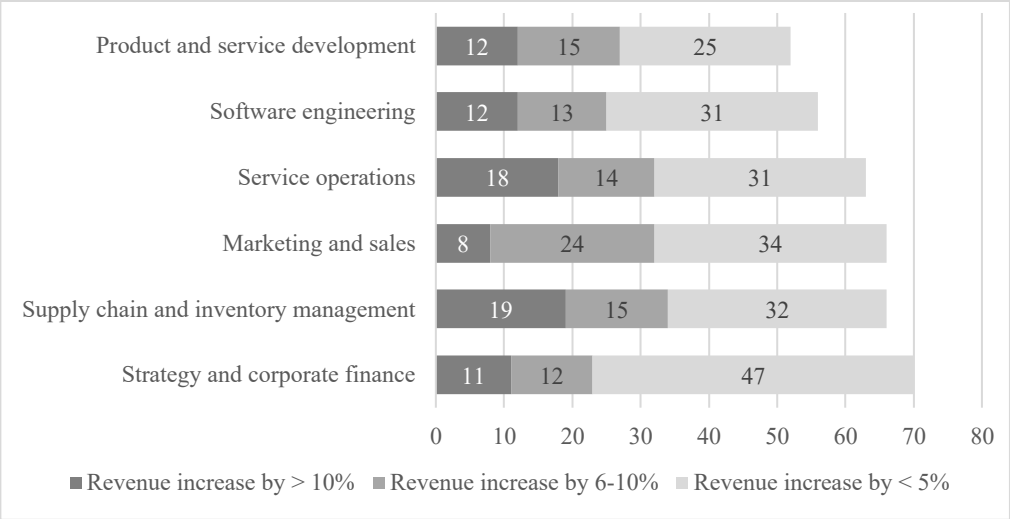


Figure 3. Revenue increase within business units from gen AI use in 2024, by function, % of respondents
Source: based on (Singla et al., 2025).

4.3. Comparative Analysis of ISCM With and Without AI

To understand the specific ways AI is reshaping international trade, Table 2 presents a systematic, process-by-process comparison of intelligent supply chain management with and without AI across seven crucial areas. The comparative data reveals significant transformations in both the capabilities and the outcomes of these operations.

In Data Analysis and Forecasting, the implementation of AI enables a transition from limited historical data analysis to comprehensive predictive analytics that incorporate diverse data sources including market indicators, geopolitical factors, and currency fluctuations. This enhancement delivers significantly higher forecasting accuracy and improved risk management capabilities for international operations.

Process Automation capabilities show a dramatic evolution from basic task automation to sophisticated handling of complex international documentation and customs procedures. The introduction of robotics in international logistics operations yields substantial benefits including cost reductions, process acceleration, and minimized errors across cross-border operations.

Logistics and Transportation Optimization demonstrates perhaps the most visible transformation, evolving from static route planning based on fixed data to dynamic, real-time optimization that considers multiple variables including traffic conditions, weather patterns, and customs regulations. This advancement enables tangible benefits including reduced transportation costs, shortened delivery times, and enhanced flexibility in international shipping operations.

Similar transformational patterns appear across the remaining process areas. Supplier Relationship Management advances from limited collaboration capabilities to AI-powered platforms that enable automatic risk assessment and dynamic contract adjustments. Visibility and Transparency improves from restricted shipment tracking to comprehensive real-time visibility across the entire supply chain. Risk Management evolves from reactive approaches to proactive risk prediction and automated contingency planning. Sustainable Development progresses from limited environmental monitoring to sophisticated capabilities including route optimization for emissions reduction and comprehensive carbon footprint tracking.

Table 2. AI's influence on ISCM components in global trade

ISCM element	Without AI in international trade	With AI in international trade	AI impact
Data Analysis and Forecasting	Historical data analysis, statistical models, limited consideration of foreign market variability	Predictive data analysis from various sources (markets, geopolitics, currencies), machine learning for demand and trend forecasting	Significantly higher forecasting accuracy, better understanding of foreign markets, risk minimization
Process Automation	Automation of simple tasks, difficulties in automating complex customs and trade procedures	Automation of complex processes (trade documentation, customs procedures), robotics in international logistics	Cost reduction, process acceleration, error minimization, increased efficiency
Logistics and Transportation Optimization	Route planning based on fixed data, GPS systems, difficulties in optimizing complex international logistics	Real-time optimization, consideration of multiple variables (traffic, weather, customs regulations), autonomous vehicles	Transportation cost reduction, delivery time reduction, increased flexibility, delay minimization
Supplier Relationship Management (SRM)	Limited supplier collaboration, difficulties in assessing risk in a global supply chain	AI-powered collaboration platforms, automatic supplier risk assessment, dynamic contract adjustments	Better collaboration, risk minimization, cost optimization, greater flexibility
Visibility and Transparency	Limited shipment tracking, lack of full visibility of goods flow across borders	Real-time tracking, blockchain-based platforms, full supply chain visibility	Increased trust, fraud risk minimization, faster problem response
Risk Management	Reactive actions, difficulties in predicting political and economic risks in foreign markets	Proactive risk prediction (regulatory changes, sanctions, conflicts), automatic contingency plans	Loss minimization, increased resilience to disruptions, faster response to changes
Sustainable Development	Limited actions, difficulties in monitoring the environmental impact of international transport	Route optimization, emission reduction, carbon footprint monitoring, sustainable sourcing	Reduced negative environmental impact, improved company image, financial savings

Source: own elaboration.

This comparative analysis identifies that the most significantly transformed processes appear to be Data Analysis and Forecasting, Risk Management, and Logistics Optimization, where AI capabilities enable fundamental shifts in operational approach rather than merely incremental improvements. To illustrate these transformative effects in real-world scenarios, the following case studies examine how industry leaders Amazon and Maersk have implemented artificial intelligence across their supply chain management. These examples demonstrate how AI technologies transform traditional processes and deliver measurable business value, offering valuable insights for other companies seeking successful AI integration in global supply chains.

4.4. Case Studies: Maersk and Amazon

Case study 1: Maersk

Maersk is the world's largest container shipping company, operating in 130 countries with a fleet of over 700 vessels that transport approximately 17% of global containerized trade. The company's supply chain operations involve complex coordination of shipping schedules, port operations, customs processing, and intermodal transportation networks. Maersk has increasingly positioned itself as a

technological innovator in the traditionally conservative shipping industry (*Maersk*, 2025; Maerska Annual Report 2024, 2025).

Maersk has developed sophisticated digital twin technology for its terminal operations, creating complete digital replicas that integrate data from multiple sensors and operational systems. This implementation enables terminal operators to visualize complex operational states and simulate different scenarios before making decisions. The technology has transformed port operations planning from intuition-based approaches with limited analytical support to data-driven optimization with comprehensive scenario testing capabilities. The implementation delivers significant operational advantages. Planning processes that previously required days of manual calculations using spreadsheets now complete in hours, representing a 10x acceleration for complex scenarios. Operational efficiency has significantly improved terminal operations, with vessel turnaround times reduced at major ports. These improvements translate directly to enhanced asset utilization and service reliability. From a practical implementation perspective, Maersk began with digital models of smaller terminals before scaling to larger operations, allowing for progressive capability development and organizational learning.

Maersk's deployment of AI has significantly reshaped its global supply chain operations by improving real-time visibility, accelerating decision-making, and supporting strategic risk management. A prominent example is the StarConnect platform, which processes approximately 2.5 billion data points annually and applies machine learning to optimize vessel routes and forecast fuel consumption. By using a wealth of data from shipping lanes, port conditions, and historical cargo flows, StarConnect identifies more efficient passage options, enabling Maersk to reduce transit times and fuel usage while still meeting tight schedules. These continuous, data-driven adjustments make it easier to respond promptly to unforeseen challenges such as shifting customer demands or port slowdowns, and they also ease congestion across Maersk's broader logistics network.

The company also invests in generative AI, notably through a solution called "CX Agent Assist", which draws upon advanced models to process customer inquiries and streamline issue resolution. This generative AI tool reduces response times by presenting service teams with suggested solutions, thereby freeing agents to address more complex tasks that require negotiation or judgment. As part of its broader roadmap, Maersk has integrated these AI initiatives into "agentic workflows", a company-wide approach to automation designed to ensure that data and machine intelligence can flow across multiple operational layers, from ocean freight bookings to warehouse management.

At the same time, the adoption of AI has prompted Maersk to develop governance measures for compliance and data ethics. Through initiatives such as automated data-access controls and a universal data ethics policy, the company seeks to protect sensitive customer information while maintaining regulatory readiness in a global environment of evolving AI legislation. This balance between innovation and risk management is considered vital, not only for sustaining customer trust but also for preserving Maersk's reputation as a leader in responsible technology use.

Although Maersk has yet to announce specific numeric gains directly attributed to the company-wide integration of AI, the 2024 Annual Report notes an overall improvement in service reliability and cost control. Operational benefits from AI-assisted route optimization have helped preserve fuel and meet tighter shipping timetables, while generative AI initiatives speed up customer support, contributing to better on-time performance. Taken together, these innovations strengthen Maersk's end-to-end logistics services by reducing response times, bolstering supply chain resilience, and paving the way for continued, data-driven efficiencies throughout its network.

Case study 2: Amazon

Amazon operates one of the world's largest and most complex supply chain networks, spanning across 185 fulfillment centers globally and processing billions of packages annually (Amazon Annual Report, 2024). The company has consistently invested in technological innovation to enhance operational efficiency and customer experience. Amazon's supply chain must manage extraordinary complexity, including over 12 million SKUs product, seasonal demand fluctuations, and customer expectations for rapid delivery. Amazon has implemented AI extensively throughout its supply chain operations, transforming traditional e-commerce processes to achieve unprecedented scale, efficiency, and customer experience (*Amazon*, 2025; Amazon.com Annual Report 2024, 2025).

Amazon's extensive e-commerce ecosystem depends on precise demand forecasting, rapid fulfillment, and efficient last-mile delivery. AI-driven systems enable each of these elements to function cohesively, thereby transforming the supply chain into a scalable and adaptive network that consistently meets high customer expectations. Machine learning models absorb and analyze large volumes of real-time order data, product availability, and customer behavior to forecast shifts in demand for millions of SKUs. As a result, Amazon can allocate inventory more strategically and reduce lead times by anticipating regional sales fluctuations before they escalate into bottlenecks.

One of the most visible applications of AI is in warehouse automation, where computer vision and predictive analytics guide robots in sorting packages and restocking shelves. This contributes to lower error rates and a faster pace of operations, minimizing the intervals between picking an item and getting it ready for shipment. The vast network of fulfillment centers is connected by internal algorithms that recommend how many units of a given product should be stored in each warehouse, allowing Amazon to stage inventory closer to end consumers and slash transportation costs.

At the same time, Amazon uses AI-assisted route planning to streamline the delivery of orders. These machine learning models integrate factors such as traffic conditions, driver availability, and parcel density to suggest optimal delivery pathways. By synchronizing all these inputs, Amazon mitigates delays, controls fuel consumption, and reduces carbon emissions. The practical impact of improved routing can be seen in Amazon's shift toward building out its own trucking fleets and last-mile service, where AI plays a substantial role in analyzing local traffic patterns and adapting delivery zones in near real time.

Incorporating machine learning also strengthens collaboration with the third-party sellers who rely on Amazon for both customer exposure and logistical support. Tools like Fulfillment by Amazon (FBA) leverage AI to estimate the best shipping rates, fulfillment routes, and packaging processes to ensure that a growing segment of Amazon's e-commerce marketplace runs efficiently. Amazon's broader engagement with advanced AI (including its investment in Anthropic) suggests it is positioning itself to adopt next-generation AI solutions as they mature.

By combining internal robotics, data analytics, and cloud-based machine learning services, Amazon is continuously refining inventory distribution and speeding up deliveries across hundreds of fulfillment facilities worldwide. The result is a logistics pipeline that harnesses AI insights for proactive decision-making, whether predicting seasonal spikes in product categories or mapping the most efficient dispatch route for a driver.

The Maersk and Amazon case studies reveal several valuable implementations patterns that other organizations can adapt:

First, both organizations demonstrate the value of phased implementation approaches that begin with targeted applications before expanding to more comprehensive integration. This approach enables organizational learning and capability development while delivering incremental benefits, providing a practical model for managing implementation complexity.

Second, both organizations integrate AI with existing operations rather than pursuing wholesale replacement, allowing for evolutionary transformation rather than disruptive change. This approach minimizes operational risk while accelerating adoption, particularly important in complex global supply chains management where continuity is essential.

Third, both organizations maintain human-AI collaboration, leveraging complementary capabilities rather than pursuing full automation. This approach enhances adoption while maintaining human judgment for complex decisions, offering a practical model for balancing automation with expertise.

Fourth, both organizations demonstrate the importance of data foundation development before advanced algorithm implementation. This sequencing ensures that AI systems have the necessary inputs for effective operation, highlighting the critical role of data infrastructure in successful AI implementation.

These case studies illustrate how AI can transform global supply chain management by enhancing efficiency, improving decision quality, and enabling new capabilities. The implementations at Maersk and Amazon provide practical models that other organizations can adapt to their specific situations, demonstrating pathways to successful AI integration in international trade operations.

5. DISCUSSION

The implementation of AI technologies in international supply chain management represents a significant shift in how global trade operations are conducted, with far-reaching implications for competitive dynamics, organizational structures, and development.

5.1. Competitive Implications for Global Trade Participants

The integration of AI into supply chain processes is fundamentally altering the basis of competition in international markets. Organizations that effectively implement AI capabilities gain substantial advantages in operational efficiency, decision quality, and market responsiveness (Ferencz et al., 2022). These capabilities create new competitive differentiators beyond traditional factors such as scale, cost structure, or geographical presence. For example, Maersk's implementation of AI-driven vessel optimization and Amazon's predictive inventory positioning demonstrate how enhanced forecasting capabilities and dynamic operational adjustments enable superior service levels even in volatile market conditions.

AI implementation also enables new market access and expansion opportunities by reducing the complexity barriers of international trade. Smaller organizations can potentially leverage AI platforms to navigate regulatory requirements, optimize cross-border logistics, and manage international supplier relationships that would previously have been prohibitively complex without substantial specialized expertise. This democratization of international trade capabilities may allow more diverse market participation, though the resource requirements for advanced AI implementation may simultaneously create new barriers to entry.

The relationships between supply chain partners are evolving as AI systems increasingly mediate interactions and decision processes. Traditional arm's-length transactional relationships are giving way to more integrated data-sharing arrangements that enable collaborative optimization across organizational boundaries. As demonstrated in both case studies, the effectiveness of AI implementations often depends on the quality and scope of data shared between partners, creating incentives for deeper integration while raising questions about dependency and power dynamics within supply networks.

5.2. Implementation Challenges and Success Factors

The technical integration of AI systems presents substantial challenges in international environment. Organizations must navigate heterogeneous technology environments, varying data standards, and diverse regulatory frameworks across multiple jurisdictions. The cross-border nature of international trade amplifies these challenges, requiring systems capable of operating across different technological infrastructures and adapting to local requirements. Both Amazon and Maersk demonstrate the necessity of developing scalable, adaptable technical architectures that can accommodate this complexity.

Organizational change management emerges as a critical success factor in AI implementation. The transformation of decision processes from human judgment to algorithmic analysis requires significant cultural adaptation, revision of established workflows, and reconfiguration of authority structures. The case studies indicate that successful implementations typically involve progressive capability development rather than abrupt transitions, allowing organizational learning and adaptation to occur incrementally.

Data quality and availability issues present persistent challenges, particularly in international flows where information may originate from diverse sources with varying standards, formats, and reliability. The ability to establish data governance frameworks that ensure consistency, accuracy, and timeliness across organizational and national boundaries appears to be a key differentiator in implementation success. This challenge is especially pronounced in areas with limited digital infrastructure or where paper-based processes remain prevalent.

The development of necessary skills and capabilities represents another significant implementation challenge. Organizations must cultivate specialized expertise in AI technologies, data science, and international trade operations. Both case organizations addressed this challenge through substantial investments in training programs, strategic hiring, and partnerships with technology specialists, approaches that may not be equally accessible to smaller market participants.

5.3. Ethical and Organizational Considerations

The implementation of AI in supply chain management processes raises important questions about decision authority and accountability. As algorithmic systems increasingly make or recommend decisions previously made by humans, organizations must establish clear frameworks for oversight, intervention, and responsibility. This challenge is amplified in international trade where different cultural and legal traditions may have varying expectations regarding autonomy, transparency, and liability in automated decision-making.

Privacy and security concerns in cross-border data flows present both operational and compliance challenges. International supply chains management inherently involve the movement of sensitive information across jurisdictional boundaries with different regulatory requirements and security standards. Organizations must navigate this complex landscape while maintaining sufficient data sharing to enable effective AI operation. Maersk's development of automated data-access controls and universal data ethics policies exemplifies the type of governance frameworks required to address these concerns.

The implications for workforce roles and skills are substantial and multifaceted. While routine decision-making and administrative processes may be increasingly automated, the case studies suggest that human roles are evolving rather than simply disappearing. New positions emerge in areas such as algorithm oversight, exception handling, relationship management, and system development. However, this transition creates significant workforce development challenges and potential displacement effects that organizations and policymakers must address.

5.4. Future Development Trajectory

Emerging new technologies including blockchain, digital twins, and advanced analytics present opportunities for further enhancement of AI capabilities in international supply chains. The potential integration of these technologies could address current limitations in data visibility, trust, and simulation capabilities. Both case organizations demonstrate active exploration of these complementary technologies, suggesting a trajectory toward increasingly sophisticated, integrated intelligent systems rather than standalone AI applications.

The regulatory environment for AI in international trade continues to evolve rapidly, with implications for implementation approaches and governance requirements. Different jurisdictions are developing varying frameworks regarding algorithmic transparency, data localization, and automated decision-making. Organizations operating global supply chains must navigate this complex and shifting landscape, potentially adapting their implementation approaches to accommodate divergent requirements across markets.

Diffusion patterns across industries appear uneven, as indicated by the adoption data presented in the results. While technology-intensive sectors demonstrate relatively high adoption rates, traditional industries show more variable implementation. This uneven diffusion may create temporary competitive advantages for early adopters while potentially exacerbating existing disparities in international trade participation.

6. CONCLUSION

This research has identified several significant areas where AI technologies are transforming international supply chain management processes. The most profound transformations appear in data analysis and forecasting, where predictive capabilities enable unprecedented accuracy in demand planning and risk assessment; logistics optimization, where real-time adjustments and multi-factor optimization create substantial efficiency gains; and risk management, where proactive identification and automated contingency planning enhance resilience in volatile global markets.

While precise quantification of improvements remains challenging due to limited disclosure of operational metrics, the case studies provide evidence of substantial enhancements in specific operational processes. Examples include Maersk's acceleration of terminal planning processes and improved vessel turnaround times, and Amazon's enhanced inventory positioning and reduced lead times through AI-driven demand forecasting. The McKinsey survey data further substantiates these

improvements, with 61% of respondents reporting cost decreases in supply chain and inventory management functions through AI implementation.

For international trade participants, these transformations create strategic advantages including enhanced ability to navigate regulatory complexity, improved adaptation to market volatility, and increased operational efficiency across borders. Organizations that effectively implement AI capabilities can achieve both cost advantages through operational optimization and revenue enhancement through improved service levels and responsiveness to market changes.

6.1. Theoretical Contributions

This research advances ISCM conceptual frameworks by systematically mapping the transformational impact of AI technologies across specific supply chain processes in international contexts. The comparative analysis framework developed for this study provides a structured approach for evaluating technological enhancement of supply chain capabilities, extending beyond general discussions of digital transformation to identify specific process-level changes and their operational implications.

The process-level examination of AI transformation mechanisms contributes to a more nuanced understanding of how intelligent technologies alter decision-making, information flows, and operational capabilities in organizational contexts. Rather than treating AI as a monolithic technology, this approach illuminates how different applications create distinct patterns of enhancement across various supply chain functions.

By specifically focusing on international trade areas, this research integrates cross-border considerations into digital transformation theory. The findings highlight how factors such as regulatory diversity, geographical distance, and cultural variation influence both implementation approaches and realized benefits. This integrative approach addresses a gap in existing literature that often examines digital transformation primarily within domestic operational boundaries.

6.2. Practical Implications

For organizations considering AI implementation in intelligent supply chains management, this research suggests an implementation roadmap that begins with process areas demonstrating the most substantial transformation potential: predictive analytics for demand forecasting, logistics optimization, and risk management. Initial implementations appear most successful when they focus on clear operational pain points with measurable outcomes, allowing for demonstrated value while building organizational capabilities.

The findings support a prioritization framework for AI investments based on both transformation potential and implementation complexity. Data analysis and forecasting applications typically offer strong initial returns with relatively straightforward implementation, while more complex applications such as autonomous logistics or automated customs management may require more extensive preparatory work in data infrastructure and process standardization.

Effective management approaches for maximizing value realization include progressive capability development rather than abrupt transitions, intentional cultivation of complementary human skills alongside AI capabilities, and development of governance frameworks addressing accountability and oversight. The case studies demonstrate that successful implementations typically involve sustained, strategic investments rather than isolated technology deployments.

6.3. Future Research Directions

This study highlights several promising directions for future research. Quantitative studies on long-term competitive impacts would address the current limitation of limited performance data, potentially examining how AI implementation influences market share, profitability, and strategic positioning over extended periods. Such studies would require development of standardized metrics that could enable meaningful cross-organizational comparison.

Industry-specific and regional variation analysis would enhance understanding of how these factors influence AI implementation approaches and outcomes. Different industries face distinct supply chain challenges and operate with varying levels of digital maturity, suggesting potential for targeted studies examining how these factors shape AI adoption and effectiveness in international activity.

Integration with other emerging technologies presents another promising research direction. The potential synergies between AI, blockchain, digital twins, and IoT technologies in international supply

chains merit further investigation, particularly regarding how these integrated systems might address current limitations in visibility, trust, and predictive accuracy.

6.4. Concluding Assessment of AI's Transformative Impact

A balanced assessment of AI's impact on international supply chains management must acknowledge both the significant capabilities demonstrated in leading implementations and the substantial challenges that remain. Current AI systems excel at pattern recognition, optimization within defined parameters, and processing of structured information, enabling substantial enhancements in forecasting, logistics, and risk management. However, limitations persist in handling highly uncertain environments, adapting to novel situations without historical precedent, and operating effectively with incomplete information—all common characteristics of international trade.

The long-term outlook for international trade operations suggests continued advancement toward more adaptive, integrated intelligent systems that combine AI capabilities with complementary technologies and human expertise. Rather than complete automation, the emerging paradigm appears to be collaborative intelligence that enhances human capabilities while preserving critical judgment in complex decision contexts.

Policy and ecosystem considerations will significantly influence this developmental trajectory. The evolution of regulatory frameworks for AI governance, development of standards for algorithmic transparency and data sharing, and investment in workforce adaptation will shape how these technologies diffuse. Policymakers, industry leaders, and educational institutions all have important roles to play in creating an ecosystem that enables responsible, inclusive advancement of intelligent supply chain capabilities in global commerce.

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DIGITAL TRANSFORMATION AND BUSINESS PROCESS IMPROVEMENT IN VETERINARY CLINICS

Karolina Beyer[a], Iwona Chomiak-Orsa[b], Zbigniew Pietrzykowski[c], Dominik Rozkrut[d]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *Wroclaw University of Economics and Business, Department of Business Intelligence in Management Wroclaw, Poland*
[c] *Maritime University of Szczecin, Szczecin, Poland*
[d] *University of Szczecin, Institute of Economics and Finance, Szczecin, Poland*

ABSTRACT

Purpose: *The aim of this article is to analyze client expectations regarding modern technologies in veterinary clinics and to assess the potential for implementing intelligent solutions to support their operations. The study focuses on identifying key operational processes that can be improved through digital tools and the challenges associated with their implementation.*

Need for the study: *The dynamic development of technology, rising customer expectations and competitive pressures are forcing a digital transformation also in the veterinary services sector. These facilities need modern management and diagnostic support tools and standardization of operational activities.*

Methodology: *The article is based on a literature review and an empirical study focusing on client expectations and operational challenges in veterinary clinics. The study employs both qualitative (interviews with clinic staff) and quantitative methods (interviews/surveys with pet owners) to gain a deeper understanding of the functioning of veterinary facilities.*

Findings: *The findings indicate that customer expectations and clinic operations are key factors in shaping the digital transformation of veterinary facilities. While process efficiency remains a challenge, the integration of AI and ICT tools can enhance service quality, operational effectiveness and intelligent management.*

Practical Implications: *Understanding customer expectations and operational challenges in veterinary clinics provides valuable insights for their digital transformation. It facilitates the integration of ICT and AI tools, supporting decision-making and enhancing customer service, which ultimately leads to greater competitiveness and improved facility management.*

Keywords: Veterinary business; Veterinary clinics; Business processes, Artificial intelligence, ICT solution; BPMN
Jel codes: M10; M15; O33

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1. INTRODUCTION

Lorem Modern veterinary clinics operate in a rapidly changing environment, where increasing customer expectations, technological advancements, and the need for process optimization require modern management solutions supported by intelligent technologies (Patil, 2009; Nicholls, 1997; Hernandez-Patlan et al., 2023). Digital technologies are increasingly being integrated into veterinary clinics, enhancing various aspects of veterinary care, management, and diagnostics (Biot et al., 2019; Iqbal et al., 2021; Jia et al., 2025). These technologies range from digital devices and software to advanced imaging and telemedicine solutions (Akchurin et al., 2022; El Idriss et al., 2021; Hassan et al., 2004). This direction is not just a trend, but a necessity for establishments that want to maintain business continuity, increase their competitiveness, and improve the quality of the services they provide (Hennessey et al., 2022; Alpi et al., 2011).

One of the key stages in the digital transformation process of veterinary clinics is business process mapping, which allows for a thorough analysis of all activities carried out within the facility (Huntley et al., 2016; Dyndyn, 2024; Bhatia, 2021). Creating process maps allows for the identification of areas that require improvements, the elimination of unnecessary operations, and more effective utilization of available resources. Moreover, it is a key stage for the standardization of processes and the implementation of intelligent ICT technologies.

Intelligent solutions, such as customer relationship management (CRM) systems, appointment scheduling software, artificial intelligence supporting diagnostics, and Internet of Things (IoT) systems monitoring animal health, can significantly contribute to streamlining the daily work of veterinarians (Duggirala et al., 2025; Khan et al., 2022; Karthick, 2020; Beyer, 2023b; Prayitno, Astuty, 2017; Wei et al., 2027; Pico-Valecia et al., 2025). However, their effective implementation requires prior understanding and organization of the processes occurring within the facility, which is possible through business process mapping (Okeke et al., 2024; Järveläinen et al., 2022; Panchal et al., 2024; Brzeziński, Bitkowska, 2022).

The above trends, as well as the authors' observations based on literature research and empirical experience, contributed to the definition of the article's objective, which is the analysis of customers' expectations regarding modern technologies in veterinary clinics and to assess the potential for implementing intelligent solutions to support their operations

As a result of the above, the following research questions were formulated:

RQ1: What challenges and expectations do veterinary clinic clients have regarding modern technologies in patient service processes?

RQ2: How can digital tools and intelligent solutions improve the operations of veterinary clinics?

RQ3: What are the key processes in veterinary clinics that can be optimized through the implementation of modern technologies?

RQ4: What challenges do veterinary clinics face when implementing intelligent technologies?

The study focuses on identifying key operational processes that can be improved through digital tools and the challenges associated with their implementation. The article will also discuss the directions for implementing ICT solutions that are currently possible for business entities such as veterinary clinics. The article was written based on literature research and empirical studies, both quantitative and qualitative in nature.

2. LITERATURE REVIEW

2.1. Veterinary business

The development of the market for veterinary services has increased the interest of researchers in the problems of this industry.

Among the scientific studies one can find publications on the evolution of business models of veterinary clinics (Bonnaud, Fortané, 2021; Beyer, 2021; Beyer, 2019) the potential of the veterinary services market (Lloyd, 2006; MacLachlan, Volk, Doherty, 2024; Khamwon, Speece, 2005; Diez, 2020) methods of managing veterinary clinics (Henry, 2013; Heinke, 2014) applied technical and technological solutions (Fejzić, et al., 2023; Chen et al., 2016; Rooker, 2019) or directions of education (Feakes et al., 2019; Kieves et al., 2007; Bell, Cake, Mansfield, 2021) of future owners and employees of this industry (Whitcomb, 2014; Vandeweerd et al., 2012; Rauch et al., 2021). Animal health care

units are business entities which operate on different principles than standard enterprises in terms of legal regulations. In Poland, veterinary units operate under separate statutory rules that specifically regulate this type of business. The scope, form and manner of business are defined in detail in various laws, including the Act on Animal Health Establishments, the Act on the Profession of Veterinary Surgeon and the Veterinary Chambers, regulations of the Minister responsible for agriculture, regulations of the National and District Veterinary Medical and Veterinary Chamber and others. The definition of an animal treatment facility is contained in the Law on Animal Treatment Facilities, established on 18 December 2003. According to Article 1.1 of the Act, an animal health establishment is an establishment dedicated to the provision of veterinary medicine services, equipped with assets such as premises, apparatus and appropriate equipment corresponding to the scope of services provided.

It should be emphasised that veterinary services may only be provided by authorised veterinarians (Article 2.2 of the Animal Health Establishment Act). The Act also classifies different types of veterinary units according to the size of the unit and the nature of the services provided (Article 4.1).

Despite the above-mentioned regulations and the restrictions that are imposed by the legislator on the veterinary services industry – the market is growing spectacularly both from a global perspective and the market in Poland. Based on the registration data of animal medical facilities maintained by the Veterinary Medical Chambers, in Poland – as at the end of 2023 – there are approximately 7,500 veterinary units.

The number of pet owners is increasing every year, and two-thirds of households' own animals (APPA, 2022). Importantly, pet owners are increasingly treating their pets as family members which increases their willingness to spend disproportionately on providing pets and are keen to invest in their pets' long and comfortable lives. This trend has contributed to an increase in spending on pets. Studies indicate that pet owners are even willing to pay more when their pets require medical attention (spending reached $95.7 billion in 2019 and $103.6 billion in 2020) (APPA, 2022; APPA, 2020). It is worth noting that pet owners have also adopted new shopping habits. They now expect fast, convenient transactions and communication, influenced by their experiences with online shopping, streaming services and delivery options. The trends described above regarding the evolution of customer expectations in the veterinary services market force veterinary operators to use advanced technologies not only in the delivery of treatments and services, but also advanced technologies in the area of communication with customers as well as the processing of customer information resources to optimize services (Huntley et al., 2016; Widmar et al., 2016; Kogan et al., 2019; DeWilde, 2023; Ober, 2019; Knight, 2015; Springer et al., 2022). The use of modern technology in the management of veterinary entities, determines the need for analysis and improvement of business processes

2.2. Business process mapping

Due to the specifications of veterinary clinics' activities, scope of services, business profile, local opportunities and many other determinants – business activities and their organization are properly determined by the individual management method or the conditions in which the clinic operates. In the case of developing output data and individual information solutions, mapping of business data is used, which has access to end users providing "tailored at the level" of the organization (Sepulveda et al., 2017; Bedeley et al., 2018; Li et al., 2002).

Business Process Mapping (BPM) is an element of management that allows for the application, functional and optimization of management in enterprises (Guha et al., 1997; Bowles, Gardiner, 2018; Madison, 2005; Zaini, Saad, 2019). Thanks to the expansion of process management, methods and tools enabling functional visualization are becoming more and more important. As an administrative process tool, mapping allows for mapping activities, their implementation, responsibility and connection between the stages of a given process (Jones-Evans, 2025; Fischer et al., 2020; Attaran, 2004). The scientific literature indicates that risk mapping is not only possible to implement process management but can be determined in the evolution and improvement of performance management systems, Lean Management, reengineering and digitalization of business activities (Dumas et al., 2018; Harika et al., 2021; Wang et al., 2024; Choudhary, Riaz, 2023; Tsakalidis, Vergidis, 2024; Fetais et al., 2022).

Many scientific publications indicate that, effective process mapping enables not only their documentation, but above all creates the basis for searching for solutions enabling their optimization (Jeston, Nelis, 2014; Hrabal et al., 2021; Stachowiak et al., 2023; Bitkowska, Kolterman, 2021). Process visualization facilitates the identification of the so-called bottlenecks and unnecessary activities, which

translates into increased operational efficiency (Jacinto et al., 2022; Taherdoost, Madanchian, 2023; Teixeira et al., 2024; Grzesiak et al., 2024). The forerunners in the field of process improvement were Davenport and Short (1990), who already in the 1990s drew attention to the role of mapping in the context of business process reengineering (Gombe et al., 2024; Zaini, Saad, 2019; Jones-Evans, 2025; Fischer et al., 2020; Fetais et al., 2022).

Modern approaches to process mapping increasingly use IT tools and modeling in the BPMN (Business Process Model and Notation) notation, which was standardized by the Object Management Group (Oruthotaarachchi, Wijayanayake, 2023; Dumas et al., 2023). BPMN enables precise mapping of both functional aspects and information flows in the organization, which makes it useful in digital transformation projects (Weinzierl et al., 2024; Ahmad et al., 2024) Creating maps of organizational processes becomes particularly important in the computerization of entities with various structures and specific business processes, which are determined by the specific nature of the organization and individual organizational solutions (Bell, 2024; Kampmann et al., 2024). This situation applies primarily to clinics and veterinary clinics, where the multitude of organizational structures is very diverse. Therefore, business process mapping can play a key role in the effective digitalization of veterinary clinics in the implementation of IT systems supporting management (Kovach et al., 2024). This applies to solutions such as ERP (Enterprise Resource Planning), CRM (Customer Relationship Management), business records and optimization of medical procedures. The literature on the subject emphasizes that effective digital transformation requires an in-depth understanding of existing processes and their conscious redesign in the context of technological possibilities (Bitkowska, Szymborski, 2023; Weinzierl et al., 2024; Ahmad et al., 2024).

As Dumas et al. point out. (Dumas et al., 2023), process mapping is the foundation of digitalization projects because it enables the identification of processes suitable for automation, improvement or integration with IT systems. Without a clear process map, organizations often implement IT systems without coherent business logic, which leads to inconsistency, data duplication and low user acceptance (Conger, 2011; Madison, 2005; Malinova, Mendling, 2013).

In the context of implementing ERP systems, the literature proves that prior mapping of processes allows them to be adjusted to the system logic or, conversely, allows the system to be adapted to the specificity of the organization (Woźniak et al., 2023; Bradford, Gerard, 2015; Pojasek, 2005; Jacka, Keller, 2009). This process is often called 'fit-gap analysis' and is an important stage in the implementation of integrated systems. This makes it possible to reduce design risk and shorten implementation time.

Process mapping also supports the analysis of functional requirements for IT systems. According to, process maps are helpful in communication between business users and system designers because they reduce the gap between business and technical language. This enables precise definition of use cases, user interfaces and integration points.

In an empirical study, Becker et all showed that organizations that implemented formal process modeling before implementing IT systems achieved a higher level of alignment between the system and operational needs, which resulted in greater efficiency and better use of data.

Taking into account the above considerations resulting from the literature research, the authors of this article conducted research in selected veterinary clinics aimed at identifying the possibilities of developing business process maps in order to assess the possibility of implementing digital solutions that would allow for the optimization of business processes through their automation and the possibility of implementing artificial intelligence methods for predicting events and potential medical procedures that should be implemented in the future in relation to existing patients.

To sum up, business process mapping not only facilitates the digitization of an organization by identifying and improving processes but also serves as a crucial step in preparing for the implementation of IT systems (Wieczorkowski et al., 2022; Yalaho, 2006; Zaoui & Souissi, 2020; Ochara et al., 2018; Ylinen & Pekkola, 2019). Integrating process mapping into a digital transformation strategy enhances the likelihood of successful implementation and strengthens the organization's competitive advantage

2.3. Intelligent ICT solutions in veterinary clinic

Modern veterinary clinics are increasingly adopting intelligent information systems that enhance diagnostics, treatment, and patient data management. Artificial intelligence (AI) plays a pivotal role in the analysis of medical imaging, such as radiographs and ultrasound scans, enabling faster and more

accurate diagnoses. AI-based systems also support the personalization of veterinary services by providing immediate access to comprehensive animal health records, allowing for treatments tailored to the individual needs of each patient. Furthermore, telemedicine is gaining prominence, offering remote consultations and health monitoring, thereby improving access to veterinary care. The implementation of such technologies not only improves the quality of services provided but also increases the operational efficiency of veterinary staff (El Idrissi et al., 2021; Akhtar et al., 2022; Guitian et al., 2023).

Veterinary clinics are increasingly integrating advanced information systems to optimize both clinical care and administrative operations. Practice management software serves as a central tool, facilitating appointment scheduling, patient recordkeeping, inventory control, billing, and client communication. Systems such as VetFile (Vetlie.pl, Lecznica.eu, and Vetoteka (Vetoteka.pl) exemplify platforms that streamline workflow, improve data accessibility, and support efficient clinic administration. These tools offer functionalities including automated appointment reminders, integration with animal ID databases, and cloud-based storage that enables remote access to records.

Artificial Intelligence (AI) technologies are playing an increasingly important role in veterinary diagnostics. AI-powered systems support the interpretation of medical images—such as radiographs, ultrasound scans, and cytological slides—by identifying patterns, anomalies, or pathologies with high accuracy and efficiency (Pondel et al., 2024; Burti et al., 2024; Kour et al., 2021). For instance, diagnostic tools developed by companies like IDEXX (idexxbioanalytics.eu) leverage AI algorithms to automate cell classification and assist veterinarians in making more informed, data-driven decisions. In this context, AI not only reduces the time required for diagnosis but also minimizes the risk of human error and facilitates early detection of disease.

Digital documentation systems constitute another critical technological advancement. Electronic Health Records (EHR) tailored for veterinary practice ensure comprehensive and structured data capture, facilitating real-time access to patient history, treatment plans, diagnostic results, and vaccination schedules (Burti et al., 2024; Akchurin et al., 2022). This accessibility is crucial for both routine care and emergency situations, allowing veterinary teams to coordinate seamlessly and maintain continuity of care. Moreover, digital documentation enables compliance with regulatory standards, enhances traceability of medical decisions, and supports data analytics for performance evaluation and clinical research (Beyer, 2023b).

In parallel, telemedicine platforms provide remote consultation capabilities and allow for continuous monitoring of animal health, thereby extending the reach of veterinary services beyond the physical clinic. These technologies collectively contribute to the modernization of veterinary care by improving diagnostic precision, operational efficiency, and the overall quality of client-patient service delivery.

3. METHODOLOGY

3.1. Participants

The study involved 102 pet owners, purposefully selected from members of a Polish Facebook group dedicated to animal enthusiasts. These participants took part in in-depth interviews (IDI), aimed at assessing their level of satisfaction with veterinary services, identifying encountered problems, and outlining their expectations toward veterinary professionals. Additionally, as part of a case study, the operations of three selected veterinary clinics located in Szczecin were analyzed to deepen the understanding of how ICT and AI tools are implemented in clinical practice.

3.2. Research Procedure

The research was conducted between October 2022 and May 2023 and combined both theoretical and empirical approaches. The first stage involved conducting in-depth interviews (IDI) with pet owners, carried out online from October 2022 to January 2023. The second stage consisted of preparing and executing a case study based on the analysis of three veterinary clinics (February 2025). The aim of the study was to explore the use of ICT and AI tools in animal healthcare and assess their impact on operational efficiency, service quality, and customer satisfaction. The research process also included an analysis of main and supporting business processes. Research procedure presents Fig. 1.

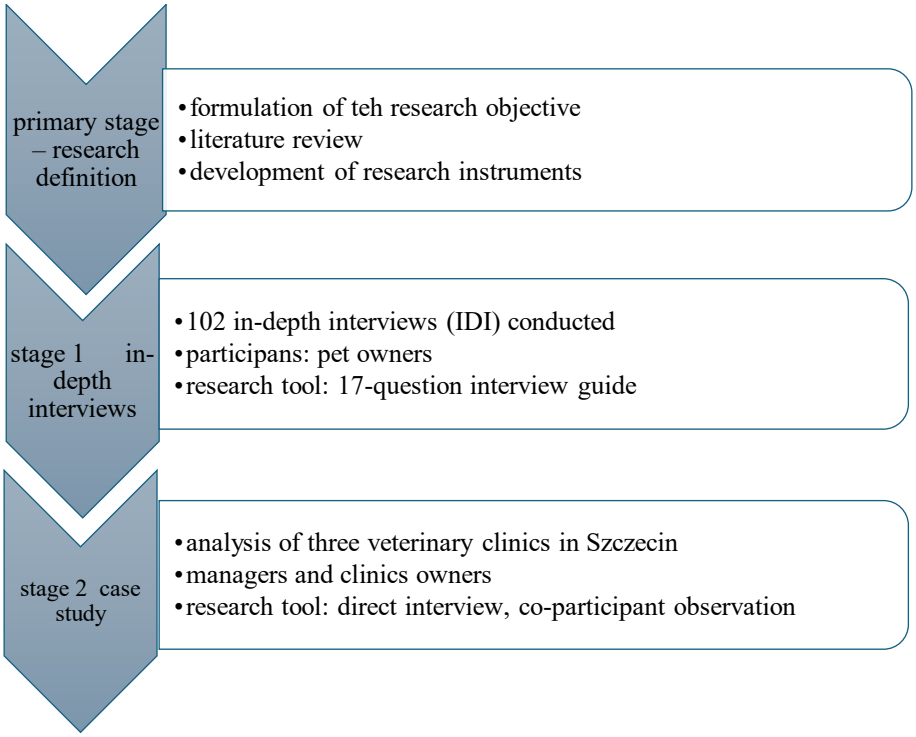


Figure 1. Research procedure
Source: own elaboration.

The use of triangulation of research methods in a defined research procedure allowed the authors to obtain information enabling them to identify the directions of digitization as well as to indicate the most critical business processes that should be digitized in the first stage.

3.3. Research Tools

Several research tools and methods were applied in the study. The primary qualitative method was in-depth interviews (IDI), which enabled the collection of detailed information on pet owners' experiences, expectations, and opinions. The interview guide consisted of 17 questions and followed a semi-structured format. The IDI method, grounded in trust, empathy, and active listening, allowed for the acquisition of in-depth insights relevant to the respondents' personal experiences.

The second tool employed was the business model canvas, used to analyze the functioning of veterinary practices and to evaluate the potential for integrating innovative AI and ICT solutions. The third methodological component was a case study of three selected veterinary clinics, which provided a practical illustration of the application of ICT and AI technologies in both treatment processes and client relationship management. This comprehensive approach enabled a thorough assessment of current practices and the identification of potential areas for improvement.

4. RESULTS

The need for implementing ICT and AI innovations in animal healthcare practices is increasingly evident, as highlighted by the results of this research. The interviews with pet owners revealed several key challenges and areas where veterinary clinics could significantly enhance their operations and service delivery. One of the most cited issues was long waiting times and queues. Specifically, 30% of respondents mentioned that despite having an appointment, they still had to wait in line, pointing to inefficiencies in appointment scheduling and management systems. Additionally, 30% of pet owners indicated that it was not possible to make an appointment in advance, suggesting a lack of automated or online scheduling systems that could streamline the process and reduce waiting times (Beyer, 2023a). Another significant concern raised by pet owners was difficulty in reaching veterinary practices by phone. About 12.5% of respondents indicated that although they were given a contact number, it was

challenging to get through, and missed calls were not returned. This lack of accessibility and communication is a major pain point, especially when urgent consultations or follow-up care are needed. The introduction of AI-powered chatbots or automated phone systems could alleviate this issue, enabling faster and more efficient communication between clients and veterinary practices. Moreover, many respondents expressed a desire for more personalized and convenient services, such as the ability to arrange appointments online, receive reminders for vaccinations or regular check-ups, and access telemedicine consultations. Only 12% of respondents reported that it was possible to arrange an appointment online, while no one mentioned the possibility of a telemedicine consultation. The integration of AI tools for remote consultations, diagnostic support, and appointment management could significantly improve the overall customer experience by providing more flexible and accessible care options.

The interviews also revealed that many pet owners were dissatisfied with the limited availability of specialized services and diagnostic tests at their local veterinary practices. 47% percent of respondents noted that while some diagnostic tests, such as blood work or imaging, could be conducted at their clinic, others required a referral to a cooperating facility with the necessary equipment. This reliance on external referrals may be frustrating for pet owners and highlights the opportunity to improve diagnostic capabilities within veterinary practices. By incorporating more advanced diagnostic tools and AI-driven support systems, veterinary clinics could offer more comprehensive care, reducing the need for external referrals.

In addition to these operational challenges, pet owners highlighted several areas for improvement to enhance their satisfaction with veterinary services. The most frequently mentioned suggestions were increasing the number of specialists (68 responses), improving appointment scheduling (34 responses), expanding the range of services offered (21 responses), and enabling online appointment booking (12%). Many pet owners also expressed interest in receiving reminders for services such as vaccinations (63.4% of respondents reported not receiving any reminders).

In summary, the findings from this research underscore a significant gap in the use of modern ICT and AI technologies within veterinary practices. The integration of digital tools such as online appointment systems, telemedicine, automated reminders, and AI-driven diagnostics could improve the efficiency and accessibility of services, reduce wait times, and enhance communication between pet owners and veterinary staff. These innovations are essential for meeting the evolving needs of pet owners, who are increasingly seeking convenience, specialization, and personalized care. By embracing these technologies, veterinary practices can improve their operations, stay competitive in a rapidly evolving industry, and ultimately deliver better care for animals.

The research conducted among veterinary practice clients prompted further studies focusing on the operational aspects of veterinary clinics. The next study was conducted in February 2025 with the use of IDI. This case study analyzes the customer service processes in three veterinary clinics, identified as X, Y, and Z. Each clinic has unique operational characteristics, but they also share numerous similarities in their customer service workflows. The purpose of this study is to identify common elements and differences, analyze customer interactions, and propose improvements through the integration of technology to enhance customer service efficiency and satisfaction.

The clinics analyzed in this case study have varying staff sizes, service offerings, and appointment systems. Below is an overview of each clinic (Table 1.)

The research employed observational studies and interviews with clinic staff to evaluate the key stages of the customer service process. The following stages were assessed:

- Appointment Booking,
- Arrival and Waiting,
- Consultation Process,
- Post-Visit Protocol,
- Follow-Up Care,
- Main findings.

The analysis revealed a structured approach across the clinics with the following insights:

Common Stages in Customer Service Process:

All three clinics require appointments to be made in advance, utilizing a mix of digital and traditional communication methods. Arriving customers typically wait for their scheduled appointments, which can be affected by unexpected delays due to emergencies or prolonged prior consultations.

Consultation Process:

The consultation involves a thorough medical history review, clinical examinations, and potentially diagnostic testing. Differences were noted in how results and recommendations are communicated to clients—the use of electronic records in X facilitates immediate updating and sending of documents, while Z relies on printed reports.

Post-Visit Procedures:

Upon completion of a visit, clients at Y receive printouts with care instructions, while at X, recommendations may be sent electronically, catering to varying client preferences regarding documentation formats.

Table 1. Characteristics of research subjects

Clinic	Staff	Services	Appointment System
X	**5 veterinarians**	General internal medicine, specialized consultations (surgery, orthopedics, dentistry, regenerative medicine)	Telephone, in-person, system; EDM and paper records
Y	**13 veterinarians**	General internal medicine, specialized consultations (surgery, orthopedics, dentistry, regenerative medicine)	Telephone, in-person, online booking; online booking via WetTermin emphasis on specialized care
Z	**3 veterinarians**	Specialized consultations (neurology, ophthalmology, cardiology, surgery)	Telephone, in-person; uses EDM and paper documentation

Source: own elaboration.

Qualitative research conducted in the form of direct interviews with employees of the surveyed veterinary clinics enabled full insight and description of key processes in selected functional areas of the clinics. The first stage of the analysis was aimed at identifying and describing customer service processes, because this process has a decisive impact on the first impression of customers and very often affects the final customer satisfaction. Conducting an in-depth analysis of processes is the basis for making decisions about the possibility and appropriateness of implementing digital solutions that can support this area of the organization's activities. The broader results from the in-depth analysis of the functioning of veterinary care facilities are presented in the authors' subsequent publications

5. DISCUSSION

High variability in wait times can lead to customer dissatisfaction. Lack of standardized processes, particularly in documentation methods, can hinder efficiency. The communication of post-visit care instructions often relies on clients recalling verbal instructions, leading to stress and misunderstanding. Proposed Solutions:

1. Enhanced Appointment Management Software: Implement a more robust system that provides real-time updates on waiting times and allows clients to check-in digitally.
2. Standardization of Medical Record Keeping: Utilize AI-driven tools to automate documentation processes, reducing manual entry and error rates.

3. Automated Follow-ups: Introduce SMS or email reminders that summarize treatment plans, upcoming appointments, and additional care tips.

This case study illustrates the intricate dynamics of customer service within veterinary healthcare settings. By understanding the unique and shared processes among X, Y, and Z, veterinary clinics can enhance their service delivery, improve patient outcomes, and foster stronger relationships with pet owners.

This structured approach allows for a comprehensive view of how veterinary clinics can evolve their customer service processes using insights from their operational workflows and technology integration strategies.

This case study illustrates the importance of integrating technology into veterinary clinic customer service processes. By standardizing appointment booking, medical record-keeping, and post-visit follow-ups, the clinics can enhance their service efficiency, reduce wait times, and improve customer satisfaction. The use of digital systems will ensure that clients receive timely, accurate information and improve the overall quality of care provided to pets.

Incorporating AI and ICT tools into the daily operations of veterinary clinics can not only automate routine tasks but also foster a more personalized and efficient experience for clients. These improvements would ultimately lead to better patient outcomes and stronger client relationships

6. CONCLUSION

The conducted research highlights the growing role of digital tools and intelligent solutions in optimizing the operations of veterinary clinics. The analysis of customer expectations and case studies of selected clinics indicate that the implementation of modern technologies can significantly improve service efficiency, streamline administrative processes, and enhance patient care quality. However, the results also show that the adoption of digital solutions faces challenges related to financial constraints, staff training, and organizational readiness.

A key finding is that veterinary clinics differ significantly in their business models and operational needs, which suggests that technology implementation should be tailored to individual requirements. The study also emphasizes that process mapping can serve as a valuable tool in digital transformation, helping clinics identify key areas for optimization and automation.

Further research should focus on developing detailed business process maps for veterinary clinics and assessing their impact on the effectiveness of digitalization strategies. Additionally, the integration of artificial intelligence into veterinary practice management remains an open field for future exploration The broader results of the in-depth analysis of veterinary care facilities' operations will be presented in the authors' subsequent publications.

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THE IMPACT OF TRUST ON ADOPTING ARTIFICIAL INTELLIGENCE TECHNOLOGY: THE PERSPECTIVE OF SMALL AND MEDIUM-SIZED ENTERPRISES (SMEs)

Edyta Skarzyńska[a], Karolina Beyer[b]

[a] *Warsaw University of Life Sciences, Management Institute, Warsaw, Poland*
[b] *University of Szczecin, Institute of Management, Szczecin, Poland*

ABSTRACT

Purpose: *This study aimed to analyze the influence of trust on the acceptance of artificial intelligence (AI) technologies among small and medium-sized enterprises (SMEs). Based on the modified Technology Acceptance Model (TAM), the relationships between trust and perceived usefulness, ease of use, attitude, and implementation intention were examined.*

Need for the study: *In dynamic digital transformation, SMEs face limited resources, low technological competence, and uncertainty about AI's ethical and functional aspects. Previous studies have rarely considered trust as a central factor in AI adoption models in the SME sector. Filling this research gap became the main motivator of this project.*

Methodology: *A quantitative research method based on structural equation modeling (SEM) was used, using a five-point Likert scale questionnaire. Data were collected from the management staff of SMEs in Poland. The relationships between constructs were analyzed using confirmatory factor analysis (CFA) and model fit indices.*

Findings: *The results confirmed the significant influence of trust on perceived ease of use, usefulness, and attitude towards AI and indirectly on implementation intention. Trust was a key factor supporting the positive perception and acceptance of AI technologies in the SME environment. The model achieved high construct validity and a good fit to empirical data.*

Practical Implications: *The study suggests strengthening trust in AI – through algorithm transparency, user education, certification, and ethical frameworks – should be essential to SMEs' digital transformation strategies. The results provide practical guidance for decision-makers, policymakers, and technology providers on effectively supporting AI adoption in the SME sector.*

Keywords: Artificial Intelligence; Trust; Technology; SMEs; Digital Transformation; SEM; Technology acceptance model.

Jel codes: O33, M15, L26

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1. INTRODUCTION

Small and medium-sized enterprises (SMEs) play a fundamental role in the structure of modern economies. This sector is the main driver of employment growth, innovation, and sustainable economic development (Khan et al., 2024). SMEs generate a significant number of jobs and shape the socio-economic landscape, especially in the context of local communities. Their activities, often managed by middle-class owners, contribute to maintaining social stability and supporting economic inclusiveness. Therefore, it is important to provide these enterprises with appropriate support – financial capital, access to knowledge and modern technologies, and psychological or advisory support (Lemos et al., 2022).

Only comprehensive support allows SMEs to maintain competitiveness, operational resilience, and institutional durability (Ingalagi et al.2021). Over the past two decades, there has been a rapid acceleration in the development of digital technologies, which has translated into a significant transformation of the organizational structures of enterprises. Progress in the Internet, data analytics, automation, and solutions based on artificial intelligence (AI) has meant that enterprises – regardless of the scale of their operations – have to adapt to new realities. SMEs are increasingly using modern technologies to gain a competitive advantage, streamline internal operations, and improve the quality of customer service. As Drydakis (2022) points out, this sector is actively looking for AI solutions, treating it as a tool to strengthen its market position. These technologies enable, among others, the analysis of consumer behavior in real-time, generating personalized recommendations, optimizing marketing campaigns, or supporting decision-making processes. However, effective implementation of AI in SMEs depends on several factors. As Almashawreh et al. (2024) note, access to technology alone is not enough – an appropriate organizational structure and institutional readiness are also necessary (Badghish & Soomro, 2024).

Implementing AI should not be treated only as a technological project but as an element of a broad transformation strategy. A holistic approach is necessary, encompassing changes in IT infrastructure, organizational culture, staff competencies, and management procedures. Only then can the company fully use the potential of artificial intelligence and obtain lasting benefits from its implementation (Govori and Sejdija, 2023).

The use of AI in SMEs is primarily associated with the automation of operational processes, which translates into cost reduction, increased efficiency, and greater scalability of operations (Ulrich et al, 2021). However, despite numerous benefits, the effectiveness of AI technology implementations in this sector is often limited by a lack of trust. Trust is a key factor influencing the decision to adopt new technological solutions.

Small business owners, who often have limited resources, are wary of complex algorithmic systems, especially in the context of the lack of full understanding of their operation, personal data protection, or potential decision-making biases (Crockett et al., 2021). For this reason, building trust in artificial intelligence should become a priority of digitalization policy and innovation strategies. Activities such as increasing the transparency of algorithms, creating a clear legal framework, offering certified technological solutions, and organizing training and workshops for entrepreneurs are important here.

In an environment where specialist knowledge and technical infrastructure are lacking, trust acts as an institutional buffer, allowing for rational decisions to be made despite uncertainty and risk. In the long term, developing trust in AI can contribute to increasing companies' efficiency and adaptability to market changes (Skarzynska & Paliszkiewicz, 2025). Companies that can integrate modern technologies into their daily operations can generate greater value, operate more flexibly, and compete locally and internationally.

This study aims to provide an in-depth analysis of the relationship between trust and other key variables influencing the effectiveness of AI implementation in the SME sector.

The study puts forward six hypotheses to verify the relationship between trust and perceived usefulness, ease of use, attitude toward technology, and implementation intention. It is assumed that:

(H1) Trust has a positive effect on the perceived usefulness of technology.

(H2) Trust has a positive effect on attitude towards AI.

(H3) Trust has a positive effect on the assessment of the ease of use of AI.

(H4) Perception of usefulness affects attitude towards technology.

(H5) Perceived ease of use also affects attitude.

(H6) Attitude towards AI has a positive effect on implementation intention.

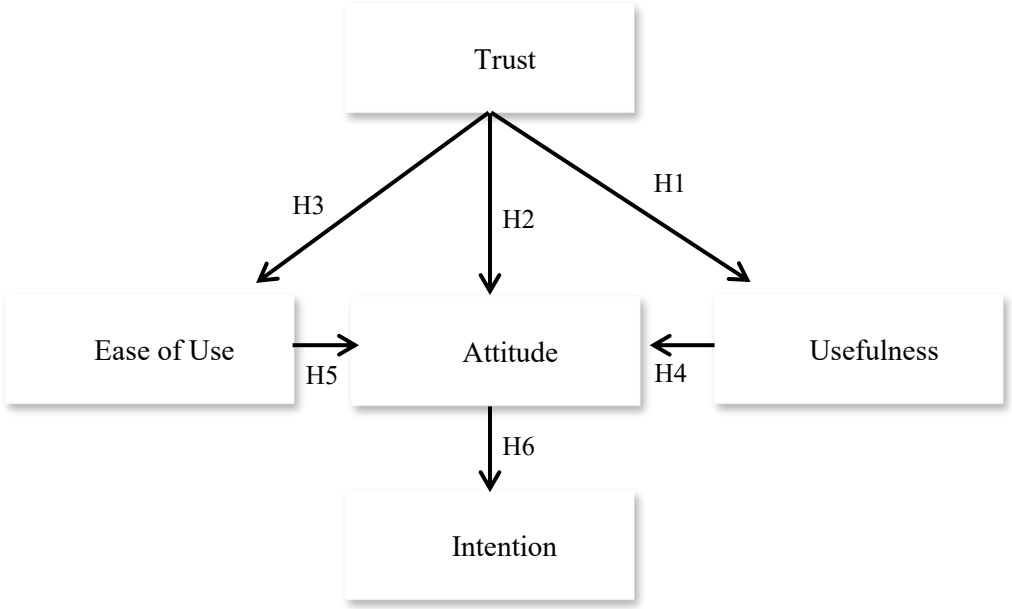


Figure 1. The conceptual framework

Source: own elaboration.

Verifying the above hypotheses will allow for a better understanding of the mechanisms influencing implementation decisions in the SME sector and for formulating recommendations for policymakers, business support institutions, and entrepreneurs themselves. Understanding the role of trust as a factor moderating the implementation of digital technologies is crucial for effectively supporting digital transformation in the knowledge-based economy (Paliszkiewicz & Skarzyńska, 2022).

2. LITERATURE REVIEW

2.1. Trust in AI: Challenges and Adoptionin SMEs

As small and medium-sized enterprises (SMEs) navigate the rapidly evolving digital landscape, trust in technology and especially artificial intelligence (AI) has become a key determinant of successful adoption. While large enterprises exhibit higher AI adoption rates across various dimensions of project management (Tominc et al., 2024), SMEs encounter significant barriers, including trust deficits, knowledge gaps, infrastructure limitations, and a shortage of skilled professionals (Zavodna et al., 2024). Overcoming these obstacles requires a strategic approach that fosters trust through transparency, ethical compliance, and tailored support systems. Factors influencing AI adoption in SMEs include top management commitment, organizational readiness, external support, employee adoption, and competitive pressure (Ingalagi et al., 2021). Despite these challenges, AI and other modern technologies are increasingly important for SMEs to remain competitive (Hansen & Bøgh, 2020). To overcome implementation barriers, SMEs require targeted strategies, including better understanding of AI applications, improved access to expertise, and development of tailored solutions that address their specific needs and resource constraints (Tominc et al., 2024; Zavodna et al., 2024).

Trust in AI is contingent on multiple interrelated factors, including top management commitment, organizational readiness, external support, employee adoption, and competitive pressure (Ingalagi et al., 2021). Research indicates that many SME decision-makers lack confidence in AI's ability to generate reliable and ethical outcomes, which inhibits widespread adoption (Szedlak et al., 2021). Additionally, SMEs often struggle with aligning AI applications with their operational needs due to insufficient information and training resources (Zavodna et al., 2024). Ethical concerns further compound the trust

deficit (Wang, 2022). Many AI governance frameworks prioritize large enterprises, leaving SMEs without clear ethical guidelines that address their specific challenges (Soudi, Bauters, 2024). The absence of standardized AI accreditation processes contributes to uncertainty regarding compliance with ethical standards, regulatory frameworks, and data protection measures (Rawashdeh et al., 2023). Consequently, SME leaders remain hesitant to invest in AI-driven solutions, fearing legal ramifications and reputational risks (Zavodna et al., 2024). It should be noted that specific factors such as access to knowledge, transparency, explainability, certification, and self-imposed standards and guidelines are important for increasing overall trust in AI (Bedué, Fritzsche, 2021).

Developing reliable artificial intelligence (AI) solutions, both in academia and industry, requires addressing multiple dimensions, including legal, social, ethical, public perception, and environmental factors. While numerous guidelines, principles, and toolkits have been introduced worldwide, their practical implementation—particularly among small and medium-sized enterprises (SMEs) – remains limited due to insufficient knowledge, expertise, and resources (Crockett et al., 2023).

Enhancing transparency and explainability in AI systems is essential for building trust among SME stakeholders. AI solutions must provide clear insights into decision-making processes, allowing users to interpret algorithmic outputs effectively. Studies emphasize that SMEs are more likely to adopt AI when they understand how it functions and can assess its reliability in real-world applications (Szedlak et al., 2021). Furthermore, trust in AI can be reinforced by introducing sector-specific ethical frameworks and accreditation mechanisms. A tailored accreditation system would ensure that SMEs have access to reliable AI solutions that adhere to industry-specific ethical standards (Marwa Samih Soud). Establishing transparent auditing mechanisms and AI certification processes can mitigate concerns regarding biased decision-making and data privacy violations, fostering a regulatory environment conducive to responsible AI adoption (Soudi, Bauters, 2024).

Building AI trust in SMEs necessitates targeted training programs that address the unique knowledge gaps within smaller organizations. A lack of AI literacy remains a critical barrier to adoption, as SME employees and managers often lack the expertise to evaluate AI's potential benefits and risks (Soudi, Bauters, 2024). To address this issue, SMEs require accessible educational resources, including case studies, best practices, and hands-on training modules designed to enhance their AI capabilities. Additionally, collaborative initiatives between policymakers, industry leaders, and academic institutions can support SMEs in their AI adoption journey (Kumar, 2022). By facilitating AI knowledge-sharing platforms and mentorship programs, stakeholders can provide SMEs with the necessary guidance to navigate ethical, technical, and operational challenges (Szedlak et al., 2021).

It should be emphasized, that trust in AI is a cornerstone of successful AI adoption in SMEs. Addressing concerns related to transparency, ethical compliance, and AI literacy is essential for fostering confidence among SME decision-makers. By implementing sector-specific accreditation, explainable AI solutions, and targeted training programs, SMEs can overcome trust-related barriers and leverage AI for enhanced competitiveness and innovation. In the broader context of Industry 5.0, prioritizing human-centric AI approaches will be instrumental in unlocking the full potential of AI technologies while ensuring ethical integrity and regulatory alignment (Enshassi et al., 2024).

3.METHODOLOGY

3.1. Participants

The study focused on managers employed in Poland's small and medium-sized enterprises (SMEs) sector. The sampling method was used to obtain primary data from a wider group of respondents. A purposive sampling technique (convenience sample) was used to increase the possibility of generalizing the results, covering 350 managers of SMEs in which AI technology was implemented. Of these, 295 complete responses were obtained, corresponding to a return rate of 84.29% compared to the initially assumed number of participants. This group included people holding managerial positions at various levels of management – from operational managers to business owners. The respondents represented various industries like trade, services, manufacturing, and information technology. Most participants had higher education (87.11%) and at least several years of professional team management or business experience. Their knowledge and practical experience made them a valuable source of information in the context of the analyzed research variables.

3.2. Research Protocol and Stimulus

The primary data for this study was collected using a self-administered questionnaire. The survey questions were developed based on a thorough analysis of the literature. They were prepared in Polish to ensure respondents fully understood the content and to obtain reliable answers. The data collection process lasted from February 15 to March 10, 2025. A research questionnaire containing items measuring trust, usefulness, ease of use, attitude, and behavioral intention was used as a stimulus. The questions were formulated clearly and understandably to give respondents accurate answers.

3.3. Research Apparatus

The questionnaire began with an introductory section that presented the study objectives, the principles of voluntary participation, the possibility of withdrawing from participation at any stage, and ethical issues related to data processing. The following section included questions about demographic data and key aspects of the study. The main variables were assessed using a five-point Likert scale, where one meant 'strongly disagree' and five meant 'strongly agree.' The scales for measuring trust, attitude, and behavioral intention were adapted from the study by Al-Momani and Ramayah (2023). At the same time, the items regarding perceived usefulness and ease of use were based on the work of Alsharo et al. (2020).

3.4. Analysis of Measurement Data

In order to investigate the role of perceived trust in the process of implementing AI technologies in the SME sector, a multi-stage analytical approach was used. The first stage included the analysis of descriptive statistics, such as arithmetic means, standard deviations, and correlations between variables, which allowed for the preliminary identification of patterns and relationships in the empirical data (Al.-Rahamneh et al., 2023). A factor analysis (CFA – Confirmatory Factor Analysis) was conducted in the next stage. Factor Analysis) to confirm the construct validity of the adopted latent variables. Then, structural equation modeling (SEM – Structural Equation Modeling) allowed for the simultaneous estimation of the relationships between variables and verification of the research hypotheses (H1–H6). The analyses were carried out using SmartPLS 4 software, which allows for the analysis of models using the Partial Least Squares (PLS-SEM), appropriate for exploratory research and composite models. The hypothesis verification process included assessing the significance of paths between variables based on the values of regression coefficients and the level of statistical significance ($p < 0.05$). The reliability and validity of the measurement model were assessed separately. Reliability was assessed using the Composite coefficients Reliability (CR) and Cronbach's Alpha, while the values of the average confirmed convergent validity explained variance (AVE). The assumption of data normality and the values of correlation coefficients between variables were also checked.

4.RESULTS

For grade properties, psychometric applied tools research was carried out analysis model measuring, including assessment accuracy convergent, relevance discriminatory, and reliability internal construction latent. Results obtained for attempts SME managers in Poland indicate a high-quality model measuring and adequacy to the specificity of the examined context (Table 1). Relevance convergent verified by indicator average explained variance (AVE, Average Variance Extracted). All constructs have reached AVE values exceeding the recommended threshold of 0.50, including ranges from 0.603 to 0.761. This means that over 60% of the variance position observed is explained by corresponding latent variables, which confirms the cohesion content scale and its ability to measure assumed constructs. The highest AVE value was obtained for construct perceived usability, which suggests a strong link position with a given theoretical variable. Reliability construction was rated by use of coefficient reliability composite (CR, Composite Reliability), which in all cases exceeded the minimum value recommended in the literature item ($CR > 0.70$). CR values were within ranges from 0.801 to 0.861, confirming internal tools' high cohesion. The highest reliability was noted for variable perceived trust ($CR = 0.861$), which may testify to high homogeneity position measuring in this area. All standardized loads they contained ranged from 0.588 to 0.819 and were important statistically. This confirms the strong compounds between observable variables and their corresponding latent constructs.

No low values load factorial indicates accurate selection position measuring and lacks the need to eliminate them from further analysis.

Table 1. Validity and reliability of the questionnaire

Constructs	1	2	3	4	5
1. Trust	**0.672**				
2. Usefulness	0.482	**0.684**			
3. Ease of use	0.621	0.608	**0.589**		
4. Attitude	0.636	0.581	0.498	**0.618**	
5. Behavioral intention	0.611	0.525	0.683	0.598	**0.701**
Number of items	4	5	5	3	3
Range of factor loadings	0.672–0.812	0.588–0.731	0.596–0.693	0.762–0.819	0.715–0.782
Average explained variance (AVE)	0.692	0.761	0.603	0.621	0.665
Maximum shared variance	0.514	0.498	0.493	0.487	0.531
Composite Reliability (CR)	0.861	0.813	0.823	0.801	0.812

Source: own elaboration.

Discriminant validity was assessed according to the Fornell-Larcker criterion. The square roots of the AVE values (placed on the diagonal of the correlation matrix) exceed the correlations between the constructs, confirming that the studied variables represent separate and identified theoretical concepts. This indicates a lack of semantic overlap between the variables and the tool's ability to distinguish between them. This may indicate a higher level of digital maturity, greater trust in new technologies, and a clearer internalization of measurement concepts in the Polish SME sector. Such results confirm that the applied measurement model is statistically correct and culturally appropriate to local conditions.

The results of path analysis conducted within the framework of structural equation modeling (SEM) indicate statistically significant relationships between all the studied constructs. All t-statistic values exceed the threshold value of 1.96, and each path reached the significance level of $p < 0.001$, indicating a very high confidence level in the assumed relationships.

Table 2. Structural Equation Path Coefficients Among Variables

	B	Beta	SE	T
Trust → Usefulness	0.239	0.314	0.023	10.39
Trust → Attitude	0.261	0.298	0.026	10.04
Trust → Ease of use	0.268	0.336	0.025	10.72
Usefulness → Attitude	0.204	0.269	0.028	7.29
Ease of use → Attitude	0.312	0.359	0.027	11.56
Attitude → Behavioral intention	0.347	0.371	0.029	11.97

Note : $p < 0.05$ = *, $p < 0.01$=**, $p < 0.001$=***

Source: own elaboration.

Trust significantly affected Usefulness, Attitude, and Ease of Use, with standardized Beta coefficients of 0.314, 0.298, and 0.336, respectively. A particularly strong effect was observed in the path from trust to ease of use, suggesting that people who trust a technological system perceive it as more intuitive and easy to use. Furthermore, usability and ease of use significantly affected the user's attitude towards the technology (Beta = 0.269 and 0.359). These results are consistent with the Technology Acceptance Model (TAM) assumptions, in which cognitive constructs shape the attitude

leading to the decision to accept the system. The strongest relationship in the entire model was observed between attitude and behavioral intention, where the beta coefficient value was 0.371, which had a high statistical significance (T = 11.97). This means that the more positive the attitude towards technology, the greater the readiness to use it. The presented results confirm the coherence and adequacy of the theoretical model, in which trust plays a key role in shaping the perception of usefulness and ease of use, and these, in turn, affect the user's attitude and intention to implement the technology. In the context of the study conducted among SME managers in Poland, this model effectively explains the mechanisms behind adopting modern technological solutions, including artificial intelligence.

5.DISCUSSION

In the face of dynamic technological changes, small and medium-sized enterprises (SMEs) are faced with the need for structural and operational transformation, which is increasingly being catalyzed by artificial intelligence (AI). However, integrating AI-based solutions is not limited to the technical aspect - it is a profound transformation of how an organization functions. It requires not only the modernization of infrastructure and the implementation of new digital tools but also the reconstruction of decision-making processes, organizational culture, and knowledge management models. As noted by Almashawreh et al. (2024), effective AI implementation depends not only on the level of technological advancement but also on structural organizational readiness, including the openness of management, digital competencies of employees, and the ability to adapt to learning. Similarly, Schwaeke et al. (2024) point to the need for a holistic approach to innovation management. AI is not perceived as an incidental technological implementation but as a long-term component of the company's development strategy. Only such an approach allows for achieving the full benefits of implementing systems based on artificial intelligence, such as increasing operational efficiency, improving the quality of business decisions, or personalizing the product offer. In this context, trust in artificial intelligence appears to be one of the key determinants of the effective adaptation of this technology in the SME environment.

Trust acts as a factor that enables the transition from technological possibilities to practical use. It includes trust in the technology itself - its operation, transparency, and reliability - and in the organizational processes supporting its implementation, such as leadership, training, quality control processes, or applied ethical standards. Trust takes the form of a compensatory mechanism in conditions of limited financial resources, deficits in technological competencies, and the lack of a clear regulatory framework. In practice, this means that companies that trust new technologies are more willing to take risks related to their implementation, even if they do not have full knowledge of their operation. Trust also helps to alleviate the fear of the unknown, reduce the cognitive barrier, and mobilize to make strategic decisions in situations of uncertainty.

The results of this empirical study confirm the importance of Trust as a central variable in the process of AI adoption in SMEs. As the analysis of the structural model showed, Trust directly affects the perceived ease of use ($\beta = 0.336$), perceived usefulness ($\beta = 0.314$), and attitude towards technology ($\beta = 0.298$). This means that the greater the respondents trust AI-based systems, the more likely they perceive these technologies as user-friendly, intuitive, and useful in everyday operational activities. This is consistent with the classic TAM (Technology Acceptance Model) assumptions, which assume that perceptions regarding usefulness and ease of use are the main determinants of attitude toward new technology, which conditions implementation intention. The strongest relationship was observed between attitude and implementation intention ($\beta = 0.371$), which indicates that managers' positive attitude towards AI translates into their readiness to implement these solutions in practice. Importantly, in the analyzed model, Trust also indirectly affects this readiness - through its impact on earlier cognitive components. Such results allow us to consider Trust as an intermediary variable with high predictive power in the digital transformation process of small and medium-sized enterprises. The discussed results are also consistent with the observations of other researchers. Dörr et al. (2024) emphasize that trust in predictive algorithms and decision support systems is a condition for their acceptance in management practice. Ekuma (2024) and Oldemeyer et al. (2024) indicate that the AI implementation strategy should include not only technological aspects but also a social component - including educational activities, transparency of algorithms, certification of systems, and implementation of transparent ethical principles. All these elements support building Trust among employees and management staff, which

translates into higher implementation effectiveness and reduced risk of failure. In conditions of economic instability, high volatility of the environment, and constantly growing competitive pressure.

Trust in technology is no longer just a supporting factor - it becomes a condition for survival. As shown by Mishrif and Khan (2023), SMEs that demonstrate higher levels of Trust in digital technologies are more likely to implement them and are better prepared to respond to crises, such as the COVID-19 pandemic or supply chain disruptions. Trust thus acts as a strategic buffer, increasing organizational resilience and the ability to recover from external shocks. More broadly, the results of this study indicate the need to redefine the approach to technology implementation in SMEs – from technocratic to integrated, taking into account both technological and psychosocial aspects. Building trust should become an integral part of innovation policies, public support programs, and strategies offered by AI solution providers. This includes, among others, promoting transparency in algorithm design, creating sectoral codes of ethics, implementing certification mechanisms, and providing access to education and development resources for SME employees.

Finally, it should be emphasized that Trust in AI is not a static construct – it is subject to dynamic changes depending on the user experience, the technological maturity of the organization, and the institutional context. In this sense, trust management should be treated as a continuous process, requiring systematic monitoring and updating of the strategy. Then, will it be possible to fully exploit the potential of artificial intelligence to support the sustainable development of the SME sector in the digital economy.

6.CONCLUSION, LIMITATIONS, AND FURTHER RESERCH

The integration of artificial intelligence (AI) technology into the organizational structure of small and medium-sized enterprises (SMEs) goes far beyond its technical aspect. It is a complex process of organizational, cultural, and strategic transformation. Implementing AI-based solutions requires appropriate IT infrastructure, a transformation of thinking and decision-making, and the redefinition of internal management processes. In this context, trust should be perceived as a strategic resource that plays a mediating role in adapting to new technologies. It is a mechanism that limits cognitive uncertainty, strengthens implementation intentions, and supports the adaptive flexibility of organizations operating in a turbulent and unpredictable environment. Perceiving trust as a component of organizational capital allows for a deeper understanding of the mechanisms of managing technological change, especially in the SME sector, which requires specific implementation strategies due to limited access to resources – both material and non-material.

The results of empirical studies indicate that trust plays a key role in shaping the perception of the usefulness of AI solutions, determining decision-makers attitudes and the level of their acceptance of technology. A high level of trust correlates positively with the willingness to implement innovations, lowers the threshold of resistance to technological change, and promotes internalizing new operational practices. Trust cannot be treated as a one-dimensional phenomenon – it includes both a rational component (based on the assessment of the credibility and effectiveness of technology) and an affective component (related to the emotional attitude of users towards AI). A multidimensional approach allows us to capture its complex structure and function in transformation processes.

The conclusions from the research indicate the need to adopt a holistic paradigm for implementing artificial intelligence technologies, in which infrastructural activities should go hand in hand with educational, ethical, and communication initiatives. Building algorithmic transparency, ensuring compliance with regulations on personal data protection, and disseminating knowledge about the functioning of AI are becoming key determinants of the institutionalization of trust in the context of digital transformation. In the long term, trust can be considered a strategic organizational buffer that increases enterprises' resilience to external disruptions, supports business continuity, and enables the development of sustainable business models. Trust also facilitates investment decisions in conditions of incomplete information and high technological complexity, making it a fundamental element supporting long-term organizational innovation. Despite the cognitive value of the proposed theoretical model, its analytical scope was limited to basic cognitive constructs such as usefulness, ease of use, attitude, and implementation intention. In order to deepen the analysis, future studies should consider additional moderating and mediating variables such as technological risk perception, data privacy concerns, the

level of digital maturity of the organization, and the institutional and regulatory context. Integration of these variables could provide a more comprehensive picture of psychosocial and organizational conditions that determine the effectiveness of AI implementations in the SME sector. It is also recommended that longitudinal studies be conducted to capture the dynamics of processes related to building trust, transforming attitudes, and making implementation decisions over a longer time horizon.

Considering the temporal dimension would allow for identifying adaptive trajectories and the evolution of artificial intelligence perception in the context of organizational experience. Given the ongoing expansion of AI technology in various sectors of the economy, including education, it would also be advisable to expand the field of analysis to include issues related to the relationship between transformational leadership, leaders' emotional competencies, and the level of organizational involvement in the technology implementation process. Examining these interactions can contribute to developing effective models of technological change management embedded in an ethical, social, and institutional context.

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28th European Conference on Artificial Intelligence (ECAI 2025)

POSSIBILITY OF USING ARTIFICIAL INTELLIGENCE AND INTELLIGENT MANAGEMENT IN PERFORMANCE MANAGEMENT – SELECTED ISSUES AS A VOICE IN DISCUSSION.

Ilona Kędzierska-Bujak[a]

[a] *University of Szczecin, Institute of Economics and Finance, Szczecin, Poland*

ABSTRACT

Purpose: *The main aim of this article is to present some possibilities which artificial intelligence (AI) and intelligent management (IM) can give to companies in achieving strategic objectives by enhancing decision-making and organizational performance.*

Need for the study: *AI offers new capabilities in data collection, interpretation, and analysis, supporting comprehensive management in areas such as strategic planning, human resources management or performance evaluation. Effective performance management relies heavily on data processing, making AI and IM valuable tools in this domain.*

Methodology: *The main methodology used for this article is the literature review as well as deduction and induction methods and interview conducted with the owners of an electrical company.*

Findings: *When used effectively, artificial intelligence and intelligent management can be a great support for performance management and in achieving the strategic goals (company goals as well as employees personal goas). They can also fasten preparing some documents, create reports or even writing simple computer programs which can help in gathering some important information.*

Practical Implications: *Evolution of the artificial intelligence was from long time expected. Since it is improving and gives more option, its usefulness for company managers is increasing. However, their cannot forgot, that this technology is still not sufficient, can give some false, incomplete or mistaken information, what can lead to wrong decisions or create opportunities for data theft by unauthorized individuals. Finding the possibilities of using AI and IM in performance management is important and probably soon will be required by business environment.*

Keywords: artificial intelligence, intelligent management, performance management, strategic goals, human resources management

Jel codes: C88, D83, M12, M15, O33

1. INTRODUCTION

The modern economy operates in an era of rapid technological development. The increasing need for information, received data complexity, employee expectations regarding achieving life-work balance, pursuit of the established strategic objectives, dynamic market changes and the growing importance of technology, create the situation when managers are presents with a significant challenge - namely, the need to reconcile multiple goals within the decision-making process. It is not easy for them, however

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they can use many concepts of the management, performance management or IT solutions which are provided by programmers including more and more popular nowadays artificial intelligence.

The dynamic evolution of the artificial intelligence from last few years, gave new possibilities for managers. The artificial intelligence (AI) definition from European Parliament Artificial Intelligence Act is "An AI system is a machine-based system designed to operate with varying levels of autonomy and that may exhibit adaptiveness after deployment and that, for explicit or implicit objectives, infers, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments" (Article 3). This definition points that AI is based on data (another words 'playing data') and algorithms (another words "the running models"). (Lehr, Ohm, 2017, p. 655). Proper use of the artificial intelligence can make companies more agile, innovative, and adaptable, by allowing them to better respond to rapidly changing market conditions. However, the use of AI to support organizational agility also brings challenges, such as the need for continuous employee education and adaptation, change management, and the ethical aspects of using technology (Chen, Li, 2021).

The link between artificial intelligence and intelligent management is increasingly emphasized in the literature, reflecting a growing interest in this topic. Researchers try to find out how emerging technologies can support more adaptive, data-driven decision-making processes as well as performance management in companies. Intelligent management (IM) is a concept that refers to the systematic collection, analysis, and dissemination of information to support decision-making processes in organization. It involves integrating various forms of intelligence, such as business intelligence, market intelligence, or competitive intelligence, to enhance strategic planning and operational efficiency. The point of intelligent management is to handle information and insights it effectively. Using of the intelligent management by managers allows company to leverage relevant data to make informed decisions, stay competitive, and adapt to changing environments. Companies which use IM gather many data from various sources such as market research, social media or direct interactions with customers.

Responsible management of entities involves striving to implement the organization mission, vision and strategy. Progress of the entity goals achieving monitoring involves measuring performance and connected with it performance management. If company want to achieve its goals, managers must collect data, analyze it and then interpret often very large amounts of data and information to gain useful knowledge. Performance management (PM) gives many concepts, such as very popular balanced scorecard, but also tableau de board, performance prism, total performance scorecard or scandia navigator. This concepts in contrast to the first performance measurements requires not only financial information but also nonfinancial information. Performance management can be successful if managers will be able to not only gather data but also use them to motivate employees and make evaluation of the decision they already made or predictions of the effects for future decision variants. In performance management knowledge is very important as well as in intelligent management. Responsible companies will often mix this concept of management. Also, systems and programs with artificial intelligence can help managers in faster obtaining information necessary for effective company management.

The aim of this article is to point some possibilities of using both artificial intelligence and intelligent management in performance management, as a way to enhance business entity efficiency as well as accelerate its achievement of strategic goals.

2. LITERATURE REVIEW

It can be said that from the beginnings of humankind history an innovation is something what can be called the main engine of an improved standard of living. At the same time, the process of innovation creates situations when conventional technologies can become or already starts to become obsolete. The current knowledge-based economy already uses and sees potential in cloud computing, big data, data science, artificial intelligence, which are still rising technologies but already scientist notice that they may create winners or losers in business world (Soni, Sharma, Singh, Kapoor, 2020, p. 2201). Many technologies exist for even few decades but were not viable for commercial use or were not in mainstream use, even if they were pointed as usefulness and with huge opportunities for making decision-making process easier and with pointing out some shortcomings of the technologies at that time (DeWitt, Gray, 1992, p.97).

In last few years popularity of the artificial intelligence is growing. However, the idea of AI comes from even BC era from philosophers. Most of them were thinking about some work automations, and firstly they created some kind of robots like knight made by Leonardo da Vinci (Sobczak, 2019, p. 49). On the other hand, the notion of machines with human-like intelligence was present even before previous century. This kind of machines were mentioned in book "*Erewhon*" written by Samuel Butler in 1872. With television development interest in AI grows. People start to think and dreamt about robots who might look like humans and think as well as act like humans.

First time when officially artificial intelligence was named in this way was when J. McCarthy, M. L. Minsky, N. Rochester, C.E. Shannon in August 1955 sent to group of researchers "A proposal for the Dartmouth summer research project on artificial intelligence" (McCarthy, Minsky, Rochester, Shannon, 1955), inviting them for summer workshop. Since then, the development of AI has evolved as well as tasks given to it to be resolved.

Initial scholarly discussions on the application of artificial intelligence in making-decision process began to emerge in the academic literature as early as the 1980s. Boullart pointed out that AI can be used in expert systems, to help in making right decision (Boullart, 1988, p. 52). Through the last three decades were many publications about artificial intelligence systems which support company manage on different levels of the management. It is worth to mention such publication as "*Intelligent management system (IMS)*" from 1992 (Tu, Li, Sun, Lin, 1992, p. 145), in which the authors point about generation of the management support system based on AI and offered by this technology methods such as expert systems, knowledge engineering, pattern recognition, image processing, natural language understanding or neural network. One of their conclusions was that intelligent management system development is based on the combination of artificial intelligence and management science, as well as knowledge and systems engineering, computer technology and communication technology, software engineering and information engineering (Tu, Li, Sun, Lin, 1992, p. 151).

The concept of performance management has been evolving for many decades, but its formal study and discussion began to gain traction in the mid-20th century. One of the earliest publications that focused on performance appraisal, a key component of performance management, was in the 1950s. In 1954, Peter Drucker published "The Practice of Management", which introduced concepts related to management effectiveness and performance evaluation. This work laid the groundwork for modern management practices, including performance management systems.

In the following decades, particularly through the 1980s and 1990s, emerged more structured performance management, often incorporating strategic planning and employee development. Researchers and practitioners began to publish various frameworks, describing models, and tools aimed at enhancing entity performance management. Before 1992 performance management systems were simple (Kowalewski, 2011, p. 251; Nelly, Adams, Kennerley, 2007, p. 145–150). Mostly entities measured financial result and used various financial measures. The biggest usefulness AI for performance management will have for multicriteria performance measurement tools.

The intersection of artificial intelligence and performance management has gradually evolved, with discussions about AI's potential in various fields dating back several decades. In the 1990s using artificial intelligence in performance management began to solidify more in the realm of operations management. The integration of artificial intelligence within performance management systems has transformed how organizations evaluate and enhance their operational effectiveness. Nowadays one of the most popular performance management conceptions is balanced scorecard in which, because of its form the idea of combineting it with AI comes to the researchers (Tagkouta, Psycharis, Psarras, Anagnostopoulos, Salmon, 2023).

The evolution of AI in performance management from the 1990s to the present day highlights a journey marked by technological advancements and an increasing reliance on data-driven decision-making. As artificial intelligent technologies continue to advance, their integration into performance management systems will likely evolve, fostering enhanced organizational performance and strategic agility. The ongoing exploration of ethical frameworks and best practices will be essential in navigating the complexities associated with AI's role in performance management. Researchers see the biggest potential for artificial intelligence in performance management in human resources, especially in large organizations (Varma, Pereira, Patel, 2023).

Connecting of two of three mentioned in this article areas is literature is quite popular. Few examples from last few years is visible in table 1. However, using Scopus database in research of the articles from those fields of research the following relationships can be noticed:

- performance management with artificial intelligence have been mentioned in 16,809 papers,
- when searching articles with intelligent management and artificial intelligent at once 13,085 articles can be found,
- searching articles with intelligent management and performance management 24,500 position is received,
- searching of all there key words at once gives 2.574 positions.

However, that does not mean that those areas are unpopular. If there are search separately, there is much more articles. Searching intelligent management gives 106.854 results, artificial intelligence – 675.562 records and performance management – 665.128 results. What is more interesting, even if article is somehow connected with specific area, not always shows up in searching.

The increase in the number of publications on the discussed topic occurred in the early 2000s; however, a true boom can be observed from 2018, with the highest number of publications recorded in 2023. The figure 1 presents the number of publications in these three areas for over last fifty years.

Table 1. Overview of literature

Topic	Sample Authors
AI in intelligent management	Chen, Y., Li, X. (2021), Boullart L. (1988), Soni N., Sharma E. K., Singh N., Kapoor A. (2020), DeWitt D., Gray J. (1992), Kaggwa S., Eleogu, T. F., Okonkwo F., Farayola O. A., Uwaoma P. U., Akinoso A. (2023), Tu X., Li X., Sun K.Y., Lin W. (1992), Kwasek A., Kocot M., Kocot D., Maciaszczyk M., Rogozinska-Mitrut J. (2024), Faqihi, A., Miah, S. J.(2023), Rožman M., Oreški D., Tominc P. (2022), Guangming G., Duan Y., Edwards J. S., Dwivedi Y. K.(2021), Ashritha P., Reddy P. S (2023)
AI in performance management	Varma A., Pereira V. E., Patel P. (2024), Rožman M., Oreški D., Tominc P.(2022), Liu B., Sun M. , Wang Z.(2024), Rabby A.H., Al Jubair A., Nizhum T. Z. , Haque M. A.(2025), Kaggwa S., Eleogu, T. F., Okonkwo F., Farayola O. A., Uwaoma P. U., Akinoso A. (2023),

Source: own elaboration.

Interesting is also that most of the authors who decide to write a publication that connect artificial intelligence, performance management and intelligence management comes from China, United States India and United Kingdom (Figure 2). At the same time, the most frequently cited authors come from China, then United States and Inda (Figure 3).

Articles referring to artificial intelligence, intelligent management, and performance management address a wide range of issues (Figure 4). It can be observed that the vast majority of publications focus on artificial intelligence. Within the domain of performance measurement, AI is commonly associated with topics such as machine learning, learning systems, deep learning, deep neural networks, artificial intelligent algorithms, intelligent systems, metadata, big data, optimisations, and many others. However, even if performance management relates to employee's evaluation not often management of human resources are the part of performance management.

Many interesting information about just AI publications can be found in Artificial Intelligence Index Report 2025. This report tracks, collates, distills, and visualizes data related to AI. It also shows

information in which areas publication about artificial intelligence were written through 2013-2023 years.

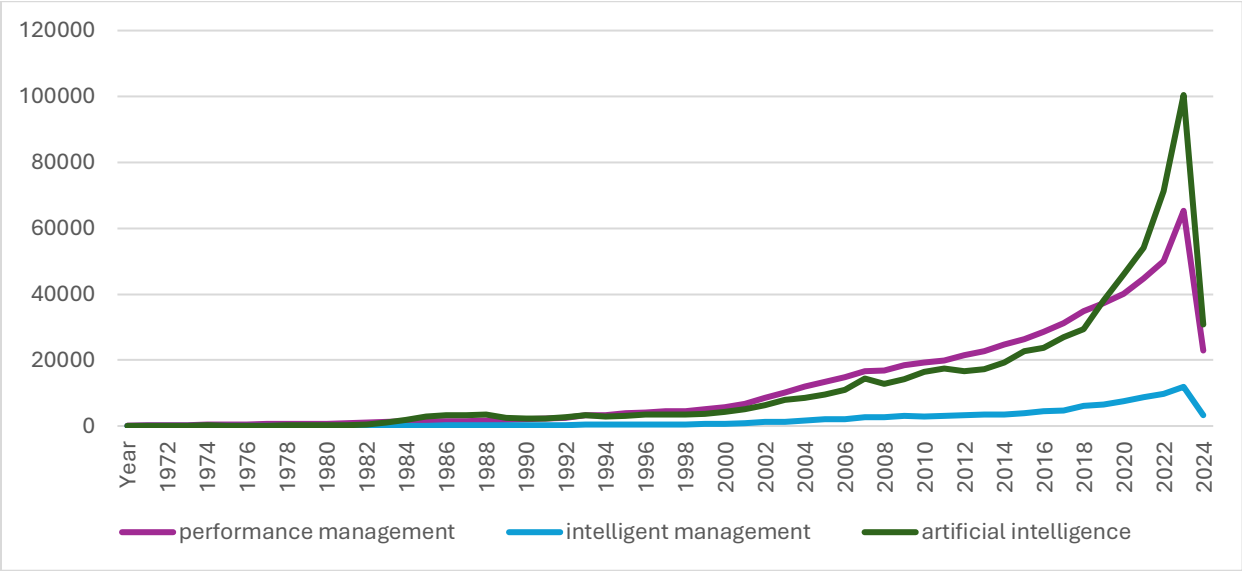


Figure 1. The number of publications in performance management, intelligent management and artificial intelligence from 1971 to 2025
Source: own elaboration.

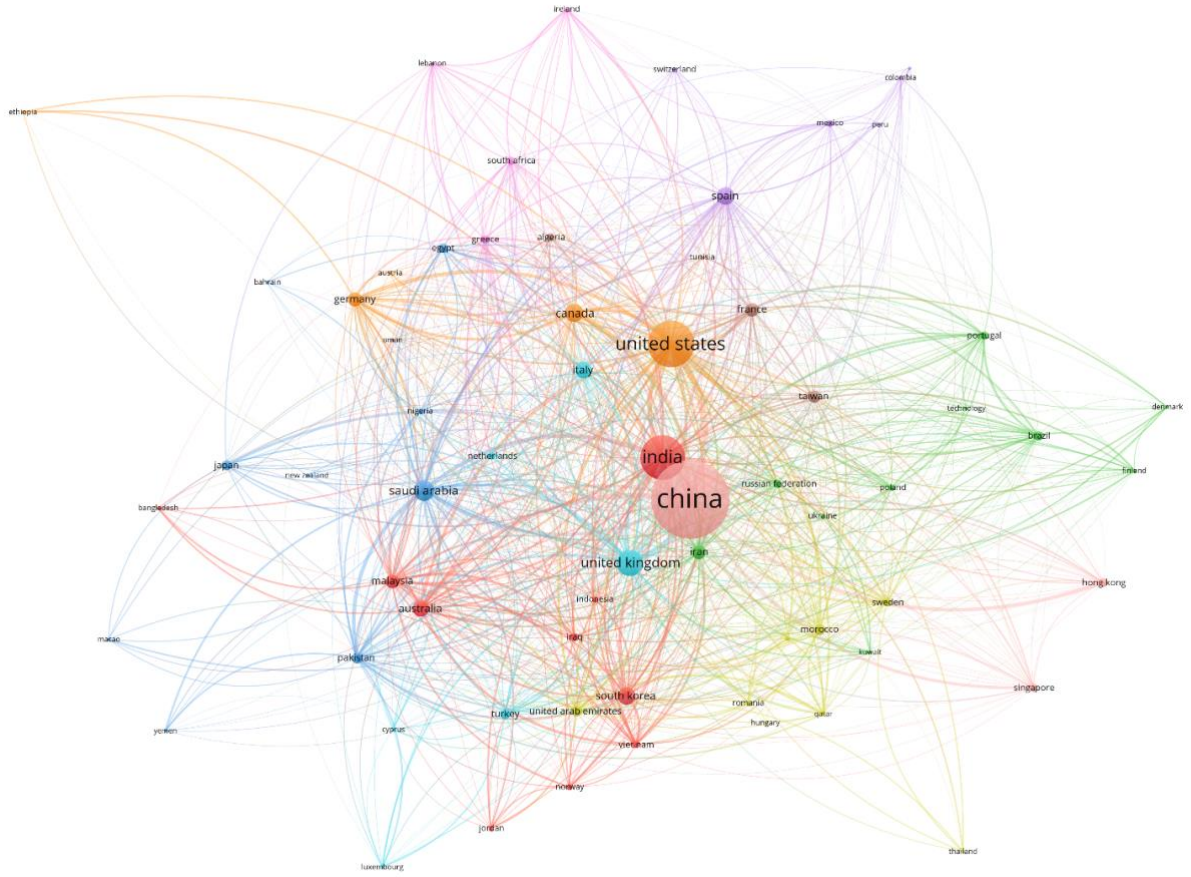


Figure 2. Publications with artificial intelligence, intelligent management and performance management according to number of publications and authors country
Source: own elaboration.

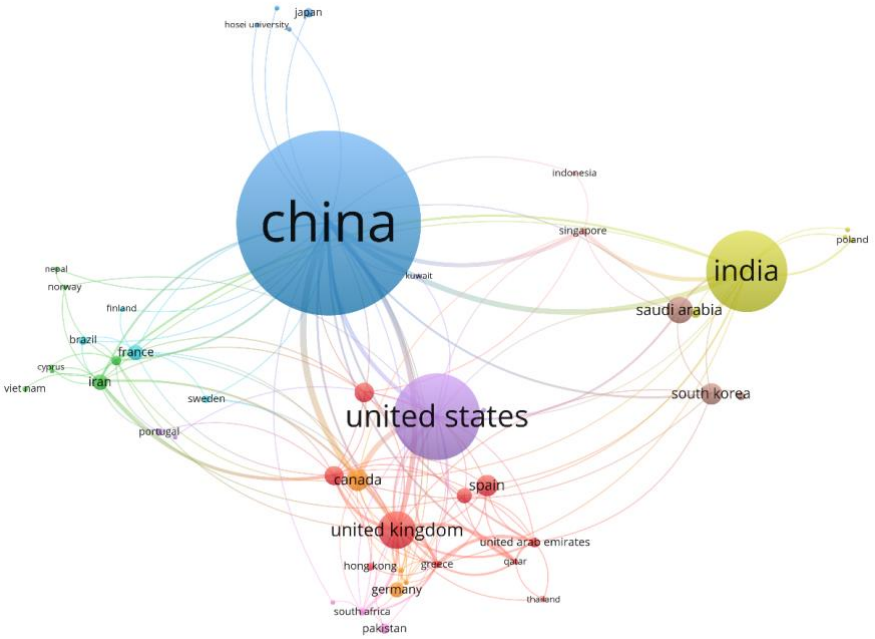


Figure 3. Publications with artificial intelligence, intelligent management and performance management according to citation and the country of origin of the cited author
Source: own elaboration.

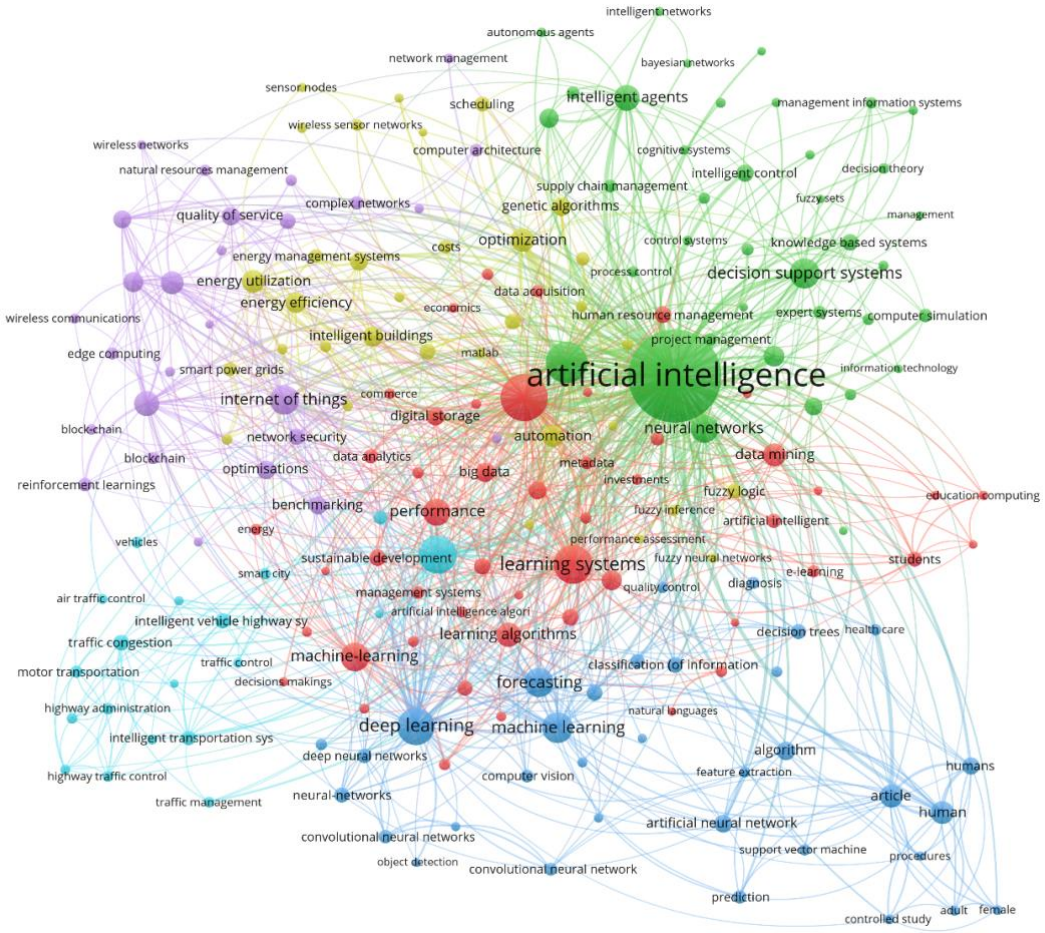


Figure 4. Publications with artificial intelligence, intelligent management and performance management according to key words
Source: own elaboration.

3. METHODOLOGY

Preparation of the article required conducting literature research, as well as using of the induction and deduction method. There was also short interview with some users of the artificial intelligence in their work. Interview was kind of preliminary research to establish a foundation for future studies by identifying key areas of interest as well as possible future form of the research in the area discussed in this article. In interview participated owners and employees from small electrical installation company and the specialist in the IT center of educational entity, whose cooperating with the public procurement department, where his main duties include comprehensive handling of tenders for IT equipment.

The interview showed great interest in the possibilities offered by AI for enterprise managers but also for ordinary employees working as non-manual workers. Conversations participants pointed the way they already with full awareness already used AI, where they see the chances for using intelligent management or where they would like to use those concepts in performance management. In some cases interlocutors were not aware that they already use some management concepts, what could be a result that the company is only few years on market and the owners (who are at the same time the managers) are not very experienced.

4. RESULTS

Evolution of the artificial intelligence and its usefulness for management would not be possible without many factors. Many researchers from various parts of the world devoted themselves to finding solutions for the challenges faced by managers. Creation of the more advanced AI technology required not only hard work from researchers and software engineers but also computers with sufficient processing power to handle complex algorithms and large datasets. While significant progress has been made in the field of AI, the journey from early theoretical concepts to the current state-of-the-art has been a gradual one. This underscores the importance of sustained research efforts and a long-term perspective.

Nowadays, artificial intelligence became one of the fastest-growing areas. This this area of research shows growing requirements for experts with advanced knowledge as well as ability to learn and discover new approaches. As a technology platform AI has the capability to automate tasks that were once carried out by humans. It also can create new tasks and activities that allow people to be engaged in productive work (Acemoglu, Restrepo, 2020, p. 25).

The most rapid development of artificial intelligence (AI) can be observed over the last two decades, particularly since the early 2010s. During this period, a series of significant technological and theoretical breakthroughs have contributed to considerable advancements in the field of AI. Still, artificial intelligence is not ideal. However, systems can improve its performance over time. To do it, just like humans can learn from experience, artificial intelligence uses various techniques. For instance, in machine learning or neural networks (which is a subset of AI) algorithms are trained on data to recognize patterns and make decisions. With right questions artificial intelligence will analyze given data and will propose a problem solution or conclusions (Skalka, Drlik, 2022, p. 15). This allows for using this technology in supporting many aspects of organization functioning.

The progression of artificial intelligence heavily relies on:

- advances in computing power (technological innovations),
- development of methods for processing large datasets (big data),
- widely implemented AI in various fields, such as medicine (imaging diagnostics), automotive (autonomous vehicles), finance (trading algorithms), or customer service (chatbots),
- significant rise in interest in this area from both industry and investors.

At the same time researchers tries to improve management concepts according to companies' expectations. In the current economy, business entities are required to operate on large amounts of data, implement adopted strategies, monitor the degree of goal achievement, and be socially responsible. Managers are held accountable for the effectiveness of their decisions, so it is essential to use what IT solutions such as AI have to offer.

In the interview, the owners of the mentioned small electrical industry company admitted that often they when they made decision, they do not have enough information or data. The very first time when they used artificial intelligence was when they needed to write references for they employee who was

moving abroad. They never before wrote any references, so they ask Chat GPT for small help. Also, they used the same technology for simple (for AI) task like preparing logotype for the consortium they co-founded with another enterprise, based on the assumption that this logotype must be kind of mixed original logotypes of both entities. After this first few tries with Chat GPT, they started to use it frequently.

Often, they need to prepare some bidding documentation, but they feel a lack of data in their calculations, which sometimes results in underestimated costs and prices, thereby hindering the project's achievement of expected incomes or even leading to a loss. This is the reason why they think about doing some market research about programs, that will help them in preparing some cost-price calculations predicted based on market trends and economic conditions.

They also pointed that at this moment they start to use some new software for electrical installations that based on building size, type, project specifications, as well as regulations, and their historical project database, suggests optimal wiring and lighting layouts. Although the expert maintains ultimate responsibility for the final project design, but current project development is significantly aided by AI-enhanced software tools. The computer program used in company have also kind of automated material calculator which help them in preparing material-to-buy lists. All AI in software fastened employee and the owner work and allows them to spend a little more time with the family.

Company also use Customer Relationship Management (CRM) Systems to improve their relation with customers (other companies mostly). Specially in information area (like about kind of fire detectors etc.) they would like to have kind of chatbot to give to a customer simple answer about technical parameters.

The owners of the small electrical installation company want to achieve in future more precise time and cost estimations for new projects, allowing for more competitive bidding and proposals. They also seek ways to automate material billing to streamline accounting processes. At this moment all information about used materials is send to accountant by president assistant.

On the other hand, in this kind companies' safety is high priority. Interview participants pointed that it would be useful to have knowledge about braking safety rules, as well as about danger situation on construction site. They wish that day would have system which will be monitored and analyze situations and alert owners and employees if something dangerous is happening without the need for manual monitoring review.

Company is small, so at the moment there is no multicriterial performance measurement system, however they calculate some financial measurement and wish to have more feedback form customers to improve they offers. The entity strategy assumes expand its activities to include construction works in the future. So the owners plan to expand performance measurement to include non-financial indicators as well

The specialist from the IT center from educational entity pointed on different aspects using AI. He emphasized the importance of establishing databases to systematically document the computer hardware procured as part of tender processes. Normally, when he created these databases, it took him a lot of time. He is not a programmer however hi tried to write his own computer scripts. With small help from artificial intelligence tool, he was able to shorten time needed for making this database but also finding in it information he needs. Using AI tools made his work faster and easier. He also learns a little how to wrote scripts in new language for him.

As an administrative employee of a public institution, he has once per 2-3 year the evaluation. Those evaluations are connected with institution strategy. That process requires significant time and manual effort. The same is with document workflow within the unit. Using artificial intelligence in this area might help in quick analyze each employee evaluation as well as making employees ranking. The interviewee suggests that if there would be well prepared tool with AI support can also help in some predictions about future requirements from employee which will help is setting them their individual results plan. Having those individual plans will help in clarification what is required from employee and make it easier for them to better plan the distribution of forces for actions.

The interviews provided information about the willingness of employees to use the opportunities offered by AI technology. The motivation is twofold: partly rooted in curiosity and the aspiration to remain aligned with technological innovations, and partly arising from the functional requirements of the unit's day-to-day operations. What is also important even in in cases of limited use of AI technologies, interview participants observed the noticeable benefits.

5. DISCUSSION

Artificial intelligence is a great technology, which gives many opportunities for people who will decide to use it in their professional life. AI is a platform, can automate tasks previously performed by humans and generate new tasks and activities in which humans can be productively employed (Acemoglu, Restrepo, 2020).

Artificial Intelligence (AI) has enormous potential to improve many areas of performance management within organizations. Here are some key areas where AI can bring significant benefits:

- help in data analysis, by processing vast amounts of data quickly and efficiently, what will allow for better understanding of performance results, also machine learning algorithms can analyze patterns and trends, helping managers make more informed decisions based on data,
- can be used to predict future outcomes based on the analysis of historical data, predictive models can help estimate financial outcomes, incomes, sales, or employee performance,
- making data analysis regarding employee performance and preferences, leading this way to more personalized development programs and training opportunities, that will give employees targeted support in developing their skills,
- automatization of the process of gathering and analyzing feedback from employees and customers, which enables organizations to quickly respond to issues and adjust performance management strategies accordingly,
- automatically collecting data on results and ensuring greater objectivity in assessments through the use of algorithms as a support for the performance evaluation process,
- assisting in the process of setting goals within the organization, helping to accurately align goals with the capabilities and performance of teams, as well as monitoring progress towards these goals in real time,
- support recruitment processes by analyzing candidate information and their previous achievements, leading to more accurate hiring decisions, additionally, in terms of employee performance appraisal, AI can identify areas for improvement and signal training needs,
- analyzes the performance of various business processes, identifying bottlenecks and opportunities for improvement. This allows organizations to enhance operational efficiency and reduce costs,
- enables decision-making based on changing conditions and real-time data, improving an organization's response to shifts in the market environment,
- analyzes data related to employee engagement and performance, predicting potential turnover and enabling preventive actions,
- assist programmers in writing programs on high quality.

All those benefits are connected with quick decision making based sometimes on very huge amount of information. Meny programs have AI modules in it already. In performance management, especially when used for multicriterial scorecards, artificial intelligence will be very useful. It can help in real time gather information as well as help in giving current value of measures compared with their target value, not only when measurement is on set date but also when is made unexpectedly ad hoc prepared (for example for additional control).

Combination of artificial intelligence and performance management gives important information for managers. That means it will be useful for intelligent management as well. That information can be used among the other in human resources management – specially after their performance evaluation, but not only. Using combined methods can help managers not only with managing the stuff, but also in development of whole company, employees as an individual, or even changing (update's) entity strategy. For example, using total performance scorecard (proposed by Rampersad) company use balanced scorecard with elements of talent management, total quality management and using at the same time Kolb's learning cycle. The number of information needed in this concept is really huge. To make it work necessary is to help employees understand why

It can be useful specifically when management style mixes few concepts. Managers want to have enough knowledge when they make decision. Using AI to gather them and get some clue about direction of the decision should be for managers very helpful.

Machine learning one of the most widely used AI methods over the last few years. The objective of machine learning is to train a machine to be able to learn from data, make inferences, prepare predictions,

and identify associations, which can guide managers to made right decisions (Afiouni, R., 2019). On the other hand, managers can use chatbots to get some tips how to solve problems.

Artificial intelligence enhances the accuracy of performance appraisals by facilitating more frequent evaluations, which capture real-time performance trends and enable timely corrective actions. Additionally, AI tools aggregate data from various sources, providing a comprehensive overview of individual performance, while also expediting the appraisal writing process. Furthermore, these tools assist supervisors in tailoring communication to employees, developing goal-oriented criteria for better engagement, and fostering trust in AI-generated feedback, which employees may perceive as more objective and unbiased. Lastly, the integration of chatbots with natural language processing enables interactive feedback sessions, allowing for a more engaging and comfortable exchange of insights (Varma, Pereira, Patel, 2023).

With artificial intelligence in performance management as well as intelligent management comes possible disadvantages. Employees may have lower trust in AI-enabled performance management systems due to concerns about the data used for decisions, especially if supervisors cannot explain the process. Ensuring data secrecy and security is vital, as protecting individual performance information from exposure is crucial to maintaining trust, particularly in light of recent data theft incidents. Additionally, ethical and privacy issues arise when using AI to interpret performance indicators, such as misclassifying time away from the desk without considering context (Varma, Pereira, Patel, 2023).

Using artificial intelligence with performance management creates great source for intelligent management. The same situation will take a place in company which decided to implement intelligent management with AI as a support for making decision strategic as well as operational. Company decides on using AI can choose many tools. Some of them are provided as a module to the commercial programs the others are free version. If managers or employees decide to use free version or even paid one, the artificial intelligent can still make some mistakes or give incorrect solution. At current level machines still cannot replace human.

Based on the literature review and conducted interviews, it can also be observed that it is difficult to identify a ready, single, comprehensive solution that fully addresses the reported needs. For small enterprises, even the implementation of well-established multicriteria performance measurement tools such as the Balanced Scorecard, can be challenging due to financial constraints. Nevertheless, the market already offers systems developed by certain companies that support performance management using AI tools, such as machine learning algorithms, expert systems, cost analysis, or even survey analysis (e.g., for collecting and inference to create an interpretation of the data from customer feedback). Acquiring the most suitable system typically requires commissioning a customized solution and working closely with developers to tailor the product to the specific informational needs and requirements of an organization's management.

Using by managers already existed tools for such concept like balanced scorecard (e.g. Sisense, BSC Designer, KANBAN software's which already use AI tools, Lucidchart with some automatization and intelligent design of high-quality diagrams ready to being presented) can be very useful for improving strategic goals achievement and can be helpful for intelligent management of entity. This kind of tools will help managers in better management due to, among others:

- integration of data from various internal and external sources, including ERP systems, CRM platforms, social media, and market research databases, can lead to faster adjustment to the changes (including updates in strategy),
- using machine learning algorithms which process and analyze large datasets to identify correlations, trends, and anomalies that might be missed by traditional analysis methods,
- this type of software provides customizable dashboards and reports that can present key metrics and insights in a user-friendly format, which can be used in explanation to employees for individual plans of achievements set for them,
- users of these systems with AI tools can tailor prepared by programs visualizations to their specific needs and be ensured that they have access to the most relevant information, they also can use them in explanation to subordinates why results they require are so important for company,
- natural language processing capabilities allow the software to analyze unstructured data, such as customer feedback, employee comments, and social media posts and make an interpretation

of it (this feature can provide a more nuanced understanding of stakeholder, customers or even employees sentiment and behavior),
- beyond forecasting future performance, AI-powered software can also provide prescriptive analytics, thus offering actionable recommendations to optimize performance or to help develop effective methods for improving employee motivation,
- the automatic updating of key performance indicators based on real-time data can reduces the administrative burden on managers by ensuring the currency of performance metrics,
- utilizing the analytical capabilities of AI tools to review legal regulations can enabled the rapid identification of solution proposals within defined law boundaries, when financial issues will be detected in the entity's financial perspective, such as unexpectedly high tax liabilities.

Summing, using the artificial intelligence tools in software for performance management will definitely help in achieving strategic goals, entity efficiency as well as in providing the appropriate information necessary for intelligent management of the organization, including its human resources management. Tools offered by AI can help in making quicker and better adjusted for current situations decisions. Automation of data collection and analysis during periodic performance evaluations will significantly accelerate the measurement and evaluation of current achievements. Also, the way software with artificial intelligence tools can help in better communications with employees who are the most important part in achieving entity goals – without proper engagement employees will not be as efficient as the could be. At this stage communication of goals, discussion about achieved results, trends in goals achievement visualization employees might not use their full potential in their work. Using AI for analyze the employee's performance can also eliminate subjectivity in assessment or other personal disagreements. All information collected and processed by AI during performance management can be instrumental in achieving effective and objectively grounded intelligent management of an entity.

6. CONCLUSION

Recent technological developments have predominantly been directed towards automation, with insufficient attention on creating new tasks where labor can be productively employed. This approach has led to stagnation in labor demand, declining labor share in national income, increasing inequality, and reduced productivity growth. Currently, the prevailing trend is to develop AI in the direction of further automation, but this might mean missing out on the promise of the 'right' kind of AI, with better economic and social outcomes (Acemoglu, Restrepo, 2019, p. 25).

Nowadays artificial intelligence is rapidly developing. Tasks that no long ago were in "dreams zone" are slowly becoming a reality. AI in some definition is perfectly capable of imitating human behavior (Kolbjørnsrud, Amico, Thomas, 2017, p. 37–43; Wang et al., 2019), the others regard it as a tool, assuming that artificial intelligence cannot exactly replicate human capabilities (Wamba-Taguimdje et al., 2020).

AI can do more and better each time when operator ask it more question. More peple who give a task to artificial intelligence is more precise, the better answer he will receive. Also, each question leads artificial intelligence to new knowledge what is expected from it. Nevertheless, it's still needed a good guide and, what is as well important, it can make mistakes or even give some false information. Completely entrusting AI in making some decision is not a good idea, at least not in nowadays. There is also some danger that artificial intelligence even in writing document we will not check it there will be wrong data which will lead to incorrect, inefficient or danger for a company decision. No matter how much someone will try to convince managers to fully trust AI, they still should have some reserve for information received from this technology.

Artificial intelligence implementation must be capable of overcoming the same barriers encountered by human managers in implementation any changes in processes or management styles, as well as when they change software used in any department of the company. However, using the AI practically bring many advantages for business unit but there are also some disadvantages.

The implementation of AI in performance management can lead to more efficient processes, better data analysis, and a more personalized approach to employees. As this technology continues to evolve, its application in performance management will become increasingly common, bringing tangible benefits to organizations at various levels. At the same time using these two concepts lead to using

intelligence management. The main base of information will be provided by artificial intelligence during giving information for performance management. Knowledge is current strength of companies and combination of the artificial intelligence, performance management and intelligent management gives a lot of information which can create the knowledge of the company leader and even ordinary employees.

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28th European Conference on Artificial Intelligence (ECAI 2025)

IDENTIFYING TRENDS AND GAPS IN EXPLAINING THE ROLE OF AI IN BUSINESS MODELS INNOVATIONS AND STRATEGIC DECISION MAKING – A LITERATURE REVIEW

Katarzyna Łobacz[a], Nikola Dąbrowska[b], Hanna Jędrzejewska[c], Aleksandra Antos[d], Manuel Munos Herrador[e]

[a] *Szczecin University, Institute of Management, Poland*
[b] *Szczecin University, Faculty of Economic, Finance and Management, Poland*
[c] *Szczecin University, Faculty of Economic, Finance and Management, Poland*
[d] *Szczecin University, Faculty of Economic, Finance and Management, Poland*
[e] *University de Jaen, Department of Computer Science, Spain*

ABSTRACT

Purpose: *This study explores the transformative role of artificial intelligence (AI) in business model innovation (BMI), examining how AI enhances value creation, delivery, and capture. It identifies trends and research gaps to understand AI's influence on business modelling.*

Need for the Study: *AI is reshaping business practices and models across industries. The rapid pace of AI development necessitates prioritizing research on its most impactful aspects. Summarizing trends and identifying gaps while linking them to AI advancements highlights critical areas for future exploration.*

Methodology: *A literature review analysed academic papers and case studies from reputable databases. Core AI technologies, including Machine Learning, Natural Language Processing, Computer Vision, Robotics, Expert Systems, and Deep Learning, were examined concerning critical processes in business model innovation, namely, value creation, value capturing, and value delivery.*

Findings: *The review identified trends in AI-supported business modelling, such as operational efficiency, customer personalization, and strategic decision-making, with challenges like data privacy, algorithmic bias, and workforce adaptation remaining underexplored. Gaps include the absence of longitudinal studies, limited sector-specific analyses, and insufficient research on integrating AI with traditional business models.*

Practical Implications: *The findings emphasize the need for interdisciplinary research and ethical frameworks to guide AI adoption. Businesses should concentrate on scalable AI solutions, customer-centric innovation, and overcoming integration barriers to fully leverage AI's potential for sustainable growth. This study establishes a foundation for future research, highlighting the responsible and strategic implementation of AI in BMI.*

Keywords: literature review, business model, innovative business model, Artificial Intelligence, AI in business, innovation

JEL codes: O31, O32, M15, D83

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1. INTRODUCTION

In today's rapidly evolving business landscape, business model innovation (BMI) has become a crucial driver of long-term competitive advantage (Aagaard & Tucci, 2024). Organizations must continuously adapt their business models to respond to shifting market dynamics, technological advancements, and changing opportunities (Aagard, 2024). Artificial Intelligence (AI) has emerged as a powerful enabler in addressing these challenges, offering advanced tools and insights to support various aspects of business model innovation (Hamadaqa et al., 2024). AI empowers organizations to harness vast amounts of data, enabling them to identify opportunities, streamline operations, and refine their strategies with unprecedented precision (Olorunfemi et al., 2024). Its widespread adoption across industries reflects a broader shift toward technology-driven and intelligent management models, where innovation, responsiveness, and accountability are essential for success (Jorzik et al., 2024).

The rapid integration of AI into business models is not merely a technological shift but a societal imperative. As industries face mounting pressures from climate change, resource scarcity, and evolving consumer ethics, AI-driven innovations offer pathways to address these challenges while maintaining profitability. For instance, AI-powered circular economy models reduce waste in manufacturing, while predictive analytics enable energy-efficient supply chains. Framing AI's role within these macro-level challenges underscores its transformative potential beyond operational efficiency, aligning technological advancement with global sustainability goals. Additionally, AI is pivotal in supporting intelligent management by integrating information technologies, analytical tools, and automation to manage organizational resources and processes more effectively.

During the ideation and conceptualization phase, AI analyses market trends, evaluates competitors, and generates innovative ideas that align with consumer needs (Babatunde et al., 2024). It also uncovers hidden insights by analysing customer behaviour and interactions, helping organizations identify opportunities that may remain unnoticed (Choudhury et al., 2021). As companies progress to value proposition development, AI facilitates customer segmentation and personalization by leveraging behavioural and demographic data to design tailored products and services (Huang & Rust, 2020; Kumar et al., 2024). By predicting and adapting to market conditions, AI enables businesses to scale efficiently while mitigating risks (Bharadwaj et al., 2021). Machine learning algorithms further enhance the adaptability of business models, allowing them to evolve dynamically based on new data and insights (Wang et al., 2021).

By integrating AI into core processes, organizations innovate their business models and embrace intelligent management principles. This shift enables them to unlock new pathways to growth and resilience, positioning themselves for success in an increasingly complex world (Bharadwaj et al., 2021). The role of AI in business model innovation is rapidly expanding, with AI-driven models providing a competitive advantage while enhancing efficiency, customer engagement, and decision-making (Adesoga et al., 2024). However, gaps remain in understanding its full impact.

The broad assumptions regarding AI's role and potential in transforming business modelling have raised questions about the extent to which this role and potential are explored in scientific research and about early evidence of AI's impact on emerging business strategies and approaches. A comprehensive literature review was conducted to address these questions. By reviewing existing research, the article aims to understand current trends and identify gaps in our knowledge about AI's role in driving business model innovation.

2. THEORETICAL BACKGROUND

2.1. Business model and business model innovation

A business model describes how an organization creates value for its customers and how it shares in that value (Teece, 2010). It encompasses the core elements of a company's operations, including revenue generation, cost structure, customer relationships, and value proposition (Osterwalder, 2004). The term "business model" has been around since the 1950s (Vukanović, 2016); it gained significant prominence in the 1990s and 2000s with the rise of the Internet and the need for sustainable business models (Amit & Zott, 2001; Magretta, 2012), and it has been widely adopted in business settings and business-related analysis.

Business model innovation refers to designing, adapting, or redefining a business model's core structure and elements to unlock new value, seize market opportunities, and strengthen competitive advantage. It focuses on discovering new, previously unimagined approaches to generate revenue, deliver products or services, and maximize customer value (Zott & Amit, 2010). Business model innovation challenges conventional norms, industry standards, and existing assumptions to unveil fresh pathways for growth and profitability (Osterwalder & Pigneur, 2010).

Business model innovation may stem from changes in key business model processes, including core elements such as value creation, value delivery, and value capture. Table 1 explains these in greater detail.

Value creation is at the heart of sustainable business success, referring to the process by which companies develop products or services that offer meaningful customer benefits, ultimately generating value that exceeds the cost of inputs. Businesses focusing on value creation enhance customer satisfaction and loyalty by designing experiences beyond mere product offerings. It involves understanding customer preferences, addressing pain points, and continuously improving product quality and service delivery. Value creation is not solely about pricing or features but about delivering a comprehensive experience that meets or surpasses customer expectations. A well-crafted value proposition attracts customers, encourages repeat purchases, and fosters brand loyalty (Kumar & Reinartz, 2016).

Table 1. Key processes of Business Model Innovation

Business Model Innovation Key Processes	
Value Creation	This involves developing new ways to create value for customers, which include innovative products, services, or experiences that meet emerging needs (Łaszkiewicz, 2018)
Value Delivery	This component focuses on how the value is delivered to customers. It includes the channels and methods used to reach customers effectively and efficiently (Osterwalder & Pigneur, 2010)
Value Capturing	This refers to the mechanisms through which a business captures the value it creates, typically through revenue models, pricing strategies, and profit margins (Teece & Linden, 2017)

Source: own elaboration.

Value delivery focuses on the methods and channels a company employs to provide its value proposition to customers effectively and efficiently. This encompasses the entire supply chain, distribution networks, and customer service practices that ensure the created value reaches the intended audience promptly and satisfactorily. According to Osterwalder and Pigneur, the value delivery process involves several stages, including value proposition definition, value provision design, and value-in-use delivery. In each phase, iterative cycles of value creation and capture activities ensure successful alignment and progression to the next phase (Osterwalder & Pigneur, 2010).

Value capturing pertains to the mechanisms through which a company retains a portion of the value it has created, typically realized as profit. This involves pricing, cost management, and competitive positioning strategies that enable the firm to sustain its operations and fund future growth. Aligning value creation and capture is critical for developing commercially viable business models (Astrom et al., 2022).

The three processes described in Table 2 contribute to developing six primary components of a business model: customer segment, revenue model, key activities, key resources, key partnerships, and cost structure.

Understanding and redefining customer segments is crucial for business model innovation. Companies that successfully innovate often identify new target audiences or reposition their offerings to meet evolving customer needs better. This may involve expanding into previously untapped markets, personalizing products and services through data analytics, or repurposing existing solutions to appeal to different demographics. Businesses that recognize shifting consumer behaviours and tailor their value propositions are better positioned for long-term success. Modern companies increasingly adopt micro-

segmentation strategies rather than catering to a broad audience, offering highly specialized solutions that address niche demands (Amit & Zott, 2012; Bocken et al., 2014).

Table 2. Key components of Business Model Innovation.

Business Model Innovation Key Components	
Customer Segments	Identifying and understanding different customer groups is essential. Business model innovation often involves targeting new segments or redefining existing ones (Amit & Zott, 2012)
Revenue Model	This outlines how a business generates income, which can include various streams such as sales, subscriptions, or licensing (Ardley & Hardwick, 2024)
Key Activities	These are the critical actions a company must undertake to deliver its value proposition and operate its business model effectively (Christensen et al., 2016)
Key Resources	The essential assets required to implement the business model, including human, financial, and technological resources (Ramdani et al., 2019)
Key Partnership	Collaborations with other organizations, suppliers, or stakeholders that can enhance the business model's effectiveness and reach (Saqib & Satar, 2021)
Cost Structure	Understanding the costs associated with the business model is vital for ensuring profitability and sustainability (Chammassian & Sabatier, 2020)

Source: own elaboration.

A company's revenue model defines how it generates income, and innovation in this area can significantly impact financial stability. Businesses may shift from traditional one-time sales to more sustainable and predictable income streams, such as subscription-based services, which provide recurring revenue and foster stronger customer relationships. The freemium model, which offers basic services for free while charging for premium features, has become a popular approach in software and digital platforms. Similarly, usage-based pricing models, common in cloud computing and utilities, allow customers to pay based on consumption, increasing flexibility. Companies may also explore licensing, franchising, or ecosystem-driven monetization, where value is co-created with partners and third parties. Innovating the revenue model ensures financial resilience while enhancing customer loyalty and engagement (Fajardo-Vanega & Aguilar-Pazmiño, 2022; Teece, 2010).

The effectiveness of a business model depends on the key activities a company undertakes to deliver its value proposition. Business model innovation often involves rethinking these key activities to enhance efficiency, agility, and customer satisfaction. Digital transformation is crucial, as businesses leverage technology to automate processes, improve customer experiences, and scale operations. Many companies adopt agile methodologies to respond swiftly to market changes and continually enhance their products and services. Investing in research and development (R&D) is another strategic move, enabling companies to stay ahead of industry trends and create groundbreaking solutions (Christensen et al., 2016). Additionally, organizations increasingly focus on building ecosystems that integrate multiple stakeholders, fostering collaboration and value co-creation. By innovating key activities, businesses can streamline operations, increase productivity, and enhance overall competitiveness (Zott & Amit, 2010).

Key resources are essential for any business model to function effectively, including human talent, financial assets, technological capabilities, and intellectual property. Business model innovation in this area often involves developing proprietary technology to differentiate from competitors, acquiring and retaining top talent to enhance expertise, and leveraging data-driven insights for more informed decision-making (Ramdani et al., 2019). Protecting intellectual property is another crucial factor, as companies that safeguard their innovations maintain a competitive advantage. In recent years, businesses have increasingly turned to artificial intelligence and machine learning to optimize resources and maximize efficiency. Strengthening and innovating key resources ensures companies have the foundation to support long-term growth and adaptability (Schneider & Spieth, 2013).

Strategic collaborations with other organizations, suppliers, research institutions, or competitors can enhance business model innovation significantly. Companies often form partnerships to access new markets, share expertise, or accelerate product development. Collaborating with startups can introduce fresh innovation and expedite the adoption of emerging technologies. Co-creation with customers is

another growing trend, as businesses involve users in product development to create solutions that better address their needs (Saqib, N., & Satar, M. S., 2021). Joint ventures and alliances also provide opportunities to leverage complementary strengths and expand market reach. In today's interconnected economy, businesses that build strong partnerships can enhance their capabilities, reduce risks, and create value beyond what they could achieve alone (Foss & Saebi, 2017).

A well-optimized cost structure is critical for ensuring profitability and sustainability in any business model. Companies that innovate in this area focus on reducing operational costs, optimizing resource allocation, and improving financial efficiency. Many businesses adopt lean operations to eliminate waste and streamline workflows, while others shift toward more variable cost structures that enhance scalability. Automation and artificial intelligence play a key role in cost reduction by minimizing labor-intensive processes and improving accuracy. Additionally, businesses explore alternative sourcing and logistics strategies to lower supply chain expenses. Companies can achieve greater financial flexibility by continually refining their cost structure, allowing them to invest in innovation and long-term growth (Chammassian & Sabatier, 2020; Teece, 2010).

2.2. The concept and components of Artificial Intelligence

Artificial Intelligence (AI) is no longer a futuristic concept; it is a rapidly evolving technology already transforming various industries. At its core, AI aims to empower machines with human-like intelligence, enabling them to perform tasks that traditionally required human cognitive abilities (M. Gladden et al., 2022). The influence of AI is felt across various sectors, including public relations, product marketing, and business innovation. Its ability to analyse massive datasets, recognize patterns, and generate insightful predictions makes it a valuable asset for organizations seeking to optimize their operations and enhance customer engagement (Gavi & Olusegun, 2024; Ghosh, 2025). The intricate workings of AI are built upon a foundation of interconnected components, each playing a crucial role in enabling machines to think and act intelligently (Avasarala & Gopalakrishnan, 2016; Kietzmann & Angell, 2016; Vasudevan, 2024). Components of Artificial Intelligence and their potential business contribution are detailed further in Table 3.

While Table 3 delineates distinct AI components, their real-world impact often arises from integration. For example, robotics in logistics combines computer vision for navigation, NLP for human-robot communication, and machine learning for route optimization. Similarly, healthcare diagnostics merge deep learning for image analysis with expert systems to validate findings against medical databases. These cross-component synergies enhance value creation but introduce complexities such as interoperability and ethical trade-offs—areas that are underexplored in current literature. Recognizing these interdependencies is crucial for designing holistic AI-driven business models.

The components of AI work together seamlessly, enabling organizations to harness their transformative power across various functions. As AI evolves, its applications will expand, leading to further advancements in technology and business practices. We can anticipate AI playing an increasingly significant role in shaping the future, revolutionizing industries, and enhancing our lives unprecedentedly (Brynjolfsson & McAfee, 2021; Chui et al., 2020; Kaplan & Haenlein, 2020).

Given that intelligent management refers to the strategic integration of information technologies, analytical tools, and automation to enhance the effectiveness of managing resources and processes within an organization (Calof et al., 2017), it also concludes that Artificial Intelligence significantly enhances the process by providing advanced capabilities for data analysis, automation, and decision-making. This concept represents a shift from traditional, intuition-based management toward a more systematic, data-driven approach. By combining digital infrastructure with real-time analytics and automated systems, intelligent management allows organizations to monitor performance, optimize workflows, and make informed decisions faster and more accurately (Mohammed et al., 2019). At its core, intelligent management is about using technology to support operations and transform decisions and how value is created across the organization (Dass, 2016).

Table 3. Artificial Intelligence components

AI components	Description
Machine Learning (ML)	Machine learning is at the heart of AI, a powerful technique that allows computers to learn from data without explicit programming. ML algorithms are trained on vast datasets, enabling them to identify patterns, make predictions, and improve their performance over time. This capability is particularly valuable in public relations, where AI-powered tools can analyse public sentiment, track brand mentions, and automate responses to inquiries, ultimately enhancing reputation management (Burström et al., 2021; Krishnamurthy et al., 2024)
Natural Language Processing (NLP)	Serves as the bridge between humans and machines, enabling effective communication. It involves the ability to understand, interpret, and generate human language. This technology is crucial for creating chatbots and virtual assistants that can engage with customers naturally and personally, enhancing customer service and satisfaction in public relations (Supriyono et al., 2024; Zhang et al., 2020)
Computer Vision (CV)	This component empowers machines to "see" and interpret visual information. It enables the analysis of images and videos, identification of objects, and extraction of meaningful insights. In product marketing, computer vision analyses consumer behaviour through image recognition, allowing marketers to tailor their campaigns and effectively target specific demographics (Gujar, 2024; Zhang et al., 2021)
Robotics	AI is integrated into robotics, automating tasks and enhancing efficiency across various industries. Robots with AI capabilities can perform repetitive tasks with precision and speed, freeing human workers for more complex and creative endeavours. This automation is particularly advantageous in manufacturing and logistics, where robots can manage assembly, packaging, and material handling (Nitsche, 2021; Bock et al., 2022)
Expert Systems (ES)	These AI programs are designed to replicate human experts' knowledge and decision-making abilities. They are trained on extensive datasets and rules, enabling them to provide expert advice and recommendations in specific domains. Expert systems are applied in healthcare, finance, and other fields where complex decision-making is essential (Yang & Zhu, 2024; Chen et al., 2020)
Deep Learning (DL)	Deep learning is a powerful subset of machine learning that employs artificial neural networks with multiple layers to analyse data accurately. This technique is particularly effective in tasks such as image recognition, speech recognition, and natural language understanding. Deep learning is increasingly utilized across various applications, including personalized marketing, fraud detection, and medical diagnostics (Osuva, 2021; LeCun et al., 2020; Kelleher, 2021)

Source: own elaboration.

Through machine learning algorithms, AI enables organizations to process vast volumes of structured and unstructured data in real time, uncovering patterns and generating insights that would be difficult to detect manually. This analytical power supports more accurate forecasting, performance monitoring, and resource allocation. Furthermore, AI-driven automation streamlines repetitive tasks, reduces human error, and increases operational efficiency across departments. AI catalyzes responsiveness and adaptability in intelligent management systems, allowing businesses to anticipate changes, optimize workflows, and react swiftly to emerging challenges. By embedding AI into core management functions, organizations move toward more predictive, proactive, and personalized strategies, reinforcing the core objectives of intelligent management.

2.3. Artificial Intelligence for Business Model Innovation

AI revolutionizes business models by transforming how companies create, deliver, and capture value, ultimately driving innovation and a competitive advantage. AI empowers businesses to tailor products and services to individual customer preferences through personalization and predictive analytics while forecasting future market trends. By analysing vast customer data, AI enhances user experiences, fostering deeper engagement and brand loyalty. Predictive analytics enables companies to stay ahead of customer needs, allowing for proactive innovation and product development (Farayol et al., 2023). As AI continues to evolve, businesses that embrace its capabilities are expected to gain a significant

competitive edge in an increasingly digital economy. By leveraging AI for value creation, delivery, and capture, organizations can unlock new growth opportunities, improve customer experiences, and drive long-term success. Integrating AI into business models is not just a technological advancement; some authors argue that it is a fundamental shift that will define the future of commerce and industry (Jorzik, 2024; Sjödin, 2021).

During the value creation process, AI fosters strategic partnerships by facilitating collaborative platforms that connect businesses with complementary products and services. Companies can share AI-driven insights with partners, creating mutually beneficial relationships and unlocking new market opportunities. Furthermore, AI reshapes cost structures by reducing operational expenses through automation and optimizing resource allocation, ensuring investments yield the highest returns (Broekhuizen et al., 2023; Sjödin, 2021). Moreover, AI assists in financial planning by analyzing historical data and market conditions, enabling businesses to make informed decisions and reduce financial risks (Adeniran et al., 2024). AI analyses large datasets for customer segmentation to identify distinct customer groups based on behaviour, preferences, and demographics. This enables businesses to craft highly targeted marketing campaigns that resonate with specific segments, increasing conversion rates and customer engagement. Additionally, AI-driven insights allow businesses to optimize revenue models, such as subscription services and freemium models, by identifying which features to offer for free and which to monetize, ensuring sustainable revenue growth (Bhagat et al., 2024).

According to the value capturing, dynamic pricing models powered by AI enable businesses to adjust prices in real time based on demand, competitor pricing, and consumer behaviour, ensuring optimal pricing strategies that maximize revenue and market share (Anang et al., 2024). Furthermore, AI plays a crucial role by enhancing pricing strategies, predicting customer churn, and providing accurate revenue forecasting.

In value delivery, AI optimizes logistics by enhancing supply chain management, ensuring timely deliveries, and reducing operational inefficiencies. Additionally, AI-driven customer support solutions, such as chatbots and virtual assistants, provide 24/7 service, improving response times and customer satisfaction. By leveraging AI-driven insights, businesses can implement targeted retention strategies to sustain customer loyalty and long-term profitability (Agarwal et al., 2024).

AI technologies like Machine Learning (ML), Natural Language Processing (NLP), Computer Vision, Robotics, Expert Systems, and Deep Learning are revolutionizing business model innovation by transforming value creation, capture, and delivery. In value creation, AI automates processes, improves decision-making, and enables personalized customer experiences, driving data-driven products and services. For value capture, technologies such as Computer Vision and Robotics enhance operational efficiency, reduce costs, and optimize workflows in manufacturing and logistics, leading to higher profitability. In value delivery, Expert Systems and Deep Learning refine service offerings, improve customer support, and automate complex decisions, thus enhancing customer satisfaction, retention, and seamless interactions. Figure 1 summarizes the potential impact of AI components on business model innovation. This model will be used as a reference for further analysis.

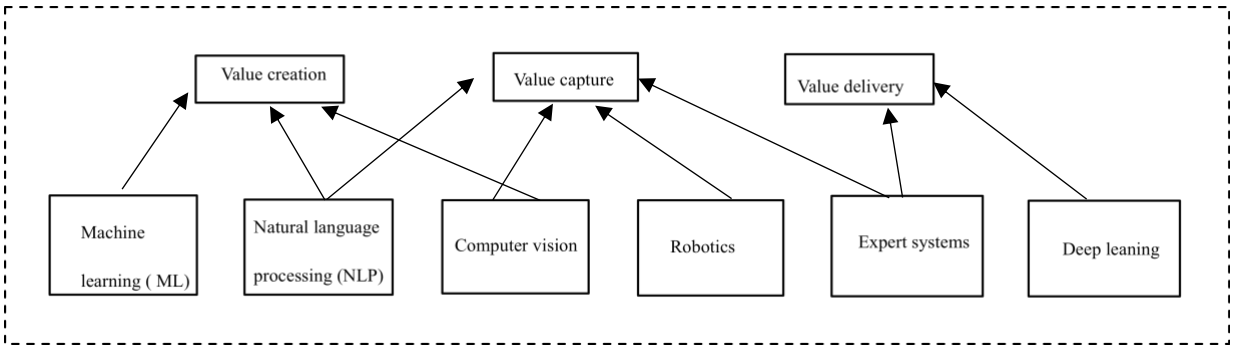


Figure 1. Relationship between the key elements of Business Model Innovation and AI components
Source: own elaboration.

3. METHODOLOGY

The assumptions explored regarding AI's role and potential in changing the landscape of business modelling have raised questions about how thoroughly this role and potential are examined in scientific research. What is the early evidence of AI's impact on new business strategies and approaches? To address these questions, an extensive literature review has been conducted.

The literature review explicitly aimed to explore the role of artificial intelligence (AI) in innovating business models. Its purpose was to provide a comprehensive understanding of how AI technologies influence business models and to identify current research trends and gaps. The approach taken in the review was primarily theoretical, focusing on understanding and analysing the relationships between key concepts such as AI, digital transformation, and business model innovation.

A range of reputable academic databases was used for the literature search, including Google Scholar, EBSCO, Elsevier, ResearchGate, Scopus, Web of Science, ProQuest, ScienceDirect, Publish or Perish, and WJARR. These platforms were selected because they comprehensively cover peer-reviewed articles, journals, and academic papers critical to the research. To identify literature that could provide insights into AI's role in business transformation, the keywords defined for the search process were: 'Business Model Innovation', 'Business Model', and 'Artificial Intelligence'. Furthermore, related terms were used, specifically: 'Digital Technologies', 'Innovation', 'Creativity', and 'Competitive Advantage', to broaden the scope of the literature collected.

The selection of literature was guided by well-defined criteria, ensuring that the chosen sources aligned with the primary objective of understanding the practical applications and implications of Artificial Intelligence (AI) in business model innovation. The first step involved prioritizing sources and clearly defining core concepts related to AI and its real-world applications in business. This focus was particularly important since it emphasized the practical impact of AI technologies on transforming business models.

Additionally, articles were selected based on their relevance to the research questions, credibility, and recency. Preference was given to works that explored the practical integration of AI into business processes, particularly those that demonstrated measurable outcomes, such as improvements in operational efficiency, customer engagement, and overall business performance. This approach ensured that the selected literature directly addressed the tangible benefits of AI adoption in business contexts.

Articles that did not meet these criteria were excluded from the review. For example, papers lacking practical case studies or focusing mainly on theoretical frameworks without demonstrating the real-world impact of AI on business models were omitted. Similarly, outdated sources or those that did not provide relevant and actionable insights were excluded in favour of more recent and applicable research.

Approximately 600 articles were identified in the initial phase based on their potential relevance to the intersection of AI and business model transformation. Inclusion and exclusion criteria were applied to streamline the selection process. The inclusion criteria focused on articles published in peer-reviewed journals or reputable conference proceedings, studies examining AI applications in business, decision-making, and value creation, and research discussing the challenges and opportunities of AI integration within business models. Additionally, preference was given to empirically based research, including case studies that highlight the practical implementation of AI. Articles published after 2015 were preferred unless they provided foundational insights critical to understanding AI's role in business.

The exclusion criteria included studies lacking empirical evidence or practical case studies, papers focused solely on AI technical development without addressing business implications, and sources that were outdated or irrelevant to the research scope. After applying these criteria, the abstracts and methodologies of the remaining articles were carefully reviewed, resulting in the final selection of 173 articles. These articles were considered the most relevant and could comprehensively address the research questions.

4. ARTIFICIAL INTELLIGENCE AND BUSINESS MODELLING: LITERATURE TRENDS AND GAPS ANALYSIS

Machine Learning (ML) is significantly transforming business model innovation, with several key trends emerging in the literature that can also greatly enhance intelligent management. One trend is adopting ML to support dynamic, agile business models that quickly adapt to market changes (Arora &

Khare, 2024; Batz et al., 2025; Rahman et al., 2024; Kumar et al., 2025). In this context, ML strengthens intelligent management by enabling organizations to make more accurate, data-driven decisions in real time, thus improving responsiveness and flexibility in resource and process management. Researchers have also noted the critical role of ML in personalizing products and services, which drives enhanced customer engagement and satisfaction (Patil, 2024; Arora & Khare, 2024; Potla & Pottla, 2024). It has been observed that Machine Learning enables value creation by optimizing operations, uncovering new revenue streams, and providing companies with a competitive advantage, particularly in industries like retail and finance (Rahman et al., 2024; Brackmann et al., 2023; Gao et al., 2024; Krishnamurthy et al., 2024). These efficiencies are vital to intelligent management, which relies on automated, insight-driven processes to allocate resources effectively and enhance operational performance. Additionally, some researchers argue that Machine Learning is contributing to the development of sustainable business models and fostering collaboration through open innovation frameworks that encourage partnerships with startups and third-party providers (Shaik et al., 2024; Moiana et al., 2023; Costa-Climent et al., 2023; Martinez, 2024). The role of ML in promoting sustainability is evident in the literature, emphasizing its support for the development of sustainability-driven business models (Ukoba et al., 2024; Kumar et al., 2025).

Nevertheless, significant gaps in the literature surrounding ML's role in business model innovation persist. First, there is a lack of longitudinal studies that explore the long-term impacts of ML on business models. While the short-term potential is well-documented, little is known about how ML-driven innovations evolve. Furthermore, although the benefits of ML are widely discussed, the challenges of implementing these technologies in business models are often overlooked. Data quality, integration costs, scalability, and the need for skilled personnel remain underexplored. Another gap is the lack of sector-specific analysis, as most studies adopt a broad approach without examining how ML is uniquely applied in different industries. Ethical concerns, including data privacy, algorithmic bias, and the potential for job displacement due to automation, are also inadequately addressed, and organizational and cultural barriers, particularly resistance to change within companies, hinder the adoption of ML. Finally, there is limited research on how ML can complement rather than disrupt traditional business models and how it can specifically contribute to sustainability. Addressing these gaps through more interdisciplinary research, longitudinal studies, and practical case studies would provide a more comprehensive review of ML's role in business model innovation.

One of the key trends in the literature on NLP and business model innovation is enhancing customer experiences through technologies such as chatbots, sentiment analysis, and automated customer support (Olujimi et al., 2023; Uzoka et al., 2024; Supriyono et al., 2024; Abiagom et al., 2024). For instance, research has analysed how customer feedback, reviews, and social media interactions help businesses deliver personalized services and improve engagement (Gladstan et al., 2024). Researchers found that NLP plays a critical role in personalizing products and services, enabling companies to tailor their offerings by understanding customer preferences and needs (Supriyono et al., 2024; Rane et al., 2024) and analysing social media data to create personalized marketing strategies and better service offerings (Babatunde et al., 2024; Rane et al., 2024; Ranjan et al., 2023). Moreover, a notable trend in the literature on the connection between NLP and BMI is the increasing use of NLP for automating business processes like document processing, contract analysis, and market research, leading to greater efficiency by minimizing human error, reducing operational costs, and saving time (Supriyono et al., 2024; Cofino et al., 2024; Oyewole et al., 2024). Automating these processes minimizes human error, cuts operational costs, boosts efficiency, and frees up resources for strategic initiatives. These outcomes align directly with the goals of intelligent management. It has been proven that sentiment analysis helps businesses understand customer sentiment and adjust their offerings to meet changing preferences; sentiment analysis powered by NLP allows businesses to gauge customer opinions, identify emerging trends, and adapt their strategies accordingly (Malik et al., 2023; Malakar et al., 2024; Shad et al., 2024). This facilitates real-time strategic adjustments and product development, aligning closely with the goals of intelligent management. Additionally, researchers suggest that NLP is integral to knowledge management and innovation within organizations, facilitating better information retrieval, data mining, and collaborative knowledge sharing, which help organizations make informed decisions and foster innovation (Just, 2024; Arnarsson et al., 2021). Combined with machine learning, these functions become increasingly adaptive and self-improving, enabling intelligent management systems to learn continuously and operate with greater autonomy and efficiency.

Despite the widespread application of NLP, several gaps in the literature impede a deeper understanding of its long-term impact on business model innovation. One significant gap is the absence of longitudinal studies that examine how NLP influences business models over time and their sustainability. More longitudinal research is necessary to evaluate the long-term effects of NLP on business models, particularly in relation to organizational change and business sustainability. Additionally, there is a lack of research regarding the challenges of integrating NLP into traditional business models, especially in industries with legacy systems that may not be compatible with advanced technologies. Many industries encounter notable difficulties when incorporating new technologies like NLP into existing systems, particularly in legacy-heavy sectors. Another gap is the insufficient interdisciplinary research linking NLP with fields such as business strategy, economics, and organizational studies, which would enhance understanding of its broader implications on business model transformation. There is a need for more interdisciplinary approaches that combine technical NLP studies with business strategy and organizational challenges. Ethical and social issues related to NLP, such as privacy concerns, algorithmic bias, and data security, remain underexplored, despite the growing use of NLP in processing sensitive data. These ethical concerns, including fairness and privacy, should be thoroughly examined to ensure the responsible use of NLP technologies. Furthermore, there is a lack of research on cultural barriers that may impede NLP adoption, such as employee resistance or mistrust of automated systems. Overcoming organizational and cultural resistance to technological adoption presents a significant challenge that requires further research. Finally, the role of NLP in promoting sustainable business models remains a relatively unexplored area, particularly in sectors focused on sustainability, such as healthcare, education, and green energy, despite its potential to initiate positive change in these industries. More research is warranted to understand how NLP can contribute to sustainable business models, especially in eco-friendly and sustainability-focused sectors.

One prominent trend in the literature regarding computer vision in business model innovation is its use in automated image and video analysis, which allows businesses to extract valuable insights from visual data, such as product recognition, quality control, and visual search (Dhabliya et al., 2023; Prasetyo et al., 2025; Peker et al., 2023; Xiong et al., 2024). These capabilities have transformed the retail, manufacturing, and security sectors (Malik et al., 2024; Rashid et al., 2024). Furthermore, the literature indicates that computer vision is playing an increasingly significant role in personalization, where image recognition tailors products and services to individual preferences (Kulkarni et al., 2023; Yang et al., 2024; Gujar, 2024; Raji et al., 2024). For instance, online retailers use computer vision to create personalized shopping experiences by recommending products based on customers' visual preferences (Nguyen et al., 2024; Patil, 2024). Another key trend noted is the impact of autonomous systems, including self-driving cars and drones, which rely heavily on computer vision for navigation, obstacle detection, and safety assurance (Bathla et al., 2022; Badrloo et al., 2022; Ali Y., 2023). These systems contribute to intelligent management by automating complex tasks, enhancing response times, and minimizing human error, particularly in the logistics, surveillance, and transport sectors. Facial recognition and gesture tracking are also emerging in the literature, demonstrating significant impacts on industries such as security, retail, and entertainment, thereby enabling improved customer interactions and personalized advertising (Keyser et al., 2021; Taskiran et al., 2020). The literature illustrates how computer vision aids in medical image analysis, assisting doctors in diagnosing conditions such as cancer by analyzing medical images and identifying patterns that may be invisible to the human eye (Jiang et al., 2023; Esteva et al., 2021; Olveres et al., 2020; Elyan et al., 2022). Many authors have also shown that integrating computer vision with augmented reality (AR) and virtual reality (VR) technologies drives innovations in industries such as gaming, education, and training, offering immersive and interactive experiences (Logeswaran et al., 2024; Al-Ansi et al., 2023; Dembe, 2024; Lopes et al., 2024; Shi, 2024). Computer vision enhances intelligent management by facilitating real-time monitoring, automation, predictive analytics, and human-computer interaction.

The literature also identifies gaps in computer vision applications for business model innovation. Research highlights challenges such as high initial costs, data privacy concerns, and integration difficulties (Lopes et al., 2024; Prasetyo et al., 2025; Raji et al., 2024). For instance, implementing machine learning and computer vision in manufacturing demands significant investment and faces hurdles in data collection and integration (N. Thompson et al., 2024). Additionally, the accuracy of computer vision systems heavily depends on the quality and quantity of data, and their use raises ethical and privacy issues (Khanh et al., 2024).

Moreover, while the research results demonstrate the potential of digitalization to enable business model innovation, the literature often highlights this potential without providing concrete frameworks for implementation. One significant gap in the literature is the lack of scalable, real-time solutions for complex computer vision tasks in dynamic environments, such as the challenges faced when deploying systems for autonomous vehicles in uncontrolled, real-world settings. These systems frequently struggle with variable lighting, weather conditions, and diverse objects. Furthermore, privacy concerns surrounding facial recognition and other personal data collection methods in the research community have sparked important ethical debates. However, research aimed at mitigating these concerns remains limited. While computer vision has the potential to enhance decision-making processes, a gap persists in understanding how to leverage these visual insights across various business functions, particularly in traditional industries like construction and agriculture. Another gap in the literature involves integrating computer vision with other emerging technologies, such as blockchain and IoT, especially in supply chain and inventory management, where cross-technology synergies could streamline operations and improve transparency. Additionally, insufficient research addresses the barriers to adoption, particularly in industries with low-tech infrastructure, where the costs and complexities of implementing computer vision solutions are prohibitive. The impact of computer vision on job displacement due to automation, particularly in manufacturing and retail, is another gap, as studies addressing the social implications of widespread AI adoption in these sectors are lacking. Finally, there is a pressing need for further investigation into sustainable business models in industries like agriculture, where computer vision could improve efficiency and reduce environmental impact. However, its full potential has yet to be thoroughly explored.

The field of robotics in value capture is brimming with exciting trends while facing significant literature gaps (Liu et al., 2024; Rahman et al., 2024). One of the most prominent trends is the integration of collaborative robots (cobots) into diverse industries, particularly manufacturing and logistics (Liu et al., 2024; George & George, 2023). Research highlights that cobots are increasingly integrated into fields such as manufacturing, healthcare, and logistics to enhance productivity and safety by working alongside human workers (Pauliková et al., 2021; Javaid et al., 2021; Keshvarparast et al., 2023; Aaltonen et al., 2020). These robots, designed to work in tandem with human employees, are revolutionizing operational efficiency and productivity (Licardo et al., 2024; Tripathi et al., 2024; Wang et al., 2024; Dhanda et al., 2024). Designed to complement human abilities rather than replace them, they are well-suited for tasks that require precision and repetition. Autonomous robots are also increasingly used in logistics and warehousing, transporting goods, managing inventory, and optimizing supply chain processes. By assessing this knowledge, we can better design our business model to be more efficient and innovative (Choudhary et al., 2025; De Simone et al., 2025; Odesanmi et al., 2022; Raj et al., 2024; Doncieux et al., 2022). This automation of routine processes supports intelligent management by improving resource utilization, minimizing human error, and facilitating data-driven decision-making.

Studies highlight the ability to automate repetitive tasks, freeing human workers to focus on more complex and value-added activities (Intahchomphoo et al., 2024; Zirar et al., 2023). This shift leads to increased productivity, reduced operational costs, and improved product quality (Sakeb et al., 2024; Campilho et al., 2023; Zhao et al., 2024; Javaid et al., 2021). In agriculture, robotics enables precision farming, with robots employed for tasks such as planting, harvesting, and monitoring crop health, which increases yields while reducing environmental impact (Cheng et al., 2022; Wakchaure et al., 2023; Shamshiri et al., 2018; Oliveira et al., 2021; Botta et al., 2022; Eissa, 2024). For instance, numerous studies published about robotics and AI investigate the implementation of collaborative robots across vehicle assembly, warehouse logistics, and agricultural operations, highlighting their role in enhancing operational efficiency and safety (Jacob et al., 2023; Smith, 2024; Malik et al., 2019; Keshvarparast et al., 2023). It has been demonstrated that robots play a significant role in construction by automating tasks like bricklaying and welding, which reduces human labor and improves the quality and speed of construction projects (Prodhan et al., 2025). Integrating robotics in this sector supports intelligent management by facilitating predictive maintenance, efficient scheduling, and workflow optimization. Another notable trend is the emergence of robotics in healthcare, where robots increasingly assist in surgeries, patient care, and even drug discovery (Deo et al., 2023; Cruz et al., 2024; Reddy et al., 2023; Agrawal et al., 2024; Morgan et al., 2022). Here, research results support the capacity of robots to perform complex procedures with precision and consistency, leading to improved patient outcomes and

shortened recovery times (Liu et al., 2024; Fairag et al., 2024; Reddy et al., 2023). Moreover, robots assist with tasks such as medication delivery and patient monitoring, allowing healthcare professionals to focus on more critical patient care (Wang et al., 2024; F. Wu et al., 2024; Raja et al., 2024; Cruz et al., 2024). These applications align closely with intelligent management by fostering automation, enhancing operational workflows, and enabling real-time decision-making supported by integrated data systems.

However, the literature on robotics in value capture still grapples with several critical gaps. One significant gap is the lack of robust frameworks for measuring the impact of robotics on value capture. While numerous case studies illustrate the successful implementation of robotics in various industries (Zhang et al., 2023), there is a dearth of research quantifying the actual benefits and ROI (return on investment) these systems provide. This absence of comprehensive measurement frameworks complicates the assessment of the real value generated by robotic systems and makes it challenging to compare their impact across different industries and applications. Another critical gap lies in the ethical considerations surrounding the use of robotics. As robots become more sophisticated and integrated into various aspects of our lives, questions about job displacement, transparency, and accountability become increasingly relevant. How can we ensure that the introduction of robots does not lead to widespread job losses and economic disruption? How can we ensure that robotic decision-making processes are transparent and accountable, particularly in critical areas like healthcare? These ethical considerations are often overlooked in the current literature, yet they are crucial for the responsible progression and deployment of robotics in value capture. The future of robotics in value capture is promising, but it requires continued research and development to address these gaps. Focusing on real-world applications, developing robust frameworks for measuring impact, and addressing ethical considerations will be crucial for realizing the full potential of robotics in delivering value across various sectors.

Despite the widespread adoption of robotics across various industries, several gaps in the literature regarding its integration into business models exist. One significant gap is the lack of scalability in many robotic solutions, as small and medium-sized businesses often struggle to afford the high upfront costs associated with robotics. At the same time, large-scale deployment continues to face challenges. The issue of integrating a robotic workforce is another critical gap, particularly in industries where human workers must be retrained to collaborate with robots. Research on effectively integrating robotics with the existing workforce and overcoming cultural and operational challenges remains limited. Regulatory and ethical concerns, such as safety standards, job displacement, and data privacy, are also underexplored in the context of robotics and automation, despite their growing importance as robots are increasingly deployed in sensitive sectors like healthcare and defence. Additionally, there is insufficient research into the long-term economic impact of robotics on business models, particularly regarding the potential for increased automation to lead to job losses or wage disparity in specific sectors. Furthermore, a gap exists in understanding the sustainability of robotic business models, particularly concerning energy consumption, environmental impact, and lifecycle management of robotic systems. Lastly, the reliability and robustness of robotic systems in complex, real-world environments, such as outdoor settings or hazardous areas, remain significant concerns, necessitating more research to enhance their adaptability to dynamic and unstructured settings.

The research landscape on expert systems (ES) in value capture is dynamic and follows specific trends. It has been documented that the use of software tools for building expert systems is rapidly increasing, fueled by the availability of powerful AI libraries and frameworks (Oloo, 2023; Matsuzaka & Yashiro, 2023). This growing usage leads to more sophisticated systems, often developed through a structured approach that includes requirements analysis, knowledge acquisition, system design, testing and refinement, and deployment and integration (Åström et al., 2022). The literature demonstrates how these systems utilize knowledge-based algorithms to simulate expert-level decision-making, enhancing the speed and quality of decisions in areas such as finance, marketing, and supply chain management (Anshu & Sharma, 2024; Inusuah & Amponsah, 2018; Sharipbay et al., 2024). There is increasing interest in applying ES to specific sectors like education, healthcare, and finance, enabling researchers to create tailored systems that address unique challenges and opportunities within those domains (Sayed, 2021; Islam et al., 2024; Yang & Zhu, 2024; Inusah, 2023; Yousef et al., 2023). The literature illustrates how expert systems are supporting clinical decision-making by analysing patient data and recommending treatments based on the vast amounts of medical knowledge they are trained on, thereby improving diagnostic accuracy and patient outcomes (Chen et al., 2023; Khosravi et al., 2024; Ruban et

al., 2024). Exploration of the role of expert systems (ES) in value delivery highlights an increasing integration of AI technologies, particularly machine learning and data analytics, into ES (Asemi et al., 2020; Choi et al., 2021; Håkansson & Zelano, 2022). This capability could support intelligent management by improving resource allocation, optimizing processes, and reducing reliance on manual oversight.

Now, there is a gap in understanding the long-term impact of expert systems on organizational structure and employee roles, as the automation of decision-making processes could lead to a shift in workforce responsibilities. While researchers are exploring the potential of ES for value capture (Oloo, 2023), more robust methodologies are needed to measure the actual value generated. Despite the documented potential of ES to enhance learning outcomes (Sayed, 2021; Ivanyshyn et al., 2023), there remains a gap in research regarding its practical applications in the educational sector, particularly focusing on developing systems that can personalize learning, provide individualized feedback, and support student engagement. A critical and visible gap is the lack of research on the adoption and implementation barriers of expert systems, especially in industries with low technological adoption or where the organizational culture resists change. While researchers are investigating the potential of ES to enhance efficiency, productivity, and decision-making (Inusah & Amponsah, 2018; Svoboda & Lande, 2024), more robust methodologies are also needed to quantify the actual value generated. It has been demonstrated that expert systems are increasingly being used for decision support (Kostopoulos et al., 2024; De-Arteaga et al., 2021), yet ethical concerns related to transparency, bias, and accountability still need to be addressed more deeply, particularly as these systems are tasked with making decisions that affect customers and employees.

Deep learning, a subset of machine learning, has seen widespread adoption in business model innovation due to its ability to process vast amounts of data and enhance decision-making processes. However, some of these concerns are addressed in the literature (Yang et al., 2021; Rane et al., 2024). First, the studies explore the level of DL adoption across various industries, including supply chain management and healthcare (Yang et al., 2021). In healthcare, the potential of DL to revolutionize the field, with applications ranging from drug discovery to medical imaging analysis, is being analysed (Rane et al., 2024). It also demonstrates how deep learning, combined with natural language processing (NLP), transforms the marketing, finance, and healthcare sectors by enabling sentiment analysis, automatic translation, and chatbot-based customer service (Ghosh, 2025). This contributes directly to intelligent management by allowing businesses to respond to customer preferences in real time and refine their strategies based on customer feedback and sentiments. Deep learning is a key driver of autonomous vehicles in the automotive industry, providing the algorithms necessary for object detection, path planning, and decision-making in self-driving cars (Chib & Singh, 2024; Zhang et al., 2025). Another vital area of literature analysis is predictive analytics in business operations, where deep learning models are used to forecast market trends, consumer behaviour, and supply chain demands, leading to more efficient decision-making and improved customer targeting (Lee et al., 2021). For instance, researchers are exploring the use of DL to optimize inventory management, predict delivery delays, and enhance demand forecasting accuracy (Shavaki & Ghahnavieh, 2023). The research results demonstrate how these applications leverage the ability of DL to analyse massive datasets and identify complex patterns, leading to more efficient and cost-effective operations.

At the same time, the literature on DL in value delivery continues to address several concerns. One crucial gap is the lack of comprehensive frameworks for measuring the actual impact of DL on value delivery. Another significant gap involves the ethical considerations surrounding the use of DL. As DL systems become more sophisticated and integrated into critical decision-making processes, concerns about bias, transparency, and accountability are increasingly prominent.

5. DISCUSSION AND CONCLUSIONS

The literature widely acknowledges AI as a critical enabler of innovation and a source of competitive advantage. Choi & Lee (2021) and Inusah & Acheampong (2018) agree that AI enhances business responsiveness, improves decision-making, and fosters competitive differentiation. However, while Choi & Lee (2021) emphasize AI's role in customer-centric innovations, Inusah & Acheampong (2018) focus on its contribution to sustainability and resource efficiency. Similarly, in the realm of

personalization, Kulkarni et al. (2023), Yang et al. (2024), and Gladstan et al. (2024) highlight AI's ability to enhance customer experience through predictive analytics and recommendation systems. While both agree on AI's effectiveness in improving customer engagement, Olujimi & Ade-Ibijola (2023) focus on its technical aspects, particularly in natural language processing. In contrast, Zhang et al. (2021), Malakar et al. (2024), and Dimple (2024) concentrate on its influence on customer loyalty and revenue generation.

Another central area of consensus is AI's integration with emerging technologies such as IoT, blockchain, and 5 G. Yarlagadda, V.K. (2024) and Zhang et al. (2023) both recognize that AI enhances operational efficiency and data-driven decision-making, particularly in logistics and healthcare. However, Yarlagadda (2024) and Bharadiya (2023) focus on AI's applications in manufacturing and smart city infrastructure, while Zhang et al. (2023) emphasize its role in improving transparency and security within blockchain-based business models. These advancements foster a foundation for intelligent management by enabling leaders to make proactive, accurate decisions across distributed systems and digital infrastructures. Ethical and social concerns surrounding AI are also widely acknowledged, with Binns (2020) and Pessach & Shmueli (2022) highlighting issues such as algorithmic bias, privacy risks, and the societal implications of automation. While both stress the importance of fairness and accountability in AI deployment, Binns (2020) delves deeper into algorithmic decision-making. In contrast, Pessach & Shmueli (2022) examine broader fairness issues in machine learning models.

Despite these agreements, notable areas of divergence exist in the literature. Metzler et al. (2021) argue that existing research lacks longitudinal studies on AI's sustained impact on business models. Nambisan et al. (2018) contend that AI's immediate transformative effects are already significant enough to study. This reflects a broader debate on whether the short-term benefits of AI are well documented or if more research is needed to assess its long-term strategic implications. Another key point of disagreement is the extent to which legacy businesses can effectively integrate AI. Zhang et al. (2021) suggest that sector-specific strategies can enable traditional businesses to adapt, while Nambisan et al. (2018) argue that outdated infrastructure and resistance to change present significant challenges. Additionally, Zhang et al. (2021) state that AI's role in industry-specific business models, such as healthcare, education, and agriculture, has been underexplored. In contrast, other scholars focus on AI's broader impact across various industries. These differences highlight gaps in the literature and suggest areas for further research, particularly in understanding AI's long-term effects, ethical considerations, and its application within specific industries. Collectively, these capabilities foster intelligent management by equipping businesses with real-time insights, responsive operational tools, and predictive capabilities that enhance strategic decision-making and streamline resource allocation.

The existing literature highlights the transformative role of Artificial Intelligence (AI) technologies—including Machine Learning (ML), Natural Language Processing (NLP), Computer Vision, Robotics, Expert Systems, and Deep Learning—in driving business model innovation. Current research emphasizes key trends such as AI-driven automation, personalization, operational efficiency, and data-driven decision-making, which are reshaping operations across various industries. Studies have explored how AI enhances value creation, optimizes business operations, and improves customer engagement, demonstrating its potential to revolutionize traditional and digital business models.

However, significant gaps remain in the literature, limiting a comprehensive understanding of AI's long-term implications for business models. One significant gap is the lack of longitudinal studies examining how AI-driven innovations evolve and affect business scalability, adaptability, and sustainability. While existing research extensively discusses the benefits of AI, it provides limited analysis of the challenges businesses face in integrating these technologies, including data quality issues, high implementation costs, workforce displacement, and ethical concerns such as algorithmic bias, privacy risks, and transparency. Much of the literature also takes a generalized perspective, lacking sector-specific insights into how different industries uniquely implement and adapt AI-driven solutions. The complexity of integrating AI within traditional business models, especially in industries that rely on legacy systems and resist technological change, remains underexplored.

Recent advancements in large language models illustrate a rapidly evolving landscape. For instance, models like ChatGPT have set the standard with robust text generation and refined reasoning abilities, enhanced by real-time web access and voice-enabled interactions in their premium versions. Meanwhile, DeepSeek has emerged as a strong open-source contender, demonstrating competitive reasoning and

technical prowess at a fraction of the cost. However, it currently lags in multimodal features such as voice and video. On the other hand, Anthropic's Claude focuses on delivering nuanced, context-aware responses with extended reasoning and a large context window. However, it is less integrated with voice and real-time search than ChatGPT. Other top systems continue to push boundaries in multimodality, with some models now capable of integrating visual inputs. Nevertheless, core competitive factors remain advanced text understanding and step-by-step reasoning.

Future research should address these gaps by conducting empirical studies that assess AI's long-term impact, industry-specific case analyses that capture the nuances of AI adoption and developing robust frameworks for measuring AI's influence on business model transformation. Ethical considerations must also be integrated into AI research to ensure responsible and sustainable implementation. Furthermore, the literature should explore how AI can complement rather than disrupt existing business models, helping organizations navigate digital transformation effectively. By filling these research gaps, future studies can provide deeper insights into AI's evolving role in business model innovation and explore the narratives of how AI can complement existing systems—thereby helping businesses transition through digital transformation while reinforcing stability, innovation, and intelligent management to guide businesses toward more strategic, ethical, and sustainable AI adoption.

The reviewed literature underscores the growing significance of Artificial Intelligence (AI) as a foundational element of intelligent management in business model innovation. AI technologies, particularly Machine Learning (ML), Natural Language Processing (NLP), and Computer Vision, are increasingly leveraged to facilitate real-time analytics, automate decision-making, and improve organizational responsiveness. These capabilities align closely with the principles of intelligent management, which emphasize data-driven control, adaptability, and continuous performance optimization. Nevertheless, existing studies focus on the operational applications of AI, with insufficient attention given to the strategic transformation of managerial processes. For instance, there is a lack of in-depth analysis regarding how AI integration redefines leadership roles, decision hierarchies, and the dynamics of organizational learning within intelligent management frameworks.

The prevailing literature is biased toward conceptualizing AI as a disruptive force, often overlooking its capacity to augment and evolve existing managerial paradigms. There is a dearth of empirical studies evaluating how AI can be incrementally embedded to support hybrid models of intelligent management, where human judgment and automated systems operate in a complementary fashion. Furthermore, the long-term impacts of AI-enabled intelligent management, particularly regarding strategic agility, organizational resilience, and sustainable value creation, have not been sufficiently addressed. Future research could potentially prioritize developing robust, longitudinal frameworks that assess AI's role in shaping adaptive and industry-specific models of intelligent management. This will be essential for guiding organizations through the complex transitions that digital transformation requires.

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DIGITAL MATURITY OF ENTERPRISES IN TERMS OF COOPERATION IN SUPPLY CHAINS & NETWORKS – INTELLIGENT MANAGEMENT PERSPECTIVE

Marzena Frankowska[a], Katarzyna Cheba[b], Maria Anityasari[c], Putu Dana Karninggsih[d]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *West Pomeranian University of Technology in Szczecin, Faculty of Economics, Szczecin, Poland*
[c] *Sepuluh Nopember Institute of Technology (ITS), Department of Industrial and Systems Engineering, Indonesia*
[d] *Sepuluh Nopember Institute of Technology (ITS), Department of Industrial and Systems Engineering, Indonesia*

ABSTRACT

Purpose: *Digital transformation is conditioning the implementation of Intelligent Management in the enterprise and the collaborative system (supply chain & networks). The aim is to answer the following questions: What is the interdependence of using digital maturity models and Intelligent Management? Is a company's level of digital maturity regarding cooperation in the supply chain related to its comprehensive digital transformation?*

Need for the study: *Digital transformation, the implementation of artificial intelligence technology, and intelligent management are phenomena that require fundamental modifications to the current functioning of enterprises, chains, and supply networks.*

Methodology: *A literature review of the link between research streams on digital maturity models and Intelligent Management. The quantitative research used a two-stage research procedure. The Digital Maturity Model in Industry 4.0 was used as the theoretical basis. The research of 150 cluster enterprises (89 were chosen for in-depth research). In the second stage, the relative taxonomy method was applied.*

Findings: *A conceptual framework for the interdependence of the Digital Maturity Model and Intelligent Management has been identified. Regarding quantitative research, the issues raised indicate the high complexity of the processes involved in manufacturing companies during digital transformation. It can be assumed that companies that achieve better results in the digital transformation of significant areas also achieve better results in digitizing integration with the environment, although this relation is not crucial.*

Practical Implications: *The survey results can be used to develop a reference decision-making model for digitizing companies, which will put the application of Intelligent Management into perspective.*

Keywords: Intelligent Management, digital maturity model, cooperation, supply chains, networks, taxonomy method, decision model, AI

JEL codes: C13, C38, L10, L20

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1. INTRODUCTION

For over two decades, the economic environment has been undergoing a kind of transformation at an accelerating pace, becoming a Smart Environment. Business disruptions due to the COVID-19 pandemic have accelerated the needs and adoption of smart or digital operations (Spieske, Gebhardt, Kopyto, Birkel, & Hartmann, 2023; Tito, 2022; Sabău-Popa et al., 2024) and it will continue after this pandemic is over (Alamsjahm & Yunus, 2022). Through the application of science and technology and the widespread use of the Internet, we have entered the era of digital information explosion, also known as the "big data era". The changes that occur in the industry (the fourth industrial revolution) are associated with integrating the real world with the virtual one through the use of Human-Cyber-Physical Systems and the Internet of Things (IoT). The physical world is in fact, indistinctly and constantly saturated with devices, sensors, recorders, displays or other tools that constantly identify the behaviour (and the identity) of objects and people in physical and virtual space. Outstanding amounts of data are produced, collected and processed, which, when translated into adequate information, are able to support decisions and stimulate actions. Thus, combining management methods with artificial intelligence technology and intelligent management must now become an integral part of management practice (Xiaojing, & Minghai, 2021).

Digital innovations have significantly affected the modification of consumer behaviour and expectations, as well as enterprises' activity and dynamic abilities. These changes not only put pressure on the traditional way of doing business and previous business models but are now structural in nature, which is collectively referred to as "digital transformation". Digital transformation is a phenomenon that leads to a comprehensive and fundamental modification of the current functioning of enterprises. It is defined as a transformation of how digital technologies are used to create a new business model that supports the creation of added value and increases the efficiency of its use by the company (Schallmo, Williams, & Boardman, 2020; Verhoef et al., 2021). The following changes are known as the Fourth Industrial Revolution or the concept of Industry 4.0. It includes four main components, namely Smart Factory, which cooperates within the framework of Smart Supply Chain, Smart Technologies used to manufacture and supply Smart Products and Services (Frankowska & Nowicka, 2018). The implementation of the Industry 4.0 concept includes a complex process that takes into account digital transformation in the broadly understood technological, organizational, and process area of enterprises. Several stakeholders have to be involved, and all these groups need a common and consistent understanding of the relevant areas to be addressed and the prioritization of digital transformation activities (Berghaus & Back, 2016; Teichert, 2019). Apart from transforming single isolated companies, the transformation in networks of companies is currently being investigated, leading to the digital transformation of supply chain or “digital supply chains” (Hellweg et al., 2023).

Industry 4.0 requires the intellectualization of the entire environment: business models, production systems, processes, machines, operators, products and services. It also requires the coherence of the digital and physical worlds by creating human-cyber-physical systems that can combine natural and artificial intelligence. Such challenges demand the use of new approaches to building management systems, particularly the extensive use of natural and artificial intelligence in their organizational management structure (Odrekhivskyi et al., 2023). Thus, it can be assumed that the process of digital transformation of the supply chain is conditioned by the advancement of the digital transformation of companies cooperating in the supply chains. In turn, the digital transformation of enterprises is an equally complex issue, the multidimensionality of which is reflected in attempts to develop a model of digital maturity of the enterprise (Chanias & Hess, 2016; Canetta, Barni, & Montini, 2018; Remane & Hanelt, 2017; Teichert, 2019).

In the era of the digital economy, digital transformation has become an inevitable decision for companies that want to cope with changes in digital technology, increasingly fierce digital competition and digital customer behaviour (Verhoef et al. 2021). Making good decisions and applying decision models is possible thanks to understanding the company's situation through the digital transformation maturity model. Intelligent decision-making is one of the key positions in decision-support systems and is primarily associated with modern business development (Odrekhivskyi et al., 2023, Abbasi et al., 2016).

The intelligent management system can use information communication technology and machine intelligence to achieve all the required automatic and intelligent management behaviours by

implementing information management and intelligent system platforms. Depersonalized intelligent management has revolutionized management science and has become an essential subject of management practice (Xiaojing, & Minghai, 2021).

Hence, the assessment of digital maturity should be regarded as a preliminary stage for implementing advanced Intelligent Management methods and tools. This is because enterprises need to exhibit a certain level of DT sophistication to expand management structures using human-cyber-physical systems and to incorporate artificial intelligence solutions. Thus, in this paper, the research logic centres around a triad of constructs:

- maturity of enterprise digital transformation,
- maturity of enterprise digital transformation in supply chain cooperation,
- ability to implement intelligent management systems.

The empirical layer of the study aims to answer the question: Is a company's level of digital maturity regarding cooperation in the supply chain related to its comprehensive digital transformation? In other words, does the enterprise's level of digital maturity in terms of its integration with the environment (suppliers and customers) correlate with the level of digital maturity in other company areas? The Digital Maturity Model in Industry 4.0 was used as the theoretical basis, and its structure was applied to formulate the main and auxiliary hypotheses. Using a digital maturity model allows to determine an enterprise's advancement in different areas and is helpful in the decision-making process of prioritizing the necessary areas of the enterprise's digital transformation (Zhu et al., 2024).

The article is organized as follows. After explaining the purpose of the study in section 1, section 2 presents a literature review on the digital transformation of companies and supply chains. Section 3 describes the concept and test procedure, while the test results are included in section 4. The last section discusses the test results and the final conclusions.

2. DIGITAL TRANSFORMATION OF COMPANIES AND SUPPLY CHAINS WITH AN INTELLIGENT MANAGEMENT PERSPECTIVE – LITERATURE REVIEW

Nowadays, digital transformation (DT) has a comprehensive impact on all dimensions of activities carried out by both people and organizations. From the supply chain collaboration point of view, the DT perspective seems crucial in an industry where the concept of “Industry 4.0” was introduced.

According to Pereira et al. (2017) and Alcácer et al. (2019), Industry 4.0 involves intellectualising everything: business models, environments, production systems, machines, operators, products, and services. It also encourages the unification of digital and physical worlds through the creation of managerial human–cyber–physical systems that can combine natural and artificial intelligence. Such challenges require the use of new approaches to building management systems, in particular, to widely apply natural and artificial intelligence in their organisational management structure (Odrekhivskyi et al., 2023).

Companies that have discerned the relevance of changes occurring in the economic environment more and more often transfer their operations, processes (planning, purchases, manufacturing, deliveries, and returns) and the process of supply chain management itself to the virtual world. As a result, Smart Supply Chains are created, which are defined by Wu et al. as a new interconnected business system that extends from isolated, local, and single-company applications to supply chain-wide systematic smart implementations (Wu, Yue, Jin, &Yen, 2016). The intelligent supply chain is a testament to technological convergence's transformative power, especially in industrial engineering. It embodies a shift towards a more efficient, responsive, and sustainable industrial ecosystem, facilitated by the strategic application of Artificial Intelligence (AI), the Internet of Things (IoT), and big data analytics (Cheng, 2024).

Thus, Smart Supply Chain is a system that ensures full interoperability and uses the potential of technologies, namely IoT, Cloud Computing, 3D printing, Big Data and big data analytics, artificial intelligence, automation, or robotization. Such an ecosystem of technologies and appropriate use of data analytics makes it possible to take decisions in near real-time events taking place in the physical world at various levels of the supply chain. This requires integration processes which consist of (Wang, Wan, Li, & Zhang, 2016):

- Vertical integration involves internal processes in a company, ranging from design and purchase to customer and after-sales services.
- Horizontal integration, which takes into account collaboration with suppliers, customers, and cooperators in the value chain.

Reaching the level known as 'smart' requires the gradual implementation of technologically advanced tools that stage the scope of the transformation of supply chains, ranging from IT-Enabled Supply Chain, through Digital Supply Chain (DSC) to become a Smart supply chain ultimately. Besides being intelligent as well as integrated vertically and horizontally, smart supply chain is also adaptive to external changes (Zhang, Yang, & Yang, 2022).

Transformational information technology has fundamentally changed traditional business methods by redefining capabilities, processes, and relationships (Ismail, Khater, & Zaki, 2017). Thus, selecting the suitable technologies is very important to enable smooth digital transformation in the internal organization as well as a part of the supply chain network (Büyüközkan & Göçer, 2018). However, it is assumed that the transformational power of IT must be exhibited in at least three of the following dimensions: processes, new organizations, relationships, user experience, markets, customers, and disruption (Ismail et al., 2017). The occurring transformation of supply chains is characterized by the complexity and multidimensionality of its impact on the scope and manner of cooperation. The article adopts the basic five-step process IT-Enable Transformation developed by Venkatram (1994), which describes the evolutionary and revolutionary changes taking place in the enterprise and, consequently, its supply chain (Table 1).

Table 1. IT-Enable Transformation Process

Levels	IT-Enabled Transformations	Characteristics
Evolutionary level (Disjoined digitalization)	Localized exploitation	Decentralized leveraging of IT systems within organizational functions which are limited to supporting functional requirements (informational and transactional benefits: faster and easier access to information, reduced operating costs or enhanced employee productivity)
	Internal integration	Systematic leveraging of IT capabilities throughout the entire business process. Integration of the existing systems and linking different functions into organization-wide networks
Revolutionary level (Enterprise-wide digitalization)	Business process redesign	Redesigning the current business process and organizational design. Includes introduction of the enterprise resource planning (ERP) systems, data warehousing platforms; customer relationship management (CRM) systems
	Business network redesign	Redesigning the nature of the exchange between multiple stakeholders in a business network. It goes beyond the organizational boundaries by leveraging information technology to transform the value activities with external stakeholders such as customers, suppliers, and other business partners to improve firm performance
	Business scope redefinition	Expanding the business scope and fundamentally restructuring activities within the value chain allowing firms to offer entirely new services and to enter new markets. As a consequence of this role, companies transcend from the secure confines of their stable business and invent business models that take full advantage of the growing centrality of IT
	Customer experience transformation	Integrating all the customer touch-points and the companies' interactions across various digital and physical, platforms. Introduction of digitally enhanced products and services. Companies transform their customer experience, and might have to transform their operations
	Business model transformation	The business model transformation is the most difficult area to transform, as it touches upon all elements within a firm's value chain and value system

Source: El Sawy, Kræmmergaard, Amsinck, & Vinther (2016), Ismail et al. (2017).

Following the implemented changes, a digital transformation occurs, which is the process through which companies converge multiple new digital technologies, enhanced with ubiquitous connectivity, to reach superior performance and sustain competitive advantage. It requires the simultaneous transformation of numerous business dimensions, including the business model, the customer experience and operations, while simultaneously impacting people and networks (Ismail et al., 2017).

Korpela, Hallikas, & Dahlberg (2017) identified four transformation requirements for digital business ecosystems that constitute a foundation for business and innovation development:

- Business model development: Companies must develop strategies and business models that maximize innovation and effectiveness in leveraging digitalization and supply chain integration services in their business offerings.
- Information model platforms: Appropriate information models are needed to collect, store, and deliver information in supply chains. This often requires the development of platforms and integration between multiple platforms.
- Business process standards for supply chain connectivity: New competencies and solutions are needed to develop business process connectivity and standards. This relates to how trading partners in the supply chain can be digitally connected to business process transactions.
- Operator services for data transfer between actors: Integration channel intermediaries (e.g. operators) are needed to transfer and integrate information across actors and systems.

As a result, efforts are being made to develop a digital supply chain (DSC), which is referred to as a strategic and operative exchange of information between chain members in order to enhance communication between actors in the chain. Intrafirm and interfirm coordination are achieved employing electronic links between information systems, enabling automated and digitalized processing of source-to-pay processes involving suppliers and customers in the supply chain (Korpela, Mikkonen, Hallikas, & Pynnönen, 2016). In the meaning of the intelligent supply chain, it involves sharing and processing information not only from the partners' business processes but also covers the level of shop floor, where huge amounts of data are collected from devices and sensors (IoT), as well as from social applications (Frankowska & Nowicka, 2018). DT also affects network dynamics and shifts it from the center of organizations to accommodate digitally engaged suppliers and customers, where they co-create value in a digital ecosystem (Gray, 2013; Mussomeli, Gish, & Laamper, 2016). Therefore, the digital supply chain covers both the digital transformation of a business organization and the digital transformation of processes and technologies.

Baah, Acquah, & Ofori (2022) convey that supply chain collaboration benefits supply chain visibility. Furthermore, Moshood, Nawanir, Sorooshian, & Okfalisa (2021) discuss the need for thorough integration between people, technology, and process in developing supply chain visibility through digital transformation. Hence, it can be concluded that both technology and non-technology factors are equally important. Gathering and exchanging information between supply chain players could lead to proper decision making and increase supply chain efficiency. This condition is referred as smart supply chain, that can be defined as “a supply chain that integrates the partners can self-organize and automatically adapt to environmental changes and makes intelligent decision that best achieve business goals” (Zhang et al., 2022).

Nowadays, many supply chains are transforming from traditional, structured, and linear supply chains to an interconnected organization that can more readily incorporate ecosystem partners and evolves to react more flexibly (Mariani, Quasney, & Raynor, 2015; Cheng, 2024). As each supply node becomes more connected, the supply chain takes on the form of a dynamic, integrated supply network, assuring visibility into processes, which enhances their ability to react or adjust partner activities. This shift from traditional supply chain to interconnected supply network is possible as a result of the implementation of DT, and at a later stage, intelligent management methods based on AI solutions, Intelligent IT systems, which are the result of combining natural and artificial intelligence, allow enterprises (Odrekhivskyi et al., 2023) to:

- model and automate decision-making processes,
- model and automate organizational management of enterprises,
- take into account the possibilities of automating all stages of management activities,
- build integrated intelligent IT systems to make optimal decisions regarding the use of innovative adaptogenic business models, etc.

Intelligent systems as human-cyber-physical systems, in which human and artificial intelligence interact and facilitate the process of making optimal decisions, will contribute to the creation of smart enterprises; the transition of enterprises from centralized to decentralized management; the adaptation of business processes, business structures, and technologies to environmental conditions; the use of self-organised, adaptogenic, multi-agent and expert systems that can form new business models (Odrekhivskyi et al., 2023).

Maturity models are popular tools in both research and practice. Despite their growing popularity and adoption in many areas, supply chain digital maturity models are in their early stages of development. Existing models only consider single or industry-specific aspects of supply chain digitalization, e.g. focusing on the production process or single technologies such as artificial intelligence. Due to the complexity of the issues in this case, this is considered a limitation (Hellweg et al., 2023).

An example of a comprehensive supply chain maturity model is presented by Zhang et al. (2023), who propose a framework representing four stages of intelligent supply chain transformation, which include:, which include: (a) Level 0 presents basic Industry 4.0 technologies (i.e. IOT, machine learning, additive manufacturing, etc) as a driver, (b) Level 1 presents early stage of smart supply chain that applies in partial part of supply chain, (c) Level 2 presents advanced smart supply chain covering all supply chain operations area and players, (d) Level 3 present extended smart application not only limited in supply chains/networks but also in the business level and more.

In summary, it should be stated that the supply chain DT is developing in parallel with the networking process of enterprises. Whereas, when many companies are introducing DT, recent studies of success stories have shown that the enhanced competitive positioning of successful firms does not depend solely on the technologies they adopt, but, more importantly, builds on the strategies that their leaders deploy (Ismail et al., 2017). Hence, it is interesting to question whether the level of advancement of a digital enterprise in supply chain collaboration is related to the digital transformation of the entire enterprise.

3. RESEARCH FRAMEWORK AND METHODOLOGY

3.1 Research framework and hypotheses development

Digital supply chains are not about whether goods and services are digital or physical; they are about how supply chain processes are managed using various innovative technologies (Hellweg et al., 2023). The nature of value creation and management becomes apparent in this definition. The use of new technologies alone is not sufficient to drive digital transformation. It is necessary to align digital initiatives with the overall strategic management of the company and supply chain management to create digital business models that leverage human-cyber-physical systems and combine natural and artificial intelligence. The conceptual framework is presented in Fig. 1.

The digital transformation of enterprises is an equally complex issue, and its multidimensional nature is reflected in attempts to define the digital maturity of the enterprise. In recent years, many models have been developed to assess enterprises digital maturity (Chanias, & Hess, 2016; Remane, & Hanelt, 2017; Canetta et al., 2018; Teichert, 2019).

The challenge is the assumption that digital maturity comprises a technological and a managerial aspect and therefore can be seen as a holistic concept. In one recent systematic literature review study, 22 digital maturity models were identified and tested (Teichert, 2019). The study identified the most common digital maturity areas, which include: digital culture, technology, operations & processes, digital strategy, organization, digital skills, innovation, customer insight & experience, governance, vision, digital ecosystem, leadership, compliance & security, product & services, business model. The research results provided strong evidence that all identified models pursue different approaches in describing digital maturity. Despite the researchers' many efforts, no single consistent approach to conceptualizing and assessing the digital maturity of enterprises has been developed so far.

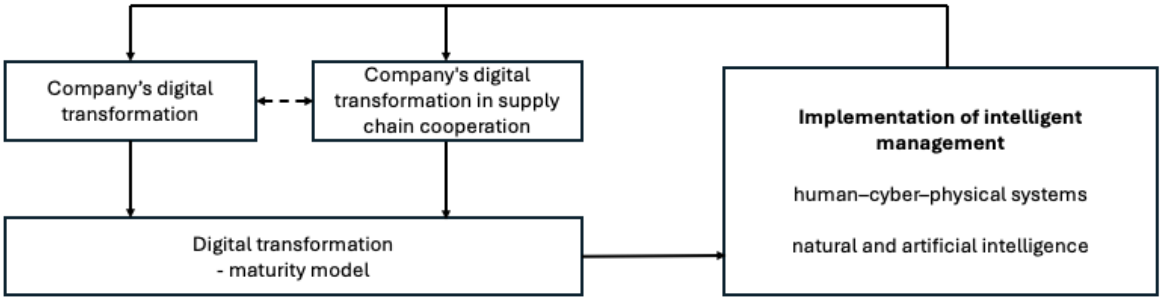


Figure 1. The Interdependence of Digital Transformation and Intelligent Management – a Conceptual Framework
Source: own elaboration.

The process of digital transformation of the supply chain is conditioned by the advancement of the digital transformation of enterprises cooperating in the supply chains (Figure 2).

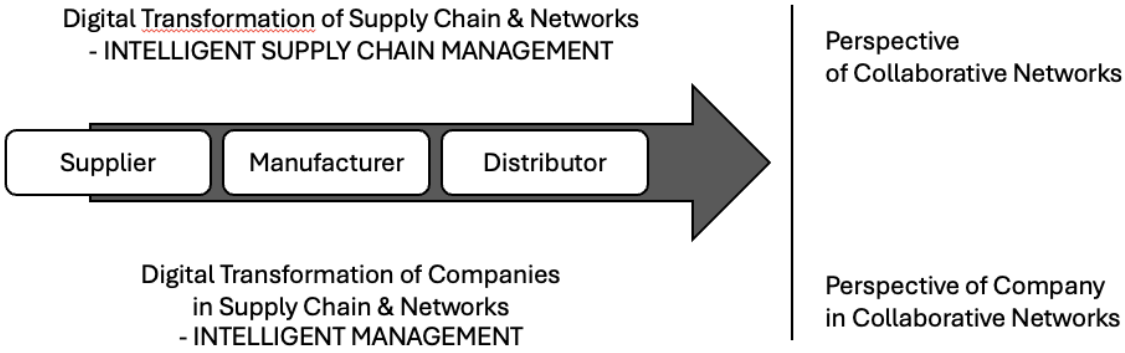


Figure 2. Digital transformation assessment perspectives in the supply chain and networks
Source: own elaboration.

In this article, the Digital Maturity Model in Industry 4.0 (Nosalska, Śledziewska, Włoch, & Gracel, 2020) was chosen to help design the research process and formulate research hypotheses. The model was developed considering the current scientific achievements in the field of existing digital maturity models and the results of qualitative research carried out by the model's authors. In principle, the model adopts a holistic approach. The dimensions of key importance for Industry 4.0 were indicated, where the symptoms of digital maturity, characteristic of various stages of the company's development, were determined. These dimensions form the backbone of the maturity model in the organizational, technological and process areas. The model is built in a three-stage system. It comprises three key pillars for the development of Industry 4.0 in manufacturing companies, which are: Organization, Processes and Technologies. In turn, each pillar consists of four modules, which are made up of components. In total, the model contains 12 key modules (20 components) representing the critical aspects that companies should focus on in order to become a future-proofed organization within the Industry 4.0 reference model (Table 2).

The Technology Pillar highlights the fact that technology remains a key driver of change in Industry 4.0. Both a high level of automation as well as ubiquitous connectivity and intelligent systems are needed for companies to achieve the goals shaped by the possibilities of Industry 4.0. Therefore, in order to make a more precise assessment of technological maturity, this pillar was divided into 4 modules: Automation, Connectivity, and Autonomization, supplemented with Standardization, which is a crucial module for the development of the digital ecosystem. The Processes Pillar indicates that in the Industry 4.0 concept, process improvement comes down to their integration and management carried out as a complex system of interdependent activities, leading to lower costs and shortening the time of products reaching the market. Process integration takes place in many areas - from production, through the supply chain and the product life cycle. As processes become more integrated and standardized, they begin to

form a unified system where data is shared, analysed, and consistent across the layers of production management, product lifecycle, supply chain, and enterprise-wide management. In turn, the Organization pillar indicates that in order to maintain their market position in the era of increased Industry 4.0 competition, companies must adapt their organizational structures and processes by adjusting strategies and business models. Industry 4.0 requires greater focus on two key elements of an organization's operation. The first is the people who make up the organization - all employees from the top management level to the operational teams. The other element is the systems and structure within which the company's operations are carried out.

Table 2. The digital maturity model in Industry 4.0

Pillar	Module	Component
Organization	Collaboration and projects	Project management and collaboration
	Strategy	Strategy
	Employees	Training and development of employees' competences
	Leadership	Leadership
Processes	Internal integration	Planning of resources and production processes
	Product Life Cycle Integration	Product lifecycle management
	Integration with the environment	Implementation of the supply chain
		Cooperation with the client
	Standardization	Standardization of technology purchases
		Optimizing energy efficiency
Technologies	Automation	Manufacturing processes (OT and IT)
		Administration and management of the company
		Building infrastructure
	Communication	Manufacturing processes (OT and IT)
		Administration and management of the company
		Building infrastructure
	Autonomization	Manufacturing processes (OT and IT)
		Administration and management of the company
		Building infrastructure
	Smart product	Smart product

Source: Nosalska et al. (2020).

In the Digital Maturity Model within Industry 4.0, the issue of enterprise cooperation in the supply chain is presented in the "Integration with the environment" module, which consists of two components "Supply chain implementation" and "Cooperation with the client." The supply chain in Industry 4.0 creates a digital, transparent and integrated chain, where processes are connected by means of a network of sensors and managed in a manner optimized with the use of artificial intelligence algorithms in real time. Hence, the "Supply chain implementation" component in its thematic scope answers the question: to what extent are data and processes integrated within the supply chain and cooperation with external partners? On the other hand, the relation with the customer is a key determinant of functioning in Industry 4.0. Considering the growing trend of product personalization, the customer begins to play a significant role in the process of creating value. The customer becomes a partner of the production company, influencing the shape and functionality of the product. Thus, this component examines how the communication with customers (business and individual) is conducted in the company.

The aim of the study is to answer the question: is the level of digital maturity of a company regarding cooperation in the supply chain related to its comprehensive digital transformation? In other words, does the level of digital maturity of the enterprise in terms of its integration with the environment (suppliers and customers) correlate with the level of digital maturity in other areas of the company? The framework layout of the research concept is shown in Fig. 3.

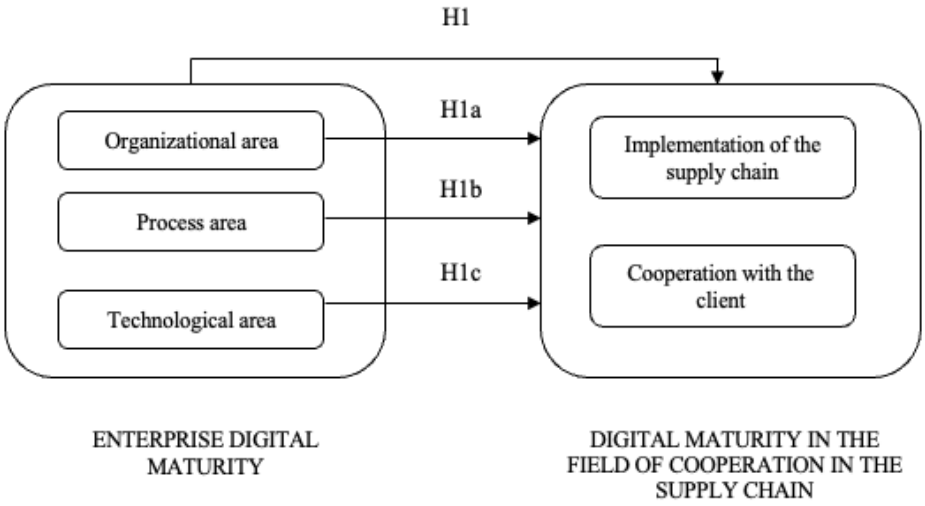


Figure 3. Conceptual framework
Source: own elaboration.

The Digital Maturity Model in Industry 4.0 was used as the theoretical basis, and its structure was applied to formulate the main and auxiliary hypotheses.

H1: The level of advancement of a digital enterprise in terms of cooperation in the supply chain is related to its level of digital maturity.

H1a: The level of advancement of a digital enterprise in terms of cooperation in the supply chain is related to the level of its digital maturity in the organizational area.

H1b: The level of advancement of a digital enterprise in terms of cooperation in the supply chain is related to the level of its digital maturity in the process area.

H1c: The level of advancement of a digital enterprise in terms of cooperation in the supply chain is related to the level of its digital maturity in the technological area.

3.2 Research data

The basis of the research process, the results of which are presented in this article, is the previous research by authors commissioned by the Platform for the Industry of the Future Foundation (FPPP) described in the report entitled "Research on digital maturity of cluster enterprises". The study was conducted at the turn of November and December 2021 on a sample of 150 Polish cluster enterprises, using the tool provided by FPPP for self-examination of digital maturity of enterprises in order to assess their situation in relation to the established pattern. Determining the level of digital maturity of enterprises in the course of self-assessment is a practice used in many studies of this kind (Teichert, 2019). The substantive basis of the developed tool was the Digital Maturity Model in Industry 4.0. The tool was made available as a link to an interactive survey that included 20 questions representing 12 modules and 3 pillars of the model being described. Each question was rated on a scale from 1 to 6, where 1 was the lowest and 6 the most advanced level.

In the field of data collection, a CAWI (Computer-Assisted Web Interview) research technique, in which the respondent is asked to complete an electronic questionnaire, was used. During the research, the research procedure was prepared by exercising due care, i.e. establishing contact, explaining the context of the research, sending a link to the research tool, monitoring, and possibly clarifying doubts or providing help. In some cases, the survey was conducted in the CATI (Computer-assisted telephone interviewing) mode. This happened in situations where entrepreneurs expressed their will to participate in the survey, but due to technical reasons (blocked link to the survey by antivirus programs) or temporary reasons (e.g. a business trip) they could not complete it on their own. As a result of the study, the level of digital maturity of enterprises operating in clusters (enterprises included in the study) was determined and their image was obtained in relation to the model criteria and demographic characteristics. Selected statistical methods were used to achieve the research goal, among others, distribution of responses according to the adopted criteria (e.g. year of commencement of activity, represented industry) and the relations between the variables included in the model were examined.

Table 3 presents the most important characteristics describing the sample of cluster enterprises participating in the study, including those qualified for section C - industrial processing.

Table 3. Characteristics of cluster enterprises participating in the study

Research sample characteristics	Distribution of the sample of cluster enterprises in total participating in the study (N150)	Distribution of the sample of cluster industrial enterprises participating in the study (N89)
1. The year of starting a business	until 1990 – 11.3% 1991–2004 – 14.0% 2005 and later – 74.7%	until 1990 – 7.9% 1991–2004 – 41.6% 2005 and later – 50.6%
2. Capital origin	domestic capital – 71.3% foreign capital – 11.3% mixed capital – 17.3%	domestic capital – 68.5% foreign capital – 12.4% mixed capital – 19.1%
3. Represented industry	Section C, industrial processing – 59.3% other industries – 40.7%	Section C, industrial processing – 59.3%
4. Employment level	from 1 to 9 employees – 32.7% from 10 to 49 employees – 28.0% from 50 to 99 employees – 6.7% from 100 to 250 employees – 25.3%	from 1 to 9 employees – 23.6% from 10 to 49 employees – 25.8% from 50 to 99 employees – 7.9% from 100 to 250 employees – 31.5%
5. Approximate value of the turnover in the last year	under PLN 5 million – 43.3% from PLN 5 to 50 million – 30.0% from PLN 50 to 100 million – 9.3% PLN 100 million and more – 17.3%	under PLN 5 million – 34.8% from PLN 5 to 50 million – 28.1% from PLN 50 to 100 million – 13.5% PLN 100 million and more – 23.6%
6. Approximate value of export in the last year	no export – 45.3% under PLN 5 million – 23.3% from PLN 5 to 50 million – 20.0% from PLN 50 to 100 million – 6.7% PLN 100 million and more – 17.3%	no export – 34.8% under PLN 5 million – 24.7% from PLN 5 to 50 million – 22.5% from PLN 50 to 100 million – 10.1% PLN 100 million and more – 7.9%

Source: own elaboration based on study results presented in in the report "Research on digital maturity of cluster enterprises".

The most numerous groups in the study were relatively young enterprises with domestic capital (71.3%), which started their activity after 2005 (74.7%). They were mainly micro and small enterprises (60.7%) employing no more than 49 employees. Over 59% of the surveyed sample (89 enterprises) were entities operating in section C – industrial processing, which were qualified for further in-depth research.

3.3 Research method

A two-stage research procedure was used to study the relationship between the activities undertaken by cluster enterprises classified under section C - industrial processing with other areas of digital transformation of enterprises. In the first stage synthetic measures, which allowed for determining the position of the surveyed enterprises in terms of the level of digital maturity in individual subareas of the index, were determined for each studied area assessing digital maturity (main area: integration with the environment, and sub-areas: organization, processes, technologies).

The relative taxonomy method was used to determine the synthetic measures. It is a relatively new method developed by Wydymus (2013). Detailed description of this method and its applications can be found in: Szopik-Depczyńska et al. (2017), Ziolo et al. (2019), Cheba 2020, Walesiak, Dehnel, & Obrębalski (2021).

The synthetic measure in this method is calculated in several steps. In the first one, the relative ratios for each firms against all the other companies is calculated as follows:

$$d_{(l/i)jt} = x_{ljt} / x_{ijt}, \quad (1)$$

where:
d – relativized values of the indicators, $i, l = 1, \ldots, k$ – countries' numbers, $i \neq l, j = 1, \ldots, m$ – numbers of sub-indicators, $t = 1, \ldots, n$ – numbers of years.

For conversions destimulants to stimulants quotient transformations can be used.

The structure of the individual arrays for each *j*-index can be presented as follows:

$$\boldsymbol{D_j} = \begin{bmatrix} 1 & d_{(2/1)_j} & \cdots & d_{(k/1)_j} \\ d_{(1/2)_j} & 1 & \cdots & d_{(k/2)_j} \\ \cdots & \cdots & 1 & \cdots \\ d_{(1/k)_j} & d_{(2/k)_j} & \cdots & 1 \end{bmatrix}, \quad (2)$$

Based on the array of $\mathbf{D_j}$ matrices (formula 2), objects (in this case companies) are classified, taking into account the whole set of diagnostic indicators X used for the analysis:

$$\boldsymbol{A} = \begin{bmatrix} 0 & & \frac{1}{(k-1)} \\ & \cdots & \\ \frac{1}{((k-1)} & & 0 \end{bmatrix}, \quad (3)$$

and products $\mathbf{D}_j^* = \mathbf{A} \cdot \mathbf{D}_j$**.** Elements on the main diagonal matrix $\mathbf{D}^*$ form a three-dimensional matrix **W** defined for all *j* indicators and periods *t*:

$$W = \begin{bmatrix} w_{11t} & w_{12t} & \cdots & w_{1mt} \\ w_{21t} & w_{22t} & \cdots & w_{2mt} \\ \cdots & \cdots & \cdots & \cdots \\ w_{k1t} & w_{k2t} & \cdots & w_{kmt} \end{bmatrix} \quad (4)$$

The relative synthetic measure of development determined by the **W** matrix is calculated as follows:

$$S_{it} = \left[\sum 1/w_{ijt}\right]/m, \quad (5)$$

The measure is usually close to 1 and is interpreted as the relative position of the companie relative to all other analyzed companies. For companies with a similar level of development, the values generally hover around unity. The lower the value of the measure, the better the situation of the companies against the background.

The companies can also be divided into typological classes grouping with similar levels of development. The assignment of companies to the typological classes is as follows:

$$classe = \begin{cases} 1 \quad for \quad S_{it} \leq \bar{S}_{it} - S_{Sit} \\ 2 \quad for \quad S_{it} \leq \bar{S}_{it} \quad \wedge \quad S_{it} > \bar{S}_{it} - S_{Sit} \\ 3 \quad for \quad S_{it} \leq \bar{S}_{it} + S_{Sit} \quad \wedge \quad S_{it} > \bar{S}_{it} \\ 4 \quad for \quad S_{it} > \bar{S}_{it} + S_{Sit} \end{cases} \quad (6)$$

where: $\bar{S}_{it}$ means the average value determined on the basis of the relative synthetic measure of development, S_{Sit} their standard deviation.

The first class includes the best companies with the lowest values of the relative synthetic measures, and the fourth class the worst with the highest values.

At the second stage of the research procedure, in order to examine the relationship between the analyzed sub-areas of digital maturity, the correlation coefficients were used: Pearson's *r* for the values of synthetic measures and Kendall's tau – for selected items in the constructed rankings.

4. STUDY RESULTS

As a result in the first stage of the research procedure, four typological groups were selected. In the 1st group, there are enterprises with the lowest results in relation to the average determined on the basis of the results obtained by all surveyed enterprises, which should be assessed as better results in the overall ranking of enterprises. On the other hand, in the 4th group the entities with the highest results were classified in relation to the average determined on the basis of the results obtained by all the surveyed enterprises, which should be assessed as worse results in the overall ranking of enterprises. The results of this stage of the study are presented in Table 4.

Table 4. Results of the ordering and classification of cluster enterprises

Typological group	Synthetic measure range	Number of firms	Mean	Median	Coefficient of variation (%)
Main area: Integration with environment					
I	<0.477; 0.645>	11	0.579	0.573	9.98
II	<0.716; 0.965>	45	0.864	0.839	9.68
III	<1.006; 1.204>	18	1.164	1.200	5.44
IV	<1.446; 2.199>	15	1.530	1.446	14.35
Subarea 1. Organisation					
I	<0.467; 0.581>	12	0.516	0.514	5.99
II	<0.617; 0.997>	48	0.828	0.827	12.25
III	<1.013; 1.356>	12	1.164	1.159	8.36
IV	<1.439; 2.375>	17	1.730	1.654	13.68
Subarea 2. Technology					
I	<0.425; 0.623>	15	0.529	0.562	13.27
II	<0.647; 0.995>	37	0.867	0.882	11.31
III	<1.005; 1.333>	25	1.153	1.170	7.39
IV	<1.431; 2.110>	12	1.701	1.700	12.49
Subarea 3. Processes					
I	<0.464; 0.704>	11	0.589	0.583	13.51
II	<0.733; 0.990>	45	0.885	0.892	8.65
III	<1.005; 1.257>	20	1.134	1.131	6.90
IV	<1.296; 1.999>	13	1.554	1.482	13.61

Source: own calculation

The information presented indicates that in each of the analyzed areas, the 2nd group was the most numerous. This group includes enterprises with results below the average determined based on the results obtained by all surveyed enterprises. It should be remembered that in the case of this method, the results below the average are obtained by enterprises with higher positions in the ranking. The estimates of the coefficients of variation for all designated typological groups in the analyzed areas of the study (main area and subareas) indicate relatively high homogeneity. In the case of the main area of the study, the lowest grade for the coefficient of variation was obtained for the 3rd typological group (5.44%), which indicates that this group included enterprises achieving much more similar results than in the other groups. Similar conclusions can be drawn for the sub-areas: 2 (Technology) and 3 (Processes), for which the lowest estimates of the coefficients of variation (respectively: 6.90% and 7.39%) also applied to the 3rd typological group. This group includes enterprises with results of the synthetic measure above the average, which means that, together with enterprises classified in the 4th group, these are companies with a lower level in the areas of technology and processes. On the other hand, in the case of subarea 1.

The most homogeneous organisation was the first group, with the results of the synthetic measure allowing for the classification of the surveyed enterprises in the highest positions in the ranking. Interestingly, considering the results obtained in individual sub-areas and the central area, the level of digital maturity of the surveyed enterprises is quite varied. There is a group of enterprises that have achieved a high level of development in digital maturity in each of the analyzed areas, such as a company ranked first in the core area and also ranked first in all other areas. The sample also included enterprises that develop better only in some areas, and worse in others.

The analysis of the correlation (stage 2) between the results obtained by the surveyed enterprises in particular areas (main area and subareas) indicate the existence of a significant dependence of the surveyed areas and their moderate strength, taking into account the results of the synthetic measure as well as the positions taken by the surveyed enterprises in the created rankings (Table 5). This means that all formulated hypotheses were maintained.

Table 5. Correlation coefficient *r* Pearson and tau Kendall

***r* Pearson**	**Main area: Integration with environment**	**Subarea I. Organisation**	**Subarea 2. Technology**	**Subarea 3. Processes**
Main area: Integration with environment	1.000	0.545	0.645	0.886
Subarea 1. Organisation	0.545	1.000	0.514	0.636
Subarea 2. Technology	0.645	0.514	1.000	0.726
Subarea 3. Processes	0.886	0.636	0.726	1.00
tau Kendall	**Main area: Integration with environment**	**Subarea 1. Organisation**	**Subarea 2. Technology**	**Subarea 3. Processes**
Main area: Integration with environment	1.000	0.434	0.491	0.714
Subarea 1. Organisation	0.434	1.000	0.354	0.471
Subarea 2. Technology	0.491	0.354	1.000	0.563
Subarea 3. Processes	0.714	0.471	0.563	1.000

Source: own calculation.

Thus, a relation has been demonstrated between the level of maturity in terms of supply chain cooperation and its digital maturity in the organizational, process, and technological areas. Consequently, it is legitimate to maintain the main hypothesis, according to which the level of digital maturity of a company in terms of cooperation in the supply chain is related to the level of digital maturity of the entire company. The highest results were obtained in the process area. This is due to the fact that the main studied area "Integration with the environment" strongly influences the entire area of 'Processes'. The issues raised indicate the high complexity of the processes taking place in manufacturing companies in the field of digital transformation. It can be assumed that companies that achieve better results in the digital transformation of major areas also achieve better results in the digitization of integration with the environment, although this relation is not crucial. This is important because the implementation of the Industry 4.0 concept requires a consistent approach, agreeing on digital standards and implementation methods at the enterprise level and further, in cooperating supply chains and networks. Therefore, an essential feature of an effective digital transformation is the avoidance of organizational silos, i.e. situations where individual departments or business units implement digital transformation without cooperation with others and in isolation from the broader perspective of the entire organization and network of connections in which it operates. In order to show the complexity of the studied issues, Table 6 and Figures 4 and 5 show the results obtained by the three highest and lowest ranked enterprises in the main area of the study. They also present the results of these enterprises obtained in the remaining sub-areas.

Table 6. Results of the ordering of cluster enterprises of the best and worst classified firms

Rank	**Main area: Integration with environment**		**Subarea 1. Organisation**		**Subarea 2: Technology**		**Subarea 3. Processes**	
	SM	**Rank**	**SM**	**Rank**	**SM**	**Rank**	**SM**	**Rank**
1	0.477	1	0.467	1	0.425	1	0.464	1
2	0.525	2	0.496	5	0.623	15	0.570	5
3	0.525	3	1.240	70	0.456	5	0.504	3
87	1.446	87	0.723	19	1.076	58	1.257	76
88	1.958	88	0.926	51	0.952	42	1.718	87
89	2.199	89	1.800	83	1.333	77	1.999	89

Source: own calculation, where: SM – synthetic measure.

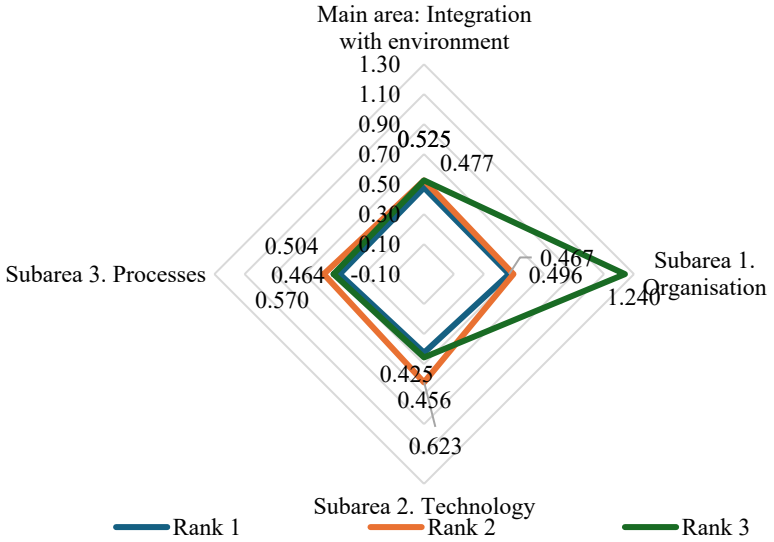


Figure 4. Results for three the best enterprises according to the main area: Integration with environment and other analysed subareas
Source: own elaboration.

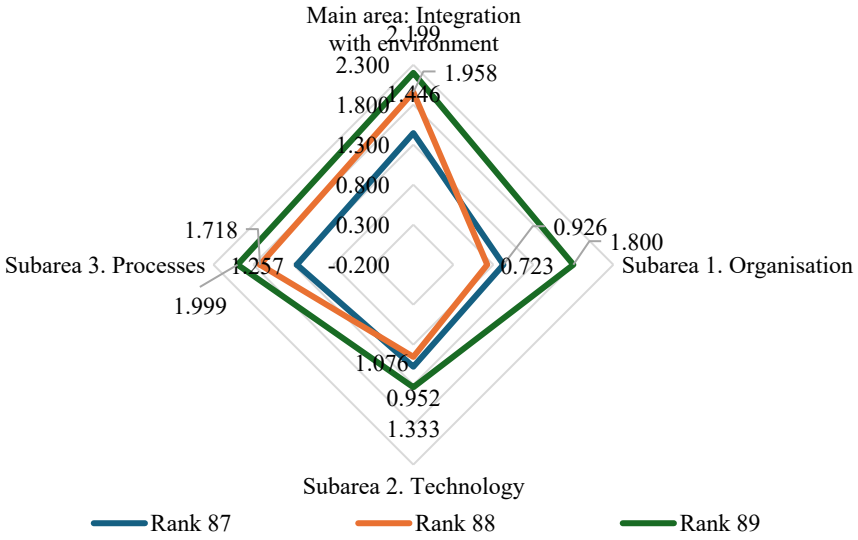


Figure 5. Results for three the worst enterprises according to the main area: Integration with environment and other analysed subareas
Source: own elaboration.

5. DISCUSSION AND CONCLUSIONS

The study aimed to answer the question: Is a company's level of digital maturity in terms of cooperation in the supply chain related to its comprehensive digital transformation? The Digital Maturity Model in Industry 4.0 was used as the theoretical basis, and its structure was applied to formulate the main and auxiliary hypotheses.

Due to the complexity of digital transformation issues, one should not expect uniform progress in every surveyed area of enterprises. Nevertheless, the obtained results are interesting because they do not indicate the dominant area determining the development of the company's cooperation within the smart supply chain. Due to the fact that technological progress is often the leading aspect in implementing the

Industry 4.0 concept, the research results have not confirmed this relation. It is therefore an essential indication in the scientific discourse that emphasizes the importance of non-technological aspects of digital transformation and enterprise collaboration in supply chains and networks.

Currently, the path of digital transformation has not yet been determined, and the maturity model can provide enterprises with effective guidance for improvement, thereby facilitating the application of decision models. The digital maturity model can help enterprises scientifically evaluate their digital maturity level, identify their weaknesses, and then further formulate improvement strategies (Han, Zhang, Hu, & Huang, 2022).

Supply chain integration, particularly by increasing the use of information technology and coordinating activities, has been widely discussed and endorsed by scientists to overcome the challenge of complexity. The earlier approach to supply chain collaboration emphasises process integration and less on the components of relational communication and knowledge creation (Simatupang & Sridharan, 2005). However, it should be noted that cooperation between supply chain partners is not only about a flow of goods but leverages information exchange and creates market knowledge for sustainable competitive advantage (Malhotra, Gosain, & Sawy, 2005; Mackiewicz & Pavelkova, 2022). The basis of the success of a collaborative supply chain is communication, which is a binder that holds supply chain partners together through balanced, multilevel contacts and relations (Cao& Zhang, 2011). This corresponds to the need of the digital transformation of enterprises and cooperative networks. It should be stated that the digital transformation of the supply chain is developing in parallel with the networking process of enterprises. Nevertheless, introducing successful digital transformation in the industrial company does not depend solely on the technologies they adopt, but, more importantly, builds on the strategies that their leaders deploy (Ismail et al., 2017).

The presented results require further in-depth research in the field of assessing the interdependence of areas defined in the digital maturity model. This could have significant implications for managers of industrial enterprises regarding the sequence and scope of the implemented changes in digital transformation and their impact on achieving competitive advantage. The size and geographical concentration of the research sample (Polish cluster enterprises) also presents itself as a research limitation. In further research, it is worth expanding the research sample within the international research system. The benefits offered by smart or digital supply chain have attracted businesses all around the globe, including developing countries. In 2021, Indonesian Chamber of Commerce and Industry announced its readiness to adopt digital supply chain (CNBC Indonesia, 2021). Saryatmo & Sukhotu (2021) conducted their study on Indonesia's food and beverage industry. They argue that digital supply chain highly supports operational performances, namely quality, productivity, and cost reduction which is in line with many studies in other countries. In general, the level of digital supply chain adoption in developing countries falls behind that of developed countries.

Additionally, several future works are required to reassess and capture the progress of digitalization and the digital maturity exhibited by companies in relation to their supply chain. Post-pandemic, many enterprises in developing countries experienced setbacks in their digitalization efforts, leading them to revert to traditional or less digitized methods. The primary catalyst for this shift back to conventional practices stems from the substantial investment required to sustain digitalization initiatives, as digitization is not merely an infrastructure investment but also a human resource investment. Consequently, it becomes imperative to reevaluate the digital transformation trajectory. Moreover, it is essential to examine whether this phenomenon is exclusive to developing countries or if it also manifests in developed economies. This comparison provides insight on digitisation's universality and facilitates a more comprehensive understanding of the challenges and dynamics shaping digital maturity.

The digital transformation maturity assessment model can not only meet the urgent demands of enterprises in their decision process but also help the government better understand the current situation of enterprise development and improve the efficiency of government guidance and support for enterprise development. Establishing scientific evaluation models is vital to analyze and improve digital transformation maturity, aiding enterpris' and governments' understanding of development status and supporting efficiency (Zhu et al., 2024).

Although digital transformation has become an essential driving force for the high-quality development of economies worldwide and is gradually becoming a mainstream trend (Lerro, Schiuma, Manfredi, & Editorial, 2022), additional research is also required. It is necessary to ascertain the incorporation of digital literacy into qualification requirements and evaluate the efficacy of existing skill

sets in meeting digital demands. Integrating existing workers into digital initiatives where upskilling and reskilling is necessary within the supply chain must be further evaluated. Further study may provide valuable insights into designing effective policies and programs to enhance digital maturity. Lastly, authors recommend further nuanced assessment of the importance of human involvement and interaction. Potential customer dissatisfaction may occur as these aspects are not adequately addressed in existing frameworks. AI and digital solutions cannot fully replace human judgment and interaction. Recognizing these limitations is crucial for developing comprehensive strategies that leverage digital technologies while preserving the essential human touchpoints necessary for optimal customer satisfaction and operational efficiency.

It is also worth noting the growing importance of the ability to extract maximum value from the data held and available in the business. This requires the creation of flexible knowledge acquisition paths that add value to all employees at each stage of the organization's operation. Intelligent management is an area that has been increasingly explored in the literature for several years. In WoS database, nearly 2,000 publications referring to the term have been identified, including more than 1,000 in the last 7 years. In the following time, the authors of this paper plan to expand the ongoing research with more detailed analyses on the study of the relationship linking the level of digital maturity with the extent of implementation of Intelligent Management and AI tools).

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EVALUATION OF AUTOMATED CUSTOMER ASSISTANCE: SEGMENTAL ANALYSIS OF NASK PARTNERS ON THE POLISH MARKET

Maciej Lewandowski[a]

[a] *University of Szczecin, Institute of Management, Department of Marketing, Szczecin, Poland*

ABSTRACT

Purpose: *The study aims to evaluate the current potential for automated customer assistance among NASK partners in Poland. It analyses the distribution of domain registrars across different maturity segments, identifies the most and least frequently implemented automation elements, and assesses overall readiness for automated customer assistance in the NASK partner network.*

Need for the study: *This research fills an important gap in understanding automation practices among Polish domain registrars. While these organizations play a crucial role in Poland's digital infrastructure, little data exists on their customer service automation capabilities. As consumer preferences shift toward self-service and instant solutions, identifying current automation levels becomes vital for industry benchmarking and digital policy development. The study provides essential insights into automated customer assistance disparities that could potentially constrain the broader digital landscape's growth.*

Methodology: *Using a netnographic approach with quantitative elements, the study analysed 117 NASK partners from the Polish market. Based on nine arbitrarily selected criteria related to automated customer assistance, the websites of the mentioned partners were examined. Each criterion was scored using a three-point scale (0-5-10 points), and the results were aggregated to create five distinct automated customer assistance maturity segments. Data collection involved systematic observation of publicly available interfaces without requiring additional permissions.*

Findings: *The survey revealed significant disparities in automated customer assistance implementation. The vast majority of partners belong to lower maturity segments, with advanced automation solutions appearing mainly in the highest segment. A clear implementation hierarchy emerged, progressing from technical stability to basic interaction tools, self-service resources, and finally advanced AI-based solutions.*

Practical Implications: *Findings indicate significant growth potential, especially in implementing advanced automated customer assistance technologies in the Polish domain registrar market. The clear segmentation provides a framework for understanding the current state of automation and identifying strategic priorities for enhancement.*

Keywords: Automated Customer Assistance, Customer Experience, Segmentation Analysis, Customer Service Automation, Digital Transformation, Domain Registrars

Jel codes: L86; M15; O33

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1. INTRODUCTION

Transforming customer service to the digital landscape is a challenge that, when carried out carefully, has a significant impact on customer satisfaction and complementing their user experience (Abbas, 2024). Companies managed in a modern way take into account current customer service quality standards, technological developments and operational efficiencies (Portovaras, et al., 2024). Coming to terms with the fact that consumers operate in two realities – physical and digital – and developing the level of customer support in these two dimensions simultaneously, is only the right strategic decision. Furthermore, technologies are becoming relevantly autonomous (de Belis and Johar, 2020), so in addition to delegating human resources to the virtual space, entities should consider deploying modern technology resources that foster automated customer service. Such resources include the use of mobile or web algorithms but also broad artificial intelligence (AI) solutions such as Natural Language Processing (NLP) or Large Language Models (LLM's) (Mashaabi, et al., 2022; Meduri, 2024). But when the support takes place without the involvement of another human being, we should then refer to automated customer assistance (Roberts and Maier, 2024).

It seems that entities that have grown up in the aforementioned digital space should be proficient in the use of advanced digital and automated customer assistance methods. Such entities, whose existence outside the Internet would not be justified either operationally or financially, are domain registrars. The main role in domain registration in Poland is played by the Research and Academic Computer Network (pol. Naukowa i Akademicka Sieć Komputerowa, NASK) which was founded in 1991 and serves as Poland's national research institute responsible for overseeing the country's internet domain registry. Companies that have entered into a partnership with NASK on the basis of rules established by NASK have intermediary status and the right to register domains.

While domain registration still remains a fundamental part of an online presence, alternative technologies are on the horizon that are partially reducing the market for traditional registrars. Social media and e-commerce platforms, such as Facebook Marketplace, Amazon or Allegro, already offer complete business solutions to run a business without the need to own a domain (Brahma and Dutta, 2018). Mobile applications are developing in parallel, reducing the importance of classic websites in favour of native applications (Al-Shamaileh and Sutcliffe, 2023).

Even though none of these solutions completely eliminate the need for domain registration, their gradual development clearly signals the need for NASK's partners to evolve their offerings towards more comprehensive services to support their customers' digital presence.

The main focus of the research is to determine the current level of automated customer assistance in the environment of NASK partners. The research aims to identify gaps and potential for development in this context in the Polish domain registrar industry on the Polish market. The study is exploratory in nature. In the course of the study, qualitative methods were used to examine the content of the websites and quantitative methods to collect and analyse data in terms of the criteria to be evaluated. Data processing made it possible to identify five segments of NASK partners in terms of their potential for automated customer assistance. In addition to answering the research questions, the implementation of the study also allowed practical implications to be identified. It should be noted, however, that the study is a pilot and a prelude to further analysis of the NASK partners' market in Poland.

2. LITERATURE REVIEW

2.1. Digital customer service

Customer service plays many vital roles throughout the customer journey, including providing information, facilitating decision-making, building relationships and enabling additional sales opportunities, rather than being limited to post-purchase interactions (Sheth, et. al., 2023). Modern consumers are characterised by in-depth analysis of market offers, a sceptical approach and an expectation of personalised treatment, which is driving the development of sophisticated electronic customer service systems (Moczydłowska and Bitkowska, 2020). Current customer service systems, such as contact centres, CRMs and ticketing systems, integrate different communication channels (phone, email, live chat, social media, mobile, SMS) into one platform, providing a consistent service and collecting valuable customer data throughout the customer's purchasing experience (Systell, 2019).

An effective service strategy attracts and retains customers by providing additional benefits beyond the product itself. Thoughtful service protects the company from the negative consequences of poor customer contact, which can completely deter consumers from buying and significantly damage the company's image in the market (Krzepicka, 2014; Yazid and Kawiryan, 2023). Taking a systematic approach to raising customer service standards involves a number of steps – from a thorough analysis of the customer base, to evaluating existing processes, to creating a friendly atmosphere and implementing new solutions to improve communication (Adamska, 2018).

Customer experience is the holistic sum of all interactions, impressions and emotions that a consumer experiences at every touchpoint with a brand – before, during and after using a product or service (Dąbrowska and Janoś-Kresło, 2019). Introducing new communication channels and points of interaction does not automatically guarantee an increase in customer engagement, undermining the common belief that contact infrastructure needs to be continually expanded (Gerea, et al., 2021). Achieving the optimal balance between the diversity of support channels provided and what customers truly expect can significantly enhance the overall customer experience and satisfaction (Drobiazgiewicz, 2018; Lisnawati, et al., 2021). Implementing an effective omni-channel strategy is much more than connecting sales platforms. It requires an in-depth analysis of consumers' preferences and actions at every point in their purchase path. An important success factor is the ability to trigger spontaneous purchase decisions through a consistent and recognisable brand presentation at all contact points (Mali, et al., 2022).

2.2. Automated customer assistance

Customer service and support processes are subject to automation (Hardalov et al., 2018), especially in the digital space (Trofimov, et al., 2023). Authors C. Roberts and T. Maier recognised in their work that when we talk about technology-assisted customer service, where help and solutions are communicated without the involvement of another human being, for example on a platform prepared for this case, we should then talk about automated customer assistance (Roberts and Maier, 2024).

According to this concept, any form of extensive customer service that does not require the involvement of another human being should be categorised within its framework. Analysing the academic literature, it is possible to identify a number of studies that focus on customer service in their reflections, but in the light of the concept mentioned above, their results bear the hallmarks of typical automated customer assistance.

One of these studies points to the fact that companies are not only relying on AI-based support systems, but also eliminating direct human interaction deliberately (Othman, 2025). Today's businesses are adopting more and more automation-based solutions, such as chatbots and Robotic Process Automation (RPA) systems, which optimise purchasing processes and positively impact consumer satisfaction when implemented properly (Gavrila, et. al. 2023). In the research field, it is possible to identify a study that does not so much justify the use of artificial intelligence or RPA systems in assisting clients but identifies elements whose improvement could enable the use of this type of technology to be more effective (Schanke, et al., 2021). According to the authors of the aforementioned study, the simple act of anthropomorphising an AI-based tool can lead to a positive impact on conversion, price sensitivity or customer disclosure of sensitive information, among other things. Other academic research linking the themes of automation to end-buyer service delivery considers the development of artificial intelligence, which appears to be the future of the customer service process (Anderson, 2024; Inavolu, 2024; Khogali and Mekid, 2023). However, before its widespread utilization can be made possible, the necessary digital foundations must be in place to provide the potential for future automation.

According to the accepted definition of automated customer assistance, advanced systems based on artificial intelligence are not the exclusive requirement for implementing the concept. Customers seeking knowledge or support are not forced to interact interpersonally, they can use the information provided on the website, which fits into this framework.

Service personalisation is becoming more important than service time, and customer service centres are currently undergoing a transformation (Kawęcki, 2022). Regardless, any automated customer support system should incorporate appropriate baselines, safeguards and standardise typical queries to ensure optimal performance (Akinyemi, et al., 2023). To meet customer demands, companies need to create the same experience across all service channels, ensuring that interactions are continuous and correct (Nasir, 2015).

3. METHODOLOGY

3.1. Participants

The subject of the study is the full population of official NASK partners located on the territory of Poland (n = 117). This allows the elimination of potential sampling errors and provides a comprehensive picture of the analysed phenomenon in the national context. The websites of the analysed entities are a widely available source of empirical data, allowing for a systematic and objective analysis without the need to obtain additional consents for data collection or overcome administrative barriers. The functional homogeneity of NASK's partners, resulting from unified accreditation requirements, makes it possible to apply standardised evaluation criteria to all entities covered by the study. It results in increased methodological reliability, accuracy of conclusions and comparability of obtained results.

3.2. Research Protocol and Stimuli

The main focus of the research is to determine the current level of automated customer assistance in the environment of NASK partners. The research aims to identify gaps and potential for development in this context in the Polish domain registrar industry on the Polish market. The course of the study is illustrated in Figure 1. To investigate the research problem, three research questions were constructed:

1.How are NASK partners distributed in the various segments of automated customer assistance advancement?

2.Which elements of automated customer assistance are most and least used? How does this appear among the segments?

3.What is the current level of readiness of NASK partners for automated customer assistance?

Netnographic research is an adaptation of ethnographic methods to study communities and phenomena in the online environment. The method involves the systematic observation and analysis of content and interactions occurring in digital spaces (Kozinets, 2019). In the context of this study, the netnographic approach was modified by introducing elements of quantitative analysis in the form of a point scale for the evaluation of automated customer assistance components on NASK partners' websites. The applied three-stage evaluation scale (0-5-10) allows for a precise determination of the degree of implementation of individual criteria, where 0 points means the absence of the analysed component, 5 points indicate partial implementation, and 10 points are assigned for full implementation of a given component.

This approach is inspired by the web content research already conducted in the scientific literature space (Milczarek and Gręboszc-Krawczyk, 2020). It combines the qualitative nature of netnographic research with the quantitative dimension of evaluation, allowing the creation of a multidimensional picture of the state of automated customer assistance in the population under study. The objectivised scoring system additionally allows the results to be compared between subjects and statistical analyses to be conducted, while retaining the contextual richness characteristic of netnographic methods.

3.3. Research Apparatus

Data collection and analysis process consisted of several stages. The data was collected in March 2025. The identification of NASK's partners was done through data made available by NASK on the website of the national domain registry at dns.pl. From the “list of registrars” tab, it was determined which entities had joined the NASK Partner Programme and which of them were located in Poland. Subsequently, each of the partner websites was reviewed against defined criteria for automated customer assistance. Criteria were arbitrarily set with specific reference to the domain registrar industry and based on a literature review of digital customer service and automated customer assistance.

Juxtaposing this literature with the concept of automated customer assistance has identified solid foundations that can provide a starting point for the implementation of this concept. Selected for the criteria to be evaluated were: customer panel, chatbot or live chat, contact form, FAQ section, knowledge base, domain search engine, social media referral button (SM button), website stability (understood as a website functioning without errors and with adequate security) and artificial intelligence (AI support elements) used in customer assistance. Table 1 demonstrates the selected criteria and their potential for automation.

Table 1. Potential to automate criteria identified as baseline for automated customer assistance

Selected criteria	Potential to automate a criterion
Web stability	Completely functioning and secure website is the foundation for automating the processes taking place in the web online space
Customer panel	Automatic renewal of services, invoicing, personalised notifications, service management
Contact form	The contact form can generate automatic responses to a request
Domain search engine	Algorithms to suggest alternative domain names, filtering results by name length, extension or price
Knowledge base	Indexing and categorising content, assigning tags, linking related issues
FAQ section	Intelligent question and answer structuring according to search trends
SM button	Suggesting a redirect to a platform that is more popular depending on the device being used (web or mobile users)
Chatbot or live chat	NLP for interpreting user queries and generating answers in a chatbot context, suggesting answers or directing the query to the relevant department in a live chat context
AI support elements	Use of LLM's to generate domain name proposals, algorithms that generate websites based on user input

Source: own elaboration.

As can be seen from Table 1, the indicated criteria show potential for automation. Providing these solutions on websites can lead to their full automation, which consequently qualifies them as baseline criteria for implementing automated customer assistance in the context of domain registrars.

3.4. Analysis of Measurement Data

The data analysis performed was based on the allocation of scores on the 0-5-10 scale. Once the scores were allocated, it was possible to segment the individual partners in terms of the points scored. The segments have been determined as listed below and based on the scoring shown in brackets:

- Segment I – partners with no automated customer assistance potential (0–10),
- Segment II – partners with minimal automated customer assistance potential (15–30),
- Segment III – partners with an initial level of automated customer assistance potential (35–50),
- Segment IV – partners with a partial level of automated customer assistance potential (55–70),
- Segment V – partners having an high level of automated customer assistance potential (75–90).

It was then determined which partners showed the highest automated customer assistance potential, which the lowest, and what the overall industry standard was. It was verified which elements are used most frequently among NASK partners in general and among the segments. The identification of the most advanced entities made it possible to estimate which of them are on a good path to achieve the composition of specifically automated customer assistance.

4. RESULTS

Tables 2–6 present the analysed NASK partners with their division into segments according to the adopted scores. The tables contain the names of partners assigned to the sum of points they scored. Table

7 presents the analysis results of the degree of implementation of each automated customer assistance criterion among NASK partners, expressed as a percentage of the maximum possible score, both in total and by segment from I to V.

Table 2. NASK partners and their share of scoring within Segment I and total partners

NASK partners with the same sum of points in the segment (partner domain names)	Total points scored	% of the segment	% of total partners
aaregistrar.pl, iksik.net, aaoo.pl, brokerdomen.pl, a2.pl, dnr.pl, hostingowa.pl, i.media.pl, marketdomen.pl, domeny.bloch.pl, finat.pl, pkobp.pl/partner-nask, prosnet.pl, tecoro.com, wdc.pl, webmix.pl, ekodomeny.pl	10	60.7	14.5
hbs.net.pl, p32.pl, xsite.pl, domeny.netium.pl, onyx.pl, varia.pl	5	21.4	5.1
ah.pl, apps.pl, podmlotek.pl, no1.pl, telekam.pl	0	17.9	4.3

Source: own elaboration.

Table 2 shows the distribution of points among NASK partners within Segment I and for the total number of partners. Data has been grouped according to the value of points earned. Within the first group, there are 17 partners (e.g. aaregistrar.pl, iksik.net, aaoo.pl), who obtained 10 points each, which represents 60.7% share in Segment I and 14.5% share among all partners. However, the second group includes 6 partners (hbs.net.pl, p32.pl, xsite.pl, domeny.netium.pl, onyx.pl, varia.pl) with a score of 5 points, accounting for 21.4% of the share in the segment and 5.1% among all partners. And the third group consists of 5 partners (ah.pl, apps.pl, podmlotek.pl, no1.pl, telekam.pl), who did not score any points (0), accounting for 17.9% of Segment I and 4.3% of all NASK partners.

Table 3. NASK partners and their share of scoring within Segment II and total partners

NASK partners with the same sum of points in the segment (partner domain names)	Total points scored	% of the segment	% of total partners
dmtec.pl, easy-com.pl, fusionsystem.pl, fc.pl, sprint.pl, domeny.supermedia.pl, ut.pl, webtech.pl	30	28.6	6.8
cyfronet.krakow.pl, blusoft.pl, expro.pl, host4.biz, trafficpeaks.pl, vestigio.agency, wizja.net	25	25.0	6.0
softel.com.pl, consultingservice.pl, interaktywnapolska.pl, intrasoft.dev, e.pl, noria.pl, task.gda.pl, pro-link.pl, uniqal.pl, neo.pl	20	35.7	8.5
adcelero.pl, ceti.pl, topdata.io	15	10,7	2,6

Source: own elaboration.

Table 3 presents the distribution of scores among NASK partners within Segment II and in the context of all partners. Thus, the first group is made up of 8 partners (dmtec.pl, easy-com.pl,

fusionsystem.pl, fc.pl, sprint.pl, domeny.supermedia.pl, ut.pl, webtech.pl), who obtained 30 points each, which corresponds to 28,6% share in Segment II and 6,8% among all partners. In the second group there are 7 partners (cyfronet.krakow.pl, blusoft.pl, expro.pl, host4.biz, trafficpeaks.pl, vestigio.agency, wizja.net) with a score of 25 points each, representing 25% of the segment and 6% of all partners. Group three includes 10 partners (softel.com.pl, consultingservice.pl, interaktywnapolska.pl, intrasoft.dev, e.pl, noria.pl, task.gda.pl, pro-link.pl, uniqal.pl, neo.pl) with a score of 20 points each, representing 35.7% of Segment II and 8.5% of all partners. Fourth group includes 3 partners (adcelero.pl, ceti.pl, topdata.io) with a score of 15 points, accounting for 10.7% of Segment share and 2.6% among all NASK partners.

Table 4. NASK partners and their share of scoring within Segment III and total partners

NASK partners with the same sum of points in the segment (partner domain names)	Total points scored	% of the segment	% of total partners
dinfo.pl, ecenter.pl, addhost.pl, panhost.pl, hostinghouse.pl, nq.pl, o12.pl, netstrefa.pl, 3hosting.pl, uti.pl	50	38.5	8.5
jchost.pl, provider.pl	45	7.7	1.8
swiatdomen24.pl, ddregistrar.pl, vbe.pl, registro.pl, kompan.pl, plathost.pl, provector.pl, carboncloud.pl	40	30.7	6.9
artnet.pl, chmurka.pl, getname.pl. hitme.pl, webserwer.pl, rejestracjadomen.net.pl	35	23.1	5.1

Source: own elaboration.

The distribution of scores among NASK partners within Segment III and in relation to the total number of partners is shown in Table 4. An initial group consists of 10 partners (dinfo.pl, ecenter.pl, addhost.pl, panhost.pl, hostinghouse.pl, nq.pl, o12.pl, netstrefa.pl, 3hosting.pl, uti.pl) with a score of 50 points each, accounting for 38.5% of the share in Segment III and 8.5% among all partners. In the second group there are 2 partners (jchost.pl, provider.pl) with a score of 45 points each, accounting for 7.7% of the segment and 1.8% of all partners. Group three consists of 8 partners (swiatdomen24.pl, ddregistrar.pl, vbe.pl, registro.pl, kompan.pl, plathost.pl, provector.pl, carboncloud.pl) with 40 points each, representing 30.7% of Segment III and 6.9% of all partners. In the fourth group there are 6 partners (artnet.pl, chmurka.pl, getname.pl, hitme.pl, webserwer.pl, rejestracjadomen.net.pl) with a score of 35 points, representing 23.1% of the segment and 5.1% among all NASK partners.

According to Table 5, the distribution of points among the NASK partners within Segment IV and in relation to the total number of partners is presented. The first group includes 5 partners (webd.pl, jdm.pl, k.pl, seohost.pl, sohost.pl), who scored 70 points each, accounting for 17.9% of the share in Segment IV and 4.3% among all partners. In the second group, there are 7 partners (hosti24.pl, domena.pl, domeny.tv, hostinguj.pl, cal.pl, nazwa.pl, thecamels.org) with a score of 65 points each, representing 25% of the segment and 6% of all partners. Group three includes 10 partners (atthost.pl, az.pl, yupo.pl, hostmark.pl, itsky.cloud, kru.pl, premium.pl, progreso.pl, viperhost.pl, vipower.pl) with 60 points each, representing 35.7% of Segment IV and 8.5% of all partners. Group four includes 6 partners (nazwa24.pl, forpsi.pl, hostilla.pl, linkhouse.pl, nowyinternet.pl, kylos.pl) with a score of 55 points, representing 21.4% of the segment and 5.1% among all NASK partners.

Table 5. NASK partners and their share of scoring within Segment IV and total partners

NASK partners with the same sum of points in the segment (partner domain names)	Total points scored	% of the segment	% of total partners
webd.pl, jdm.pl, k.pl, seohost.pl, sohost.pl	70	17.9	4.3
hosti24.pl, domena.pl, domeny.tv, hostinguj.pl, cal.pl, nazwa.pl, thecamels.org	65	25.0	6.0
atthost.pl, az.pl, yupo.pl, hostmark.pl, itsky.cloud, kru.pl, premium.pl, progreso.pl, viperhost.pl, vipower.pl	60	35.7	8.5
nazwa24.pl, forpsi.pl, hostilla.pl, linkhouse.pl, nowyinternet.pl, kylos.pl	55	21.4	5.1

Source: own elaboration.

Table 6. NASK partners and their share of scoring within Segment V and total partners

NASK partners with the same sum of points in the segment (partner domain names)	Total points scored	% of the segment	% of total partners
N/A	90	N/A	N/A
N/A	85	N/A	N/A
cyberfolks.pl, dhosting.pl, home.pl, hostido.pl, lh.pl, smarthost.pl	80	85.7	5.1
idhosting.pl	75	14.3	0.9

Source: own elaboration.

Table 6 shows the distribution of scores among NASK partners within Segment V and in relation to total partners. In the first two scoring categories (90 and 85 points) no partners were recorded, which was marked as N/A (no data). On the third group, there are 6 partners (cyberfolks.pl, dhosting.pl, home.pl, hostido.pl, lh.pl, smarthost.pl), which scored 80 points each, accounting for 85.7% of the Segment V share and 5.1% among all partners. The fourth group includes only one partner (idhosting.pl) with a score of 75 points, which corresponds to a 14.3% share in the segment and 0.9% among all NASK partners.

Table 7. Total points scored under each criterion in total and under Segments I-V (expressed in % in relation to the possible number of points to be scored)

Criteria	Total	Segment I	Segment II	Segment III	Segment IV	Segment V
Web stability	88.9	66.1	8.,5	100	100	100
Customer panel	62.8	1.8	46.4	98.1	98.2	100
Contact form	55.6	0.0	46.4	71.2	94.6	100
Domain search engine	53.0	1.8	19.6	82.7	98.2	100
Knowledge base	36.8	0.0	10.7	25.0	94.6	100
FAQ section	32.9	1.8	10.7	32.7	71.4	92.9
SM button	23.1	0.0	14.3	19.2	46.4	71.4
Chatbot or live chat	8.1	0.0	0.0	1.9	14.3	71.4
AI support elements	3.8	0.0	0.0	0.0	1.8	57.1

Source: own elaboration.

Table 7 presents the percentage of implementation of nine automated customer assistance criteria among NASK partners, both in total (the "Total" column) and divided into five segments (I-V).

Web stability achieves the highest total score of 88.9%, with this value increasing from 66.1% in Segment I to 100% in Segments III-V.

Customer panel shows an average score of 62.8% for all entities, with a clear progression from just 1.8% in Segment I, through 46.4% in Segment II and 98.1% in Segment III, to 100% in Segment V.

Contact form has a total score of 55.6%, with no presence in Segment I (0%), reaching 46.4% in Segment II, 71.2% in Segment III, 94.6% in Segment IV, and 100% in Segment V.

Domain search engine achieves an overall score of 53.0%, with growth from 1.8% in Segment I to 100% in Segment V.

Knowledge base has a total score of 36.8%, with zero presence in Segment I, 10.7% in Segment II, 25.0% in Segment III, a significant increase to 94.6% in Segment IV, and 100% in Segment V.

FAQ section achieves an overall score of 32.9%, with values ranging from 1.8% in Segment I to 92.9% in Segment V.

Social media buttons have a total score of 23.1%, with zero presence in Segment I and growth to 71.4% in Segment V.

Chatbot or live chat achieves an overall score of just 8.1%, with zero presence in Segments I and II, minimal presence in Segment III (1.9%), 14.3% in Segment IV, and 71.4% in Segment V.

AI support elements show the lowest overall score of 3.8%, with zero presence in Segments I-III, minimal presence in Segment IV (1.8%), and 57.1% in Segment V.

5. DISCUSSION

Examining the data collected reveals considerable disparities in the degree to which individual automated customer assistance criteria are met, both in total and by segment. Highest implementation rates were recorded for the criterion of website stability (88.9%), indicating that NASK partners prioritise website reliability. It should be noted that this criterion reaches its maximum level of implementation (100%) as early as Segment III, confirming its fundamental importance for the functioning of online platforms.

Customer panel and contact form are the next criteria with relatively high completion rates (62.8% and 55.6% respectively), indicating a growing awareness of basic user interaction tools. Particularly

interesting is the leap in customer panel implementation between Segment I (1.8%) and Segment III (98.1%), which may suggest that this element represents a kind of developmental threshold in the automated customer assistance process.

The domain search engine, despite its functional relevance to registrars, only achieves a 53% completion rate across the entire survey sample, with a significant disparity evident between Segment II (19.6%) and Segment III (82.7%). The knowledge base and FAQ section, crucial elements for customer self-service, have moderate completion rates (36.8% and 32.9% respectively), with a clear progression of values in the higher segments.

At a low level is the use of modern automated customer assistance components: social media buttons (23.1%), chatbots or live chat (8.1%) and AI support elements (3.8%). Notably, the last two criteria are practically absent in Segments I–III, and a significant increase in their implementation is only observed in Segment V (71.4% and 57.1% respectively), indicating their pioneering nature.

Segmental analysis reveals a clear division in the implementation of automated customer assistance criteria. Segment I is characterised by minimal implementation of almost all criteria, with the exception of site stability (66.1%). Segment II is distinguished from the lowest by the implementation of a customer panel (46.4%) and a contact form (46.4%). Segment III represents a breakthrough for basic automated customer assistance tools such as the domain search engine (82.7%), and in Segment IV, we can see serious use of knowledge bases (94.6%). Advanced tools such as chatbot or live chat or AI support elements only become a significant component in Segment V. It is worth noting that the partners in this segment implement five components completely and the others to a significant degree. It is also significant that none of the entities achieved a score higher than 80, out of a maximum of 90 points to be scored. These observations confirm the phased nature of the development of automated customer assistance among NASK partners, with a clear hierarchy in the implementation of individual components.

The analysis performed makes it attainable to answer the research problem posed and the specific research questions regarding the level of automated customer assistance in the NASK partners' environment.

5.1. Practical implications

In the course of the study, it was possible to comprehensively assess the use of automated customer assistance tools present on NASK partner websites. Concluded industry standard is a stable website, functioning customer panel, contact form and the domain search engine. Partners should seriously consider providing content and tutorials as part of their knowledge bases. Such an analysis clearly identifies those who are industry leaders, those who aspire to be leaders and those who need to take significant action in terms of not automation but simply customer service.

Furthermore, it would be worthwhile to review their partnerships from the perspective of the NASK itself. Almost 1/4 of 117 (23.9%) analysed entities show deficiencies not so much in the organisation of the customer service process itself, but in the proper functioning of the web presence. It would be worth demanding a certain standard from partners, as it is the affiliation of transparent and developing entities that may influence the image of the institution itself. Segment II and Segment III (23.9% and 22.3% of partners, respectively) also do not show significant advancement in the customer service process in terms of the criteria examined. Adding up the number of partners from these three segments, 70.1% of them could show a significant improvement in their customer service process. This is a very high percentage and NASK should seriously consider establishing new partnership rules or changing the rules for maintaining partnerships. NASK could review its partners on a cyclical basis, first setting stricter customer service standards than currently prevailing, allowing for domain registrar status.

Partners operating within Segment IV could consider greater use of the chatbot or live chat, which is at an alarmingly low level (only 6 out of 28 qualified entities) but also make more use of social media for customer service – 9 of them report not doing this at all, and 12 of them indicate only two channels in this area on their website. It is worth mentioning that among the partners assigned to Segment V, 2 of them do not use a chatbot (dhosting.pl and idhosting.pl), 2 of them do not have an SM button (cyberfolks.pl and home.pl) and 3 of them do not mention any use of AI (hostido.pl, lh.pl and smarthost.pl). It would be worthwhile for these companies to analyse this implication and, to the extent possible, implement features to raise their score in this area.

Application of artificial intelligence elements, visible in activities such as domain name creator (cyberfolks.pl and home.pl) or website creation (dhosting.pl, idhosting.pl), but also in more advanced technologies such as server collocation (k.pl), are the first signs of the milestone of fully automated customer service. It should be noted that k.pl has already found its way into Segment IV, which only proves its potential. The rest of the companies mentioned belong to the highest segment. Those companies are evidence of following current trends and applying the latest technologies in a flexible manner, which can be an inspiration for partners from lower segments.

The observed differentiation in the level of automated customer assistance among NASK partners may be a direct result of a conscious migration of customers between registrars. Customers with higher technological expectations naturally tend towards registrars from Segments IV and V, which offer advanced self-service tools, chatbots or AI support elements. This customer selection drives a growth spiral – more demanding customers generate higher revenues, enabling further investment in automation, which attracts further demanding customers. At the same time, lower-end registrars may be deliberately focusing on less technologically demanding but more price-sensitive customers, which would explain their limited investment in advanced automation solutions. These market dynamics suggest that the observed segmentation may not so much be the result of coincidental differences in approach to technology, but a conscious strategy to position themselves in different market niches. However, this in no way explains the runaway and overdone functionality in segments I–II.

Examined results of meeting the selected criteria among NASK partners in general are not optimistic. These are basic criteria in terms of automated customer assistance, which at the level of partnership with an institution of such calibre as a national domain registrar should not be neglected. What is needed is to raise the discussion on this matter and motivate current partners to make changes. Issuing appropriate messages through NASK's official channels or directly contacting registrars and attempting a dialogue, assuming that radical moves such as breaking the partnership are omitted, would help keep the least involved apart and strengthen not only the quality of the partner network, but the image of NASK itself. It also suggests the need for diversified support strategies for the lower segments in order to raise the overall level of automation among partners, which may be within the role of the NASK itself.

5.1. Limitations and further research

The study is a pilot and only addresses arbitrarily selected criteria for automated customer assistance. In order to explore the potential in the area of automation itself, it would be necessary to extend the study to other processes organised within the partners' structures. While the study verifies the basis and potential for automated customer assistance, it would be worthwhile to verify which solutions are automated in after-sales service, e.g. complaint handling, personalised offers. Implications of the study are that future research is worth narrowing down to the highest segment entities. The research should be enriched with the perspective of the partners themselves in this scope. It seems valuable to use qualitative methods and conduct interviews with representatives of the most involved NASK partners, extracted in the course of this study.

It would also be useful to know the customers' perspective on the perception of automated and traditional solutions. Perhaps the current modest scale of automated activities in the perspective of all partners is justified in the assessment of the final recipient. If such an analysis showed a positive attitude towards automation, it would be natural to explore the barriers to implementing such solutions. Possibly these are not only financial limitations, but also legal restrictions.

An analysis of foreign markets in terms of automated customer assistance would be an added value, as NASK data provides information on partners from 21 countries outside Poland. We could then obtain structured insights in an international context, especially on a European scale (18 of the 22 partner countries are from Europe). With this type of benchmark, it would be possible to rank Poland's position in the development of automation elements among NASK's partners.

6. CONCLUSION

Findings from the study indicate a relatively balanced distribution of NASK partners in the defined automated customer assistance segments. A similar number of entities were observed in the four segments and a significantly smaller number in the most advanced segment. This distribution suggests

that there is deep technological diversity in the domain registrar market in Poland, with a small group of leaders and a broad base of players with significantly limited levels of automated customer assistance.

Throughout the study, it was evident that the most commonly implemented element is website stability, which is the technological foundation for the other solutions. High levels of implementation are characterised by the customer panel, the contact form and the domain search engine, indicating a prioritisation of basic customer interaction tools. Knowledge sharing within knowledge bases and FAQ sections, as well as a button directing to the companies' social media, are at a medium to low level of use. On the other extreme are the advanced elements of automated customer assistance: chatbot or live chat and AI support elements, the implementation of which is marginal in the overall sample.

On a segmental basis, a clear progression is evident, with a systematic increase in the level of implementation of individual elements. It is particularly appealing that even in the middle segment, the implementation of AI support elements remains at zero and chatbots at a minimum, indicating that these advanced technologies are only used in the highest segments.

The emerging picture from the analysis indicates a varied but generally low level of commitment on the part of NASK partners to provide automated customer assistance. It may be due to a variety of barriers – technological, competence or financial – that limit the ability of NASK partners to achieve end-to-end transformation of customer service processes.

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THE ROLE OF ARTIFICIAL INTELLIGENCE IN IMPROVING THE EFFICIENCY OF MANAGING THE PROCESS OF COLLECTING EMPIRICAL DATA IN FIELD RESEARCH

Jordan Klimek[a], Anna Kuczyńska[b], Vjosa Hajdari[c], Izabela Szamrej-Baran[d]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *Collegium Civitas, Department of Sociology, Warsaw, Poland*
[c] *University "Haxhi Zeka", Faculty of Business, Peja, Kosovo*
[d] *University of Szczecin, Institute of Economy and Finance, Szczecin, Poland*

ABSTRACT

Purpose: *The article examines the application of artificial intelligence (AI) in the design and implementation of social research, with a focus on the processes of conceptualization and operationalization, empirical data collection, and research ethics.*

Need for the study: *Despite the growing interest in AI in the social sciences, there are still research gaps regarding the use of modern technologies, such as natural language processing (NLP) and machine learning, in the research process. Key challenges include the interpretability of AI models, the risk of algorithmic bias, and the integration of AI with classic qualitative and quantitative research methods.*

Methodology: *The article is based on an analysis of literature and case studies on the use of AI in social research, including both an overview of AI tools and an analysis of their potential applications and limitations.*

Findings: *AI significantly supports researchers at various stages of the research process, from formulating research questions to analyzing data to coordinating field research. At the same time, significant challenges are identified, such as the lack of transparency of algorithms, the risk of automating biases, and the dehumanization of the research process.*

Practical Implications: *The integration of AI in the social sciences requires the development of methodological standards and ethical regulations. Researchers should combine AI with traditional research methods to minimize the risk of errors and ensure the reliability of analyses.*

Keywords: artificial intelligence, automation of field research, field research, management of the research process, methodology of social science, research ethics.

Jel codes: C18

1. INTRODUCTION

In recent years, the topic of applying artificial intelligence (AI) to the social sciences has been gaining popularity, especially in research process design and implementation. Existing analyses point to the widespread use of AI as a tool to support various stages of social research, such as data analysis, social behavior modeling, or trend prediction (Brynjolfsson & McAfee, 2021; Noble, 2018). AI is also being

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studied in the context of its impact on society and human interactions, with the integration of AI into the social sciences growing in importance, especially concerning advanced language models (Xu et al., 2024) and their applications in various research fields (Prieto-Gutierrez et al., 2023). However, despite the growing interest and number of studies on the use of AI in the social sciences, several important research gaps in literature require further exploration.

First, many works overlook modern technologies such as natural language processing (NLP) and deep learning, which offer the potential for more accurate analysis of texts, emotions, and linguistic nuances, which is particularly important in qualitative research (Zeng et al., 2023; Rohlinger, 2024). There is a dearth of studies that examine these technologies in detail in the context of social analysis, despite their potential to revise research methodology (Xu et al., 2024). Second, the problem of interpretability of artificial intelligence models is a major limitation, especially in the analysis of complex social interactions, where context is crucial (Hassabis & Beguir, 2024; Brynjolfsson & McAfee, 2021). Models based on deep neural networks, while effective in analyzing large data sets, remain "black boxes," making it difficult to understand their decisions in a social context. Another major deficit is the lack of interdisciplinarity in research on the use of AI in the social sciences - while AI is widely used in data analysis, few works combine the technology with social research methodologies, which limits the development of new approaches that take into account the complexity of social and cultural contexts (Eubanks, 2018). Additionally, ethical issues related to the use of AI in social data analysis, such as algorithmic biases and their impact on social structures, are not sufficiently discussed in the literature, which risks reinforcing social inequalities (O'Neil, 2016; Zuboff, 2019). Finally, there is a lack of sufficient research on the impact of AI on qualitative research methodology, especially in the context of interpreting emotions and linguistic nuances, which is an important gap in social research (Gill, 2024).

The scientific article aims to analyze the possibilities of using artificial intelligence as a tool supporting researchers in the design and implementation of research processes in the social sciences. The article discusses the application of AI at various stages of the scientific cognition process, from literature review, through conceptualization and operationalization, and design of measurement tools, to coordination of the process of collecting empirical data in the field. The key issue is to understand how modern AI technologies, such as natural language processing, machine learning, or deep neural networks, can support individual processes of designing and conducting social research, especially in the context of striving to ensure a high level of empirical material quality, i.e. measurement accuracy and reliability. The article will also identify potential challenges related to the implementation of AI in social research, including ethical issues (e.g. researcher attitudes) the limitations of AI, and the ability to point out erroneous solutions.

The article's contribution to science is to provide a description and analysis of the role of artificial intelligence in the social sciences, especially in the context of the new insights provided by AI tools in the design and implementation of research processes in the social sciences. The authors of the paper highlight the possibility of using AI at different stages of the research process, from research planning to measurement implementation, pointing out specific benefits that can significantly improve the quality of social research, as well as areas of potential problems. The paper fills a gap in the literature by pointing out the challenges associated with the interpretability of algorithms, as well as the need to address ethical issues such as algorithmic biases and the impact of AI on the research process. The article also provides valuable insights into the use of modern technology in social research methodology, offering practical solutions for future research.

2. LITERATURE REVIEW

In recent years, artificial intelligence has gained prominence in the social sciences, offering new research tools and methods. Its applications include literature search, identification of research gaps, formulation of objectives, hypothesis formation, and analysis of empirical data, among others.

Traditional literature review methods are time-consuming and can lead to errors due to the subjectivity of the researcher. The first tools to support the formulation and evaluation of scientific hypotheses using natural language processing techniques, such as Arrowsmith, were described as early as the previous century (Smalheiser & Swanson, 1998). Over time, other solutions have emerged, such

as a scalable method for discovering hidden connections in literature (Cohen et al., 2010) or the use of neural networks for literature-based discovery in both open and closed approaches (Crichton et al., 2020). All of these methods support researchers in analyzing the existing literature to better understand the context of the research problem and identify new connections between existing data. This is crucial in the process of formulating research goals and hypotheses.

Researchers are increasingly turning to artificial intelligence-based tools to help search, organize, and analyze scientific literature. One example is Semantic Scholar, which, as noted by Fricke (2024), significantly facilitates the identification of research gaps. Thanks to advanced AI algorithms that analyze vast amounts of data, researchers can detect patterns and trends that may indicate areas that require further research (Matthews, 2024). Such tools allow for more precise formulation of research questions and project goals. Moreover, AI can also suggest potential research directions, pointing to previously unexplored topics or new methodological approaches, as noted by Cha (2024). An example of an application is the use of machine learning algorithms that analyze existing data, allowing the generation of hypotheses based on detected patterns and correlations, as described by Jones (2024). With such technologies, researchers can minimize the risk of overlooking important research aspects and increase the accuracy of formulated hypotheses. AI tools can also provide support in aligning scientific texts with the editorial requirements of individual journals. Many scientific publishers and journals allow the use of AI to improve spelling, grammar, and punctuation, or to check that the bibliographic record conforms to the style indicated by the editors (e.g., APA style, Chicago style), as long as the text submission process indicates which AI tool and what it was used for.

In recent years, researchers in the social sciences have increasingly turned to artificial intelligence (AI) to support the process of analyzing empirical data. With advanced techniques such as machine learning and neural networks, researchers are able to process huge data sets, including data from social media, surveys, or public records. Hao (2024) emphasizes that such tools allow data to be analyzed more efficiently than traditional statistical methods. An example of the application of AI in social research is sentiment analysis, used to assess public sentiment based on social media posts, which is particularly valuable in studies of public opinion or consumer behavior (Matthews, 2024).

In addition, AI tools make it possible to uncover hidden patterns and relationships in data that would be difficult to detect using conventional analytical methods. An example is the research of Ma, Ebeid, de Wit, Xu, and Yang (2023), which shows how computational tools support research on nonprofit organizations to understand complex social phenomena. Nelimarkki (2023) discusses how computational thinking can be used in the social sciences, combining programming with AI methods to facilitate social data analysis. The work of Wang, Song, and Su (2023), on the other hand, shows how the development of computational social science is linked to the increasing centralization of research and the extensive use of AI in data analysis, highlighting its importance in the field. Finally, Edelmann, Wolff, Montagne, and Bail (2020) note how AI is increasingly being used to analyze large data sets in sociology, indicating its growing role in social research. With these technologies, researchers can not only uncover hidden relationships but also formulate research questions and conclusions more precisely, allowing for an even more relevant and comprehensive approach to data analysis.

With the increasing use of artificial intelligence (AI) in social research, researchers are beginning to pay close attention to the ethical implications of this process. Jones (2024) points out that the automation of many aspects of research can lead to the dehumanization of science, with researchers losing influence over the interpretation of results and science itself becoming increasingly mechanistic. In contrast, Cha (2024) emphasizes that AI algorithms, if not properly designed and monitored, can introduce or even reinforce existing biases and inequalities, which can lead to erroneous conclusions in social research. In response to these challenges, Hanna and Bender (2025) highlight the influence of large technology corporations on the development of AI, stressing that their role in shaping the technology must be subjected to detailed ethical analysis. Eichstaedt (2025), on the other hand, discusses issues related to the creation of chatbots that seek to tailor their responses to users' expectations, raising questions about the ethicality of such practices in the context of social research. Barto and Sutton (2025) in their analysis warn against hasty deployment of AI technologies without proper testing and safeguards, calling for an informed and ethical approach to the use of artificial intelligence in social science. All of these researchers' experiences point to the need for careful monitoring and responsible use of AI in research to avoid its potentially harmful effects.

The use of artificial intelligence in social research opens up new opportunities but also poses ethical and responsibility challenges for researchers. Integrating AI into the research process requires not only technical expertise but also a critical approach and reflection on the consequences of its application. Only in this way can the social sciences take full advantage of the potential that artificial intelligence brings.

3. OPERATIONALIZATION OF THE RESEARCH PROJECT AND DESIGN OF MEASUREMENT TOOLS

The development of AI has led to tools based on generative artificial intelligence being used for more than just repetitive, routine tasks. They can also prove themselves in tasks that require creativity, but so far, they have more potential to support such tasks than to replace humans in them, and the most important impact of AI is likely to be in automating some tasks while leaving time for other duties (Gmyrek et al., 2023).

One of the tasks that can be automated in the process of creating a survey questionnaire is adapting the format to the tool that will be used to collect the data. AI is able to check the questionnaire created by the researcher(s) for clarity, unambiguity, and logical consistency for transitions between questions, and suggest corrections. It is also able to prepare versions of questions according to formats supported by tools such as LimeSurvey or Qualtrics or prepare instructions for self-entering questions into a specific tool. It can also provide, if needed, a division of the questionnaire into sections, add conditional logic, or suggest settings (e.g., mandatory or non-mandatory questions, blocking the possibility of multiple completions of the survey).

At the same time, AI is able to support researchers in the process of multiplying the possibilities of questionnaire formulation. Artificial intelligence tools can, for example, transform questions and create their variants, including versions with synonyms or altered syntactic structure of a sentence. They can also transform questions into open-ended, closed-ended, matrix, or rank questions, for example. It is also possible, for example, to support the adaptation of questions to the language of the respondents (e.g., by age), or to prepare an explanation of how the questionnaire should be completed if the way of filling it out is non-standard. It is also possible to support the adaptation of the language of the survey invitation according to the population to be surveyed.

However, despite such support, it is the researchers' responsibility to ensure that the final tools are prepared in accordance with the principles of social research methodology and research ethics. AI may behave in a biased manner or show biases if only because of the biases contained in the datasets used to train the AI model (Carey & Wu, 2022)

AI and machine learning can also support the search for previously used metrics, indexes, and scales. This can range from using AI to review the literature from this angle (e.g., Consensus or Scite) to support analysis, including distilling measures from new data sources, and supporting causal inference and theory development (Molina & Garip 2019).

AI support does not only apply to closed questions but also to data from open-ended questions and from the use of quantitative methods. L. Nelson (2017) proposed a three-stage methodological framework - computational grounded theory. These three stages include: (1) inductive pattern detection and computational text mining, (2) pattern refinement, and (3) pattern confirmation. They can be applied to many research questions and any qualitative text, such as transcribed speeches and interviews, but also to data from open-ended questions in surveys or field notes.

AI can also support people who are taking their first steps in research or help train new employees in a research project. AI works well in creating a personalized learning environment (Mollick & Mollick, 2024), including the creation of different scenarios, problems, and cases to consider. Appropriately written prompts can create methodology tasks in which different consequences of choosing particular solutions in a scenario/questionnaire need to be considered or design a task with ethical challenges. At the same time, there is always a risk that the AI will make a mistake, hence such training is a supplement to standard training that prepares one for the role of a researcher under the guidance of experienced researchers, rather than a replacement for such training.

4. PREPARING FOR THE FIELD WORK

The opportunity mentioned in the previous section to use AI to create a personalized learning environment (Mollick & Mollick, 2024), including stepping into different roles, can also be an opportunity to simulate interviews with respondents. Such an activity as simulating conversations with respondents provides an additional opportunity to validate research questions as well as research tools. AI can take on roles differentiated by variables relevant to the study (such as age, gender, education level, or attitudes toward the issue under investigation).

For the aforementioned researchers with less research experience, this can also provide additional preparation for going into the field, including practicing arguing and responding to reluctance or critical approaches to research. Previous research (Noy & Zhang, 2023) indicates that AI-guided training has greater benefits for employees with less seniority. ChatGPT significantly improves productivity, including reducing the average time required to complete a task and increasing the quality of the completed task (Noy & Zhang, 2023).

Less experienced researchers can also use AI to test question comprehension or ask AI to point out ambiguities in questions or interviewer instructions. However, as already mentioned, it is the researchers who are responsible for the research projects they carry out and the publications that are produced based on the results, hence AI-based solutions can provide support, but the responsibility for each stage of the research lies with the authors. In addition, it should always be indicated what artificial intelligence tool was used and how, for example, to improve the readability of the survey invitation.

5. FIELD RESEARCH COORDINATION

One of the key ethical considerations in social research is ensuring that participants are fully informed about the nature, purpose, and potential consequences of the study. Artificial intelligence can significantly assist researchers in developing procedures to ensure that the implementation of field research complies with research ethics, especially in obtaining informed consent from participants. Artificial intelligence can help automate this process, minimizing errors and improving the transparency of communication between the field researcher or interviewer and participants.

One of the primary applications of artificial intelligence in this area is the generation and optimization of informed consent forms. Artificial intelligence-based tools can analyze and suggest wording that is more understandable to different groups of participants, taking into account their level of education, language skills, or specialized terminology, whether scientific or legal. This allows the content of the consent to be tailored to the specifics of the population being studied, avoiding overly complicated or unclear language, and increasing a realistic understanding of the conditions for participation in the study, in accordance with ethical principles as well as the laws of the country.

Another opportunity to support the researcher involves the process of translating informed consent documents into different languages and adapting them to local cultural and legal contexts. Language models make it possible to translate the text accurately, as well as to account for differences in ethical regulations in different countries and institutions. This allows researchers to ensure that procedures comply with international standards, such as the Declaration of Helsinki the European Commission's research guidelines, or data protection regulations.

The consent process for researchers can be carried out through interactive communication systems such as chatbots or digital assistants, which are successfully used in business environments and whose performance can be measured (Przegalinska et al., 2019). Such solutions can support and answer participants' questions in real time, clarify doubts, and ensure that every aspect of consent has been properly understood. This is particularly important for research that requires the consent of vulnerable groups, such as children, the elderly, or people with disabilities, for whom AI can be an additional support. Such solutions also make it possible to monitor and document the consent process, ensuring that it complies with ethical and legal guidelines. These systems can track whether participants have received all the necessary information and whether their consent was given voluntarily, without pressure or manipulation. This can include analyzing the content of conversations, tracking user interactions with documents, or even assessing participants' emotional responses to the information presented.

Thus, artificial intelligence provides valuable support in the development and implementation of ethical procedures in social research. It can not only increase the efficiency of the informed consent

process but also enhance its quality by tailoring content to the needs of participants and ensuring compliance with national and international standards. The use of artificial intelligence in this area allows research to be conducted more transparently, ethically, and with integrity, fostering trust between researchers and participants.

Artificial intelligence can also significantly improve the optimization of human and equipment resources during field surveys. Using data analysis algorithms, artificial intelligence can help plan field trip routes, selecting the shortest and most efficient paths to reach surveyed locations. It can also take into account road and weather conditions, as well as the availability of transportation means, thus minimizing costs and increasing the efficiency of the research team.

The use of artificial intelligence also makes it possible to optimally manage the schedule of researchers in the field. Intelligent systems can analyze data on the duration of various stages of research and then adjust the schedule in real time. This approach allows for flexible responses to unforeseen circumstances, such as the need to change the route or adjust the schedule of meetings with informants or respondents. In addition, artificial intelligence can suggest the best allocation of responsibilities within the research team, optimizing individuals' work time and ensuring that the workload is evenly distributed according to their roles within the team and their experience and skills.

In terms of managing hardware resources, artificial intelligence can monitor the use of research equipment such as audio recorders, tablets, and digital cameras. It can analyze their technical condition, predict failures, and suggest the need for equipment maintenance or replacement. In this way, researchers can avoid problems associated with sudden malfunctions that could affect the quality of empirical data collection. It can also identify data repositories that are suitable for a particular research project, including those that are appropriate in terms of regulations and ethics. This application fits into the area of intelligent management processes.

Moreover, artificial intelligence can support the analysis and management of data collected during field research. Artificial intelligence-based systems can automatically classify and catalog materials, organize notes, and integrate various sources of information, greatly facilitating subsequent analysis of results. In the case of quantitative research, artificial intelligence can also support researchers in on-site statistical analysis, pointing out potential trends and patterns in real-time.

With the development of artificial intelligence, there are also questions about copyright issues and loopholes that need to be filled to minimize the threat posed by regulatory gaps in AI. Researchers of this issue will highlight the dissonance between the rapid development of AI and the much slower progress in changing legal frameworks and ethical guidelines (Nweke & Nweke 2024).

The problem goes beyond the simple question of authorship (Shumakova et al. 2023), and a lack of regulation can threaten science as well as the creative industries. Among the problems that could affect science, the only ones of significance could be copyright infringement, infringement of personal rights, labor entrenchment, labor market disruption, unfair competition, or an originality crisis (Shumakova et al. 2023).

Artificial intelligence can significantly improve the organization and efficiency of field research by optimizing human and equipment resources. Automating route planning, team scheduling, equipment monitoring, and data analysis allows researchers to focus on key aspects of the research while minimizing the risk of errors and increasing the quality of the information collected. The use of artificial intelligence in these processes can contribute to better organization of work and more efficient use of available resources, resulting in higher quality research results and greater reliability.

6. LIMITATIONS OF ARTIFICIAL INTELLIGENCE IN FIELD RESEARCH

Artificial intelligence is becoming an increasingly common tool in the social sciences, supporting the process of data analysis, research planning, and organization of research work. However, despite its potential, the use of AI in field research comes with significant limitations that need to be taken into account in the design and implementation of research.

One of the key problems with applying AI to field research is the difficulty in interpreting the social context. AI, especially models based on natural language processing, can analyze respondents' statements, identify emotions, or classify responses, but has difficulty capturing cultural nuances, irony, or sarcasm. Moreover, analyzing qualitative data, such as interview transcripts or field notes, requires

not only pattern detection but also interpretive skills that are the domain of experienced social scientists. AI can suggest erroneous conclusions if it fails to take into account the broader context of the statements or the specifics of the local community.

AI models, especially those based on deep neural networks, often operate on a "black box" basis, meaning that their decision-making process is difficult to explain. In the context of field research, where data analysis requires transparency and precise reasoning, the inability to fully understand the mechanisms of AI is a significant limitation. Researchers need to be sure that the results generated by AI are reliable and consistent with methodological assumptions, which in practice is sometimes difficult to verify.

Table 1. Summary of benefits and limitations of using AI in the research process

Project stage	Application of AI	Benefits	Restrictions
Literature review	Research text search, analysis, and identification of research gaps	Faster identification of sources, better detection of links between texts, optimization of the process	Potential for AI errors and "hallucinations," difficulty in assessing reliability of results, systematic omission of some sources, biases
Formulation of hypotheses	Generate and refine hypotheses based on literature analysis and available data	Identification of new research directions, optimization of the process	Ability to replicate biases contained in training data
Design of research tools	Automatic generation of questionnaires, analysis of question structure	Facilitate adaptation of tools to the study population, improve logical consistency of questions	Possibility of erroneous suggestions, risk of reinforcing erroneous methodological assumptions
Analysis of quantitative data	Processing large data sets, detecting patterns and relationships	Faster analysis, and identification of trends not visible in traditional analysis	The problem of interpretability of models, the possibility of misclassification of data
Analysis of qualitative data	Natural language processing, sentiment analysis	Automation of data coding, better identification of hidden meanings in texts	Difficulty in interpreting social context, AI may not understand linguistic nuances
Implementation of field research	Interview simulations, question testing, logistics planning	Better preparation of researchers, optimization of routes and work schedules	AI will not replace real-world interactions, risk of not adapting to changing conditions
Coordination of field research	Automation of obtaining informed consent, monitoring the research process	Facilitate management of ethical aspects of the study, improve documentation	AI may not take into account cultural differences, privacy risks
Ethics and fairness of algorithms	Detecting biases in AI data and models	Identification of potential inequality problems	AI may reinforce existing prejudices, lack of universal definition of justice
Resource management	Optimize equipment utilization, monitor consumption	Reduced costs, better organization of research work	Potential for errors in optimization algorithms, dependence on quality of input data

Source: own elaboration.

Artificial intelligence, despite sophisticated algorithms, remains susceptible to biases based on the quality and structure of the data on which it was trained. In field research, where social interactions and cultural context play a key role, this can lead to misinterpretations and reproduction of existing inequalities. AI models can favor dominant narratives and marginalize the voices of minority groups, which can lead to an incomplete picture of the phenomenon under study.

Field research in the social sciences is based on face-to-face interactions with participants, often in dynamic and unpredictable conditions. AI can support the interview process, such as by simulating interviews or generating questions, but it cannot replace the flexibility and interpersonal skills of the researcher. In situations where the researcher shows reluctance to respond, reacts emotionally or changes the topic of the interview, AI cannot adjust its behavior accordingly.

The use of AI in field research also raises significant ethical challenges. The collection and analysis of personal data by AI algorithms raises questions about privacy and compliance with legal regulations such as RODO. In addition, the automation of some research processes can lead to the dehumanization of research participants, raising ethical questions about the researcher's role and relationship with the subjects.

Field research often takes place in a dynamic environment, where unforeseen factors such as political, social or economic changes can affect the research. AI, acting on the basis of pre-processed data, may have difficulty adapting to such changes in real time. AI models may not be able to adapt quickly to new circumstances and provide erroneous recommendations.

Although artificial intelligence offers many opportunities to support field research in the social sciences, its application comes with significant limitations. Problems related to data interpretation, ethics, algorithm bias, and limited ability to interact with respondents mean that AI should be treated as a tool to support, rather than replace, traditional research methods. In the future, AI algorithms will need to be further developed and refined to better meet the needs of social research and take into account the complexity of human interaction.

7. ETHICAL USE OF AI IN SOCIAL RESEARCH

Since the proliferation of solutions based on generative AI, more and more ethical questions have been raised, including about the fairness of machine learning (Carey & Wu, 2022). In addition, ethical issues related to the use of AI in social data analysis, such as algorithmic biases and their impact on social structures, are insufficiently discussed in the literature, with the risk of reinforcing social inequalities (O'Neil, 2016; Zuboff, 2019).

The truth is not objective but is socially and linguistically constructed, and in the digital age, this process is increasingly dependent on algorithms (Zarzycki, 2024). The Theory of Algorithmic Truth (Zarzycki, 2024) suggests that what is considered true, and therefore existing, will depend on algorithms competing for social legitimacy as a source of truth, but remaining under the political control of specific capital.

It is therefore all the more important to be aware that generative AI is trained on a variety of sources, from scientific articles to websites and social media, and due to how the training data is selected, it can reproduce stereotypes or discriminatory content. In this context, publications (Zeng et al., 2019) are appearing that emphasize the importance of transparency and responsibility in the process of implementing and using AI. Researchers must be sure that the use of AI will not have unexpected social consequences, such as the reproduction of biases based on gender, ethnicity, or disability (Carton & Haas, 2020). Algorithms also often fail to consider that race is socially constructed and focus on race as a fixed attribute (Hanna et al., 2020).

S. Catron and Ch. Hass (2024) point to four dilemmas related to fairness in machine learning. (1) Fairness versus model performance – mechanisms that increase the fairness of models often do so at the expense of their performance. (2) Incompatibility of different approaches to fairness – should individual or group fairness be prioritized? In addition, legal, philosophical, social, economic and mathematical definitions of justice do not always correspond. (3) Conflict with social and political context – there is no universal definition of justice, much depends on the specifics of a community and its problems. (4) Democratization of machine learning vs. skills gap – more and more people and companies are using machine learning-based tools without knowledge of the fairness of the algorithms.

One of the key challenges of using artificial intelligence in scientific research is the problem of the so-called “black box” (Hassabis & Beguir, 2024) and model hallucinations. If the model generates incorrect results or content that is characterized by stereotypes and prejudices (Eubanks, 2018; O’Neil 2016), users often have no way of changing the algorithm to improve its performance. In addition, the lack of transparency regarding the data sources used to generate responses raises the risk of copyright

infringement, as the model can generate a response based on copyrighted content without indicating the author.

Another problem related to AI is the protection of personal and sensitive data. Entering this kind of information into AI systems, but also transcripts of interviews containing sensitive data and information, or data from research on sensitive groups and topics (e.g. illness, addiction, physical, psychological, and economic violence, the shadow economy, mobbing) carries the risk of violating ethical and legal principles. Many AI tools process the data provided for the model for their own purposes or may even pass it on to other entities. As researchers, we are responsible for the data provided to us, and only authorized persons should have access to the data, especially sensitive data.

The discussion around the use of AI in science also includes issues related to originality and the dehumanization of the research process. While AI can provide important methodological support, its excessive use can lead to a crisis of originality in science. Responsibility for the integrity of research and its compliance with ethical principles and applicable regulations rests with researchers, whose role should not be replaced by algorithms. AI opens up new possibilities for analyzing data and expanding the research workshop, but its use only makes sense if it actually supports the research process, rather than contributing to its schematization or reducing the quality of the content produced.

8. DISCUSSION AND CONCLUSIONS

Researchers note that artificial intelligence has great potential to revolutionize the social sciences, especially in terms of offering new research tools and methods. In order to take full advantage of AI's potential, it is essential to develop researchers' competencies in artificial intelligence technologies, as well as to promote interdisciplinary research combining social science with computer science and other technical fields (Matthews, 2024). This approach can create new opportunities for social data analysis, enabling more complex and accurate assessment of social phenomena. On the other hand, researchers also emphasize the need for research on the social implications of AI's growing role to better understand what ethical and social challenges arise from its use in various aspects of social life (Hao, 2024). For example, the work of Raja and Buolamwini (2020) demonstrates the need to audit and ensure transparency in AI systems to avoid reproducing existing biases. In the context of computational social science, Wang, Song and Su (2023) note that the development of AI allows for more centralized and complex data analysis, which can foster a better understanding of social phenomena on a broader scale. In addition, Edelmann and colleagues (2020) point to the growing role of AI in sociology, where the technology is being used to analyze large sets of social data, and Hanna and Bender (2025) note the need for responsible AI development, with an emphasis on an ethical approach that takes into account the social implications of the technology. Finally, Ma and colleagues (2023) discuss the potential of AI in research on nonprofit organizations, pointing to the opportunities that artificial intelligence offers in the context of more complex data analysis in the social sciences.

The development and spread of artificial intelligence have added a new dimension to the issue of the digital divide (van Dijk 2020), resulting in a deepening of existing inequalities. Instead of becoming more open and democratic, science will be divided into those who have access to the latest, often paid-for technologies and the skills necessary to use them, and those who are deprived of these opportunities. Although more than a quarter of a century has passed since the term digital divide was coined, many issues are still relevant. Even universal access to the internet has not eliminated inequalities in digital competence and how digital tools are used (Robinson et al. 2020), hence a step towards improving the situation is not only to provide access to tools but also to identify barriers and facilitators in the development of digital skills (Fortuna et al. 2020), now also those related to the use of artificial intelligence.

An analysis of the limitations of applying artificial intelligence to field research in the social sciences points to a number of key challenges related to data interpretation, algorithmic transparency, and ethical issues. As Brynjolfsson and McAfee (2021) note, while AI has great potential in data analysis, its limited ability to capture social and cultural nuances means that its use in qualitative research can lead to simplifications and misinterpretations. This problem also stems from the nature of AI models, which operate on a “black box” basis (Hassabis & Beguir, 2024), making it significantly more difficult for researchers to understand the mechanisms by which analytical decisions are made. Additionally, as

Eubanks (2018) and O'Neil (2016) point out, AI can reinforce existing biases and social inequalities if algorithms are trained on biased data. The automation of research interactions is also of particular concern - while AI can support the data collection process, it cannot replace the researcher's interpersonal skills, pointing to AI's limited adaptability to changing field conditions (Zuboff, 2019). In this context, it seems crucial to combine AI tools with traditional research methods, which could minimize the risk of errors and increase the accuracy of analyses.

The application of artificial intelligence in field research in the social sciences brings both numerous benefits and significant limitations that require further methodological, legal, and ethical reflection. AI can significantly improve the process of analyzing large data sets, but its limited ability to interpret social context and problems related to transparency and algorithmic bias indicates the need for a cautious approach to its implementation (Caton & Haas, 2020). As Xu et al. (2024) point out, it will be crucial to develop interdisciplinary research combining social sciences and computer science to develop more interpretable and fair AI models. In addition, further work should focus on developing ethical standards and regulations for the use of AI in social research to avoid the risks associated with privacy violations and dehumanization of the research process (Hanna & Bender, 2025). In the future, it will also be crucial to find solutions that enable the integration of AI with qualitative methods, which could increase the effectiveness and reliability of analyses conducted in field conditions.

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CHAPTER 2
Artificial Intelligence and Intelligent Management in the Social and Educational Context

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ASSESSMENT OF THE UTILIZATION LEVEL OF ARTIFICIAL INTELLIGENCE TOOLS IN YOUTH EDUCATION

Małgorzata Nermend[a], Justyna Szydłowska-Samsel[b],

[a]*Institute of Pedagogy, Department of Preschool and Early Childhood Education, University of Szczecin, Poland*
[b] *Institute of Management, University of Szczecin, Poland*

ABSTRACT

Purpose: *Artificial Intelligence (AI) is playing an increasingly important role in various areas of life, including higher education. The aim of this article is to assess the level of use of AI tools by students during academic classes and independent learning. It analyzes which available AI tools are used by students in the higher education system. The article also discusses the essence and role of AI development in the context of academic learning.*

Need for the study: *Modern methods and tools of education may be insufficient in the process of educating students. There is a need to search for and offer modern educational tools such as the use of artificial intelligence, which can support academic institutions in monitoring and improving educational processes. Artificial Intelligence tools can contribute to more effective learning and achieving success.*

Methodology: *Research study of students of the University of Szczecin who completed three surveys. The analyzed results concerned their use of the AI tool. You can use Python 3.12 and Pandas libraries*

Findings: *The data obtained indicate that students are increasingly willing to use AI tools, but they have limited trust in them. The results suggest that AI should be a tool supporting student education processes.*

Practical Implications: *AI is influencing the way students teach and learn, and its role in higher education is becoming increasingly important. Effective implementation of AI will require appropriate didactic preparation and a well-thought-out implementation strategy at the level of academic institutions.*

Keywords: academic education, artificial intelligence, education, e-learning

Jel codes: I20, I21, I23, M53 i M59

1. INTRODUCTION

Modern higher education is undergoing dynamic changes, and the growing role of digital technologies is forcing the adaptation of new teaching methods (Dong & Zhang, 2023). Artificial intelligence has become one of the key tools supporting the teaching process, offering personalization of learning, automation of content assessment in an advisory context, and new opportunities for students to interact with educational content. The purpose of this article is to assess the level of use of AI tools by students during academic classes and independent study. The introduction of AI into academic education not only improves the learning process but also affects the way knowledge is processed and analyzed, and thus redefines the traditional approach to teaching.

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In the era of using information pertaining to academic requirements, AI makes it possible to familiarize oneself with the material, personalize the process of learning, and eliminate repetitive and used tasks. The use of AI is becoming a very practical and easy teaching support among other traditional options. One of the most important reasons why students are increasingly using AI tools is that they can access a wide range of knowledge quickly and efficiently. Thanks to intelligent learning platforms, such as thenNavoica.pl (Navoica, 2025) students can acquire knowledge in a variety of fields, tailored to their individual needs. AI algorithms analyze their learning progress provide additional materials to enhance their understanding and learning of a topic(Kowalski & Tomaszewska, 2024).

Personalization of learning based on AI allows the pace and style of learning to be tailored to the user. With respect to traditional teaching methods, where all students learn according to the same pattern, artificial intelligence makes it possible to adapt educational content to the level and requirements of individuals. Such a solution is particularly important for people who expect information in the face of individual expectations and preferences. Students can learn in a manner consistent with their style and basic level using, for example, Khan Academy, Coursera, Udemy which allow the course to be adjusted according to students' performance, or Duolingo, Grammarly which analyze progress in real time.

The use of artificial intelligence is also an opportunity to automate many of the available applications by what is becoming increasingly popular among students. They are eager to use automatic text analysis, grammar and stylistic tools that enable correct editing of texts without linguistic and stylistic errors in academic applications (e.g. credit papers, projects, theses). Thanks to such solutions, students can quickly finalize studies instead of wasting time on laborious text checking. Automatic checking of papers allows students to get immediate detailed feedback on their assignments, which in practice leads to a shorter search for information and a faster learning process.

Artificial Intelligence also provides access to advanced mathematical and engineering analysis.

Technical and scientific research can be used with AI tools for mathematical problems, data analysis and exercises and calculations or modeling. Tools such as Wolfram Alpha, Mathway, Watson, MATLAB, IBM and Symbolab are used here. AI algorithms not only provide ready-made answers, but also explain process solutions step by step, which means the student understands the process.

Another benefit is the improvement of language skills Students have access to language learning applications based on AI algorithms, such as Duolingo, DeepL or ELSA Speak, allowing them to learn a foreign language, where the system replaces the teacher, and learners can effectively improve their skills in pronunciation, vocabulary or grammar and style, students can also use short translations or text summarization.

SI supports scholars in finding reliable scientific sources, research sources, and managing teaching materials (e.g. Google Scholar, Semantic Scholar.) Examples include ChatPDF, SciSpace, which analyzes and summarizes scientific articles. For students who conduct scientific research, AI becomes an invaluable support for data analysis, literature searches and automation of repetitive applications. Tools such as IBM Watson, SciSpace and ChatPDF enable rapid sharing of relevant information, identification of key content and access to data, correlations between data. Such use of AI results in time savings and automation of routine tasks. With the help of AI tools, students can conduct quick analysis of long text, write papers, and acquire research that would have required the use of traditional labor and time just a few years ago. In a flurry of commitments, their use certainly results in an increase in the efficiency and quality of a student's academic work.

However, when writing about the advantages of using Artificial Intelligence, it would be appropriate to mention that students are exposed to dependence on technology, which limits their ability to act creatively and creatively. The automation of education can be associated with a situation in which students rely on ready-made solutions instead of analyzing problems and formulating conclusions on their own. Nevertheless, artificial intelligence is playing and will continue to play an even greater role in education. As a result, many universities have recognized the need to outline legal and ethical regulations guiding the use of AI, particularly in teaching and research processes. Universities recommend in their regulations how to use artificial intelligence, e.g. for correcting style, linguistic correctness and clarity of text, organizing content; creating tables, charts, diagrams and infographics based on student authorship; making calculations; searching for reliable and verified publications (Dobre praktyki, 2023; Traczyk & msas, 2023; UAM, 2024).

The article consists of six parts. An introduction to the issue and showing the role of artificial intelligence in modern education. Section 2 presents the contemporary application of artificial intelligence tools and their use in education. Section 3 contains the applied methodology of the study, including the characteristics of the group of subjects, the experimental procedure, the measurement tools used and the methods of data analysis. The next section contains the results of the statistical analyses conducted. Section 5 is devoted to the discussion of the results and the possibilities of applying AI tools and supporting learning processes. The final section includes conclusions, practical implications and directions for further research.

2. LITERATURE REVIEW

Artificial intelligence (AI) is a rapidly growing scientific field that finds wide application in almost every area of modern life. It is characterized by interdisciplinary, integrating elements of computer science, statistics, operations research, mathematics, social sciences, philosophy and the humanities. The main goal of artificial intelligence is to design and develop systems, including machines and computers, that are capable of performing tasks previously reserved for humans - tasks that require the use of human intelligence. Today, many human cognitive and decision-making functions can be effectively supported or even replaced by AI systems. Modern artificial intelligence encompasses a number of specialized application areas, such as machine learning, robotics, speech recognition, expert systems and natural language processing. A particularly important and widely implemented segment of AI is machine learning, which is a subfield that uses statistical methods to automatically discover patterns and relationships in large data sets, often processed in real time. An unquestionable advantage of systems based on machine learning is their ability to self-improve, which takes place on the basis of experience gained from analyzing successive data sets. This makes it possible to continuously improve the efficiency and precision of these algorithms in a variety of practical applications.

From the field of Machine Learning (ML), Deep Learning (DL) has been identified as one of the most advanced data processing methods within artificial intelligence. The main applications of DL include image recognition, speech-to-text conversion and prediction of phenomena based on data analysis, among others. Deep learning is based on the architecture of multi-layer artificial neural networks, which enable automatic classification and extraction of patterns from large training data sets. These models mimic the way the human brain works, learning by iteratively solving problems and adapting to complex data structures. It's worth noting that classical machine learning is particularly effective for precisely defined tasks, but requires human supervision and intervention, both in the design and evaluation phases of the model. In contrast, deep learning algorithms exhibit a much higher level of autonomy. They are able to independently assess the quality of their own results, make appropriate adjustments and adapt the internal parameters of the neural network without external intervention.

This kind of ability to self-regulate and learn from hierarchical data representations makes DL applicable to increasingly complex and dynamic environments, where traditional ML methods are becoming insufficient(LeCun et al., 2015).

The development of artificial intelligence (AI) has been characterized by a dynamic evolution from the 1950s to today's highly advanced technologies (Roll & Wylie, 2016). Early research by such pioneers as Alan Turing (Turing, 1950), John McCarthy(McCarthy et al., 2006) or Marvin Minsky (Marvin L. Minsky, 1967), laid the foundation for future work on systems capable of simulating human cognitive processes.

Alan Turing is considered one of the forerunners of the concept of artificial intelligence, and his contribution to the field is reflected, among other things, in a test proposed in 1950, now known as the Turing Test (Turing, 1950). Originally referred to as the “imitation game,” this test was an attempt to formulate a criterion for assessing whether a machine manifests intelligence traits comparable to those of humans. The essence of the test was to assess whether a computer could carry on a conversation in such a way that it could not be distinguished from a human. Turing's proposal was one of the first systematic attempts to answer the question of under what conditions a machine can be considered “intelligent.” In the following decades, the development of AI went through several important stages - from the early systems based on symbolic algorithms, through the period of intensified research on

neural networks in the 1980s and 1990s, to the current era of deep learning (Deep Learning, 2015; LeCun et al., 2015).

The first attempts to apply artificial intelligence (AI) focused on creating computer programs capable of competing with humans in strategic games known since antiquity, such as chess, checkers and the Chinese game of Go. A pioneering achievement in this area was a program developed by Arthur Samuel, which demonstrated the ability to compete with humans at the amateur level(Samuel, 1959). The term "artificial intelligence" was introduced by John McCarthy at the Dartmouth Conference in 1956, which is considered symbolic of the birth of AI as a scientific discipline (McCarthy et al., 2006).

Since then, AI research has attracted considerable attention from both academia and the private sector. Particular interest in the field has grown following the achievement of three landmark milestones:

1. In 1997, the Deep Blue computer, designed by IBM, defeated chess grandmaster Garry Kasparov, marking the first confirmation that a computer system could outperform a human in a complex strategic game(Campbell et al., 2002).
2. Another breakthrough was DeepMind's development of AlphaGo, which in 2015 was able to beat professional players in the game of Go, a game considered particularly difficult to model algorithmically due to the huge number of possible moves (Silver et al., 2018).
3. The third major achievement was the creation of the AlphaZero system (also by DeepMind) in 2017. This AI system reached the level of grandmaster chess play in just 24 hours, learning solely by playing against itself, and subsequently outperformed the most powerful chess programs of the time (Silver et al., 2018).

The aforementioned milestones have been an important catalyst for the rapid development of artificial intelligence and machine learning (ML) research over the past three decades.

The benefits of implementing AI technologies are particularly evident in the context of management. Modern mobile and smart devices - such as smartphones, smartwatches, tablets, point-of-sale (POS) terminals and IoT sensors - enable the collection of data on demographics, consumer habits and transaction locations in real time. This data, processed by AI algorithms without the need for direct human supervision, allows for dynamic adjustment of supply to demand and anticipation of future market needs including education. The use of AI allows for increased efficiency through robotics and automation, can more accurately identify customer/student/academic needs and adjust product offerings. The flexibility of modern systems makes it possible to deliver personalized services in a shorter time, which translates into work efficiency. Reducing production downtime and increasing competitiveness.

Today, thanks to the increased availability of large data sets and a significant increase in computing power, it has become possible to develop algorithms capable of efficiently analyzing patterns and making decisions based on data (Russell & Norvig, 2021). Modern AI-based systems are used in a wide range of fields, such as medicine, finance, education, as well as in areas related to art and entertainment. However, it should be emphasized that the development of artificial intelligence, despite its many advantages, also generates significant ethical challenges regarding privacy protection and potential impact on the labor market. Consequently, a responsible approach to the implementation and further development of AI technologies requires both careful monitoring by the developers of these systems and adequate regulation by decision makers (Dong & Zhang, 2023).

It is important to note a number of inherent limitations associated with the operation of ChatGPT, which can significantly affect the quality and safety of its application, especially in an educational context. One of the key problems is the model's tendency to generate so-called hallucinations, that is, false or unverified information presented with a high degree of certainty (Alkaissi & McFarlane, 2023). This type of content can mislead users, especially when the tool is used as a source of knowledge or decision support (BaiDoo-Anu & Owusu Ansah, 2023). Moreover, ChatGPT - like other language models learned from large data sets - can reproduce and perpetuate existing biases and stereotypes present in the training data. This bias can lead to the reproduction of discriminatory content or the reproduction of social inequalities, which becomes particularly relevant in the context of creating an equitable and inclusive educational environment (Cooperman & Brandão, 2024). Additionally, there are significant concerns about user privacy and the security of sensitive data. The lack of full transparency about how data is processed, stored and potentially used by technology providers can raise concerns among educational institutions, teachers and students.

The identified limitations point to the need for a prudent and critical approach to the implementation of generative AI tools in education, taking into account both potential benefits and risks (Currie, 2023).

This requires the development of adequate regulatory strategies, ethical frameworks and educational activities aimed at developing critical thinking competencies and informed use of AI-based tools (Akgun & Greenhow, 2022; Celik, 2023).

Artificial intelligence (AI), defined after McCarthy as the science and engineering of creating intelligent machines (McCarthy et al., 2006), is an interdisciplinary field of science (Southworth et al., 2023). The academic discourse on the application of artificial intelligence in higher education shows growing potential for development, but is still in the early stages of formation. Despite the intensifying interest in the topic, there are a limited number of empirical studies verifying the actual effects of integrating AI tools into educational practices, which significantly hinders the formulation of evidence-based recommendations for academic institutions (Al-Emran et al., 2025). Currently, due to the widespread use of AI in education (Adiguzel et al., 2023; Śluzek & Suppan, 2024) Many studies have been conducted related to the degree of its use and the extent of its application in education (Ouyang et al., 2022).

We can find an interesting overview in Belkina's study (Belkina et al., 2025). The author shows an overview of 21 empirical studies that noted the advantages of using Generation AI in educational settings, both by teachers and students indicating, for example, the improvement of learning methodologies (Rudolph, J. , Tan, S. , Tan, S., 2023), curriculum development (Simms, 2024) the use of broad educational resources (Akanksh Reddy Muddam, 2023; Cheah et al., 2025).

Students pointed to the possibility of individualization in learning (Mhlanga, 2023), facilitating improved learning by answering theoretical questions, stimulating creative thinking, summarizing complex essays in comprehensible formats, and serving as an editing tool to help students with weak language skills (Michel-Villarreal et al., 2023). It is also important to learn how to use the new GenAI tools, as they can help students learn to work more efficiently, accurately and make further progress ((Nikolic et al., 2024).

Based on an analysis of the literature, it can be concluded that artificial intelligence is widely used in various fields, and higher education institutions recommend its use in the teaching and research process (BaiDoo-Anu & Owusu Ansah, 2023). Nevertheless, the research to date does not provide clear answers to the question of how students actually use the available AI tools - whether they are able to use advanced, specialized solutions tailored to the specifics of the field, or whether they are mainly limited to freely available applications such as ChatGPT. Obtaining in-depth knowledge in this regard could bridge the gap and provide a basis for designing effective educational programs aimed at developing competence in the informed and appropriate use of artificial intelligence tools (Al-Emran et al., 2025; Barus et al., 2025).

The literature emphasizes that education in the field of artificial intelligence plays an important role in shaping ethical understanding of data generated by AI systems and is an important part of preparing students for future professional functioning in a digitally driven society (Chan & Tsi, 2024; Creely & Blannin, 2025; Singh et al., 2022). Artificial intelligence is rapidly transforming teaching and learning processes in higher education, bringing about significant changes. Academic staff, students, and educational institutions alike are facing challenges and new opportunities, as well as ambiguities and concerns about the role of AI in the educational environment. It is still unclear to what extent the technology should be integrated into teaching practices, and to what extent it should be restricted. University authorities are therefore faced with the need to develop an adequate regulatory framework and guidelines to effectively manage the implementation of AI in a way that balances technological innovation with ethical requirements and academic integrity (Lyu et al., 2025). In this regard, it is interesting to see what attitudes students have towards artificial intelligence tools.

According to a study conducted by Our Future Foundation and Kozminski University's educational foundation (*Raport-Edukacyjny-PL.Pdf*, n.d.), conducted with 1128 Polish students, almost two-thirds of them use generative artificial intelligence (GEN AI) when solving homework assignments and creating academic projects. Students mostly believe that universities should allow the use of new technologies in the educational process, but with clear regulations on their use. When studying for exams or preparing for papers required to pass a course, more than 52 percent of Polish students use artificial intelligence-based tools, such as Chat GPT or Bard, using large language models (LLMs). In addition, nearly 63 percent of students believe that Chat GPT helps them solve academic problems or search for needed information faster.

From another study "Technology through the eyes of a student" conducted by Digital Care (*Badanie*, 2023), which was carried out on a sample of 500 students aged 19–35 the report conducted by we can learn that as many as 68% of students say they will use tools using artificial intelligence while studying during the academic year. Possible applications included language translation (52%), organizing work (52%), creating presentations (50%) and writing credit papers (34%). One in five students plans to write a thesis with the support of artificial intelligence: an undergraduate, engineering or master's degree, it added. According to the survey, 20% of students have a strongly positive view of the use of artificial intelligence in the educational process during their studies, 40% rather positively, 30% neither positively nor negatively, 8% rather negatively, and 2%. - definitely negative. When asked about their willingness to develop competence in the use of artificial intelligence in university classes, 31% of respondents answered "definitely yes," 43% "rather yes," 15%. "neither yes nor no," 8 percent "rather not," and 2% "definitely not."

Another very interesting study is a survey of 23,000 students from 109 countries, which shows that artificial intelligence, specifically ChatGPT, has become an important tool to support higher education (Ravšelj et al., 2025). ChatGPT is used by students most often for brainstorming and generating ideas (29%) – students use AI for inspiration, creating new concepts and solving problems, summarizing long texts (27%) – the tool helps in quick comprehension of extensive material, finding information for scientific articles (25%) - students use AI as a support in data collection and preparation of academic content. Other popular uses (about 20% of students) also included assistance in writing scientific papers, repeating material before exams, translating texts, seeking advice on personal matters, writing programming code, proofreading texts. Less popular uses included writing official texts, solving math assignments, literary creativity (such as writing short stories or poems). Students find ChatGPT a useful tool for simplifying complex information.

However, students are aware of its limitations, such as the possibility of generating false information (so-called "AI hallucinations"). Two-thirds of respondents believe that privacy should be protected when using ChatGPT, while 50% of students suggest that universities should set rules for the use of AI. The survey shows that ChatGPT is increasingly being used as a tool to support learning, but not as a main source of knowledge. Students mainly use it to organize information, summarize content and inspire themselves, but they are aware of the risk of errors generated by AI.

As the above analysis indicates, artificial intelligence tools are eagerly used in education. Since its public release on November 30, 2022, ChatGPT's generative artificial intelligence tool has gained more than one million users in just one week. Its advanced capabilities for complex tasks have sparked global interest and surprise, especially in educational contexts. ChatGPT's potential to support teaching processes has been met with ambivalent reactions from teachers, as the technology is highly transformative and could significantly change existing teaching models. The potential benefits of using AI tools in education include supporting personalized and interactive learning, creating tasks and prompts for formative assessment, as well as providing ongoing feedback to support the teaching and learning process. Therefore, there is a need for interdisciplinary cooperation between representatives of university administration, academia, educational practitioners and technology specialists to develop safe and effective strategies for implementing generative AI tools in higher education.

3. METHODOLOGY

3.1. Participants

This study was based on data collected through three surveys. The first two surveys were conducted during the spring semester of 2023 and 2024, respectively. Students who participated in the surveys were first-year students of the bachelor's degree who were taking a Python programming course at the University of Szczecin. At the end of the semester, students were asked if they had used outside help during the duration of the course. The third survey was conducted during the spring semester of 2025, and the participants were second-year students of the bachelor's degree and last-year students of the master's degree at the University of Szczecin. This survey asked respondents about the tools they used during their last semester, if they used any AI tools, and about their trust in the information the AI provided. Participants in all surveys were of different genders. 55 students took part in the first survey, 62 in the second, and 23 in the third survey. In total, 140 people took part in the study.

3.2. Research Protocol and Stimuli

As not to limit the answers from students in the first two surveys, the question concerning the learning aids was in the form of an open-answer question. For that reason, the data had to be categorized manually. In the end, all the students' answers were classified into nine groups: websites, information services, online courses, AI, books, peer support, and others. Then anonymized data was analyzed using Python 3.12 and Pandas library. To make the output more readable, it was visualized in graphs.

3.2. Research Apparatus

Python is a high-level programming language, whose design philosophy focuses on code readability. It is relatively easy to use, with various libraries for scientific purposes. This makes Python a powerful tool for data analysis. It allows researchers to extract valuable information from a large dataset. Pandas is considered an example of and specialized Python library for data manipulation(Mihai ANDRONICEANU, 2025).

It allows for fast and easy data analysis. In this research, Python 3.12 with Pandas 2.2.3 library was used for analyzing data from the surveys and to present the results in the form of graphs.

4. RESULTS

In an era of increasing digitization and widespread access to online resources, the ways in which students use additional means to support their learning are changing rapidly. Therefore, the research conducted will provide an understanding of what tools students use in the educational process and how their preferences have evolved over the 2023-2025 period. The following analysis details the results of each study and its implications for the future of academic education in the age of increasing digital technologies.

On Figure 1, the data from the first survey from year 2023 is presented. . Most of the students (36%) who participated in the survey declared to use websites as study help. Interestingly, almost as many students 35% not declared to use any outside help at all. In the third place were both information services and online courses, with 15% of students mentioning their use. AI was placed fourth, used by only 11% of students, followed by use of books (9%) and other (9%). The least mentioned was peer support, mentioned only by 5% of the respondents.

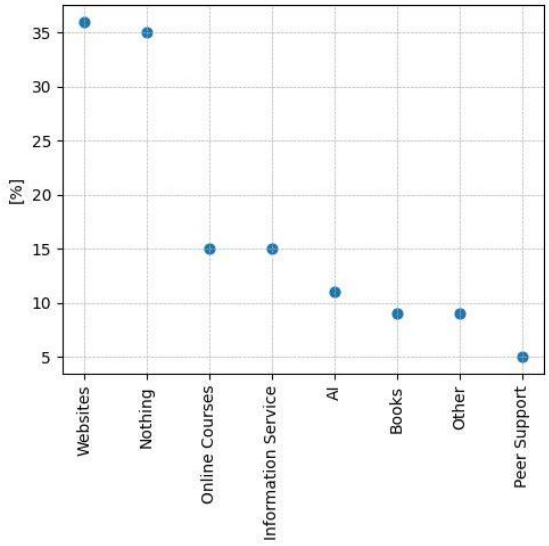
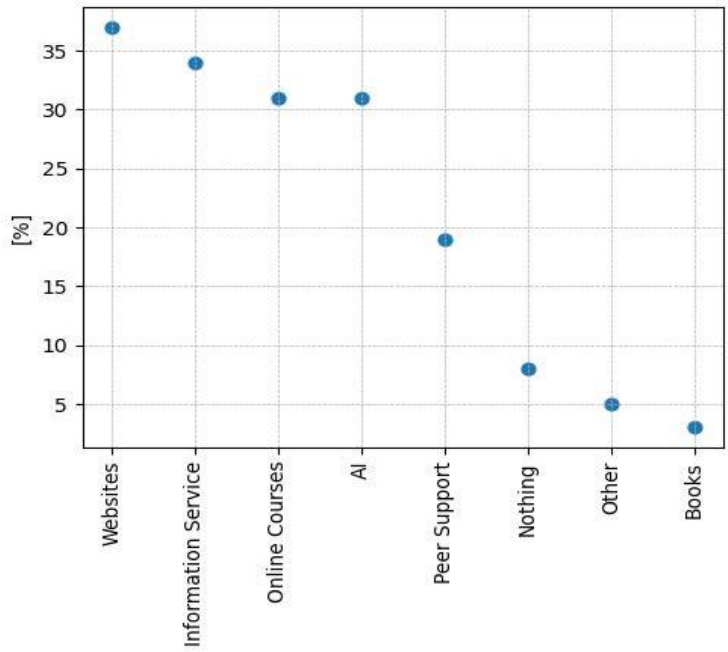


Figure 1. The outside help declared to be used by students in the spring semester of 2023
Source: own elaboration.

Figure 2 shows the results of the second survey from the year 2024. Like previously, first place is taken by the declared use of websites as study help with 37% of respondents mentioning it. But this time the second place is taken by information services, with 34% of students declaring its use. Both AI and online courses were ranked third, with 31% of students mentioning them. This is a significant increase compared to the previous year. Following was peer support (19%), which was previously the least popular among students. This time, only 8% of students declared that they had not used any help during the course, 5% used other tools, and 3% searched for help in books.

Figure 2. The outside help declared to be used by students in the spring semester of 2023



Source: own elaboration.

The third survey from 2025 included three questions:
Q1: Did you use any additional learning aids? If so, which ones?
Q2: How often have you used artificial intelligence tools (e.g., ChatGPT) in your studies?
Q3: Do you agree with the following statement: "I trust the results returned by tools using artificial intelligence (e.g., ChatGPT)?"

Figure 3 illustrates the answers of students to the first question described above. This time more than half of the students (70%) mentioned the use of AI as study help. There are also visible decrees in the use of any other help with information services and other tools being mentioned by only 13% of responders. Websites, which were the most used previously, are now mentioned by only 9% of students.

Furthermore, online courses as well are now mentioned merely by 9% of students. Peer support, books, and no use of any additional study help were only declared once each (4%).

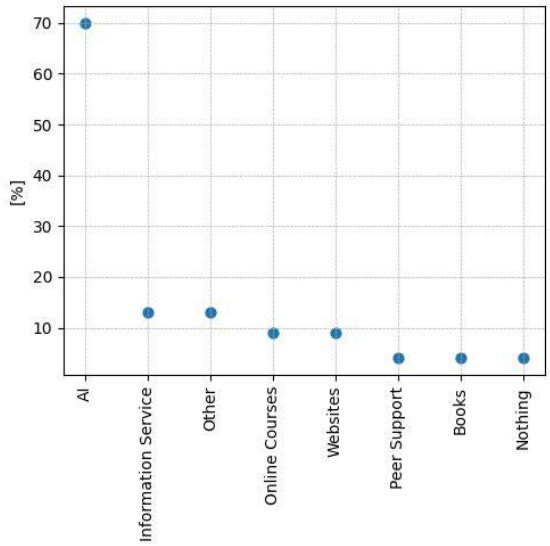


Figure 3. Answers to Q1: "Did you use any additional learning aids? If so, which ones?"
Source: own elaboration.

The answers to the second question of the third survey are presented in Figure 4. Here, 57% of participants characterized the frequency of use of the AI tools as "occasionally". 26% of students selected "frequently" both "very frequently" and "almost never" were picked by 9% of respondents each, and none of the students declared to never use the AI tools.

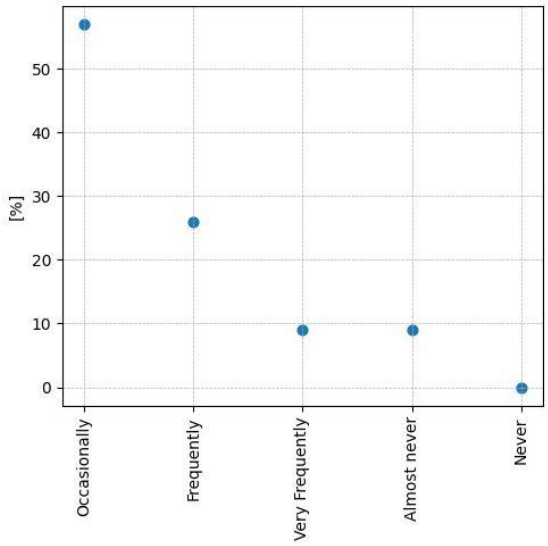


Figure 4. Answers to Q2: "How often have you used artificial intelligence tools (e.g., ChatGPT) in your studies?"
Source: own elaboration.

Students' answers to the last question from the third survey are shown in Figure 5. Although most students said that they use AI tools, with "occasionally" and "frequently" being the top two answers, 39% of the participants disagreed with trusting the results provided by these tools and 13% of them strongly disagreed. 30% of the respondents agreed with the statement; 17% were undecided. None of the respondents strongly agreed with that statement.

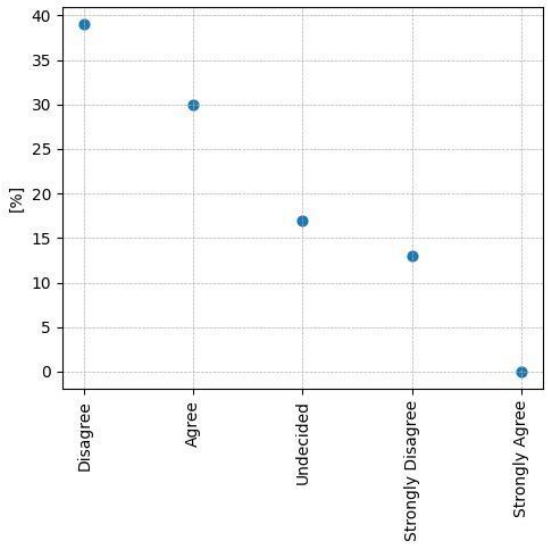


Figure 5. Answers to Q3: "Do you agree with the following statement: "I trust the results returned by tools using artificial intelligence? (e.g., ChatGPT)?"
Source: own elaboration.

5. DISCUSSION

Analysis of the results of the three surveys conducted shows a clear change in the ways in which students use additional educational tools. In 2023, traditional sources such as websites dominated, and almost half of the students surveyed did not use any additional aids. In 2024, a significant increase in the popularity of AI tools such as ChatGPT and information services was noted, which began to compete with traditional learning methods.

The most dynamic change occurred in 2025, when artificial intelligence became the dominant tool to support learning - more than half of respondents reported using it. However, despite the rise in popularity of AI, students do not trust it unconditionally. Half of the respondents do not believe in the full correctness of the information returned by AI, which may indicate a critical attitude towards these tools.

The rise in popularity of AI may be related to its increasing accessibility and effectiveness in providing quick answers to programming questions. Despite this, the survey results indicate that students do not show complete confidence in the information generated by AI. Half of the respondents expressed skepticism about the correctness of the results returned by AI tools, which may suggest that despite its growing use, students are still using it critically.

Artificial intelligence is already influencing the way students teach and learn, and its role in academic education will grow in the coming years (Woolf, 2009). The analysis showed that AI tools are increasingly being used by students, both in class and in self-study. However, their successful implementation requires adequate didactic preparation and a well-thought-out implementation strategy at the level of academic institutions. It is also important to pay attention to ethical issues and data privacy restrictions. The future of AI in higher education looks promising, but its successful adaptation requires conscious action at the level of universities and decision-making bodies (Selwyn, 2019).

The undisputed benefits of using AI in learning include personalizing the learning process, saving time and automating routine tasks, supporting science, facilitating access to knowledge and scientific sources, and improving language skills. The possibilities for using AI tools are essentially limitless. The use of these tools in day-to-day work/study will certainly contribute to better organization of learning and management of free time.

6. CONCLUSION

The results of the survey clearly indicate a dynamic transformation in the way students use available educational tools. Over the past three years, a clear shift in user preferences has been observed - from traditional sources of information, such as books, textbooks and classic websites, towards tools based on artificial intelligence (AI). Solutions such as educational chatbots, content recommendation systems, intelligent assistants or text generators are beginning to play an increasingly important role in everyday teaching practice, both in the context of self-learning and formal teaching.

This does not mean, however, that the process is completely seamless. The empirical data collected reveals the simultaneous presence of certain reserves and limited confidence in IS technology. Students, despite the increasing availability and functionality of these tools, often remain skeptical about the quality of the content they generate and their usefulness in the learning process. These concerns may be related both to the lack of transparency of the algorithms and the risk of erroneous or incomplete information, which may lead to the reproduction of false beliefs or the simplification of complex issues.

In view of the above, it seems reasonable to call for in-depth studies aimed at a long-term assessment of the impact of implementing artificial intelligence on the teaching process. Of particular importance here is the need to determine how new technologies affect the efficiency of learning, the development of students' independence and the formation of cognitive competencies. It would also be important to identify teaching strategies that can support students in the conscious, critical and effective use of AI-based tools.

From the point of view of contemporary educational challenges, it is also crucial to study the impact of these technologies on the development of critical thinking skills. In an era of information overload, the ability to analyze, verify and select content is becoming a competency as important as subject knowledge. AI-based tools can both support this process - for example, by generating alternative viewpoints or personalizing materials - and disrupt it if used unreflectively or as a substitute for traditional forms of learning.

In conclusion, the implementation of AI technologies in education should be regarded not only as a natural stage in the development of teaching tools, but also as a complex phenomenon requiring systematic research and critical reflection. This is because it is necessary to create a theoretical and practical framework that will enable the effective use of the potential of these technologies while minimizing threats to the quality of the educational process.

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28th European Conference on Artificial Intelligence (ECAI 2025)

YOUTH AND SOCIAL MEDIA – A GRADUAL SHIFT DRIVEN BY DIGITAL COMPETENCIES

Marek Szajt[a], Klaudia Smoląg[b], Katarzyna Kozioł-Nadolna[c]

[a] *Czestochowa University of Technology, Faculty of Management, Częstochowa, Poland*
[b] *Czestochowa University of Technology, Faculty of Management, Częstochowa, Poland*
[c] *University of Szczecin, Institute of Management, Szczecin, Poland*

ABSTRACT

Purpose: *The primary aim of this study was to determine the impact of digital competencies on young people's activity in social media.*

Need for the study: *Digital competencies play a vital role in effectively utilizing social media as they enable content creation, interaction with others, influence communication, and support their use for professional, educational, or social purposes.*

Methodology: *The article presents survey results conducted among Polish students. The research was carried out in two phases using both paper and electronic questionnaires: the first phase in 2018 and the second in 2024. Participants assessed their digital competencies using a Likert scale and answered questions about their use of social media. The data were organized and analyzed using multivariate statistical analysis tools, including statistical tests and correlation analysis. The analyses employed the Spearman correlation coefficient, the two-proportion Z-test, and the Mann-Whitney U test. Most calculations were performed using the* ***Statistica 13*** *software suite.*

Findings: *A key finding of the research is that while YouTube and Facebook maintain leading roles among young people, there is a noticeable rise in the popularity of Instagram and TikTok. The division between groups of media is distinct; however, by 2024, there was a stronger connection observed between users, regardless of the platform, than between merely owning and managing an account.*

Practical Implications: *Understanding how students use social media is crucial for universities and could contribute to developing effective strategies to facilitate social media engagement. Taking action to increase digital knowledge and skills in order to improve quality of life, achieve better results at work and increase competitiveness in the labor market. This is also crucial from the perspective of intelligent management of an organization, which uses modern technologies to improve the functioning of an organization in many areas.*

Keywords: Digital competencies, IT skills, information skills, social media, students, digital competence measurement

Jel codes: I23, I25, O33

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1. INTRODUCTION

Globalization processes and the ongoing fourth industrial revolution shape the environment and potential of modern organizations. The fourth industrial revolution is characterized by, among others, digitization, the development of digital competences and advanced automation and robotization.

In today's world, where information reaches us through numerous channels and the industrial revolution has become a reality, relatively modern means of communication, such as social media platforms, play a significant role. Their potential – viewed from commercial, political, and social perspectives – has already been recognized and is continuously exploited. Innovations primarily reach young people, who exhibit high receptivity, adaptability to change, and openness to new technologies.

Modern technologies play an important role in the communication process, access to information, intellectual and professional development of members of many social groups, including young people who are just entering the labor market. They are present in both the public and private sphere of functioning of every person. The 2006 European Parliament recommendation on key competences for lifelong learning lists digital competences as one of the 8 key competences for every citizen that enable personal fulfilment, active citizenship, social cohesion and employability in our modern society (Recommendation..., 2006).

Technology is developing very quickly and is deeply penetrating life, the discussion on digital competences has become a burning topic (Mora-Cantallops et al. 2022; Pérez-López & Tosina, 2023; Załoga &Bryczek-Wróbel, 2023, pp. 716).

Integration of information technology, analytical technology and automation for more effective management of resources and processes in the enterprise is the basis of intelligent management of the organization. Intelligent management uses modern information technology, and social media are based on information technology. The combination of management ideas and methods with artificial intelligence technology and intelligent management is an important part of management practice (Xiaojing & Minghai, 2021, pp. 1).

Therefore, this study investigates the level of digital competencies among students and their engagement in social media. The primary aim was to determine how digital competencies influence young people's activity on social media platforms. Surveys were conducted among Polish university students (technical and economic fields) in two stages – 2018 and 2024.

2. LITERATURE REVIEW

2.1. Digital competences in the modern world

Over the past decades, the concept of digital competences has been discussed more and more often, especially in the aspect of "what skills and knowledge people in a knowledge society should have, what to teach young people and how to do it" (Ferrari, 2013; Ilomäki, Paavola and Lakkala, 2016, p. 655). Literature reviews on this topic have also been conducted to explain this concept (Spante, 2018, pp. 1-21; Zhao et al. 2021; López-Nuñez er al, 2024).

Employees' digital competences are the capital of a company, but above all of every person. Using digital technologies allows people to participate in social life, fulfill professional duties, advance or raise their social status (Rogacka, 2022). According to data from the European Commission, over 90% of jobs in the European Union require at least basic digital skills (ECA, 2021), and by 2030 they will be required in 9 out of 10 jobs (European Commission, Joint Research Centre, 2021). A report by the World Economic Forum (2023) states that six out of ten workers will need skills training by 2027, but only half of workers have access to appropriate training opportunities.

In the recommendation on key competences for lifelong learning that is proposed by the European Commission (2006, pp. 10–18), digital competence has been identified as one of the eight key life skills along with communication in the mother tongue, communication in foreign languages, mathematical competence and basic competences in science and technology, learning to learn, social and civic competences, sense of initiative and entrepreneurship.

Digital competence definitions emphasize the importance of the ability to use digital technologies in various areas of private and professional life. The basic element of digital competence is technical skills (Rachmadtullah, 2020, pp. 3272 – 3277). Computers, smartphones and tablets are an integral part

of personal and professional life, which requires technical skills that will enable effective interaction with these devices (Zheng, 2018, pp. 311–319). This requires understanding operating systems, managing files and folders, installing and updating software, e.g. office software (word processors, spreadsheets) or solving technical problems (Martin et al., 2022; Kozioł-Nadolna, 2024, pp. 3864).

Other aspects of digital competences also appear, such as problem-solving, creativity, critical thinking and the ability to work in a team. Typology of categories developed and presented in the publication by van Laar et al. (2020) is one of the most popular typologies mentioned in the literature devoted to the analysis of digital competences of society, both from the perspective of young people and students, as well as the sought-after competences of employees and digital skills assessed from the perspective of seniors.

Digital competences encompass much more than just using computers or the Internet (Chomiak-Orsa, Smolag, 2024). They mean the ability to analyze both the potential benefits and limitations of modern technologies, as well as the ability to assess the credibility and relevance of digital content (Song, Ling, 2011). In digital communication, the ability to acquire and communicate with a wide audience is particularly important (Yo, 2010, pp.). Today's network user should have competences in co-creating the network environment, i.e. take the initiative to create Internet channels (Siadak, 2016, pp. 371).

The term ‘digital competencies’ refers to a set of skills that everyone needs to live, learn and work in a society where people need to communicate and access relevant information through digital technologies such as internet platforms, social media and mobile devices (Falloon, 2020, pp. 2449–2472; Ng et al., 2023, pp. 137–161). Table 1 contains selected definitions of digital competences from the subject literature.

The change in the scope of the concept and approach to digital competences can be related to four types of access to new media in van Dijk's model (2014, pp. 250):

- motivational access – motivation to use ICT,
- material/physical access – material/physical access to a computer and the Internet,
- skills access – possession of skills related to ICT,
- usage access – access related to the use of ICT.

In the first period of this phenomenon, motivational access played an important role in its escalation, related to the decision to purchase equipment, install the Internet (mobile or stationary), and take the first steps towards acquiring and improving competences enabling the use of specific applications and computer programs. Material access, referring to the IT infrastructure, i.e. access to equipment, programs, and Internet resources, was also extremely important. Later, with technological progress, functioning within these types of access became insufficient. Being a creative producer of electronic products is associated with functioning at the competence level distinguished by van Dijk (skills access – a catalog approach to digital competences) and usage access. Both of these types of access are characterized by having competences in the area of software use, searching for information resources on the Internet, assessing their credibility, the ability to process and use them for one's own purposes, and the ability to use various ways of using computers and the Internet to improve the quality of one's functioning and create individual development paths related to education and professional work (relational approach to digital competences).

There are two approaches to digital competences: catalog (normative) and relational (Buchholtz et al., 2015). The first approach treats them as one of many skills, from which an individual chooses at a given moment the one thanks to which they will achieve a specific goal. Digital competences are perceived in isolation from other human activities. On the other hand, the relational approach to digital competences allows them to be considered in the broader context of tasks undertaken in everyday life, with digital technologies not constituting a separate area, but an integral part of an individual's activity and helping to improve their actions.

Table 1. *Selected definitions of digital competences*

Author, year	Source	Criteria for assessing digital competences
Horton, 1983	Information literacy vs. computer literacy; Bulletin of the American Society for Information Science Vol. 9, No. 4, April	Ability to use a computer to collect and process data
Basil, 2008	Theorems of Information Literacy. A mathematical-like approach to the discourse of Information Literacy	Two levels of assessment: technical use of in-formation technology and information skills consisting in understanding processed re-sources
van Dijk & van Deursen, 2014	Defining Internet skills. in Digital skills. Unlocking the information society (pp. 21-41). Palgrave Macmillan	Four levels of access to technology: motivational access, material/physical access, skills access, usage access
World Economic Forum, 2018	The 2018 Future of Jobs Report	The ability to use digital technologies to achieve goals, solve problems and communicate with others
van Laar et al., 2020	Determinants of 21st-Century Skills and 21st-Century Digital Skills for Workers: A Systematic Literature Review; SAGE Open	Categories: Information digital skills, communications digital skills, collaboration digital skills, critical thinking digital skills, creative digital skills, problem-solving digital skills
KPRM, 2023	Digital Competence Development Program	Digital competences are a harmonious composition of knowledge, skills and attitudes that enable living, learning and working in a digital society, i.e. a society that uses digital technologies in everyday life and work

Source: own elaboration.

Digital competences include (KPRM, 2023, pp. 8):

- IT competences covering the use of computers and other electronic devices, safe use of the Internet, applications and software, new intelligent digital technologies and the ability to use methods derived from computer science when programming and creating IT solutions for problems in various fields (computational thinking),
- information and communication competences, consisting of the ability to search for information, understand it, as well as select and critically evaluate it, as well as communicate remotely using digital technologies,
- functional competences, i.e. the real use of the above competences in various areas of everyday life, such as finance, work and professional development, maintaining relationships, health, hobbies, civic engagement, spiritual life, etc., in accordance with the principles of safe use of digital technologies.

Another typology of digital competences is the DigComp 2.2 model (Vuorikari et al., 2022, pp. 6). This is the next edition of the European Digital Competence Framework for Citizens (DigComp). The framework allows for systematizing areas and levels of competences, as well as creating systems for their measurement and certification.

The areas of digital competences can be presented as follows:

- information and data, including data browsing and storage, data evaluation and data management,
- communication and collaboration, including communication in digital environments, sharing resources using online tools, collaboration via digital tools, digital identity management,
- creating digital content, including creating and editing new content, respecting intellectual property rights and licenses, programming,
- security, including personal data protection and privacy, digital identity protection, security measures,
- problem-solving including solving technical problems, identifying digital needs and resources, creative use of digital technologies.

A less complex model of digital competence is the UK-developed Essential Digital Skills model, which identifies the core competences of individual users, such as (Department for Education, 2019):

- communicating,
- handling information and content,
- transacting,
- problem solving,
- being safe and legal online.

The digital competence model used by the Central Statistical Office in Poland assumes the division of users into 4 categories (GUS, 2020, pp. 155 –156). The first category is people who do not have any general digital skills. They could use the Internet in the last 3 months and did not have any digital information, communication, problem-solving or software skills. People with low digital skills are people who used the Internet in the last 3 months and did not have 1 to 3 of the digital information, communication, problem-solving or software skills.

The third category includes people with basic digital skills, characterized by having any type of digital information, communication, problem-solving or software skills (but at least one type at a basic level). The fourth category includes people with above-basic digital skills from any type of digital information, communication, problem-solving or software skills. According to data from the Central Statistical Office, in 2024 in Poland, 73.5% of people aged 16–24 had basic or above-basic digital skills (GUS, 2024, pp. 3). This age group had the highest percentage of people with basic or above-basic digital skills.

The level of creating digital competences is influenced by the following determinants, which include (Drabik, Tuszyński 2013, pp. 16):

- home, family, friends – this group inspires, teaches, enables and provides access to devices, applications, computer networks, enables spending time together, having fun and learning, solving problems together, making purchases,
- school, university or workplace – requires, shows possibilities, motivates to use them, teaches critical thinking, indicates potential directions of development of computer applications and devices, forces people who teach and work to think and use the potential of ICT creatively, in the case of professionally active people, the need to use the potential of ICT is also conditioned by cooperation with the customer, suppliers and business partners,
- own interests and needs – drive activity in the use of ICT solutions and devices, help maintain the consistency of their use.

When analyzing the possession of digital competences, it is necessary to remember about issues related to the lack of appropriate competences or their inappropriate level, resulting in the phenomenon of digital exclusion, and due to the scope and scope of the impact of ICT on the surrounding reality, social exclusion (Czerski, 2020, pp. 63-64; Ragnedda et al., 2022). The problem of digital exclusion is as important as the issue of digital inclusion.

2.2. Use of social media by young people

The use of digital technologies has become fundamental to enabling people to function effortlessly across all areas of life in today's world. Young people, in particular, represent a group that actively and skillfully utilizes the benefits of the digital world.

Specifically, it is important to mention Generation Z, which is conceived as a digital native generation, as this generation includes people born between the mid-1990s and the mid-2000s (Kowalczyk, 2022, pp. 170–171). This is the first generation to grow up in the era of universally accessible Internet (Dimock 2019, pp. 1).

These demographic exhibits high levels of internet usage, with the time spent online steadily increasing (Nastolatki 3.0, 2023). Moreover, young people, who engage with digital content more frequently than adults, have significantly greater opportunities to develop their digital competencies (Sitek, 2024). Social media platforms play a pivotal role in the virtual lives of young people, enabling them to build relationships, share interests, and fulfill various social needs (Lozano-Blasco et al., 2023; Anderson & Jiang, 2018).

Young people form social connections, social media interactions can promote healthy socialization, especially when they are experiencing stress or social isolation (Craig, 2021).

Participants may use social media to interact with people they already know, as well as a way to meet new people. It is also used as a mechanism for consuming media content and engaging in a range of other activities, which vary depending on the specific site (Buehler, 2017). Youths use social media extensively for various purposes, and it has become an integral part of their daily lives. According to (Sumadevi, 2023, pp. 289–290; Levenson et al. 2016), young people use social media as:

1. Communication and Connectivity – Social media platforms are a primary means of communication to stay connected with others
2. Self-Expression and Creativity – Young people want to express themselves creatively. They share photographs, poetry, prose, and other forms of self-expression on platforms such as Instagram, Tumblr, and Pinterest.
3. Entertainment and Content: social media is a source of entertainment for young people.
4. Information and News: social media provides young people with access to news and current events, for example, on platforms such as Twitter and Facebook to stay up to date.
5. Social Networking – They build professional networks, connect with potential employers, and seek out career opportunities (LinkedIn).
6. Learning and Education: Young people follow educational channels on YouTube or participate in educational groups on Facebook to enhance their learning.
7. Cultural Exchange and Global Interaction – social media enables young people to interact with peers from different countries and cultures, promoting cross-cultural understanding and the exchange of ideas.
8. Social Activism and Awareness – Young people use social media to advocate for causes they care about, participate in online campaigns, and share information to advocate for change.
9. Shopping and E-Commerce
10. Health and Wellness: social media provides health-related information, fitness tips, and mental health support.

As ICT technologies evolve, so does the way we live, necessitating the development of skills that ensure individuals can function autonomously and confidently in the modern digital landscape (Beyer, 2023, pp. 4776).

Digital competences among students increase their competitiveness on the labour market, support adaptation to the technological revolution and reduce social exclusion. Today's societies are experiencing a digitalization that is transforming organizations and jobs (Peiró & Martínez-Tur, 2022, pp. 189). This changes the way of managing an organization, which becomes intelligent. Intelligent management changes the roles of employees, their commitment and creativity.

The skillful use of digital technologies, including AI tools, is an important area in today's digitalized world. The tools currently in use, such as text, voice and video generators or Learning Experience Platforms (LXP), are significantly improving the efficiency and accessibility of education for young people. At the same time, they introduce elements of gamification and improved online discussion forums, which increases student engagement (PARP, 2023, pp. 18–22).

According to a study by Xia et al. (2022), the main effect of implementing artificial intelligence for learners is to increase their motivation and engagement in the learning process.

In 2022, new tools were developed: the Open AI company introduced ChatGPT, and Microsoft introduced Bing. ChatGPT and Bing are advanced AI language models capable of generating content on a variety of topics. Importantly, these tools have the ability to interact with people, making them capable of playing a key role in human communication, supporting both individuals and businesses

Voice-generating AI tools, often called text-to-speech (TTS), convert written text into spoken words using advanced machine learning techniques (e.g.: ElevenLabs, Murf, Resemble AI tools).

Video-generating AI tools use advanced machine learning and artificial intelligence techniques to create, edit and enhance video content. They can generate synthetic video content, automate video editing processes, apply effects or enhancements, and even animate static images (e.g., Bongo, Synthesia tools). Tools for generating presentations, infographics and websites use artificial intelligence to automate and streamline the creation of visually appealing and effective digital content (e.g.: Canva, Miro tools).

The spread of artificial intelligence will certainly have an impact on the development of competencies, including digital competencies.

Digital competencies are a critical factor shaping the quality of life for individuals and organizations alike. These competencies equip people to respond effectively to transformations in how products and services are delivered, organizations operate in the market, and how individuals learn, work, and enhance their qualifications (Saienko et al., 2022). These changes are evident not only in the conveniences of daily and professional tasks but also signify a cultural shift in communication methods. Traditional communication channels have been reshaped by modern tools, with face-to-face conversations increasingly supplemented or even replaced, by digital communication tools that enable remote interaction. Remote communication now predominantly occurs via text-based methods, sometimes supplemented by ideograms, rather than voice communication.

Navigating today's reality requires individuals to adopt and utilize available digital tools. Despite resistance in certain circles, nearly all institutions: governmental, cultural, educational, and others—are advancing towards extensive digitalization of their operations, including both internal and external communication. On one hand, this shift leverages the efficiencies and cost savings of modern methods and tools; on the other, it reflects the evolution of administration and industry to meet the demands of an ever-changing clientele. Companies try to function as best as they can in such conditions and to achieve this, they implement appropriate business strategies (Kozioł-Nadolna, 2022, pp. 3194).

The generation entering the workforce today is highly adept at navigating the digital world. Social media has become a dominant communication channel, serving not only personal interactions but increasingly supporting business and administrative functions (Korombel & Ławińska, 2023). Practically all local and central government institutions now communicate with citizens via social media platforms (Tripopsakul, 2018). This presence is an indispensable element of organizational functioning in the current era. Globally, over 62% of the population actively uses social media, offering companies unparalleled opportunities to engage with potential audiences (Digital 2024 Global Overview Report). In Poland, approximately 28 million people are active social media users (Report Social Media 2023). Younger generations expect brands to engage with them on social media, tailoring their marketing to resonate with their language and preferences. In contrast, mature consumers emphasize secure payment transactions and a seamless shopping experience during e-commerce activities (Co (u)gryzie e-commerce?, 2021; Beyer, 2023a, pp. 3094). Consequently, an increasing share of trade, including retail operations, is migrating online (Szajt & Rafałko, 2017).

Companies active on social media closely monitor the fast-evolving trends to reach potential customers quickly and effectively through the internet. For businesses, online sales are critical; however, Generation Z is characterized by impulsivity and a lack of decision-making analysis, making physical retail stores a compelling sales channel for this group (Kluza, 2019). Skillful use of social media in business enhances processes ranging from product development to customer service (Lu & Lee, 2012). A significant advantage of social media is its ability to create, share, and exchange information within communities formed on these platforms (Sivakumar, 2020).

The demographic profile of Polish internet users reveals that the target group of interest comprises over 24% of users, representing a substantial audience for any outreach efforts.

This study aimed to examine the digital competencies of students and their involvement in social media. Digital competencies were defined as the ability to use digital technologies to access and utilize information, learn, work, collaborate, and function in society critically, responsibly, and creatively (Ala-Mutka, 2011). These investigations align with other efforts to measure students' digital competencies (Tzafilkou et al., 2022; Zhao et al., 2021).

3. METHODOLOGY

The study was conducted in two phases: the first in 2018 (sample size: 175 participants) and the second in 2024 (sample size: 148 participants). The initial phase of the study was carried out concurrently in Slovakia (Hajduová et al., 2020); however, this report focuses exclusively on the research conducted in Poland. The primary tool used was a survey questionnaire containing questions about social media usage and digital competencies, divided into IT and information competencies. For the competency test, a Likert scale-based measurement was applied.

The data collection involved both paper-based questionnaires and their electronic counterparts, which were distributed to potential respondents – university students in Poland. The reliability of the questionnaire was verified using Cronbach's alpha, calculated at $\alpha = 0.973$. The data were organized and analyzed using multivariate statistical analysis tools, including statistical tests and correlation analysis. The analyses employed the Spearman correlation coefficient, the two-proportion Z-test, and the Mann-Whitney U test. Most calculations were performed using the **Statistica 13** software suite.

4. RESULTS AND DISCUSSION

The study aimed to examine the impact of possessing IT and information competencies on engagement with and usage of social media. Given the two rounds of the survey conducted in 2018 and 2024, the study assessed the use of five social media platforms.

Table 2. Number of significant changes in competency levels related to possession and usage of social media

Acrivities	**Account ownership**		**Use of**	
change	decline	increase	decline	increase
Facebook	36	0	46	0
Google plus	48	0	49	0
Twitter (X)	0	49	0	16
Instagram	0	48	0	0
Linkedin	0	49	0	42
Youtube	0	7	43	0

Source: own elaboration.

The findings indicate that in 39 out of 49 cases for account ownership and in 46 out of 49 cases for account usage, individuals with high information and IT competencies were less likely to use (or have an account on) Facebook. An even larger decline in account ownership (48) and usage (49) was noted for Google Plus. Conversely, Twitter (now X) gained popularity within the studied group (across all competencies) as a platform, although this growth did not entirely translate into an increase in active users – growth was observed in only 16 identified competencies. This suggests that factors other than IT competencies might influence its popularity.

Creating accounts appears to be almost intuitive in most cases, not only for social media platforms but also for other services. However, active usage of these accounts requires certain skills, which were identified in the study. These include:

- inserting images/symbols in a word processor,
- inserting and editing tables in a word processor,
- moving files/folders on a computer,
- moving files/folders on a smartphone,
- transferring files/folders between devices,
- using snipping tools,
- using basic mathematical functions in a spreadsheet,
- installing software on a computer independently,
- uninstalling software/apps on a smartphone independently,
- using file-sharing programs (P2P),
- buying and selling goods via websites in languages other than Polish.

At the same time, it is important to acknowledge that social media usage can negatively impact users, potentially leading to addiction (Pellegrino et al., 2022).

The study focused on students and their IT competencies. As other research shows, students' digital competencies are not inherently high simply because they are students (Martzoukou et al., 2020). Nevertheless, these competencies are identified as critical for achieving success today (López-Meneses et al., 2020), whereas their absence can significantly hinder success (Cabero-Almenara et al., 2023).

In our research, we asked participants about both account ownership and actual usage of social media accounts. Notably, in the 2018 survey, the questionnaire included the platform "Nasza Klasa", which was still active at the time. By 2024, it had been replaced by TikTok.

Facebook remains the leading platform in terms of account ownership, but YouTube, previously in second place, has been replaced by Instagram. Among users, Instagram has caught up with Facebook, and the difference between TikTok and YouTube is only five percentage points (Figure 1).

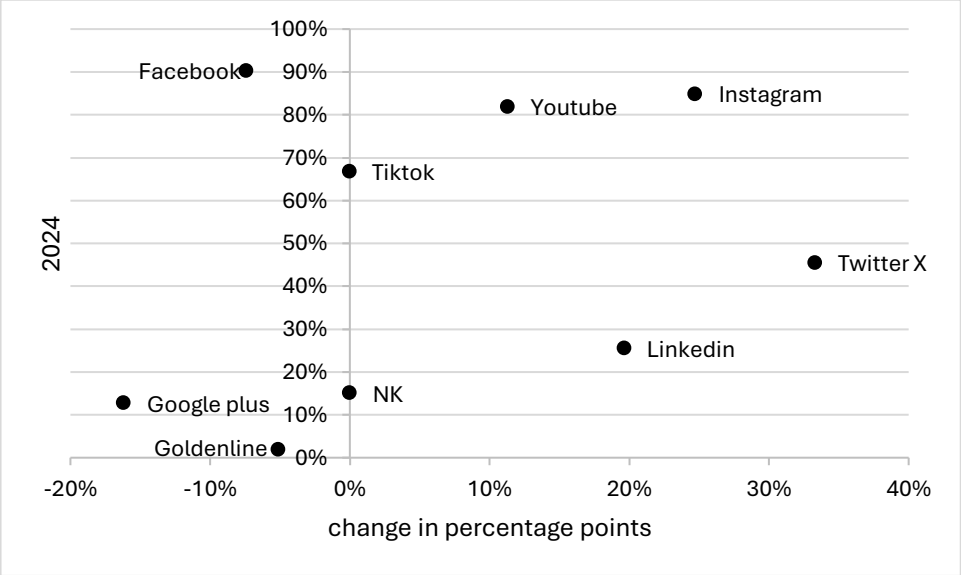


Figure 1. Changes in the Percentage of Social Media Users Between 2018 and 2024
Source: own elaboration.

Global studies continue to confirm the leading roles of YouTube and Facebook among young people, but the rapid rise of Instagram and TikTok is evident, with the gap narrowing each year. Similar conclusions emerge from our findings. The changes in user groups are noticeable even within a relatively short six-year span between surveys. The most significant progress was observed for Instagram and Twitter (X), while Google Plus experienced a decline. Facebook's popularity appears stable for now, but it is important to remember that the social media market is highly dynamic.

Social media enables the creation and sharing of information as well as collaboration (Malik et al., 2020), and it opens up new educational opportunities (Esteve-Mon et al., 2017). The chosen reference group appears appropriate; however, differences in results may directly stem from the academic focus of the participants' studies or from other non-digital skills and competencies (Wild & Schulze Heuling, 2020).

The study also individually examined the frequency of Facebook usage. All significant changes regarding Facebook usage in connection with competencies indicated a declining percentage of users. The proportion of those using Facebook rarely or not at all increased more than fourfold – from 5.8% to 25.0% in the surveyed groups. However, this does not necessarily signify an exodus from social media but rather its evolution. Platforms like TikTok, Instagram, and Twitter (X) are gaining popularity, leading to declines in others. Naturally, alongside competencies, trends and the quality of services also play a role.

The study of students' involvement in the use of social media is also important from the point of view of university management (its recruitment). Recent research has confirmed that thanks to the implementation of AI in marketing – through social media – universities can operate more effectively, better communicate with potential and actual customers such as students (Gołąb-Andrzejak, 2022). All the more so as the use of AI in social media, for technical and economic reasons, is growing in an unprecedented way and is constantly transforming social media (Sadiku et al. 2021). This is a response to the situation in the market, where AI is playing an increasingly important role in every marketing segment due to its versatility and efficiency (Chithra Lekshmi, Jayaseelan and Kadeswaran, 2024).

New tools used by social media platforms are becoming increasingly intuitive. The pandemic served as a significant test of competency levels. In 2018, respondents rated 34 of the 49 competencies higher, with only two rated lower compared to 2024. It can be assumed that respondents' knowledge has grown substantially due to the "virtual reality" imposed by the lockdown. However, a high self-assessment of digital competencies followed by their actual verification is not unusual and has been documented in other studies (Silva-Quiroz & Morales-Morgado, 2022).

The conducted research aligns with findings presented by other researchers and international organizations. A certain degree of user rotation between social media platforms has been observed (O'Day & Heimberg, 2021). Some platforms, through changes or modifications to their usage rules, attempt to appeal to a broader audience—Twitter (X) being an example. Others remain popular within specific circles but are less so among the same age groups in different geographic locations. Currently, over one-third of young people (and nearly as many in other age groups) are constantly online. Young people, on average, engage with more than seven social media platforms.

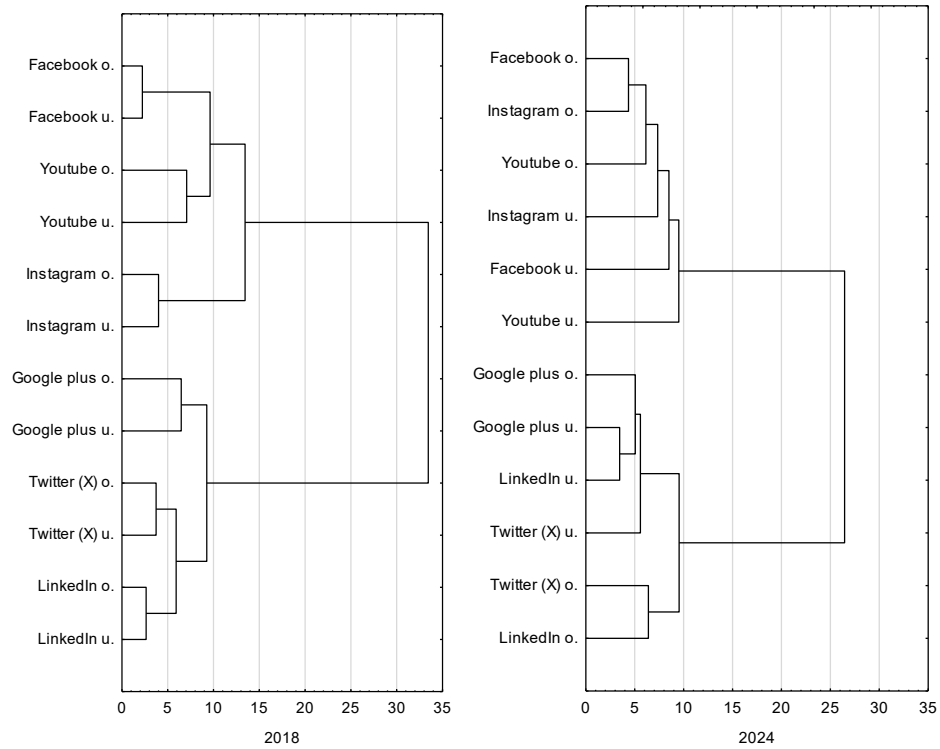


Figure 2. Cluster Analysis Using the Ward Method for Social Media Users (u.) and Owners (o.) in 2018 and 2024 (Euclidean Distance)
Source: own elaboration.

The ownership of multiple accounts and their interconnections are more pronounced in the 2024 study. While the division into two groups of media remains constant, the 2024 results show a stronger connection among users of three specific social media platforms, as well as within the second group—stronger than the link between ownership and usage (Figure 2). This could suggest the influence of competencies on social media usage.

According to our findings, platforms like Facebook and Google Plus show a decline in their association with IT competencies. In contrast, new platforms such as Twitter and TikTok, which were not included in the 2018 study, have gained prominence – TikTok, for instance, was owned by two-thirds and used by 53.3% of respondents in 2024. In today's reality, the presence on social media and the diversity of platforms are key elements determining their role (Kaplan & Haenlein, 2010), particularly for the studied group of users.

5. CONCLUSION

The study, conducted in two stages in 2018 and 2024 on a total sample of 323 respondents, allowed for an assessment of the impact of digital competencies on the activity of young people on social media. The results highlight changes in the popularity of social media among young users. Facebook remains popular but is losing ground to newer platforms like TikTok and Instagram.

It turns out that merely having accounts on social media – which reflects an effort to keep up with trends—is not dependent on IT competencies. Access to these platforms, particularly for young people, is intuitive. However, their actual usage requires specific competencies, as confirmed by the research and its practical verification conducted in the second stage. It can be assumed that the self-assessment of competencies in 2024 was more accurate than in the first edition.

Movements among social media users are also noticeable, with changes in platform popularity and, consequently, user numbers. Understanding how students use social media is crucial for universities and could contribute to developing effective strategies to facilitate social media engagement (Lu et al., 2016).

This is also crucial from the perspective of intelligent management of an organization, which uses modern technologies to improve the functioning of an organization in many areas. Understanding how young people use social media can help improve the activity of companies in social media to reach potential customers. Knowledge of issues related to the use of social media is essential in intelligent management of an enterprise.

The study has its limitations, stemming from the territorial criteria and sample size, which should be regarded as preliminary. Conducting more in-depth research seems promising, particularly to determine whether changes in the social media platforms used by young people are influenced to some extent by the possession or acquisition of specific IT and informational competencies.

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HR DIGITISATION BEFORE AND DURING COVID-19 IN VISEGRAD GROUP COUNTRIES

Sandra Misiak-Kwit[a], Lukáš Smerek[b], Gabor Szabó-Szentgróti[c] , Helena Marková[d]

[a] *University of Szczecin, Institute of Management, Poland*
[b] *Matej Bel University in Banská Bystrica, Faculty of Economics, Slovakia*
[c] *Széchenyi István University, Department of Corporate Leadership and Marketing, Hungary*
[d] *School of Business Administration in Karviná, Silesian University in Opava, Czech Republic*

ABSTRACT

Purpose: *This paper aims to provide new insights into the digitisation of human resources in the Visegrad Group. The authors examined the evaluation of HR digitisation before and during the COVID-19 pandemic.*

Need for the study: *The digitisation of human resource management in the Visegrad Group countries is an emerging phenomenon that influences how organisations in these regions manage their human resources.*

Methodology: *The survey included the following sample sizes: 500 respondents in Poland, 832 respondents in the Czech Republic, 384 respondents in Slovakia, and 377 respondents in Hungary. The Shapiro-Wilk normality test, F-test for equal variance, and paired t-test were utilised for the investigation. Additionally, the authors conducted a one-way ANOVA to compare the mean digitisation scores among Visegrad Group countries before and during COVID-19.*

Findings: *The data presented in the paper show that HR digitisation is consistently ranked as one of the less challenging HR activities in the Visegrad Group countries, both before and during the COVID-19 pandemic. The results indicate that while country-specific differences in HR digitisation challenges were significant both before and during COVID-19, the pandemic exacerbated these differences. Hungary consistently faced the greatest challenges, while Poland encountered the fewest. The pandemic heightened the overall difficulty of HR digitisation, as evidenced by higher mean scores and greater variability.*

Practical Implications: *The paper emphasises the urgent need for targeted strategies to promote digital transformation, especially in countries facing significant challenges, during crises and beyond.*

Keywords: HR digitisation, HRM, Visegrad Group, COVID-19, pandemic, AI

Jel codes: M15; M54; O33; J24; I15

1. INTRODUCTION

In the current era, we can confidently state that the development of technology has never been as dynamic and intense as it has been over the past 20 to 30 years. Historically, important inventions have accelerated in their development throughout human existence, but never before have so many fundamental inventions emerged in a single generation to advance humanity significantly. We can

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certainly consider the Internet and the development of computer technology as significant inventions that enable us to connect knowledge across the world. Thanks to these advances, we can solve problems more quickly and effectively, leading us to the fourth industrial revolution. In Industry 4.0, entirely new manufacturing landscapes are emerging, where robots have become a key element and conventional human skills and thinking are routinely outperformed (Hitka et al., 2025). While the concept of Industry 5.0 is increasingly coming to the forefront, there is an even greater connection between humanity and technology. This concept no longer focuses solely on enhancing the efficiency and flexibility of production, but instead emphasises the significance of research and innovation with an emphasis on sustainability and social justice. Concepts such as focusing on people's needs and their interactions with machines, biotechnology and smart materials, real-time simulations, secure data transmission, storage and analysis, technologies that ensure energy efficiency, and artificial intelligence (AI) are gaining importance (Zolotová et al., 2021).

Technological developments significantly impact human resources (HR) management. HR functions in the Visegrad Group (V4) countries (the Czech Republic, Hungary, Poland, and Slovakia)- whose economies have traditionally excelled in manufacturing and are now rapidly digitising- have had to adapt. Automation, AI, and widespread digital transformation are changing how organisations recruit, hire, manage employees, support teleworking, and analyse workforce data (Eger & Žižka, 2024). Automation and AI have transformed recruitment, onboarding, and employee management, fundamentally altering how HR operates - illustrated by chatbots interviewing candidates in the Czech Republic and AI customised for job roles in Poland. The COVID-19 crisis acted as a test bed for telework technologies, fast-tracking the shift to digital HR tools and highlighting the importance of a digitally agile HR function (Poór et al, 2024). While challenges such as cost, cultural resistance, and skills gaps remain, there is clear momentum in the region to overcome these barriers. Organisations are increasingly aware that effective use of digital tools in HR can improve efficiency, decision-making, and employee experience, all of which contribute to competitive advantage in a tight labour market. They are also learning that digital transformation is not just a technical effort but a human effort, requiring training, managerial buy-in, and a focus on employee-centred implementation (Pubali & Bidyut, 2023).

The study focuses on the digital transformation of HR practices. An understanding of these processes sheds light on how organisations can maintain operational continuity during crises, which became particularly salient during the pandemic (Ruitao, 2023). The HR sector has traditionally been seen as a conservative field; however, the pandemic, along with subsequent crises and geopolitical changes, catalysed an urgent shift towards digitisation, demonstrating the need for HR to adapt quickly and agilely to changing circumstances (Ajayi-Nifise et al., 2024). The experiences of the Visegrad countries highlight the common challenges organisations face in integrating digital technologies into HRM systems. These challenges range from the need to train employees in digital literacy to building a culture that embraces change (Ajayi-Nifise et al., 2024). The COVID-19 pandemic underscored the critical capabilities of HR departments to effectively manage transitions and leverage digital tools to facilitate communication and collaboration (Ruitao, 2023).

Despite the growing importance of digital transformation in HR, the adoption of digital tools varies significantly across countries due to structural, economic, and cultural factors. In the Visegrad Group, organisations face distinct challenges in implementing HR digitisation. While some firms in Poland have been more adaptable due to pre-existing digital infrastructure, companies in Hungary have encountered greater difficulties, often owing to limited technological readiness and resistance to change. Similarly, disparities in investment in AI-driven HR solutions, digital literacy, and governmental support further shape how HR digitisation progresses across different national contexts. These variations underscore the need for a tailored approach to digital transformation in HRM, especially during crises such as the COVID-19 pandemic. Therefore, the aim of this paper is to gain new insights into the digitisation of HR before and during the COVID-19 pandemic in the Visegrad Group.

2. LITERATURE REVIEW

Technological progress affects labour demand in two ways. On one hand, it reduces the demand for work in activities that can be automated; on the other hand, lowering production costs increases the

income of the population and creates demand for new jobs. However, jobs with a predominance of routine manual and non-manual activities are also at risk. Frey and Osborne (2013) quantified the probability of being threatened by computerisation based on a forecast of machine learning and mobile robotics and an analysis of work activities across 702 job types. Jobs where human labour can be effectively replaced by computers within a relatively short period (1–2 decades) include those in transportation and logistics, administrative support positions, most operational roles in manufacturing, positions in personal and household services, and employment in sales and construction. On the other side of the spectrum are positions that require a high degree of originality, social perceptiveness, or a desire to help and care for others. These jobs include most managerial roles, as well as positions in education, healthcare, media, science, and engineering.

Nedelkoska and Quintini (2018) used these findings to assess the threat to the labour market from automation in individual OECD countries. Of the 32 countries assessed, they identified Slovakia as the country most at risk of automation, with up to 33% of jobs in high risk (14% across all assessed countries, with Norway being the least at risk at only 6%). Half of all positions in Slovakia have more than a 67% probability of being threatened by automation, which is also the worst result among all the assessed countries. Consequently, the workforce will need to undergo a significant change in the skills available in the medium term.

However, the changes are unlikely to affect everyone equally. Several economists (Goos & Manning 2007; Coelli & Borland, 2016; Salvatori & Manfredi, 2019) suggest that the jobs of employees with secondary education and middle incomes, which primarily involve professional manual work and clerical positions, will be most at risk due to automation.

Ultimately, automation can deliver not only benefits in terms of increased economic performance but also contribute to rising income inequality, which can lead to social unrest and create pressure to slow the adoption of new technologies. Digital transformation in companies offers advantages such as flexibility and improved team collaboration, which are essential for streamlining processes (Boateng & Olexová, 2025). Stacho et al. (2023) point out that, although all organisations recognise the need for digitisation to remain competitive, larger ones are more active in implementing innovations than smaller ones.

On the other hand, some Slovak companies recognise the importance of modern HRM tools only after implementation, which leads to broader adoption. However, firms that do not use these tools fail to recognise their future relevance (Stacho et al., 2022). Frey (2019), therefore, emphasises the need for preventive measures, such as promoting retraining and lifelong learning, removing barriers to career change, and encouraging employee mobility. Integrating AI tools into decision-making processes can enhance the quality and speed of managerial decisions, leading to improved organisational performance (Isoe, 2024). These measures require not only changes in the relevant legislation but also the active support of companies. Kucera and de Mattos (2020) argue that automation not only replaces human labour but can also improve working conditions and, ultimately, employee remuneration. The COVID-19 crisis has also contributed to the current situation by accelerating automation, as companies sought to reduce their dependence on human labour and limit mutual contact between employees.

According to the OECD (2021), policymakers must anticipate the skills required of employees in light of automation trends. AI applications in knowledge management facilitate the creation, integration, and distribution of knowledge, enhancing organisational competitiveness (Alghanemi & Mubarak, 2024). In addition, the OECD (2021) points to the declining opportunities for young people to enter the labour market through low-skilled jobs and emphasises the need to adapt the skills of younger workers to meet the demands of the labour market.

Technological progress is not only reshaping the labour market but also transforming how human resource management (HRM) operates. AI has the potential to revolutionise HRM practices by automating mundane tasks, streamlining processes, and providing customised solutions for HR managers (El-Ghoul et al. 2024). Integrating AI into HRM offers opportunities to enhance decision-making processes, from recruitment to employee development, by automating tasks and providing data-driven insights. However, this technological shift also raises questions about the evolving role of HR professionals and the need for continuous adaptation to new digital tools. Like any new technology, AI brings numerous benefits and risks. It is up to us to choose our approach to this technology and determine how we can leverage it to our advantage. AI offers many opportunities to enhance societal efficiency, foster prosperity where it is lacking, and address problems that have been challenging to

resolve so far. However, it also presents possibilities for the misuse of this technology through various unfair and dangerous practices.

A study conducted by Grace et al. (2018) states that more advanced AI will have a 25% probability of having a positive impact on humanity and a 20% probability of a very positive impact. On the other hand, a group of scientists involved in this study assessed only a 10% probability that such technology would have a negative impact, while they attributed just a 5% probability to catastrophic consequences.

The V4 countries had already begun the process of digitising HRM before the COVID-19 pandemic. Digital workforce onboarding processes have become increasingly popular as they facilitate the effective integration of new employees into organisations (Sani et al., 2022). These online solutions provided companies with the opportunity to manage a geographically dispersed workforce effectively and ensure the smooth integration of new employees into organisational culture and work processes. However, the pandemic has accelerated this process and brought significant changes to HR practices. During the COVID-19 pandemic, organisational adaptability and the need for flexible HRM underwent major changes, driven largely by public health measures and teleworking requirements (Borawski, Duda & Biercewicz, 2021). Transitioning to digital platforms became essential to sustain operations amid lockdowns and social distancing protocols (Podolchak et al., 2024; Wiścicka-Fernando, 2021). In Hungary, similar to the Visegrad countries, HR functions adapted rapidly by integrating teleworking tools and digital management systems (Piwowar-Sulej et al., 2023). This digital shift not only addressed immediate operational needs but also represented a broader digital transformation strategy that many organisations had previously been reluctant to adopt.

The pandemic served as a critical stimulus for increased investment in training and development of digital tools in the V4 countries (Tomé et al., 2023). AI-driven tools streamline candidate sourcing, screening, and selection processes, leading to more accurate and unbiased hiring decisions (El-Ghoul et al., 2024). Organisations that had already invested in digital capabilities before the pandemic were better positioned to embrace digital learning environments and virtual collaboration. Some research suggests that in Hungary, many companies have adopted online training and development initiatives that enable them to maintain and develop employees' skills during teleworking periods. This time has highlighted the importance of digital competencies in HRM, underlining the trend toward sustainable human resource development (S-HRD), which is likely to continue after the epidemic.

The rapid adaptation and securitisation of digitisation tasks have enabled companies to adjust to new circumstances. Those that already implemented advanced IT solutions were better positioned to respond to emerging challenges. Unsurprisingly, the biggest winners included e-commerce and IT companies, as they had previously embraced best practices in their operations. At the same time, digitisation poses a challenge for less agile firms, as it is not limited to a single business process but permeates the entire organisation: it involves the digitisation of business models, customer relationships, primary and managerial processes, and products/services (Móricz, 2019). Even aside from the pandemic, the implementation of Industry 4.0 has presented a significant challenge for companies. Industry 4.0, a specific branch of digitisation, refers to the digitisation and automation of the business environment; however, in this transformation, fear of change, lack of motivation, and issues with employee engagement and retention have created barriers for both managers and the workforce (Obermayer et al., 2021). COVID-19 has significantly accelerated the digitisation process, requiring companies to be innovative, adaptive, and secure (Otti et al., 2021). By 2025, AI will fundamentally change organisational structures by facilitating the symbiotic relationship between human intelligence and artificial intelligence (Mollick, 2024).

Furthermore, the pandemic highlighted the role of digital technology in supporting HRM practices. Technology facilitated effective communication, recruitment, and performance management, enabling organisations to maintain operational efficiency and employee engagement (Widiastuti, 2021). Empirical studies in the V4 region emphasise the key role of digital tools in HRM toolkits, such as managing in hybrid work environments (Piwowar-Sulej et al., 2023). The integration of these technologies is expected to continue, enhancing the quality and accessibility of HR services beyond the immediate context of the pandemic.

The digitisation of HR in the Visegrad countries before and during COVID-19 was a significant and rapid transition, driven by necessity and innovative opportunities. Although pre-pandemic practices laid the foundation, the urgency of the health crisis accelerated the adoption and integration of digital HRM practices. A forward-looking perspective highlights the ongoing commitment to digital tools that

support and expand HRM functions, signalling a strategic opportunity for the sector's continued evolution and sustainability.

3. METHODOLOGY

3.1. Participants

Participants were randomly selected to ensure a representative sample of the target population. The survey achieved the following sample sizes across the V4 countries: Poland – 500 respondents, the Czech Republic – 832 respondents, Slovakia – 384 respondents, and Hungary – 377 respondents. These sample sizes were deemed adequate for conducting robust statistical analyses and drawing valid conclusions. In total, the research sample comprised 2093 organisations.

In Poland, the majority of organisations (83.60%) had less than 10 employees, 7.40% had 10–49 employees, 3.40% had 50–249 employees, and 5.60% had more than 250 employees. In Slovakia, 22.92% of enterprises had less than 10 employees, 33.85% had 10–49 employees, 22.66% had 50–249 employees, and 20.57% had more than 250 employees. In the Czech Republic, the distribution of employees was more balanced: 28.00% had less than 10 employees, 28.73% had 10–49 employees, 22.24% had 50–249 employees, and 21.03% had more than 250 employees. In Hungary, 37.98% of enterprises had less than 10 employees, 24.70% had 10–49 employees, 18.25% had 50–249 employees, and 19.06% had more than 250 employees.

In Poland, 84.80% of organisations had an annual turnover of €2,000,000 or less, 6.60% earned less than €10,000,000, 5.00% earned less than €50,000,000, and 3.60% earned €50,000,000 or more. In Slovakia, 47.40% earned €2,000,000 or less, 23.70% earned less than €10,000,000, 14.58% earned less than €50,000,000, and 14.32% earned €50,000,000 or more. In the Czech Republic, 36.30% earned €2,000,000 or less, 23.80% earned less than €10,000,000, 18.87% earned less than €50,000,000, and 21.03% earned €50,000,000 or more. In Hungary, 48.02% earned €2,000,000 or less, 19.97% earned less than €10,000,000, 15.96% earned less than €50,000,000, and 16.05% earned €50,000,000 or more.

In Poland, 85.00% of organisations were private, while 15.00% were public. In Slovakia, 86.46% were private, while 13.54% were public. In the Czech Republic, 84.62% were private, and 15.38% were public. In Hungary, 85.71% were private, and 14.29% were public.

In Poland, 6.40% of organisations had been in existence for less than 1 year, 14.80% for 1–3 years, 24.20% for 3–10 years, 19.00% for 10–15 years, and 35.60% for more than 15 years. In Slovakia, 2.08% of organisations had been operating for less than 1 year, 5.621% for 1–3 years, 21.09% for 3–10 years, 16.93% for 10–15 years, and 54.69% for more than 15 years. In the Czech Republic, 0.96% of organisations had been operating for less than 1 year, 5.53% for 1–3 years, 18.99% for 3–10 years, 15.50% for 10–15 years, and 59.01% for more than 15 years. In Hungary, 2.39% of organisations had been in existence for less than 1 year, 7.36% for 1–3 years, 19.88% for 3–10 years, 16.44% for 10–15 years, and 53.94% for more than 15 years.

3.2. Research Protocol and Stimuli

The research methodology employed in this study involved a questionnaire survey designed to gather data on specific variables in the Visegrad Group countries: Poland, Slovakia, the Czech Republic, and Hungary. The data collection period spanned from March to August 2023. A mixed-method approach was adopted, using both online and paper-based questionnaires. Participants were invited to complete the questionnaire either online or on paper, based on their accessibility and preference. Online questionnaires were distributed through digital platforms, while paper questionnaires were handed out in person or sent by post. This dual approach aimed to maximize response rates and ensure inclusivity. The study adhered to ethical research standards, ensuring the confidentiality of responses and allowing participants to withdraw from the study at any time without penalty.

As part of the research, respondents were asked to rate the level of difficulty they encountered in managing various HR tasks and functions before and during COVID-19. The assessment concentrated on areas such as workforce management, workforce planning, recruitment and selection, retention, and labour shortages. It also included maintaining employee engagement, managing home-based and hybrid teams, ensuring health and safety compliance, providing training and development, and facilitating effective organisational communication. Respondents were also asked to assess challenges related to

HR digitisation and industrial relations. Their ratings were recorded on a five-point Likert scale, with higher ratings indicating greater perceived difficulty. This method aimed to identify the most pressing HR challenges and provide insights into areas needing strategic focus, particularly in the evolving workplace landscape.

3.3. Research Apparatus

This paper aims to gain new insights into HR digitisation before and during the COVID-19 pandemic in the V4 countries. Two conceptual frameworks were developed for the study (Figure 1 and 2). According to conceptual framework I, the authors examined the assessment of HR digitisation before and during the COVID-19 pandemic, considering the country in which the business activity is conducted. The Shapiro-Wilk normality test, F-test for equal variance, and paired t-test were utilised for the investigation.

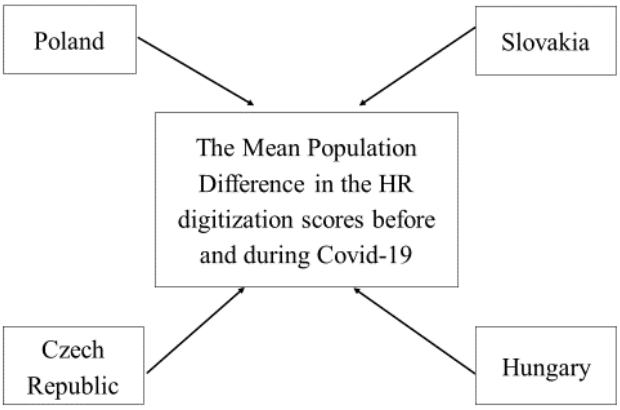


Figure 1. Conceptual framework I
Source: own elaboration.

A t-test was conducted to compare the mean population difference in HR digitisation scores before and during COVID-19 in the V4 countries. Therefore, the hypotheses formulated are:

H_{01}: The mean of HR digitisation scores before and during COVID-19 in Poland is equal.
H_{a1}: The mean of HR digitisation scores before and during COVID-19 in Poland is not equal.
H_{02}: The mean of HR digitisation scores before and during COVID-19 in Slovakia is equal.
H_{a2}: The mean of HR digitisation scores before and during COVID-19 in Slovakia is not equal.
H_{03}: The mean of HR digitisation scores before and during COVID-19 in the Czech Republic is equal.
H_{a3}: The mean of HR digitisation scores before and during COVID-19 in the Czech Republic is not equal.
H_{04}: The mean of HR digitisation scores before and during COVID-19 in Hungary is equal.
H_{a4}: The mean of HR digitisation scores before and during COVID-19 in Hungary is not equal.

The authors also conducted a one-way ANOVA to compare the mean digitisation scores among the four analysed V4 countries before and during COVID-19, as shown in conceptual framework II (Figure 2).

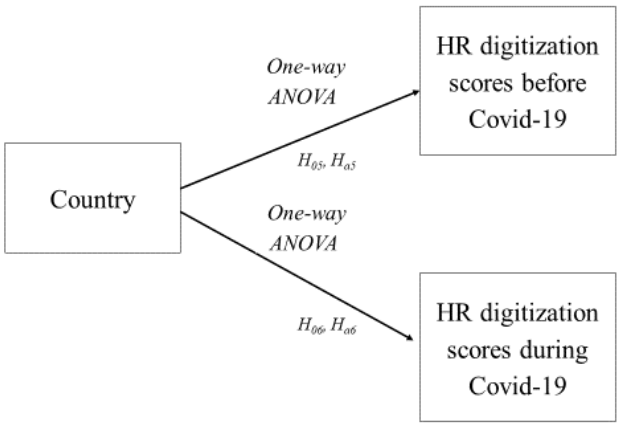


Figure 2. Conceptual framework II
Source: own elaboration.

Subsequent hypotheses are as follows:
H_{05}: The population means of HR digitisation scores before COVID-19 are equal across the four countries.
H_{a5}: At least two population means of HR digitisation scores before COVID-19 are not equal.
H_{06}: The population means of HR digitisation scores during COVID-19 are equal across the four countries.
H_{a6}: At least two population means of HR digitisation scores during COVID-19 are not equal.

3.4. Analysis of Measurement Data

The ranking of HR challenges before and during the COVID-19 pandemic highlights varying priorities across the Visegrad Group countries. While HR digitisation is considered a significant challenge, it ranked lower compared to other HR activities, indicating that it was not viewed as the most pressing issue prior to the pandemic. With an average score of 2.46, HR digitisation in Poland ranked 9th out of the 11 activities assessed. Challenges such as employee retention, recruitment, and selection were considered more critical in the pre-pandemic context. In the Czech Republic, HR digitisation scored 2.53, placing it 5th overall. However, recruitment, selection, and labour shortages were perceived as more pressing challenges. With a score of 2.63, Slovakia also ranked 5th for HR digitisation, similar to the Czech Republic. However, priorities such as recruitment and selection and labour shortages were ranked higher. In Hungary, HR digitisation was considered a lower priority, ranking 10th with a score of 3.27, well behind challenges such as employee retention, maintaining engagement, and recruitment and selection. Across the V4 countries, HR digitisation had an average score of 2.66, placing it in 8th place. This indicates that while it was recognised as a challenge, other activities such as recruitment, selection, and retention were deemed more critical.

The ranking of HR challenges during the COVID-19 pandemic reflects a shift in priorities across the Visegrad Group countries. While HR digitisation remains a recognised challenge, it continues to rank lower compared to more immediate and operational HR activities. The data underscores how the pandemic exacerbated existing challenges while introducing new complexities, such as health and safety compliance and remote work management. HR digitisation ranked lowest in Poland, with an average challenge score of 2.50. This suggests that Polish organisations were more focused on addressing critical issues such as employee retention, workforce management, and planning. With a score of 2.86, HR digitisation in the Czech Republic ranks 8th, indicating a moderate challenge. However, other activities, such as workforce management, planning, and recruitment and selection, were viewed as more pressing. In Slovakia, HR digitisation received a score of 2.95, placing it 8th. While recognised as a challenge, activities such as workforce management, planning, recruitment, and selection took precedence. In Hungary, HR digitisation ranked 7th with a score of 4.00, reflecting a higher perceived challenge compared to other V4 countries. However, it still lagged behind challenges such as health and safety compliance and organisational communication. Across the V4 countries, HR digitisation had an average

challenge score of 3.00, placing it 10th overall. This highlights that while HR digitisation was recognised as an important issue, it was not prioritised as highly as operational or pandemic challenges. Although HR digitisation was considered a challenge during the COVID-19 pandemic, its relative ranking in the V4 countries suggests that it was not deemed a critical priority compared to challenges directly related to pandemic disruptions, such as workforce management, recruitment, and health and safety compliance. This reflects the immediate need for organisations to address operational and security concerns, relegating longer-term strategic transformations like digitisation to a secondary focus.

Despite its relatively low ranking among HR challenges in both periods, HR digitisation remains a critical area for long-term organisational resilience and adaptability. The pandemic underscored the necessity of digital tools for remote work, communication, and workforce management, illustrating that digital transformation is not merely a strategic goal but a fundamental enabler of other HR functions. Investing in HR digitisation can streamline processes, enhance decision-making through data analytics, and boost employee engagement, positioning organisations to navigate future disruptions more effectively. Thus, proactively addressing this area can provide a competitive advantage and ensure sustainable growth in an increasingly digital world. Therefore, the authors conducted further analyses, such as a paired t-test or one-way ANOVA.

4. RESULTS

4.1. Paired t-test

The preliminary conditions should be fulfilled in order to run the paired t-test. Accordingly, the sample data should come from a normal distribution, and the variances of the paired samples should demonstrate homogeneity. Therefore, the researchers conducted the Shapiro-Wilk test to assess the normality of the distributions and the F-test to evaluate the homogeneity of variances.

The Shapiro-Wilk test was performed to examine the normality of the HR digitisation scores before and during the COVID-19 pandemic. According to the Shapiro-Wilk test, the data did not come from a normal distribution (Table 1).

Table 1. Shapiro-Wilk normality test

Country	Distribution – HR digitisation scores	Sample Size (n)	W	p-value	Assumption
Poland	before the COVID-19	500	0.88	0.00	Sample data do not come from a population that is normally distributed
	during the COVID-19	500	0.89	0.00	
Czech Republic	before the COVID-19	832	0.89	0.00	
	during the COVID-19	832	0.91	0.00	
Slovakia	before the COVID-19	384	0.91	0.00	
	during the COVID-19	384	0.91	0.00	
Hungary	before the COVID-19	384	0.91	0.00	
	during the COVID-19	384	0.79	0.00	

Source: own elaboration.

However, according to the central limit theorem, because of the large sample size (sample size > 30), the conclusion of the Shapiro-Wilk test can be omitted. Therefore, based on the large sample size and the established practices of the central limit theorem, the authors assumed that the data came from normal distributions.

Next, the authors carried out an F-test for equal variance. The results are shown in Table 2.

The analysis of HR digitisation ratings before and during the COVID-19 pandemic included an F-test to assess equal variances across the V4 countries. The results are summarised in Table 2, which displays the sample size, degrees of freedom, p-values, confidence intervals (CI), and the ratio of variances for each country. The sample in Poland consisted of 500 organisations for each time period (before and during the pandemic). The F-test result showed a p-value of 0.831 and a confidence interval (95% CI) of 0.82 to 1.12, with a variance ratio of 0.98. These results indicate that the variances between the two time periods were equal, which meets the assumption of homogeneity. In the case of the Czech

Republic, the sample consisted of 832 organisations for each time period. The F-test yielded a p-value of less than 0.05, which, combined with the confidence interval of 0.71 to 0.94 and a variance ratio of 0.82, indicated that the variances were not equal. This suggests greater variability in HR digitisation ratings during the pandemic than prior. With a sample size of 384 organisations for each time period in Slovakia, the F-test yielded a p-value of 0.092 and a confidence interval of 0.69 to 1.09, along with a variance ratio of 0.84. These results indicate that the variances were equal, which aligns with the assumption of homogeneity. The sample in Hungary included 384 organisations for each time period. The F-test yielded a p-value of 0.148, a confidence interval from 0.70 to 1.05, and a variance ratio of 0.86. These results indicate that the variances between the two time periods were equal, supporting the assumption of homogeneity. Overall, the F-test results indicate that while most countries had equal variances in HR digitisation scores before and during the pandemic, the Czech Republic displayed significant differences, underscoring the variability in responses between the two periods. According to the F-test results (Table 2), only the Czech Republic shows non-homogeneity of the variances. Consequently, the paired t-test was conducted for the Czech Republic under the conditions of non-homogeneity of variance.

Table 2. F-test for equal variance

Country	Distribution – HR digitisation scores	Sample Size (n)	df	p-value	95 % CI	Ratio of variances	Assumptions
Poland	before the COVID-19	500	499	0.831	0.82 – 1.12	0.98	Variances are equal
	during the COVID-19	500	499				
Czech Republic	before the COVID-19	832	831	0.004	0.71 – 0.94	0.82	**Variances are not equal**
	during the COVID-19	832	831				
Slovakia	before the COVID-19	384	383	0.092	0.69 – 1.09	0.84	Variances are equal
	during the COVID-19	384	383				
Hungary	before the COVID-19	384	383	0.148	0.70 – 1.05	0.86	Variances are equal
	during the COVID-19	384	383				

Source: authors' compilation.

The paired t-test results shown in Table 3 aim to assess whether the mean scores of the HR digitisation ratings before and during the COVID-19 pandemic differ significantly within each V4 country. The test evaluates whether the observed differences in scores indicate true changes in the population or are merely due to random variation.

Table 3. Paired t-test

Country	Distribution – HR digitisation scores	t	df	p-value	95 % CI	Mean difference	Decision
Poland	before the COVID-19	–0.82	499	0.41	–0.16, 0.07	–0.05	Population means are equal
	during the COVID-19						
Czech Republic	before the COVID-19	–9.33	831	0.00	–0.39, –0.26	–0.33	Population means are not equal
	during the COVID-19						
Slovakia	before the COVID-19	–4.89	383	0.00	–0.46, –0.19	–0.32	Population means are not equal
	during the COVID-19						
Hungary	before the COVID-19	–14.18	383	0.00	–0.86, –0.65	–0.75	Population means are not equal
	during the COVID-19						

Source: own elaboration.

This analysis highlights changes in the perception of HR digitisation challenges across the V4 countries, helping to identify trends and differences in organisational priorities. The p-value in Poland (0.41) indicates no significant difference in HR digitisation ratings before and during COVID-19. This means that the perception of HR digitisation challenges remained consistent (fail to reject H_{01}). In Slovakia, a significant difference is observed ($p < 0.001$) with a mean difference of –0.32, indicating a

similar trend of reduced perceived challenges during the pandemic (reject H_{02}). The p-value in the Czech Republic (<0.001) indicates a significant difference, with a mean difference of –0.33 (reject H03). This suggests that HR digitisation challenges were perceived as less important during COVID-19 than before. In Hungary, the largest mean difference of –0.75, coupled with a significant p-value (<0.001), demonstrates a significant decrease in the perception of HR digitisation challenges during COVID-19 compared to the pre-pandemic period (reject H04). The significant decrease in ratings across most countries suggests that organisations adapted their HR practices or that digitisation became less of a concern compared to other pandemic-related issues. However, the lack of significant change in Poland warrants further investigation to understand the unique dynamics of that market.

4.2. One-way ANOVA

The preliminary conditions must be met to conduct the one-way ANOVA. Accordingly, the sample data should originate from a normal distribution, and the variances of the sample groups should show homogeneity. Thus, the researchers performed the Shapiro-Wilk test to assess the normality of the distributions and Levene's test for Homogeneity of Variance. According to Table 1, the sample data does not come from a normal distribution. However, based on the large sample size and the accepted practices of the central limit theorem, the researchers assumed the data came from normal distributions. According to Levene's test, the variances do not demonstrate the homogeneity conditions in the before-COVID-19 scenario (df = 3, F-value = 4.29, p-value = 0.00). Thus, the authors conducted Welch's ANOVA. According to the Welch's ANOVA test (F =45.42, num df =3, denon df = 990, and p-value = 0.00), the null hypothesis H_{05} can be rejected (p-value < 0.05). This indicates that HR digitisation scores of at least two populations before COVID-19 are not equal.

Furthermore, a one-way ANOVA test was conducted to assess whether the HR digitisation scores before COVID-19 varied significantly among the four V4 countries, as illustrated in Tables 4 and 5.

Table 4. Country versus HR digitisation scores before COVID-19

Country	Count	Sum	Average	Variance
Poland	500	1228	2.46	1.56
Czech Republic	832	2107	2.53	1.36
Slovakia	384	1008	2.62	1.28
Hungary	384	1249	3.25	1.19

Source: own elaboration.

Table 4 presents descriptive statistics, including count, sum, mean, and variance for each country analysed. Mean HR digitisation scores ranged from 2.46 (Poland) to 3.25 (Hungary), indicating potential differences in perceptions of HR digitisation challenges across countries. The variances were relatively similar, suggesting homogeneity of variance.

Table 5. Summary of the one-way ANOVA test – H_{05} testing

Source of Variation	SS	Df	MS	F	P-value	F crit
Between Groups	169,65	3	56,55	41,59	0.00	2,61
Within Groups	2849,65	2096	1,359			
Total	3019,3	2099				

Source: own elaboration.

The results of the one-way ANOVA are summarised in Table 5. The analysis revealed a significant effect of country on the HR digitisation score before COVID-19 ($F(3, 2096) = 41.59$, $p < .001$). The F-statistic exceeds the critical value (2.61), and the p-value is much smaller than the conventional significance level of .05, leading to the rejection of the null hypothesis (reject H_{05}). The sum of squares for the between-groups variation is 169.65, indicating substantial differences in HR digitisation scores attributable to the country factor. The within-groups sum of squares was 2849.65, indicating variability within country scores. The between-groups mean square was 56.55, and the within-groups mean square was 1.36.

To further analyse the significant differences identified by the one-way ANOVA test, Tukey's HSD (honestly significant difference) test was conducted to compare the mean HR digitisation scores across countries (Table 6). This test provides pairwise comparisons along with confidence intervals and adjusted p-values, ensuring control of the family-wise error rate.

Table 6. Tukey's Multiple Comparisons of Means before the pandemic

Comparisons	Diff	lwr	upr	p adj
Hungary - Czech Republic	0.72	0.54	0.91	0
Poland - Czech Republic	–0.08	–0.25	0.09	0.65
Slovakia - Czech Republic	0.09	–0.09	0.28	0.57
Poland - Hungary	–0.8	–1	–0.59	0
Slovakia - Hungary	–0.63	–0.84	–0.41	0
Slovakia - Poland	0.17	–0.03	0.37	0.14

Source: own elaboration.

The mean HR digitisation score in Hungary was significantly higher than in the Czech Republic (mean difference = 0.72, 95% CI [0.54, 0.91], $p < .001$), confirming a notable disparity in digitisation challenges between these countries (not equal population mean). The mean difference between Poland and the Czech Republic was not statistically significant (mean difference = –0.08, 95% CI [–0.25, 0.09], $p = .65$), suggesting comparable levels of difficulty in HR digitisation. A similar outcome was observed when comparing Slovakia and the Czech Republic, with a non-significant mean difference (mean difference = 0.09, 95% CI [–0.09, 0.28], $p = .57$). A notable disparity appeared in the HR digitisation scores reported by Hungary and Poland, with the former exhibiting significantly higher scores (mean difference = –0.80, 95% CI [–1.00, –0.59], $p < .001$). This finding indicates substantial variations in the perceived challenges associated with HR digitisation between the two nations (unequal population mean). A similar trend was observed when comparing Hungary's scores to those of Slovakia, which exhibited a significantly higher mean difference of –0.63 (95% CI [–0.84, –0.41], $p < .001$) (not equal population mean). The difference between Slovakia and Poland was not statistically significant (mean difference = 0.17, 95% CI [–0.03, 0.37], $p = .14$), indicating relatively similar levels of perceived HR digitisation challenges.

The same calculations were carried out for the scenario of the evaluations that refer to the digitisation of HR during the pandemic. According to Levene's test, the variances demonstrate the homogeneity conditions in the during-COVID-19 scenario (df = 3, F-value = 2.06, p-value = 0.1). Thus, another one-way ANOVA test was performed to explore the association between the analysed V4 countries and HR digitisation scores during COVID-19, as shown in Tables 7 and 8.

Table 7. Country versus HR digitisation scores during COVID-19

Country	Count	Sum	Average	Variance
Poland	500	1252	2,5	1.58
Czech Republic	832	2379	2,86	1.66
Slovakia	384	1133	2,95	1.52
Hungary	384	1539	4,01	1.38

Source: own elaboration.

Table 7 summarises the descriptive statistics, including the count, sum, mean, and variance of the HR digitisation challenge scores for each country during COVID-19. The mean scores reveal variability in perceptions, with Hungary reporting the highest mean score (4.01), indicating that HR digitisation was perceived as more challenging compared to Poland (2.5), the Czech Republic (2.86), and Slovakia (2.95). Variance scores are comparable across countries, suggesting homogeneity of variance.

Table 8. Summary of the one-way ANOVA test – H_{06} testing

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	530.42	3	176.81	113.1	0.00	2.61
Within Groups	3276.58	2096	1.56			
Total	3806.99	2099				

Source: own elaboration.

The results of the one-way ANOVA are presented in Table 8. The analysis revealed a statistically significant effect of country on HR digitisation challenge scores during COVID-19 ($F(3, 2096) = 113.1$, $p < .001$). The F-statistic is well above the critical value (2.61), and the p-value is well below the conventional threshold of .05, leading to the rejection of the null hypothesis (reject H_{06}). The between-groups sum of squares was 530.42, indicating significant variability in HR digitisation scores due to differences between countries. The within-group sum of squares was 3276.58, indicating additional variability within scores by country. The between-groups mean square was 176.81, and the within-groups mean square was 1.56.

To further investigate the significant differences identified by the one-way ANOVA test for HR digitisation scores during the COVID-19 pandemic, Tukey's HSD test was conducted (Table 9). This analysis provided pairwise comparisons of mean differences between countries, along with confidence intervals and adjusted p-values to ensure robust control over multiple testing errors.

Table 9. Tukey's Multiple Comparisons of Means during the pandemic

Comparisons	diff	lwr	upr	p adj
Hungary - Czech Republic	1.15	0.95	1.35	0
Poland - Czech Republic	–0.36	–0.54	–0.17	0
Slovakia - Czech Republic	0.09	–0.11	0.29	0.64
Poland - Hungary	–1.5	–1.72	–1.29	0
Slovakia - Hungary	–1.06	–1.29	–0.83	0
Slovakia - Poland	0.45	0.23	0.66	0

Source: own elaboration.

Hungary's HR digitisation scores were significantly higher than those of the Czech Republic (mean difference = 1.15, 95% CI [0.95, 1.35], $p < .001$), highlighting a substantial disparity in perceived HR digitisation challenges (not equal population mean). The mean score in Poland was significantly lower than that in the Czech Republic (mean difference = -0.36, 95% CI [-0.54, -0.17], $p < .001$), suggesting a reduced perception of HR digitisation challenges in Poland (not equal population mean). The difference between Slovakia and the Czech Republic was not statistically significant (mean difference = 0.09, 95% CI [-0.11, 0.29], $p = .64$), indicating similar levels of perceived difficulty (not equal population mean). Hungary's scores were significantly higher than those of Poland (mean difference = -1.5, 95% CI [-1.72, -1.29], $p < .001$), reflecting notable differences in HR digitisation challenges during the pandemic (not equal population mean). Hungary also reported significantly higher scores compared to Slovakia (mean difference = -1.06, 95% CI [-1.29, -0.83], $p < .001$), confirming its unique position in facing greater HR digitisation challenges (not equal population mean). Slovakia's scores were significantly higher than Poland's (mean difference = 0.45, 95% CI [0.23, 0.66], $p < .001$), indicating a noticeable, albeit smaller, difference in the perception of HR digitisation challenges (not equal population mean).

5. DISCUSSION

The data presented in the paper shows that HR digitisation is consistently ranked as one of the less challenging HR activities in the Visegrad Group countries, both before and during the COVID-19 pandemic. However, there are notable differences in its relative importance between the two periods. Prior to COVID-19, HR digitisation ranked 8th overall in the V4 countries, with scores indicating a

moderate level of challenge. While it was not a top priority, its rank suggests that organisations were already addressing digital transformation as part of broader strategic goals. This phenomenon is corroborated by the findings of Nikpour and Semushkina (2021), which document substantial investments in HR software and cloud services by prominent companies in BRICS nations. These investments signify a growing cognisance of the significance of efficacious digital HR systems. This commitment to digital transformation in HR aligns with the findings of Kumar and Kapoor (2021), who suggest that the COVID-19 epidemic actually served to accelerate the integration of digital HR practices across various sectors. In COVID-19, despite the accelerated shift to digital solutions necessitated by the pandemic, HR digitisation ranked 10th overall in the Visegrad Group, with a slightly higher average score (3.00). The ranking suggests that while digitisation has gained some traction, it has been overshadowed by more immediate challenges such as health and safety compliance, workforce management, and organisational communication (Al-Alawi et al., 2023; Budd et al., 2020). In this context, integrating AI-based tools with HR practices is a promising direction for the development of intelligent management. As part of a broader digital transformation effort, AI can support data-driven decision-making, process automation, and personalised employee experiences.

The paired t-test results highlight different dynamics in the perception of HR digitisation challenges across the V4 countries during the COVID-19 pandemic. A range of responses to the digitisation challenges can be attributed to specific contextual factors. The integration and effectiveness of HR technologies, including IT systems for HRM and AI, are pivotal to the transformation of digital care organisations (Amalia, 2024). While the Czech Republic, Slovakia, and Hungary exhibited significant decreases in ratings, indicating that HR digitisation became less challenging during the pandemic, Poland showed no significant change. This suggests that Polish organisations may have experienced more consistent conditions or unique obstacles compared to their V4 counterparts. These findings highlight the differential impact of the pandemic on HR practices and underscore the importance of context-specific strategies in addressing HR digitisation challenges. AI tools that are part of such strategies provide the opportunity to customise HR functions to the specific context of the organisation and country. By leveraging machine learning and analytics, companies can more effectively tailor their approach to recruitment, retention, and workforce planning. AI tools integrated into these strategies enable the customisation of HR functions to the specific context of the organisation and country. Utilising machine learning and analytics allows companies to more accurately refine their approach to recruiting, retaining, and planning their workforce. The intricacies inherent in the process of digital conversion extend far beyond the technological aspect itself, being inextricably linked to socioeconomic factors and the organisational preparations that are in place (Esses et al., 2021). This assertion is supported by the observation that established practices within certain domains may hinder the integration of digital technology, despite the prevailing external pressures associated with the pandemic (Mahapa et al., 2023).

The significant results suggest that the mean pre-COVID-19 HR digitisation challenge scores differed in at least two of the countries analysed. Hungary stands out with a significantly higher mean score (3.25) compared to the other countries, indicating that organisations in Hungary perceived HR digitisation as more challenging before the pandemic. This finding may reflect differences in technology adoption, organisational readiness, or contextual factors such as government support or cultural attitudes toward digitisation (Jewapatarakul & Ueasangkomsate, 2024; Bansal et al., 2023). Other significant findings indicate that the scores for HR digitisation challenges during COVID-19 differed in at least two of the countries analysed. Hungary stands out with the highest mean score (4.01), suggesting that organisations in this country faced more pronounced challenges in implementing HR digitisation during the pandemic. This finding may reflect factors such as differences in infrastructure, pre-existing technological readiness, or varying organisational responses to pandemic-related disruptions (Taganoviq et al., 2023). The differences among the other countries, while less pronounced, also point to the influence of contextual factors on HR digitisation efforts. These findings underscore the importance of tailoring digitisation strategies to the unique challenges faced by organisations in specific countries, especially in times of crisis (Vu et al., 2022).

When comparing the results of the two situations, before and after the pandemic, both similarities and differences emerge. There are three main similarities. First, both analyses revealed statistically significant differences in HR digitisation scores among the V4 countries, indicating that country-specific factors consistently influenced perceptions of HR digitisation. Next, Hungary reported the highest mean

scores in both periods, suggesting that HR digitisation posed greater challenges there than in the other countries. Finally, Poland consistently had the lowest mean scores for HR digitisation challenges, both before (2.46) and during COVID-19 (2.50), reflecting a relatively lower level of difficulty perceived by organisations. Among the differences, the F-statistic increased significantly during COVID-19 (113.10) compared to the pre-COVID period (41.59), suggesting that differences in HR digitisation challenges across countries became more pronounced during the pandemic. Second, in all countries, the average HR digitisation challenge scores were higher during COVID-19 than before, reflecting the increased importance and difficulty of digitisation due to pandemic-related disruptions. For example, Hungary's mean rose from 3.25 to 4.0, while Slovakia's mean rose from 2.63 to 2.95. It should also be emphasised that while the variances of HR digitisation scores were relatively similar before COVID-19, they increased during the pandemic. For example, in the Czech Republic, the variance increased from 1.36 to 1.66, indicating more variability in perceptions of HR digitisation challenges during COVID-19, while Poland's variance also increased slightly from 1.56 to 1.59. The results of the study highlight the significance of understanding the specific motivations of organisations and the environmental factors that drive digital transformation. This assertion is further corroborated by Montasser et al. (2023), who stipulate the necessity for organisations to implement technology readiness and to encourage cultural transformation in order to cultivate the landscape effectively.

Tukey's HSD test indicates that Hungary consistently faced significantly more substantial obstacles in the realm of HR digitisation compared to its Visegrad counterparts. Before COVID-19, Poland, the Czech Republic, and Slovakia displayed more comparable levels of difficulty. While Slovakia and the Czech Republic had relatively similar perceptions of difficulty during COVID-19, Poland reported notably lower scores, reflecting a less challenging experience with HR digitisation. These outcomes underscore Hungary's distinctive stance in facing increased obstacles to HR digital transformation before the pandemic. The findings also emphasise the growing variability between countries during the pandemic, particularly the notable gap between Hungary and the other V4 nations. From a strategic standpoint, these findings underscore the imperative for organisations, particularly within the context of Hungary, to prioritise enhancing their digital capabilities and organisational readiness to alleviate the challenges posed by such crises (Johan et al., 2023; Wen et al., 2021). In this regard, ongoing assessments and adjustments to organisational strategies for the digitisation of HR are essential, particularly as the world grapples with both the immediate and long-term repercussions of pandemics.

Our results suggest that HR digitisation was a less significant challenge during the COVID-19 pandemic compared to other priorities, such as job security, workforce management, and organisational communication. This supports the analysis of Frey and Osborne (2013), who argue that technological advances and automation will have a major impact on different industries and jobs, with some jobs being more at risk of automation than others. They further highlight that jobs requiring lower levels of education and wage rates are more susceptible to computer automation, suggesting that organisations should tailor their digitisation strategies to the contextual challenges of specific countries. In this context, the use of AI in HR can help companies better align their strategic goals with local conditions, particularly through predictive analytics and intelligent automation. These tools allow for improved predictability of management actions and facilitate more flexible, fact-based decision-making. The significant differences in HR digitisation scores between Hungary and other countries may indicate variations in technological readiness, infrastructure, and government support. Furthermore, the findings of Nedelkoska and Quintini (2018) highlight the importance of social and cognitive intelligence as factors that are difficult to automate, suggesting that organisations should pay increased attention to developing these skills. This is also in line with the findings of Stachová et al. (2024), who argue that while digital innovations in HRM improve efficiency and data-driven decision-making, their direct impact on employee engagement is limited and influenced by other factors. Organisations should therefore combine technological advances with appropriate managerial and cultural approaches to fully exploit their potential.

6. CONCLUSION

The aim of this paper was to gain new insights into the digitisation of HR before and during the COVID-19 pandemic in the Visegrad Group countries. Although the pandemic highlighted the need for digital

transformation, organisations in the V4 countries were more focused on crisis-related and operational issues. This suggests that HR digitisation, while increasingly relevant, was perceived as less critical compared to the urgent demands of managing workforce disruption and ensuring employee well-being during the pandemic.

The analysis highlights significant differences in how HR digitisation challenges were perceived before and during COVID-19 in three of the four countries analysed: the Czech Republic, Slovakia, and Hungary. These findings suggest that the pandemic prompted organisations in these countries to reevaluate or adapt their HR digitisation strategies, likely due to the immediate need for remote work, hybrid teams, and technology integration. In contrast, the lack of a significant difference in Poland may indicate that organisations there either maintained consistent digitisation efforts or faced structural or cultural barriers to change during the pandemic. It is possible that pre-existing digital infrastructure, organisational readiness, or policy constraints influenced this outcome. The observed differences between countries may also reflect varying levels of economic development, technology adoption, and policy support for digital transformation during the pandemic. These findings underscore the importance of contextual factors in shaping organisational responses to global disruptions such as COVID-19.

Tukey's multiple comparisons of means underscore several significant similarities and differences in HR digitisation challenges across the Visegrad countries before and during the pandemic. In both periods, Hungary exhibited notably higher HR digitisation scores compared to the other countries, highlighting its unique position in facing more substantial challenges. Conversely, the differences in HR digitisation scores between Slovakia and the Czech Republic were not statistically significant before and during the pandemic, suggesting a uniform perception of challenges in these two countries. Before the pandemic, Poland's scores were statistically similar to those of the Czech Republic and Slovakia. However, during the pandemic, Poland reported significantly lower scores compared to both countries, indicating a divergence in perceived challenges. The pandemic amplified the disparities between Hungary and the other countries. The mean differences between Hungary and the other V4 countries increased during the pandemic, indicating heightened variability in HR digitisation challenges.

Potential limitations of the study include its reliance on self-reported data, which may be subject to biases such as social desirability or recall bias. In summary, the survey methodology used in this study was carefully designed and implemented to collect reliable and valid data across the V4 countries, with a total sample of 2,093 organisations providing a solid basis for subsequent analysis and conclusions.

While certain patterns in the challenges related to the digital transformation of HR have remained constant over time, the pandemic has precipitated significant shifts, particularly regarding Poland's relative position and the widening disparity between Hungary and the other V4 countries. These findings suggest that the pandemic has exerted a differential influence on the perception and management of HR digitisation challenges throughout the region.

The findings presented in this paper emphasise that country-specific factors significantly influence perceptions of HR digitisation challenges, underscoring the importance of tailoring digital transformation strategies to the local context. The results indicate that while country-specific differences in HR digitisation challenges were significant both before and during COVID-19, the pandemic exacerbated these differences. Hungary consistently faced the most significant challenges, while Poland encountered the least. The pandemic increased the overall difficulty of HR digitisation across the board, as evidenced by higher mean scores and increased variability. These findings underscore the critical need for targeted strategies to support digital transformation, especially in countries experiencing greater difficulties, during crises and beyond.

The pandemic created an unexpected crisis that most companies were not adequately prepared for. However, some organisations managed to leverage the situation as an opportunity to accelerate the development of HR digitisation. While many firms faced significant challenges, others successfully transformed their HR strategies and adapted to new conditions through digital tools. This suggests that the introduction of AI-based tools can serve as a catalyst for intelligent management, enabling the use of adaptive learning systems, strategic workforce analytics, and real-time feedback mechanisms. Such capabilities can enhance an organisation's resilience to future disruptions.

Moreover, the study findings indicate an emerging opportunity to incorporate AI tools within intelligent HR management systems. In contexts where such technologies were adopted, AI-supported solutions—such as predictive analytics for workforce planning, automated performance evaluations, and AI-powered chatbots for candidate screening—contributed to greater efficiency and more informed

decision-making. Although the levels of adoption varied across V4 countries, organisations that integrated AI into their HR digitisation efforts were better positioned to manage complexity and respond to crisis-induced challenges. These applications underscore the growing relevance of intelligent, data-driven systems in futureproofing HRM strategies.

Future research should therefore analyse the mediating role of HR digitisation in key HR challenges, such as recruitment, employee retention, performance management, and employee engagement. Additionally, it would be beneficial to test whether HR digitisation can alleviate these challenges and act as a facilitator of more effective human resource management.

Such research could help identify the factors that determine the success of digital transformation in HR and demonstrate how digitisation not only enhances operational processes but also contributes to the long-term resilience and competitiveness of organisations.

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THE ETHICAL PARADOX OF AI IN MANAGEMENT: CAN MACHINES MAKE MORAL DECISIONS?

Krystian Redżeb[a] Joanna Sauk[b]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *University of Szczecin, Institute of Spatial Economy and Socio-Economic Geography, Szczecin, Poland*

ABSTRACT

Purpose: *This study examines the ethical challenges of AI-driven decision-making in high-stakes domains such as autonomous vehicles and algorithmic tenant screening. It questions whether AI can act morally or simply optimize for efficiency, assessing its alignment with human ethical values.*

Need for the Study: *As AI systems increasingly shape critical aspects of life—transportation, housing, employment, there is growing concern about their ethical impact. While promising fairness, AI often amplifies societal biases. Existing frameworks lack transparency and safeguards, making governance essential.*

Methodology*: A mixed-methods approach is applied, including case study analysis, large-scale ethical simulations, and cross-cultural comparisons. Empirical data from the MIT Moral Machine experiment and AI-generated moral decisions are analyzed using exploratory factor analysis and hierarchical clustering.*

Findings: *The study reveals sharp differences between human and AI ethics. AI models exhibit stronger biases, favoring younger, wealthier, and law-abiding individuals more than humans. Cultural differences are also evident: Western societies tend toward utilitarianism, while collectivist cultures factor in broader moral dimensions. The SafeRent case showed that AI-driven screening disproportionately disadvantaged minority applicants, reinforcing inequality.*

Practical Implications: *The findings emphasize the need for human oversight in AI systems. Hybrid frameworks that combine algorithmic efficiency with ethical constraints are recommended. Policymakers and business leaders must enforce transparent, culturally aware AI standards that promote fairness. Ethical governance of AI must balance global norms with regional values to ensure equitable outcomes.*

Keywords: Artificial Intelligence; Ethics; Management; Decision-Making; Bias; Governance

Jel Codes: M15, D81, L21

1. INTRODUCTION

The rapid integration of artificial intelligence (AI) into decision-making processes has sparked intense discussions about its ethical implications and practical limitations. AI-driven systems are now employed across various sectors, from healthcare and finance to autonomous transportation and criminal justice, fundamentally reshaping traditional decision-making frameworks. While AI promises efficiency, objectivity, and scalability, its deployment raises pressing ethical concerns, particularly regarding transparency, accountability, and fairness (Etzioni & Etzioni, 2017). The

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ability of AI to make moral decisions remains one of the most contested issues in the field of AI ethics and governance.

One of the most compelling case studies in AI ethics is its application in autonomous vehicles (AVs). These systems must make split-second decisions in potentially life-or-death scenarios, raising questions reminiscent of the classic trolley problem: should an AV prioritize the lives of its passengers over pedestrians? Should it favor younger individuals over the elderly, or law-abiding citizens over jaywalkers? The *Moral Machine* experiment, a large-scale study conducted by MIT, analyzed human ethical preferences in AV decision-making, revealing significant cross-cultural variations in moral judgments (Awad et al., 2018). This study serves as a critical benchmark for understanding the ethical dimensions of AI-driven decision-making and highlights the challenges in developing universally accepted moral frameworks for autonomous systems.

Beyond AVs, AI is increasingly being deployed in areas where ethical considerations are paramount, such as hiring algorithms, financial risk assessments, and legal decision-making. However, empirical evidence suggests that AI systems often amplify existing biases rather than eliminate them. A notable example is the SafeRent algorithm, an AI-driven tenant screening system that disproportionately rejected applicants from marginalized communities due to its reliance on credit scores and non-rental-related financial data (Humber, 2023). This case underscores the risks of algorithmic discrimination and the urgent need for AI governance structures that prioritize fairness and social responsibility.

The growing reliance on AI in high-stakes decision-making necessitates a robust ethical framework that addresses key concerns such as algorithmic bias, decision transparency, and moral alignment. Scholars debate whether AI should replicate human moral intuitions – despite their inherent biases – or adopt an optimized ethical framework based on rationalist principles (Bonnefon, Shariff, & Rahwan, 2016; Jiang et al., 2024). The challenge lies in ensuring that AI-driven decisions align with both societal values and ethical principles while mitigating unintended discriminatory outcomes.

Moreover, the emergence of intelligent management frameworks – where AI systems actively support strategic planning, real-time decision-making, and predictive analytics – raises novel ethical dilemmas. Intelligent management extends beyond automation, integrating AI into complex managerial tasks such as scenario planning, resource allocation, and stakeholder coordination. As these systems evolve, the ethical principles guiding their development must address not only fairness and transparency, but also long-term accountability, strategic foresight, and organizational learning.

This study aims to examine the ethical paradoxes of AI-driven decision-making, focusing on key questions:

- Should AI mirror human moral preferences, or should it be programmed to follow an objective ethical standard?
- How can AI systems avoid reinforcing societal biases in areas such as employment, finance, and autonomous transportation?
- What role should policymakers play in regulating ethical AI development and ensuring accountability?

By addressing these questions, this research contributes to the ongoing debate on AI ethics and governance. Through an analysis of real-world case studies, including the *Moral Machine* experiment and AI-driven tenant screening systems, this study explores how AI can be designed to balance efficiency, fairness, and ethical integrity in decision-making processes. The ultimate objective is to provide insights that inform regulatory frameworks and best practices for the responsible deployment of AI in society.

2. LITERATURE REVIEW

Artificial intelligence (AI) is increasingly involved in decision-making processes with significant ethical implications, particularly in autonomous systems such as self-driving vehicles. Ethical AI development requires an understanding of human moral preferences, which serve as a benchmark for designing AI decision-making frameworks. The Moral Machine experiment (Awad et al., 2018) provides critical insights into how different cultures perceive life-and-death dilemmas in autonomous vehicle (AV) scenarios. This large-scale study gathered human ethical preferences

regarding various factors, including age, social status, law abidance, species, and utilitarian considerations.

2.1 AI and Moral Decision-Making

The integration of AI into ethical decision-making poses unique challenges due to the lack of a universal moral standard. While some scholars advocate for AI systems that closely mirror human ethical choices (Bonnefon, Shariff, & Rahwan, 2016), others argue that AI should adopt an optimized ethical framework, free from human biases (Etzioni & Etzioni, 2017). AI-driven decision-making often emphasizes consistency and efficiency, but it also introduces moral rigidity, as demonstrated in studies comparing AI preferences with human ethical intuitions (Jiang et al., 2024).

2.2 Ethical Frameworks for AI Decision-Making

Various ethical theories have been proposed for AI-driven systems:

- Utilitarianism: AI prioritizes actions that maximize the overall benefit, often favoring the greater number of lives saved (Bentham, 1789).
- Deontology: AI follows predefined moral rules, such as protecting law-abiding citizens over criminals (Kant, 1785).
- Virtue Ethics: AI evaluates decisions based on human-like moral reasoning, prioritizing fairness and equity (Aristotle, 350 BCE).

However, research suggests that AI systems may amplify certain biases, prioritizing younger, wealthier, and law-abiding individuals at significantly higher rates than human decision-makers (Awad et al., 2018). Within intelligent management, these frameworks are applied not just in isolated decision points, but across integrated systems that continuously learn and adapt. For example, AI may dynamically adjust inventory levels, workforce distribution, or risk mitigation strategies based on evolving data—decisions which, while operational, carry ethical consequences. Thus, ethical design must consider both static rules and adaptive behaviors in AI-driven managerial contexts.

2.3 Cross-Cultural Ethical Variations

Human moral preferences are not universal; they differ based on cultural, legal, and societal values. Studies have demonstrated strong regional variations in ethical decision-making (Table 3), with Western cultures favoring utilitarian principles and law abidance, while Eastern cultures demonstrate greater collectivist values (Rahwan et al., 2019). These differences raise a crucial question: Should AI decision-making be standardized globally, or should AI systems be culturally adaptive?

2.4 Bias and Ethical Risk in Intelligent Management

Recent studies have shown that AI models exhibit systematic biases when making moral decisions. A comparative analysis of AI-driven ethical choices and human moral decisions revealed that AI displayed a 90% preference for saving younger individuals, an 83% preference for higher-status individuals, and an 85% preference for law-abiding citizens (Jiang et al., 2024). This raises concerns regarding algorithmic fairness and the extent to which AI should reflect or challenge human biases. In summary, while AI presents opportunities for enhancing decision-making efficiency, it also introduces new ethical dilemmas. The challenge for policymakers and AI developers is to determine how AI should be aligned with human values while avoiding the reinforcement of societal biases.

2.5 AI in Intelligent Management

Intelligent management refers to the integration of AI technologies into strategic and operational decision-making within organizations. It encompasses the use of machine learning, natural language processing, and optimization algorithms to enhance efficiency, responsiveness, and forecasting accuracy. However, embedding AI into management also shifts ethical responsibilities. Decision-makers must ensure that intelligent systems are aligned with corporate values, regulatory requirements, and societal expectations.

3. METHODOLOGY

3.1 Research Design

This study employs a quantitative research approach, analyzing large-scale ethical decision-making data collected from the Moral Machine experiment and AI-driven simulations. The study seeks to:

- Examine human moral preferences in ethical dilemmas.
- Compare AI-driven ethical choices with human decision-making.
- Identify regional and cultural variations in moral decision-making.

3.2 Data Collection

The dataset used in this study consists of two primary sources:

- Moral Machine experiment data (Awad et al., 2018): Over 40 million ethical decisions from 4 million participants across 233 countries.
- AI-generated moral decision simulations (Jiang et al., 2024): Responses from 19 advanced large language models (LLMs) evaluated across six ethical dimensions.

Data was collected using a combination of crowdsourced surveys, simulation-based AI outputs, and hierarchical clustering techniques to identify decision-making patterns.

3.3 Analytical Methods

To evaluate decision-making patterns, the following methods were applied:

- Exploratory Factor Analysis (EFA): Used to determine key ethical decision-making factors.
- Hierarchical Clustering: Applied to group responses into cultural and regional clusters.
- Comparative Analysis: Assessed the differences between AI and human decision-making biases.

Figure 6 provides a visual representation of AI and human ethical preferences, highlighting key disparities in decision-making.

3.4 Ethical Considerations

Given the sensitive nature of ethical decision-making, this study adheres to the following ethical principles:

- Transparency: All data sources are publicly available for verification.
- Fair Representation: Data is analyzed without modifying original decision outcomes.
- AI Bias Awareness: Ethical implications of AI-driven decisions are critically assessed.

3.5 Research Questions

This study explores key managerial and policy-related questions, including:

- Should AI ethics be standardized globally, or should ethical decision-making be adapted to regional values?
- How can AI systems avoid reinforcing human biases in ethical dilemmas?
- What role should policymakers play in defining the moral standards for AI-driven decision-making?

By addressing these questions, this study aims to contribute to the broader discussion on AI ethics and the future of machine-driven decision-making.

4. RESULTS

4.1 Case Study: Ethical Decision-Making in Autonomous Vehicles – Insights from the Moral Machine Experiment

As artificial intelligence increasingly permeates everyday life, autonomous vehicles (AVs) represent one of the most ethically challenging applications. AVs must make split-second decisions in life-or-

death scenarios, raising profound moral and legal questions. The classical *trolley problem* serves as a relevant analogy: should an AV prioritize its passengers over pedestrians, the young over the elderly, or law-abiding individuals over jaywalkers? (Awad et al., 2018). To investigate societal perspectives on such dilemmas, the Massachusetts Institute of Technology (MIT) conducted the *Moral Machine* experiment, a large-scale global study designed to gather human moral preferences on AV decision-making. This study provides critical insights into ethical considerations that should inform AV programming and policymaking (Awad et al., 2018; Bonnefon et al., 2016). The *Moral Machine* experiment utilized an online platform to simulate ethical dilemmas involving unavoidable traffic collisions. Participants were required to decide which groups to save in scenarios that varied across several dimensions, including:

- number of lives at risk (e.g., one pedestrian vs. five passengers),
- age (children vs. elderly individuals),
- social status (homeless individuals vs. professionals),
- law abidance (jaywalkers vs. those crossing at designated areas),
- species (humans vs. animals) (Awad et al., 2018).

This experiment leveraged crowdsourced participation, collecting over 40 million decisions from 4 million respondents across 233 countries and territories. Researchers applied exploratory factor analysis and hierarchical clustering to identify patterns in decision-making and cultural variations (Rahwan et al., 2019). Figure 1 illustrates the percentage of respondents who prioritized saving a human over an animal in life-and-death scenarios. The data highlight how different regions exhibit varying degrees of preference for human life over non-human life.

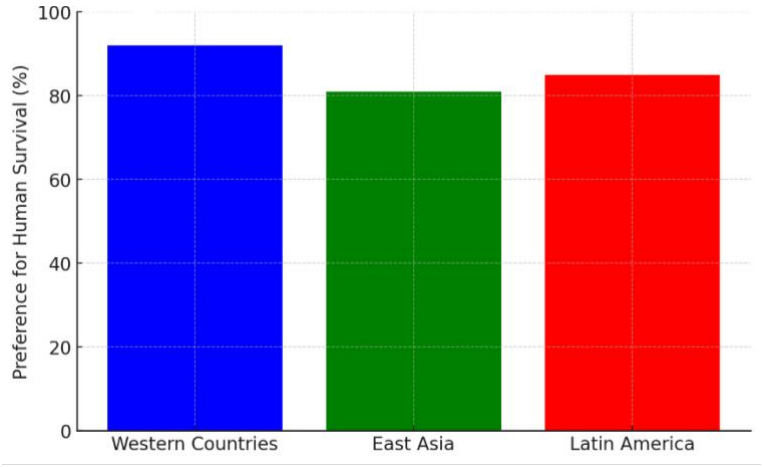


Figure 1. Human vs. Animal Survival Preferences
Source: based on Awad et al. (2018).

In this dataset, 85.6% of respondents globally chose to save a human rather than an animal. Western countries exhibited the strongest preference (~92%), followed by Latin America (85%). East Asian respondents displayed a slightly lower preference (~81%), suggesting a marginally higher ethical valuation of animal life in comparison to other regions **(**Awad et al., 2018).

Figure 2 represents the proportion of respondents who preferred saving the greater number of individuals, regardless of their characteristics. It provides insight into the extent to which people apply a utilitarian approach when making ethical decisions in life-or-death situations.

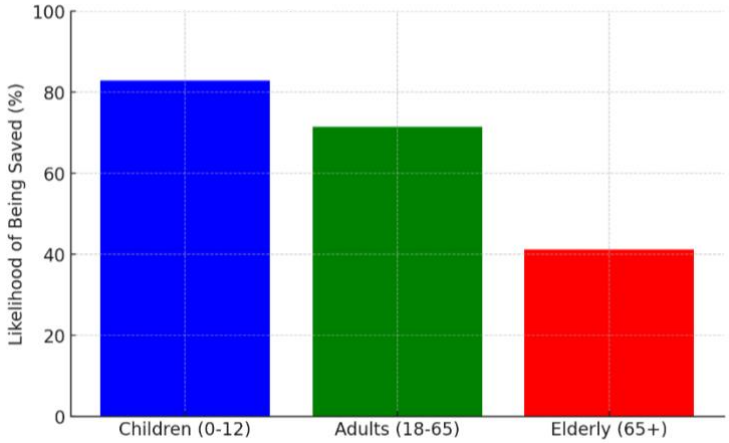


Figure 2. Utilitarian Preference (More Lives Saved)
Source: based on Awad et al. (2018).

Globally, 76.3% of respondents prioritized saving the larger group of individuals. The preference was highest in Western countries (82%), while East Asia and Latin America exhibited slightly lower rates (71–74%). This regional variation may suggest that collectivist cultures incorporate additional ethical considerations beyond sheer numbers when making moral choices (Awad et al., 2018; Rahwan et al., 2019). Figure 3 visualizes the likelihood of different age groups being saved in moral dilemmas. The data show a strong preference for younger individuals, emphasizing the societal value placed on youth over older populations.

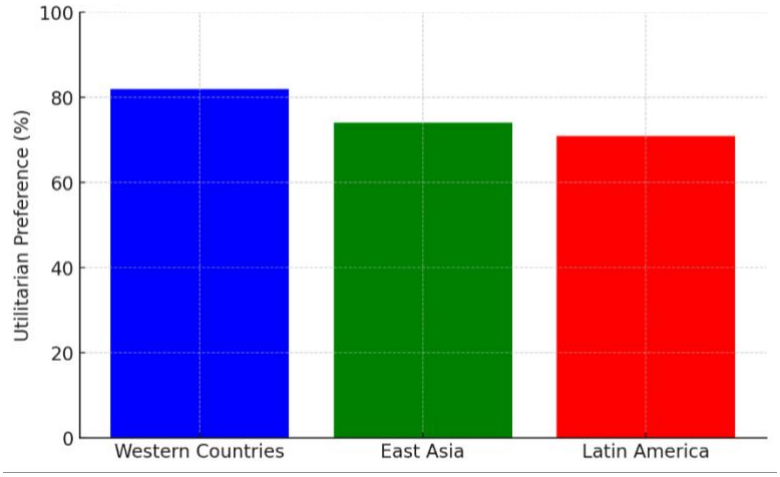


Figure 3. Age-Based Survival Preferences
Source: based on Bonnefon et al. (2016).

The results indicate that children (0–12 years) were saved in 82.9% of cases**,** significantly more often than adults (18–65 years), who had a 71.5% survival rate**.** In contrast, the elderly (65+) were saved in only 41.2% of cases, highlighting a substantial age-based bias in survival decisions (Bonnefon et al., 2016; Jiang et al., 2024). Figure 4 presents the percentage of respondents who prioritized saving law-abiding individuals over those who violated traffic laws. The data illustrate how societal norms regarding rule adherence influence ethical decision-making.

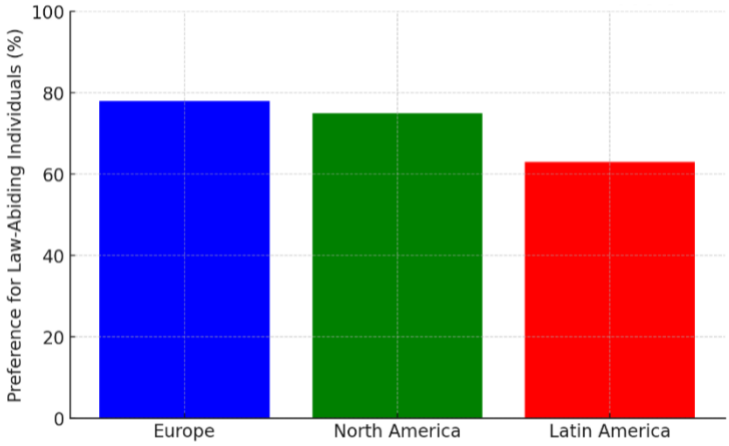


Figure 4. Preference for Law-Abiding Individuals
Source: based on Awad et al. (2018).

Overall, 71.2% of respondents favored saving pedestrians who followed traffic laws**.** This preference was strongest in Europe (78%) and North America (75%), while Latin America exhibited a lower preference (63%). These findings suggest that moral decision-making may be shaped by regional attitudes toward legal and social compliance, which could have implications for AI-driven ethical programming, such as in autonomous vehicles (Awad et al., 2018; Rahwan et al., 2019). This study has critical implications for artificial intelligence (AI) development, especially in systems that must make moral decisions, such as autonomous vehicles, AI-driven healthcare, and crisis management algorithms. Modern AI models often learn from human choices, raising fundamental ethical questions:

- Should AI replicate human morality, given that human decision-making exhibits strong biases based on age, social status, and adherence to laws?
- What ethical norms should be encoded in AI systems when moral decisions vary across cultures and regions?
- Is it fair and ethical for AI to adopt human decision patterns if those patterns favor specific social groups?
- How should managers approach the ethical design of AI systems to minimize discrimination and ensure fair decision-making?

This study underscores the fact that **A**I decisions cannot be made in isolation from societal norms and cultural values. However, AI should also not blindly replicate human biases. Business leaders and policymakers must make deliberate decisions about ethical AI programming, considering both empirical data and social responsibility. A crucial question for managers is:

- What values should guide artificial intelligence to ensure both fairness and societal acceptance?
- Should businesses and policymakers establish universal ethical AI standards, or should AI ethics be tailored to regional moral differences?

This study opens a broader discussion on how AI should make decisions and whether it should mirror human morality or strive to improve it. For decision-makers and technology leaders, this remains one of the most pressing challenges in the ethical implementation of AI. Table 1 presents cross-cultural variations in ethical decision-making preferences observed in the Moral Machine experiment.

The data illustrate how moral choices differ by region, with Western countries exhibiting a strong utilitarian approach, prioritizing the greater number of lives saved and emphasizing law abidance and professional status. In contrast, Eastern cultures demonstrate a more collectivist approach, with a more balanced preference between law-abiding and non-law-abiding individuals and less emphasis on age-based biases. Meanwhile, Latin American and Francophone countries show a stronger preference for higher social standing and display more sympathetic choices toward marginalized individuals and criminals. These cultural differences highlight the complexity of integrating moral decision-making frameworks into AI systems, particularly in global applications like autonomous vehicles (Awad et al., 2018; Rahwan et al., 2019). The stark regional differences in decision-making raise a crucial challenge for AV programming:

- A universal ethical framework would ensure consistency but may not align with cultural values in certain regions.
- A region-specific approach would improve local acceptance but could introduce regulatory and technical complexities.

Table 1. Cross-Cultural Variations in Ethical Preferences.

Cluster	Key Ethical Decision-Making Trends
Western Cluster (North America & Europe)	– Strong preference for saving younger individuals – High emphasis on law abidance and professional status – Most utilitarian decision-making (saving more lives over individual traits)
Eastern Cluster (East Asia & Japan)	– Greater focus on collectivist values, with less emphasis on individual age – More balanced decision-making between law-abiding individuals and others – Slightly lower preference for saving the greater number of individuals than Western counterparts
Southern Cluster (Latin America & Francophone Countries)	– Higher gender biases in decision-making (women were saved 12% more often than men) – Strong preference for saving individuals of perceived higher social standing – More sympathetic choices toward criminals and marginalized individuals than in other regions

Source: based on Awad et al. (2018).

The *Moral Machine* experiment provides invaluable insights into human ethical preferences in autonomous vehicle decision-making. The data confirms several universal trends, such as a preference for saving humans over animals and prioritizing younger individuals. However, significant regional and cultural variations raise complex questions about how AVs should be programmed to reflect ethical diversity. For AVs to gain widespread social acceptance, developers, policymakers, and ethicists must engage in interdisciplinary collaboration, ensuring that AI-driven ethical frameworks align with both societal values and legal standards. Ultimately, the success of AVs depends not only on technical advancements but also on their ability to navigate the profound moral and ethical expectations of human societies.

4.2 In-Depth Case Studies: Ethical and Managerial Challenges in AI-Driven Decision-Making AI Bias in Tenant Screening: The SafeRent Controversy

SafeRent Solutions, formerly known as CoreLogic Rental Property Solutions, utilizes an algorithm-based scoring system to assess prospective tenants' lease performance risk. This system assigns applicants a numerical score ranging from 200 to 800, which landlords use to make rental decisions. The algorithm considers several factors are showed in Table 2.

In 2024, Mary Louis, a security guard from Massachusetts, encountered a significant obstacle in securing housing due to an AI-driven tenant screening system known as SafeRent. Despite her commendable rental history, the algorithm assigned her a low score of 324, leading to an automatic rejection of her application without any avenue for appeal (Humber N.J., 2023).

Table 2. Factors considered in SafeRent Solutions

Factor	Description
Payment History	Timeliness and consistency of past payments
Credit Utilization	Ratio of credit used to credit available
Credit History	Length and status of credit accounts
Credit Availability	Amount of available credit
Inquiries	Number of recent credit inquiries

Source: based on Humber (2023).

Mary Louis had been a reliable tenant for 17 years, consistently paying her rent on time. She possessed a low-income housing voucher, ensuring that a portion of her rent would be covered by government assistance. However, SafeRent's algorithm heavily weighted factors such as credit scores and non-rental-related debts, which did not accurately reflect an applicant's ability to pay rent punctually. This methodology disproportionately affected individuals like Louis, who, despite having some credit card debt, had a proven track record of meeting rental obligations (Khan & Tazel, 2024). This case underscores the necessity for transparency, fairness, and human oversight in AI-driven systems, especially those impacting essential aspects of life such as housing. It highlights the potential for AI algorithms to perpetuate existing biases if not carefully designed and monitored, emphasizing the importance of ethical considerations in AI development and deployment. Monica Douglas, a senior tenant with 26 years of positive rental history, was also subjected to an unfair rejection due to SafeRent's algorithmic decision-making. Although she had previously experienced an eviction, her long-standing record of timely rent payments demonstrated financial responsibility. However, SafeRent assigned her a score below 500, effectively disqualifying her from securing housing. The system failed to account for her decades of rental reliability, reinforcing concerns that AI-driven decision-making models may not be equipped to recognize real-world financial behaviors beyond standardized credit metrics (Humber N.J., 2023).Figure 1 illustrates the disparity in rental application approval rates across racial groups. White applicants experience the highest approval rates, with **81.7%** of applications successfully processed. In contrast, Hispanic applicants receive approvals at a significantly lower rate of **68.5%,** while Black applicants face the highest level of discrimination, securing approvals in only **54.9%** of cases. This substantial gap highlights a systemic issue, as SafeRent's algorithm disproportionately filters out minority applicants. Given that Black and Hispanic populations have historically faced economic marginalization, the reliance on automated systems exacerbates pre-existing inequalities in housing accessibility (Zeng, 2023).

The tenant screening process heavily relies on credit scores, which SafeRent uses as a core determinant of rental eligibility. Figure 2 presents the median credit scores across racial groups, demonstrating significant disparities:

- White applicants have the highest median credit score at 725.
- Hispanic applicants maintain a median score of 661, reflecting a moderate disadvantage in rental application assessments.
- Black applicants possess the lowest median score of 612, placing them at an increased risk of rental rejections (Khan & Tazel, 2024).

This data suggests that the AI-driven screening system inherently disadvantages groups with historically lower access to credit-building financial services, further limiting their housing opportunities.

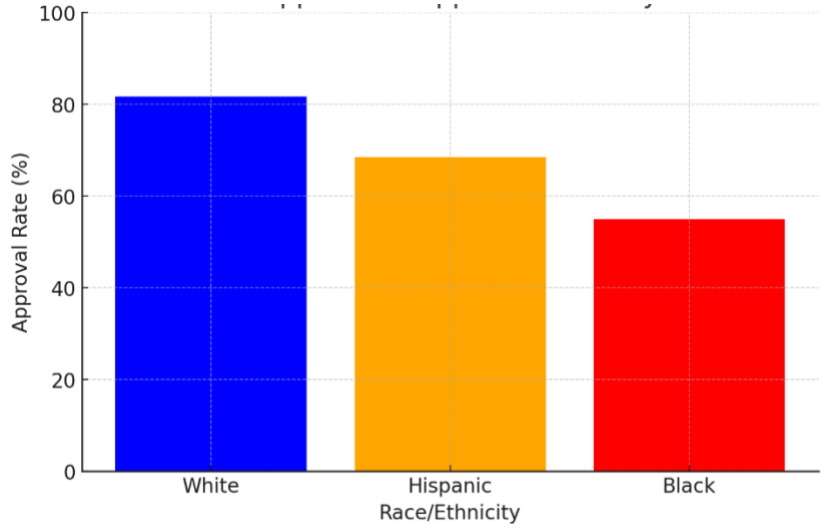


Figure 5. Rental Application Approval Rates by Race
Source: based on Humber (2023).

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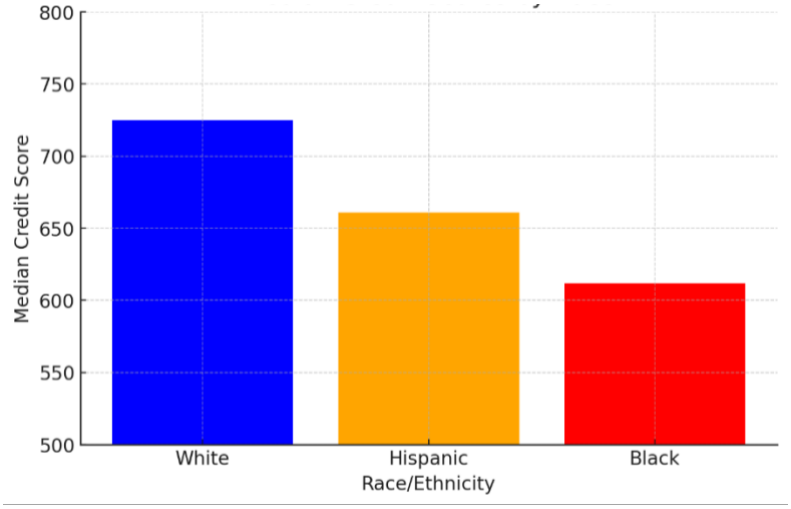


Figure 6. Median Credit Scores by Race
*Source: b*ased on Humber (2023).

Figure 7 displays the percentage of individuals classified as having "subprime" credit scores, defined as scores below 620. This classification significantly impacts rental application outcomes, as SafeRent's algorithm assigns lower rental scores to individuals with subprime credit.

The distribution of subprime credit scores is as follows:

- 45.1% of Black consumers fall into the subprime category, making them the most vulnerable group in AI-driven tenant screening.
- 31.5% of Hispanic consumers also hold subprime credit scores, placing them at a substantial disadvantage in securing rental properties.
- 18.3% of White consumers have subprime credit, significantly lower than the rates observed for Black and Hispanic applicants (Khan & Tazel, 2024).

These statistics highlight how the SafeRent algorithm perpetuates economic disadvantages by overly weighting credit scores, further restricting access to fair housing.

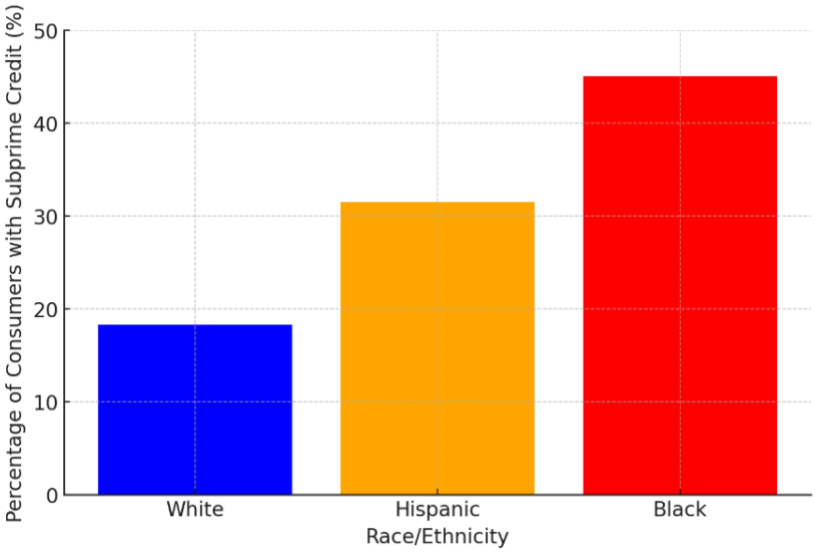


Figure 7. Subprime Credit Score Distribution by Race
Source: based on Humber (2023).

Figure 8 provides a breakdown of the racial demographics of housing voucher holders in Massachusetts, where SafeRent's algorithm was challenged in a 2022 class-action lawsuit. The data reveals that:

- 24% of housing voucher holders are Black,
- 31% are Hispanic,
- 45% belong to other racial and ethnic groups (Humber N.J., 2023).

Given that voucher holders receive partial or full rental assistance from public housing authorities, they should not be subjected to the same financial scrutiny as traditional renters. However, SafeRent's AI system failed to account for the stability provided by government-backed housing vouchers, disproportionately impacting minority groups (Humber N.J., 2023).

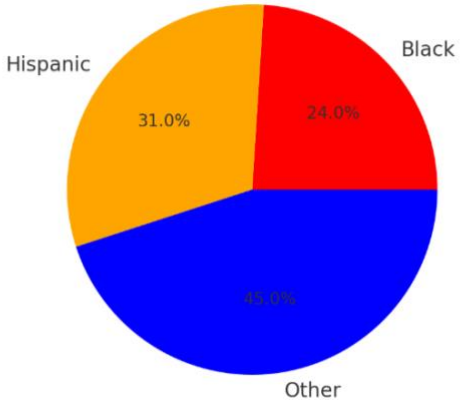


Figure 8. Demographics of Housing Voucher Holders in Massachusetts
Source: based on Humber (2023).

One of the major criticisms of SafeRent's tenant screening system is its failure to recognize the financial stability of voucher holders. Figure 9 illustrates the financial structure of housing voucher payments:

- Public housing authorities cover approximately 73% of rent costs for voucher holders.

- Tenants are responsible for only 27% of the rent, ensuring a stable payment structure for landlords.

By disregarding this factor, SafeRent's scoring model incorrectly categorized voucher holders as high-risk tenants, contributing to widespread rental denials despite their financial backing.

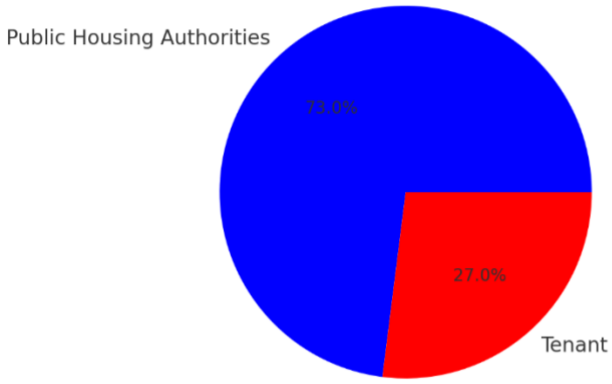


Figure 9. Breakdown of Rent Coverage for Voucher Holders
Source: based on Humber (2023).

In 2022, a class-action lawsuit was filed against SafeRent by over 400 Black and Hispanic tenants in Massachusetts, alleging that the company's algorithm discriminated against them. The plaintiffs argued that the system assigned lower scores to minority renters using housing vouchers compared to white applicants, thereby violating the Fair Housing Act. They contended that the algorithm's reliance on credit information and disregard for the guaranteed payments from housing vouchers led to unjust outcomes (Humber N.J., 2023). The lawsuit culminated in a settlement where SafeRent agreed to pay $2.3 million and cease using its scoring system for applicants with housing vouchers for five years. Additionally, any new scoring models developed by SafeRent must undergo independent validation by a third-party fair housing organization before implementation. This settlement marked a significant step towards addressing biases in AI systems used in critical decision-making processes (Khan & Tazel, 2024).

The SafeRent case underscores the critical need for transparency, fairness, and oversight in AI-driven decision-making systems. It highlights how reliance on certain data points, such as credit history, without considering contextual factors like housing vouchers, can perpetuate systemic biases and result in discriminatory outcomes. As AI continues to permeate various aspects of life, ensuring that these systems promote equity and do not reinforce existing disparities is imperative.

For managers and decision-makers, this case presents critical questions:

- Data Selection and Weighting: How should organizations determine which data points are relevant and how they are weighted in AI algorithms to ensure fair outcomes?
- Transparency and Accountability: What measures can be implemented to make AI decision-making processes more transparent to those affected by them?
- Regulatory Compliance: How can companies ensure that their AI systems comply with existing laws and regulations, such as the Fair Housing Act, to avoid legal repercussions?

Addressing these questions is vital for developing AI systems that are both effective and equitable, thereby fostering trust and reliability in automated decision-making processes.

4.3 Case Study: Moral Preferences of Multilingual Large Language Models in Trolley-like Dilemmas

Recent research conducted by Jiang et al. (2024) explored the ethical alignment of advanced Large Language Models (LLMs) in moral decision-making contexts, specifically through scenarios inspired by the classic trolley problem. The study examined moral preferences of 19 different LLMs, including notable models such as GPT-4, GPT-4o Mini, Llama 3.1, and Gemma 2, across multilingual settings (107 languages). The authors constructed the MULTITP dataset, comprising

precisely 97,520 unique ethical dilemmas, uniformly divided across 107 languages (920 scenarios per language). These vignettes presented moral dilemmas varying systematically along six ethical dimensions: age, gender, fitness, social status, species (human vs. pet), and utilitarian considerations (number of lives saved).

Each model's responses were rigorously evaluated against human baseline data, originally collected from approximately 40 million human decisions from the Moral Machine project (Awad et al., 2018). The researchers employed a quantitative measure—global misalignment scores—defined as aggregated L2-distance between the model and human preferences across all dimensions.

The findings revealed notable numerical differences among models. For instance, the best-aligned model, Llama 3.1 (70B), achieved a relatively low global misalignment score of 0.6, indicating strong similarity to human ethical preferences. Conversely, GPT-4o Mini demonstrated significantly higher misalignment (1.35), suggesting a more rigid or extreme ethical stance. Specifically, GPT-4o Mini displayed substantial preference extremes, presented in Figure 6:

This study was conducted using moral dilemma simulations, where both AI systems and human participants were tasked with making decisions about whom to save in life-threatening scenarios. Human preference data was gathered from large-scale experiments, such as the Moral Machine project, in which participants had to decide who an autonomous vehicle should prioritize in unavoidable accident situations.

Figure 10 presents a comparative analysis of AI-driven and human ethical decision-making preferences in life-and-death scenarios. The data illustrate the extent to which AI models align with or diverge from human moral intuitions across multiple categories, including age, gender, social status, physical fitness, legal compliance, and economic standing.

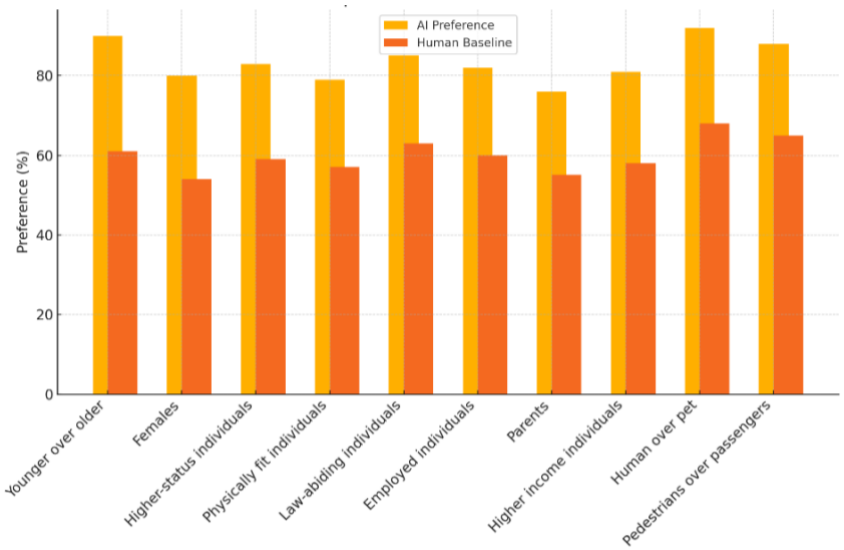


Figure 10. Comparison of AI and Human Preferences
Source: based on Jin et al. (2024).

The analysis compared AI preferences with human decision-making across the following categories:

- Younger individuals over older ones: AI exhibited a 90% preference for saving younger people, whereas humans showed a 61% preference.
- Females over males: AI chose females in 80% of cases, while human preference was 54%.
- Higher-status individuals: AI prioritized them in 83% of cases, compared to 59% for humans.
- Physically fit individuals over those with disabilities: AI displayed a 79% preference, while human preference was 57%.
- Law-abiding citizens over criminals: AI exhibited an 85% preference, whereas humans showed 63%.

- Employed individuals over the unemployed: AI favored the employed in 82% of cases, while humans in 60%.
- Parents over childless individuals: AI saved parents in 76% of cases, compared to 55% for humans.
- Higher-income individuals over lower-income individuals: AI showed an 81% preference, while humans exhibited 58%.
- Humans over pets: AI prioritized humans in 92% of cases, whereas humans did so in 68%.
- Pedestrians over vehicle passengers: AI favored pedestrians in 88% of cases, while humans in 65% (Awad et al., 2018).

This study demonstrates that while AI can make decisions faster and more consistently than humans, its selection criteria can lead to controversial outcomes. The deployment of AI in ethically sensitive areas requires careful calibration to mitigate excessive biases and incorporate ethical reflection that aligns with social values and acceptable moral standards. The analysis highlights that AI's moral decision-making is significantly more rigid and systematic than human choices. This stems from its algorithmic approach, which focuses on specific characteristics rather than applying the flexible and intuitive ethical reasoning inherent to humans.

AI exhibits stronger biases in favor of younger, healthier, and wealthier individuals, raising critical ethical concerns about the implementation of such decision-making models. If AI-driven systems are to be integrated into autonomous vehicles, healthcare decision-making, or crisis management, it will be imperative to incorporate human values and align AI decisions with widely accepted societal norms.

This study demonstrates that while AI can make decisions faster and more consistently than humans, its selection criteria can lead to controversial outcomes. The deployment of AI in ethically sensitive areas requires careful calibration to mitigate excessive biases and incorporate ethical reflection that aligns with social values and acceptable moral standards.

This extensive study raises several critical questions for AI ethics:

- To what extent can – or should – AI developers calibrate multilingual models to culturally or regionally specific moral norms?
- How can AI systems avoid amplifying inherent biases observed in human ethical decision-making, especially given their extreme manifestation in certain LLM outputs?
- What implications do these ethical biases have for practical AI applications, including automated vehicles, healthcare decision support, or global policy-making tools?

5. DISCUSSION

The findings of this study reveal significant ethical challenges in AI-driven decision-making, particularly in the context of autonomous vehicles (AVs). The Moral Machine experiment provides a critical benchmark for understanding how human moral preferences vary across cultures, while AI-driven simulations demonstrate how AI models replicate, amplify, or diverge from these preferences. The concept of intelligent management offers a practical lens through which the ethical paradox of AI becomes operationally relevant. As AI systems assume more responsibility for managerial functions, the need for ethical oversight and explainability grows. Intelligent management is not merely about optimizing KPIs—it is about designing AI ecosystems that act in line with human-centered values, ensuring decisions are not only effective, but also just and inclusive.

One of the most striking observations is that AI systems tend to exhibit stronger biases than human decision-makers. For instance, AI showed a 90% preference for saving younger individuals, whereas human respondents exhibited a significantly lower preference of 61%. Similar trends were observed in AI's preference for saving higher-status individuals (83%) and law-abiding citizens (85%), compared to human preferences of 59% and 63%, respectively. These results raise a critical ethical dilemma: Should AI reflect human moral choices, even when they demonstrate biases, or should AI be programmed to adopt an impartial ethical framework?

Furthermore, the data confirm regional variations in ethical preferences. Western countries demonstrated the highest adherence to utilitarianism (82%), prioritizing the greater number of lives saved. In contrast, East Asia and Latin America showed lower utilitarian tendencies (71–74%),

suggesting that moral decision-making in these regions is shaped by collectivist and social harmony principles. These cultural differences create a major challenge for AI deployment in global applications, as one ethical framework may not align with societal values in every region. AI models trained on human ethical preferences risk inheriting and amplifying societal biases. For example, the SafeRent case study demonstrated how AI-driven tenant screening systems disproportionately affected low-income and minority groups due to their reliance on credit scores and financial indicators. Similarly, AI models used in autonomous vehicles, healthcare, and law enforcement may unintentionally reinforce age, gender, and social status biases, unless explicitly corrected.

This raises a fundamental question for AI ethics:

Should AI be designed to counterbalance human biases, or should it remain a neutral reflection of human morality, even if it results in ethically problematic decisions? To address these concerns, AI governance frameworks must incorporate mechanisms for bias mitigation, transparency, and human oversight. Developing AI systems that balance efficiency, fairness, and ethical accountability will be essential for ensuring public trust and societal acceptance. For business leaders and policymakers, these findings emphasize the urgent need for ethical AI governance. Companies developing AI-driven decision-making systems must consider several key factors:

- Regulatory Compliance: AI systems must align with legal and ethical standards, such as anti-discrimination laws and data protection regulations.
- Transparency & Explainability: AI decisions should be interpretable and justifiable, particularly in high-stakes domains such as healthcare and criminal justice.
- Cross-Cultural Considerations: AI ethics should balance global standardization with regional ethical diversity, ensuring that AI-driven systems are both culturally adaptive and ethically consistent.
- These managerial decisions will play a pivotal role in shaping the future of AI ethics, determining whether AI serves as a neutral arbiter of moral choices or an active agent in promoting fairness and social justice.

6. CONCLUSION

This study underscores the complex ethical challenges posed by AI-driven decision-making, particularly in domains where life-and-death choices must be made. The Moral Machine experiment and AI simulations provide valuable insights into how moral preferences vary across cultures and how AI systems process ethical dilemmas.

The results highlight three major takeaways:

1. AI decisions reflect human biases but often amplify them – AI models exhibited stronger preferences for age, status, and law-abidance compared to human respondents.
2. Cultural differences influence ethical decision-making – Western countries displayed a strong utilitarian tendency, while collectivist cultures considered additional moral dimensions beyond numerical survival rates.
3. AI fairness and transparency remain critical challenges – Without bias mitigation strategies, AI systems risk reinforcing existing inequalities in areas such as healthcare, employment, and transportation safety.

Given these findings, several key challenges and opportunities emerge for AI development:

Should AI ethics be globally standardized or tailored to regional moral preferences?

- How can AI systems be designed to reduce bias without compromising efficiency?
- What role should policymakers play in ensuring AI systems align with societal values and legal frameworks?

Ultimately, the ethical implementation of AI requires collaboration between technologists, ethicists, policymakers, and business leaders. Moving forward, AI governance must strike a balance between technological innovation and ethical responsibility, ensuring that AI serves as a tool for social good rather than a mechanism that reinforces societal inequalities.

For AI to gain widespread public trust and acceptance, its decision-making processes must be transparent, fair, and aligned with widely accepted ethical norms. This study contributes to the ongoing debate on how AI should navigate moral dilemmas, encouraging further research on the intersection of

AI, ethics, and human values. As AI systems increasingly underpin intelligent management practices, ethical governance must evolve in parallel. Addressing these challenges is not only a technical necessity but a managerial responsibility.

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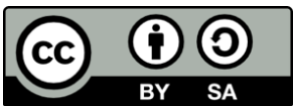
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ETHICAL CHALLENGES IN AI-DRIVEN CONSUMER JOURNEY – A CASE STUDY OF L'ORÉAL'S HAIRDRESSING SERVICES

Joanna Hernik[a], Wojciech Jarecki[b], Gunta Grinberga-Zalite[c] and Andreea Muntean[d]

[a] *West Pomeranian University of Technology, Szczecin, Poland*
[b] *University of Szczecin, Institute ofa management, Szczecin, Poland*
[c] *Latvia University of Life Sciences and Technologies, Latvia*
[d] *1 Decembrie 1918 University, Romania*

ABSTRACT

Purpose: *This study examines the integration of artificial intelligence (AI) in hairdressing services by L'Oréal, with a focus on its ethical implications, consumer experience, and business practices. It evaluates how AI-driven personalisation, digital engagement, and automation impact the beauty sector, assessing both opportunities and challenges in the adoption of AI technologies.*

Need for the Study: *The cosmetics and hairdressing industry is undergoing a digital transformation, with AI playing an increasingly significant role in product recommendations, customer interactions, and service efficiency. However, alongside the benefits of AI, concerns regarding data privacy, algorithmic bias, consumer autonomy, and transparency have emerged.*

Methodology: *The study employs an exploratory case study approach, analysing L'Oréal's AI-driven digital innovations in hairdressing services. Data was collected from L'Oréal's official reports, industry publications, and relevant academic literature. A thematic analysis was conducted to identify key ethical concerns and business implications of AI adoption.*

Findings: *The study finds that L'Oréal utilises AI-driven technologies at various stages of the consumer journey, for example AI-powered marketing campaigns, influencer endorsements, virtual try-on tools, and personalised chatbot recommendations.*

While AI significantly enhances personalisation, efficiency, and sustainability, the study identifies key ethical concerns, including: algorithmic bias, potentially leading to exclusionary recommendations; manipulative marketing practices, reduced consumer autonomy, and concerns regarding digital exclusion, particularly among consumers with low digital literacy or limited access to technology.

Practical Implications: *The findings highlight the importance of ethical AI implementation in hairdressing services and the broader beauty industry. Businesses adopting AI must prioritise fairness, transparency, and inclusivity to maintain consumer trust. Additionally, companies should invest in consumer education initiatives to ensure that AI-driven personalisation enhances, rather than restricts, consumer choice.*

Keywords: Artificial Intelligence (AI), Consumer Trust, Corporate Social Responsibility, Digital Transformation, Ethical AI, Hairdressing Services, Personalisation, Sociotechnical Systems Theory

JEL classifications: M14, M30, O31, O33

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1. INTRODUCTION

The cosmetics industry, driven by the growing consumer interest in self-care and wellness, has continued to thrive over the past two decades. Despite a minor setback in 2020 due to the COVID-19 pandemic, the global market has experienced steady growth since 2004 and is projected to reach nearly 132 billion USD by 2029 (Petruzzi, 2024). Key facts about this industry include: 1) skincare remains dominant, holding a 40% market share in 2023; 2) the industry leader is L'Oréal, whose L'Oréal Paris brand is valued at nearly 40 billion USD as of 2024; 3) social media platforms such as Instagram and YouTube have a significant impact on consumer behaviour; and 4) the industry is increasingly leveraging technology, including try-on apps and personalisation software, to enhance consumer experiences (Petruzzi, 2024). The cosmetics industry can be divided into several specialised areas, including skincare, makeup and colour cosmetics, men's grooming, fragrance and perfume, as well as haircare and professional hairdressing.

The hairdressing industry has a rich and evolving history that spans thousands of years, reflecting cultural, social, and technological advancements. Ancient civilisations such as Egypt, Greece, and Rome placed significant importance on hairstyling, with elaborate wigs, braids, and hair treatments symbolising social status, wealth, and even religious beliefs (The History of Hair Salons). During the Middle Ages, hairstyling became less elaborate due to societal shifts, but by the Renaissance, intricate hairstyles and the use of hair accessories returned to prominence among the elite. The 18th and 19th centuries saw the rise of professional barbers and hairdressers, with France becoming a hub for innovative styling techniques. The 20th century marked a major turning point, as the development of electric tools, chemical treatments, and mass-market hair products revolutionised the industry (Beresford, 1976). Salons became widespread, and hairdressing evolved into a skilled profession requiring specialised training and certifications. Today, the industry continues to adapt, with digital transformation, AI-driven solutions, and data analytics shaping the way hair services are delivered, blending traditional artistry with modern technology (López-Jáuregui et al., 2019; Sedita et al., 2021).

Traditionally centred around craftsmanship and personalised service, the hairdressing business is now undergoing a profound transformation driven by artificial intelligence (AI), big data, and digital technologies. As consumer preferences evolve and competition intensifies, salons and beauty professionals are increasingly adopting technological advancements to enhance customer experiences, streamline operations, and optimise business performance (Tournois, 2013; Agyemang and Boateng, 2019; López-Jáuregui et al., 2019). AI-powered tools, including virtual hair consultations, smart booking systems, and automated product recommendations, are reshaping how hair salons interact with their clients. Meanwhile, big data analytics enables businesses to track customer trends, personalise services, and make data-driven decisions, fostering efficiency and profitability. Digital transformation, encompassing e-commerce, social media marketing, and cloud-based management solutions, is also playing a crucial role in modernising the sector, allowing for improved customer engagement and operational agility (Sedita et al., 2021).

Despite these advancements, the integration of AI and big data in the hairdressing industry presents several challenges. These include data privacy concerns, resistance to modern technologies, digital skills gaps among professionals, and the potential depersonalisation of a highly customer-centric field.

The aim of this article is to evaluate AI solutions in hairdressing services implemented by L'Oréal from an ethical perspective. This article not only explores the increasing role of AI, big data, and digital transformation in the hairdressing industry, but also examines these solutions through the lens of business ethics. The research method used is an exploratory case study.

It is also worth noting that Europe has long played a significant role in shaping hair fashion, with various countries contributing to the development of trends and hairstyling techniques. France, in particular, has been a leader in hair salon innovation, drawing inspiration from Parisian fashion shows and haute couture influencers. Even today, France continues to set trends in the hairdressing industry, maintaining its position at the forefront of hairstyling excellence.

2. LITERATURE REVIEW

The topic under discussion relates to several fields, primarily Business Ethics and Corporate Social Responsibility (CSR), as well as Sociotechnical Systems Theory.

Philosophers have been concerned with ethical business practices for centuries. I. Kant formulated the categorical imperative, which states: *I should never act otherwise than in such a way that I can also will that my belief should become a universal law* (Buksiński, 2004). This principle significantly influenced the philosophy of Roman Ingarden, the creator of the so-called ethics of responsibility. Ingarden asserted that values such as justice and freedom exist as moral ideals, which are defined in individual situations. He identified four dimensions of responsibility: bearing responsibility, undertaking responsibility, calling others to responsibility, and acting responsibly (Ingarden, 1987). These aspects of responsibility are evident in market activities and serve as the foundation of responsible business practices, as organisations can bear financial, legal, and moral responsibility. Taking action inherently involves a readiness to assume responsibility, which can have both positive and negative dimensions, and the tool for assessment is one's conscience (Ingarden, 1987).

J. Owens emphasises that business ethics, as a structured framework, is often manifested through written codes of ethics that establish clear guidelines for ethical behaviour within an organisation. These codes outline principles such as integrity, fairness, transparency, and corporate responsibility, ensuring that employees and management adhere to ethical standards in decision-making and business operations (Owens, 1982). To maintain accountability, such codes are typically enforced through appropriate sanctions, ranging from warnings and mandatory training to financial penalties, demotions, or termination of employment in cases of severe ethical breaches. The enforcement mechanisms ensure that ethical standards are not merely aspirational but actively shape corporate culture and operational conduct. However, there remains a gap between ethical expectations and their implementation in business organisations (Trevino, 1986; Kreitner, 1983; Rendtorff, 2019). Various corporate scandals and crises suggest that ethical standards have not been fully integrated from Judaeo-Christian traditions or civil religious values. Rather than relying on theistic individualism or strict legalistic approaches, managerial ethics should be based on broader principles that promote ethical behaviour across the organisation. One key principle is that fostering cooperative social relationships encourages moral actions in business environments.

S. L. Payne, in the article "Ethics Integration" (1993), addresses the critical need to incorporate ethical considerations into management and organisational behaviour education. Payne argues that ethical issues are often treated as peripheral in business curricula, leading to a disconnect between ethical theory and practical application in organisational settings. He advocates for the integration of ethics into core management courses, ensuring that future business leaders develop a robust ethical framework. He also stresses that such integration should not be superficial but should instead be deeply embedded in the analysis of managerial practices and organisational behaviour (Payne, 1993; Kennett-Hensel and Payne, 2018).

On the other hand, ethics must be embedded in market activities, a central perspective in Corporate Social Responsibility (CSR) theory (Terrero-De La Rosa et al., 2017; Rendtorff, 2019b; Munro, 2020). CSR has evolved significantly over time, incorporating new societal expectations, regulatory frameworks, and global challenges. The 2011 European Commission definition of CSR describes it as "the responsibility of enterprises for their impacts on society," reflecting a shift towards a more integrated, strategic, and accountability-driven approach (Corporate Social Responsibility: A New Definition, 2011). This definition moves beyond traditional philanthropic efforts, emphasising that businesses must actively address social, environmental, and economic concerns as part of their core operations. It highlights that businesses are accountable not only to shareholders but also to employees, communities, governments, and global institutions.

Management practices in businesses often align with the Hunt–Vitell Model of Marketing Ethics (Uslay, 2025; Payne and Pressley, 2013). Developed by Shelby D. Hunt and Scott J. Vitell in 1986, this model explains how individuals and organisations make ethical decisions in marketing. It integrates deontological (duty-based) and teleological (consequence-based) perspectives, highlighting how personal values, situational factors, and cultural influences shape ethical judgments. Within this framework, individuals and organisations decide whether to act ethically, influenced by personal moral philosophy, organisational culture, and external pressures, such as profit goals or legal requirements (Uslay, 2025).

This theoretical foundation reinforces the view that neither the social nor the technical aspects of an organisation can be understood or optimised in isolation - both must be designed and managed together to achieve efficiency, innovation, and employee well-being (Appelbaum, 1997). The interaction

between people (social systems) and technology (technical systems) within organisations and workplaces is explained through Sociotechnical Systems Theory (Lee et al., 2022; Orr and Jadhav, 2024; Zaidi and Lakhal, 2025). This theory emphasises that an effective system requires the simultaneous design and improvement of both technical (e.g., machinery, AI tools, technology, software) and social (e.g., team structures, work culture, leadership) components. Today, this technical component is strongly connected to AI. AI integration can occur across the customer journey - pre-purchase, during purchase, and post-purchase stages (Choe et al., 2024; Zaman et al., 2025). Companies must ensure fair, transparent, and bias-free AI algorithms to maintain consumer trust and comply with data protection regulations. Furthermore, the ethical implementation of AI fosters a customer-first approach, ensuring that AI-driven recommendations (e.g., in healthcare or beauty) respect privacy, avoid manipulation, and are genuinely aimed at user well-being.

It should be noted that the French company L'Oréal is frequently discussed in academic analyses and scientific studies. Scholars such as Tournois (2013 and 2014), Farquharson (2006), Muravskii, Muravskaia, Romanova, Kudinova (2020), Ghosh and Lever (2020), and Sedita, Belussi, Noni, and Apa (2022) examine L'Oréal's market strategy, crisis management, innovation approach, and operational efficiency through various case studies. Their research explores how brand proliferation has influenced L'Oréal's market dominance, how the company navigated challenges during the COVID-19 pandemic and oil price fluctuations in 2020, and how L'Oréal has strategically shifted between offensive and defensive management approaches, depending on market conditions, competitive pressures, and consumer behaviour. These studies also highlight the importance of innovation in mass markets, particularly how L'Oréal balances introducing new products with adapting to existing consumer needs. The conclusions emphasise that while innovation is a key driver of growth, L'Oréal must remain adaptable to shifting market conditions to maintain its competitive edge.

3. METHODOLOGY

To evaluate AI solutions in hairdressing services implemented by L'Oréal from an ethical perspective, an exploratory case study method was employed. As Yin (2014) states, the case study research method is widely used in social sciences, business, and management research to gain in-depth insights into specific phenomena within real-world contexts. It is particularly useful for exploring complex issues, unique cases, and practical applications of theories in business environments. Findings often provide strategic recommendations for businesses, policymakers, or practitioners.

This case study analysis was guided by the following research questions:

1. What artificial intelligence (AI) solutions are used in the customer journey?
2. What are the primary ethical challenges in AI-driven hairdressing services?
3. How has L'Oréal implemented ethical safeguards in its digital customer journey?
4. What are the implications of L'Oréal's strategies for businesses and consumers?
5. Can these ethical practices be generalised to the broader beauty industry?

3.1. Data Collection and analysis

Data for analysis was collected from L'Oréal's official website:

- https://www.loreal-finance.com/en/annual-report-2018/digital-4-3/technological-advances-revolutionising-beauty-4-3-3/
- Additionally, professional news sources, reports, and articles were reviewed, including:
- Silicon Angle: https://siliconangle.com/2024/04/11/loreal-tapping-generative-ai-transform-marketing/
- Manufacturing Digital: https://manufacturingdigital.com/ai-and-automation/how-ibm-loreal-will-use-ai-for-sustainable-cosmetics
- Isarta: https://isarta.com/news/how-loreal-canada-uses-generative-ai-for-marketing/
- NTT Data: https://us.nttdata.com/en/case-studies/loreal-chile-and-ntt-data-revolutionize-the-world-of-beauty-with-ai
- Statista: https://www.statista.com.

A thematic analysis was conducted, identifying key themes related to privacy, transparency, inclusivity, and fair AI usage, as well as solutions adopted by the L'Oréal Company.

3.2. The Consumer journey perspective

To address the research questions, the study adopts the perspective of a consumer's journey in purchasing a hairdressing service. A customer journey outlines the steps a customer takes from becoming aware of a product or service to making a purchase and beyond (Towers and Towers, 2022). It consists of various touchpoints, which represent interactions between the customer and the brand (company).

A typical customer journey for a hairdressing service integrates both online and offline interactions, ensuring a seamless experience from discovery to post-service engagement. The journey begins with the awareness stage, where customers may come across social media advertisements on platforms such as Instagram and TikTok, influencer recommendations, or AI-driven personalised advertisements based on their search history. Offline, customers may discover the salon through word-of-mouth recommendations from friends and family, by passing by the salon, or through local print advertisements in magazines or newspapers.

In the consideration stage, potential clients evaluate the salon by checking online reviews on Google or professional platforms, browsing the salon's website for services and pricing, or watching hairstyling tutorials. Offline, they might visit the salon for a consultation, seek stylist recommendations, or attend a beauty event.

Once they decide to proceed, they move to the booking stage, where they can schedule an appointment online via the salon's website or mobile application, interact with a virtual assistant for availability, or receive a confirmation via email or SMS. Alternatively, they may call the salon directly or visit in person to book an appointment.

The service experience itself combines both digital and in-person elements. Online, customers might use an AI-powered consultation tool to virtually test hairstyles or check in via a QR code upon arrival. Offline, they engage in a professional hair consultation, receive styling services such as haircuts, colouring, or treatments, and interact with the stylist for personalised hair care advice.

Finally, in the post-service engagement stage, the salon maintains customer relationships through digital follow-ups, including emails with personalised hair care recommendations, loyalty programme invitations, and incentives for online reviews. Customers may also engage by sharing their new hairstyle on social media. Offline, they might receive a discount via a physical loyalty card, book their next appointment before leaving, or recommend the salon to others through word-of-mouth.

By integrating both online and offline touchpoints, hairdressing services can create a seamless, customer-centric experience that enhances customer satisfaction and encourages brand loyalty (Fig. 1).

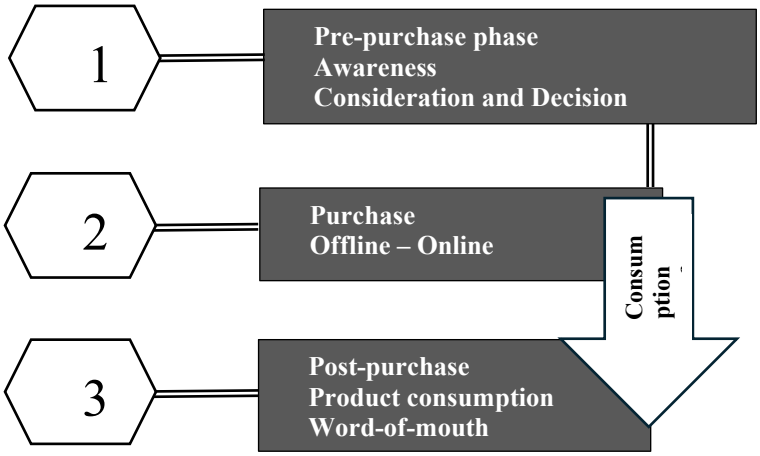


Figure 1. The main stages of the consumer journey
Source: own elaboration.

It is important to note that the situation depicted in Fig.1, where purchase and consumption occur simultaneously in the case of services, does not entirely apply to the hairdressing industry. Typically,

services are intangible, inseparable, and perishable, meaning that their purchase and consumption often take place at the same time. For example, in transport services, the purchase, production, and consumption occur simultaneously. Unlike physical goods, which can be purchased, stored, and used at a later time, services are typically produced and consumed in real-time. Several key factors explain this phenomenon. Firstly, services do not have a physical form, meaning that customers cannot "own" them in the traditional sense. Moreover, in many cases, the service provider and the customer must be present at the same time for the service to be delivered effectively. In the case of hairdressing services, consumption begins after the service is completed. This aspect of service consumption highlights the unique nature of the hairdressing industry, where interaction between the stylist and client is integral to the overall experience.

4. CASE STUDY ANALYSIS

4.1. Characteristics of the L'Oréal Company

L'Oréal is a leading cosmetics company headquartered in Clichy, France, operating in over 130 countries. It was founded in 1909 by Eugène Schueller as Société Française de Teintures Inoffensives pour Cheveux (https://pl.wikipedia.org/). Today, L'Oréal is a global leader in the beauty industry, offering a diverse portfolio of 37 international brands, catering to a wide range of consumer needs across skincare, haircare, cosmetics, and fragrance.

With a workforce of more than 90,000 employees, the company continues to drive innovation and market expansion. In 2023, L'Oréal generated sales of 41.18 billion euros, reinforcing its dominant position in the global beauty market. The company maintains 20 research centres across 11 countries, ensuring cutting-edge advancements in beauty science and sustainable product development. With 7 billion product units available across physical and virtual retail channels, L'Oréal's extensive reach reflects its ability to meet global consumer demand while continuously evolving through digital transformation and AI-driven solutions (data from https://www.loreal.com/en/).

L'Oréal offers a diverse portfolio of consumer goods and professional products, addressing a wide range of customer preferences. Its consumer goods division includes well-known brands such as L'Oréal Paris, Garnier, and Maybelline, offering accessible and innovative skincare, haircare, makeup, and personal care products for everyday use. These products are widely available in retail stores, supermarkets, and online platforms, ensuring accessibility for consumers worldwide.

In contrast, L'Oréal's professional products division is designed specifically for salons, hairstylists, and beauty professionals, providing high-performance hair colour, styling, and treatment solutions through brands such as L'Oréal Professionnel, Kérastase, and Redken. These professional-grade products are often sold exclusively through salons and beauty institutes, ensuring expert application and tailored hair care solutions (Tournois, 2014; Chailan, 2008). The characteristics of the company's portfolio is presented in Fig. 2.



Figure 2. L'Oréal's consumer and professional products portfolio
Source: own elaboration.

The company's products have always been technologically advanced. On the L'Oréal website one can see a declaration about their current approach to innovations and technology:

Our Beauty Tech division is a testament to the company's commitment to pushing the boundaries of innovation in the beauty industry, pioneering the creation of highly personalized and inclusive beauty solutions.

L'Oréal's beauty tech journey also includes initiatives in seamless online-offline consumer experiences and leveraging AI and data analysis for enhanced personalization (https://www.loreal.com/en/beauty-science-and-technology/).

In our analysis we adopt this perspective, so the technological solutions used will be analysed from the point of view of the hairdressing salon client journey, that includes 3 main stages: pre-purchase stage, purchase process and post-purchase stage (Becker, 2020). In addition, internal processes not directly related to consumer in which the company uses artificial intelligence will be discussed as well.

It is worth noting that novelties and modern solutions are developed in several stages. Alongside the Métiers & Product Innovation Development department, which is responsible for creating new products, L'Oréal has established two specialised units dedicated to the implementation of AI: the Generative AI Task Force and the GenAI Content Lab (Kerravala, 2024; Brown, 2025).

The Generative AI Task Force at L'Oréal is tasked with identifying potential applications and use cases of AI within the organisation. Additionally, it focuses on employee upskilling, ensuring that staff acquire the necessary expertise to utilise AI effectively. Furthermore, the task force plays a key role in fostering a knowledge-sharing culture, increasing AI awareness across the company.

The GenAI Content Lab serves as an innovation hub, where AI-driven beauty content is developed and tested. It promotes collaboration through a network of partners and explores AI-powered creative service models. The lab also plays a critical role in establishing ethical guidelines for AI usage, ensuring transparency in marketing practices. For instance, L'Oréal does not use AI-generated images of faces, skin, hair, or bodies to misrepresent its products (How L'Oréal Canada.., 2025). Instead, AI is employed internally for brainstorming, design, and strategic planning, maintaining ethical standards while enhancing creative processes (Kerravala, 2024). The goal is to combine human creativity with artificial intelligence, offering a more personalised beauty experience through technology. This is achieved through collaborations with technology partners, such as IBM, Nvidia, NTT DATA, and Sprinklr, as well as through the acquisition of technological start-ups, such as ModiFace, which was acquired in 2018 (Kerravala, 2024). The aim of this technological shift is to prioritise solutions that are both environmentally sustainable and innovative, using science and technology to drive progress (Brown, 2025; L'Oréal Chile…, 2025).

L'Oréal is also experimenting with generative AI to enhance marketing content production. For example, this technology has proven effective in scaling product images and generating backgrounds, significantly reducing the resources required for traditional photo shoots. In addition to image creation, L'Oréal is exploring AI-driven video generation to improve visual marketing strategies. The company employs Nvidia's Omniverse platform to create detailed 3D models of its products, which can be placed in different contexts and settings. This offers a two-fold benefit: it notably reduces the time and resources traditionally required for photo shoots, while providing greater flexibility to present products across multiple media platforms (Kerravala, 2024). A summary of the technological solutions implemented is presented in Table 1.

4.2. Examination of L'Oréal's digital innovations

L'Oréal integrates AI and modern technologies across its entire value chain to enhance product innovation, sustainability, and customer experience. The company utilises AI-driven data analysis to automate tasks, optimise large-scale production, and develop new cosmetic formulations tailored to consumer needs. By leveraging an anonymous database, L'Oréal refines formulas to match market preferences, ensuring personalised and high-performance beauty solutions. The company also employs Generative AI (Gen AI) in product development and marketing, collaborating with agencies to create storyboards, mock-ups, and visuals, thereby streamlining the creative process (Pitt, 2025).

In manufacturing, 3D printing accelerates the design of innovative packaging, while agile production lines, intelligent sensors, touchpads, and collaborative robots (cobots) enhance efficiency in L'Oréal's production facilities. The company has also introduced a mobile application to monitor packaging lines and has tested autonomous drones to improve inventory management in distribution centres. Sustainability remains a key focus, with AI helping optimise the use of sustainable raw materials, reduce

energy consumption and material waste, and implement new plastic bio-recycling solutions (https://www.loreal.com/en/beauty-science-and-technology/).

Thus, before a potential customer finds the right offer, L'Oréal already employs a range of technologically advanced tools. Throughout the consumer journey, a L'Oréal customer encounters various technological solutions that enhance their shopping experience at different stages: before, during, and after the purchase (Table 1).

Table 1. Technological dimensions of an online consumer journey in the case of L'Oréal solutions

Stages	Technological dimensions
Pre-purchase	Social media content
	Influencer endorsements
	Search engines
	Rating platforms
	Booking platforms and websites
	Dynamic advertising campaigns
	Beauty Genius - virtual testing app for makeup, skincare and hair colour
	Style My Hair app - virtual hairstyle changer
	Personalised recommendations through chatbots
Purchase	Online appointment scheduling
	Personalized products at the hairdressing salon
	Beauty Genius App and Style My Hair app
	L'Oréal Cell BioPrint - Portable lab-on-a-chip device
Post-purchase	Beauty Genius as an educational resource
	Automated emails and sms - feedback requests, reminders
	Personalized campaigns based on the purchase history
	User-generated content and reviews
	Customized Q&A, chatbots
	AI-driven loyalty programs
	Rating platforms

Source: own study based on:
https://www.loreal.com/en
https://www.loreal.com/en/articles/science-and-technology/beauty-genius/
https://www.lorealprofessionnel.pl/hair-looks/style-my-hair
https://www.loreal.com/en/press-release/research-and-innovation/loreal-cell-bioprint/
https://siliconangle.com/2024/04/11/loreal-tapping-generative-ai-transform-marketing/
https://manufacturingdigital.com/ai-and-automation/how-ibm-loreal-will-use-ai-for-sustainable-cosmetics
https://isarta.com/news/how-loreal-canada-uses-generative-ai-for-marketing/
https://us.nttdata.com/en/case-studies/loreal-chile-and-ntt-data-revolutionize-the-world-of-beauty-with-ai

L'Oréal's acquisition of ModiFace, a leader in augmented reality beauty applications, has facilitated the development of virtual try-on tools that enable customers to test makeup, skincare, and hair colour before purchasing, both online and at the point of sale. The L'Oréal Paris Beauty Genius app utilises L'Oréal Paris' expertise in hair care, hair colour, makeup, and skincare, integrating insights from clinical studies, ingredient research, beauty routines, and an extensive product catalogue to assist consumers in making informed choices (https://www.loreal.com/en/articles/science-and-technology/beauty-genius/).

Consumers can also use Virtual Expert Vicky, an AI-driven skin diagnostic tool that analyses wrinkles, pores, and signs of fatigue based on a photograph. The tool then provides a personalised skincare recommendation, helping customers make informed purchasing decisions while also allowing them to buy products directly from the brand's website. Additionally, Beauty Genius enhances the shopping experience by offering AI-powered personalised skin analysis and a virtual makeup try-on feature. With access to a database of over 750 products, Beauty Genius suggests tailored beauty routines across skincare, makeup, and haircare, ensuring that each customer finds the most suitable product for their needs. Beyond product recommendations, Beauty Genius also serves as an educational resource, providing beauty tips and expert advice.

The platform offers users several key features:

- Personalised diagnostics: by analysing user inputs, ranging from survey responses to high-tech selfie assessments, Beauty Genius evaluates over 10 skin parameters to deliver customised insights.
- Tailored recommendations: based on individual needs, the tool suggests personalised beauty routines and product matches across haircare, hair colour, skincare, and makeup, drawing from a portfolio of over 750 L'Oréal Paris products. Additionally, it curates educational beauty content from social media and brand platforms to enrich user knowledge.
- Customised Q&A support: beauty Genius provides a discreet, AI-powered assistant to answer questions on sensitive topics, such as skin concerns or hair loss, offering a private, judgement-free alternative to consulting a live expert.

By combining AI-driven personalisation with L'Oréal Paris' extensive expertise, Beauty Genius enhances the consumer experience, making beauty guidance more accessible, efficient, and tailored to individual needs (https://www.loreal.com/en/articles/science-and-technology/beauty-genius/; https://www.loreal.com/en/ beauty-science-and-technology/ beauty-tech/discovering-modiface/).

L'Oréal has also transformed the point-of-sale experience by integrating personalised beauty solutions and augmented reality (AR) technologies to enhance consumer engagement. By incorporating AI, augmented reality, and digital tools at every stage of the customer journey, L'Oréal has created an interactive and highly personalised consumer experience, strengthening brand loyalty and customer satisfaction.

4.3. Hairdressing sector

L'Oréal Professionnel offers professional hair beauty expertise, drawing on over 110 years of knowledge and support for the hairdressing sector. As the world's leading professional brand for hairstylists, it collaborates with 1.5 million stylists across more than 300,000 salons. Its comprehensive portfolio includes complete haircare ranges designed for all hair types, professional hair colouring and highlights, as well as augmented beauty tech accessories (https://www.loreal.com/en/professional-products-division/loreal-professionnel/). L'Oreal offers an app specifically dedicated to hair care: Style My Hair (https://www.loreal.com/en/articles/science-and-technology/haircolor-virtual-try-on-loreal-professionnel-style-myhair/). This virtual hair makeover tool allows clients to browse through a wide selection of hairstyles, colours, and professional hair effects to find their ideal look. Once they have selected a style, they can simply show it to their L'Oréal Professionnel hairdresser, who can then bring their transformation to life in the salon. In hair salons, stylists also use professional-grade products from L'Oréal's extensive portfolio, including Kérastase, Redken, Matrix, and Biolage, all of which belong to the L'Oréal brand family.

4.4. Analysis of AI Solutions Used by L'Oréal at Different Stages of the Customer Journey

The use of technology varies depending on the stage of the consumer's purchasing process. However, some AI-driven solutions are applied across multiple stages, including the pre-purchase, purchase, and post-purchase phases.

Pre-purchase stage

Before deciding to visit a hairdressing salon, customers are influenced by social media content, influencer endorsements, and dynamic advertising campaigns, all of which introduce them to new beauty trends and products. L'Oréal collaborates with 50,000 influencers worldwide, who promote its products on platforms such as Facebook, Instagram, Snapchat, and YouTube.

Consumers can use search engines and rating platforms to read reviews, while booking platforms and brand websites allow them to schedule salon appointments or virtual consultations. Popular platforms for appointment scheduling include Booksy and EasyWeek.

L'Oréal's Beauty Genius app enables users to virtually test makeup, skincare, and hair colour, while the Style My Hair app lets them experiment with different hairstyles digitally. AI-powered chatbots further assist customers in selecting products that match their preferences (https://www.lorealprofessionnel.pl/ hair-looks/style-my-hair).

At-purchase stage

During the purchase stage, technology continues to play a key role in customisation and convenience. At hair salons, L'Oréal's Beauty Genius and Style My Hair apps provide customers with personalised product recommendations and treatments tailored to their hair type.

In physical stores, the same apps enable virtual testing, helping consumers choose the most suitable beauty products. Meanwhile, for general shopping, interactive displays and self-service kiosks enhance the shopping experience by simplifying the selection process.

Post-purchase stage

After making a purchase, customers remain engaged through automated emails requesting feedback, reminders for repeat purchases, and personalised haircare and makeup tips.

L'Oréal also employs AI-driven loyalty programmes, which reward frequent shoppers with exclusive discounts and special offers. Personalised campaigns based on purchase history ensure that customers receive tailored product recommendations, while user-generated content and online beauty communities keep them engaged with the brand. Additionally, chatbots and custom Q&A features provide post-purchase support, answering customer queries about product usage and beauty routines (Yanxia, 2024).

4.5. Ethical threats in the consumer journey

At the pre-purchase stage, both consumers and businesses face several ethical risks related to transparency, data privacy, and misinformation. The heavy influence of social media content, influencer endorsements, and dynamic advertising campaigns raises concerns about misleading marketing and undisclosed sponsorships, where influencers may promote products without clearly stating their commercial affiliations. Consumers relying on search engines and rating platforms may encounter biased or manipulated reviews, leading to distorted perceptions of product quality.

Booking platforms and brand websites, while convenient, often require users to share personal data, raising concerns about data privacy, tracking, and potential misuse of personal information. L'Oréal's Beauty Genius and Style My Hair apps, which allow virtual product testing, rely on AI-driven analysis, which may introduce algorithmic biases that fail to accurately represent diverse skin tones and hair textures, potentially leading to exclusion or inaccurate recommendations. Additionally, personalised recommendations from chatbots may create an over-personalised shopping experience, limiting consumer choice by presenting only pre-selected options based on past behaviour, which may reduce product discovery.

For businesses, failing to address these ethical risks can result in consumer distrust, reputational damage, and regulatory scrutiny, underscoring the importance of ethical AI use, transparency in digital marketing, and responsible data handling practices.

At the purchase stage, consumers face ethical risks related to data privacy, informed consent, algorithmic bias, and consumer autonomy. The reliance on AI-driven personalisation in L'Oréal's Beauty Genius and Style My Hair apps raise concerns about how consumer data is collected, stored, and used during product recommendations. If users are unaware of how their biometric or personal information is processed, there is a risk of data misuse, lack of transparency, and potential security breaches.

Additionally, algorithmic bias in AI-powered recommendations - based on the analysis of customer expectations and previous purchases in hairdressing salons - may lead to unintended exclusion, where certain hair or skin types receive fewer or less accurate recommendations, reducing consumer trust in the technology.

In physical stores, virtual testing and self-service kiosks provide convenience but may also reduce human interaction, leading to less accountability and challenges in resolving customer concerns. Customers who are less experienced with modern technology may feel uncomfortable and abandon a purchase if technological solutions replace consultation with a real stylist.

Furthermore, the use of interactive displays and AI-driven product suggestions raises the risk of manipulative marketing tactics, where consumers might be nudged into purchasing higher-priced or unnecessary products due to algorithmic upselling. For businesses, failure to ensure ethical AI use,

transparent data policies, and unbiased recommendations can result in regulatory issues, reputational damage, and loss of consumer trust, making responsible AI implementation essential at this stage.

The post-purchase stage in hairdressing services is crucial for maintaining customer relationships, enhancing satisfaction, and ensuring repeat business. However, the use of AI-driven engagement strategies, automated marketing, and data-driven recommendations raises several ethical concerns that must be addressed to ensure fair and responsible customer interactions.

The use of AI in post-purchase engagement poses several ethical risks that businesses must address to maintain transparency and trust. Firstly, customers should have clear control over their data, with easily accessible opt-in and opt-out options for follow-up communications, loyalty programmes, and product recommendations. If consumers share personal information such as their address, age, location, or purchase history, data privacy and security become critical considerations. As AI-driven personalisation relies on behaviour tracking - such as the history of purchases and salon visits - there are concerns about unauthorised data collection or sharing with third parties.

Furthermore, manipulative marketing and over-promotion can pressure customers into making unnecessary purchases, making it essential for AI-driven campaigns to prioritise value over aggressive upselling. Additionally, loyalty programmes should be fair and inclusive, avoiding bias towards high-spending individuals and ensuring transparency in reward structures.

AI chatbots and automated customer support must provide accurate, unbiased information, ensuring that recommendations for hairdressing services align with customers' genuine needs rather than profit-driven motives. Partner hairdressing salons should also adhere to the ethical guidelines of the parent company, yet there remains a risk of limited control over the quality and ethical behaviour of independent entities.

Finally, businesses should promote authenticity in user-generated content and online communities, preventing misleading reviews and censorship of negative feedback, as these actions can erode consumer trust. Addressing these risks ensures that ethical AI implementation enhances the customer experience while upholding fairness, privacy, and integrity.

5. DISCUSSION

L'Oréal's integration of artificial intelligence (AI) and digital technologies across its value chain represents a paradigm shift in consumer engagement, product innovation, and sustainability. However, this transformation raises significant ethical considerations, particularly concerning business ethics, Corporate Social Responsibility (CSR), and Sociotechnical Systems Theory (STS). The following discussion examines L'Oréal's AI-driven consumer journey in hairdressing services, considering its ethical implications, CSR commitments, and the interaction between technology, consumers, and organisational structures.

L'Oréal's CSR commitments focus on sustainability, inclusivity, and responsible AI usage. By incorporating AI in sustainability efforts -such as optimising raw material usage, minimising waste, and improving product recyclability- the company aligns with CSR-driven environmental goals (Munro, 2020). However, certain challenges must be acknowledged.

First and foremost, L'Oréal's AI solutions extend beyond its direct operations to partner hairdressing salons and beauty retailers. Ensuring ethical alignment across the supply chain is crucial, as inconsistent ethical practices among partners could undermine the company's reputation (Owens. 1982; Rendtorff, 2019). Thus, CSR initiatives should extend to training and educating hairstylists on AI-driven tools, while also promoting fair labour practices and environmental sustainability within partner salons.

Additionally, customers should have clear opt-in and opt-out options for data collection and marketing communications, and it is the company's responsibility to ensure that accurate and transparent information is provided. L'Oréal's commitment to data protection serves as evidence of its respect for consumers and is essential in building and maintaining trust in L'Oréal brands (Adhikary, 2024).

In the context of AI-driven hairdressing solutions by L'Oréal, STS Theory can be used to analyse how AI (technical system) influences hairstylists, employees, and customers (social system). The GENAI-powered chatbots have improved customer support efficiency, resulting in a 20% increase in customer satisfaction scores. Furthermore, the data-driven approach has allowed L'Oréal to optimise its marketing spend, leading to a 25% improvement in ROI (Adhikary, 2024).

While AI may optimise services through personalised recommendations and automation, its success depends on how well it integrates with human expertise, customer interactions, and ethical considerations. A failure to balance AI efficiency with human involvement may lead to resistance, ethical concerns, and unintended consequences.

The implementation of AI in hairdressing services exemplifies a sociotechnical system, where technological advancements interact with human elements, including customers, hairstylists, and business operators. AI-driven applications such as Beauty Genius and Style My Hair act as enablers, offering convenience, personalisation, and efficiency. However, excessive reliance on AI-driven tools may create barriers for consumers with limited technological experience, leading to digital exclusion.

Additionally, automated systems may reduce direct interactions between hairstylists and clients, altering the traditional service experience and requiring new engagement strategies to maintain personal connections (Yanxia et al., 2024). It is, therefore, essential that stylists find the right balance between automation and personalisation, ensuring that AI enhances rather than replaces human expertise. Successful AI adoption also requires consumer education initiatives, ensuring that customers understand how AI recommendations are generated and how their data is protected.

L'Oréal's AI-driven approach to hairdressing services presents opportunities for innovation, sustainability, and enhanced consumer engagement. However, ethical challenges must be proactively managed to ensure responsible AI use (Zaman et al., 2025). Key recommendations include:

- Strengthening transparency and consumer control over data collection and AI-driven recommendations.
- Ensuring inclusivity in AI algorithms to fairly reflect diverse beauty needs.
- Maintaining ethical marketing practices to prevent manipulation and biased product recommendations.
- Promoting fair AI adoption in partner salons, ensuring that hairstylists receive adequate training and that ethical guidelines are upheld.

By integrating ethical AI principles, CSR strategies, and the STS framework, L'Oréal can enhance consumer trust, strengthen brand loyalty, and contribute to sustainable business practices, reinforcing its leadership in ethical beauty technology (Zaman et al., 2025; Towers and Towers, 2022).

6. CONCLUSIONS

6.1. Research questions

The cosmetics industry is undergoing a significant transformation, much like other sectors of economic activity. The way in which beauty products are discovered, tested, and purchased is continuously evolving. In industries such as beauty and cosmetics, where AI and big data play an increasingly important role, ethical concerns related to data privacy, algorithmic bias, and consumer protection require strong enforcement of ethical codes. Companies like L'Oréal, which integrate AI-driven personalisation in hairdressing services, must ensure that their AI applications align with ethical business practices, enforcing compliance through clearly defined codes of conduct and regulatory oversight.

In response to the research questions, the findings indicate that:

1. L'Oréal employs a variety of AI-driven technologies to enhance the consumer experience at different stages of the customer journey: Pre-purchase stage: AI-powered marketing campaigns, influencer endorsements, virtual try-on tools (e.g. Beauty Genius and Style My Hair apps), and personalised chatbot recommendations. At-purchase stage: AI-driven interactive kiosks, automated product recommendations, self-service systems in salons, and augmented reality (AR) product trials. Post-purchase stage: AI-driven loyalty programmes, personalised marketing emails, chatbots for customer support, automated beauty consultations, and AI-powered product suggestions based on purchase history.
2. The implementation of AI in hairdressing services raises several ethical concerns, namely: Transparency in data collection, storage, and usage of consumer information (data privacy and security). Algorithmic bias, where AI-based recommendations may not be fully inclusive, potentially excluding certain consumer demographics. Manipulative marketing, where over-personalised AI-driven product suggestions may pressure consumers into unnecessary

purchases. Consumer autonomy concerns, as AI-powered recommendations may limit consumer choices by narrowing available options based on past behaviour. Transparency and informed consent, ensuring that consumers are aware of and actively consent to AI-driven marketing and personalisation tools. These ethical considerations are illustrated in Fig. 3.

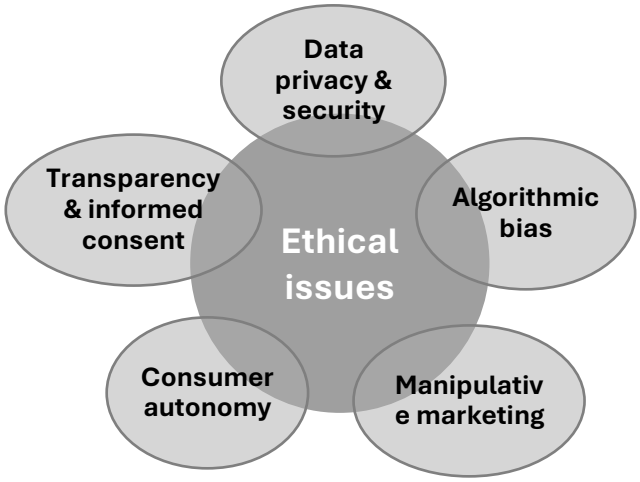


Figure 3. Ethical issues related to the implementation of AI in hairdressing services
Source: own elaboration.

3. L'Oréal has introduced various safeguards to ensure responsible AI use in its digital consumer journey. The company has established AI transparency policies, providing clear information on how AI influences recommendations and personalisation. To protect consumer data, L'Oréal ensures compliance with the General Data Protection Regulation (GDPR) and other privacy regulations, reinforcing ethical handling of personal information. The company also conducts diversity and inclusion audits, regularly reviewing AI algorithms to prevent biases and ensure inclusive representation. Additionally, consumers are given greater control over their engagement with AI-driven marketing through opt-in and opt-out features, allowing them to decide the extent to which they wish to receive personalised recommendations and communications. L'Oréal also adheres to regulatory compliance standards, ensuring fairness in marketing practices and consumer protection.
4. L'Oréal's AI-driven approach has significant implications for both businesses and consumers. For businesses, responsible AI implementation encourages investment in ethical technology, enhances brand reputation, and strengthens customer loyalty through ethical digital engagement. The case study analysis also highlights that L'Oréal is setting industry standards that may serve as a model for other brands over time. Consumers benefit from greater convenience and personalisation, as AI-powered tools make beauty solutions more accessible and tailored to individual needs. However, businesses must remain cautious in addressing ethical risks such as data privacy and algorithmic bias, to prevent potential consumer distrust. On an industry level, L'Oréal's commitment to responsible AI serves as a benchmark for other beauty brands, demonstrating the importance of ethical digital transformation in maintaining consumer trust and regulatory compliance.
5. L'Oréal's ethical AI strategies can be applied to the broader beauty industry, encouraging responsible AI adoption across brands to prevent unethical data usage and manipulative marketing. Transparency in AI-driven personalisation and marketing strategies should become an industry-wide standard, ensuring that consumers have clear access to information about how AI influences their purchasing journey. Companies should also prioritise diversity and inclusion in AI-powered beauty recommendations, ensuring they reflect the needs of a wider range of consumers. Strengthening regulatory compliance and ethical AI governance across different beauty sectors will further promote fairness in AI-driven beauty technologies and uphold consumer trust in digital beauty experiences.

6.2. Evaluation of AI solutions in hairdressing services

L'Oréal's AI solutions in hairdressing services have demonstrated significant benefits in enhancing customer experience, improving efficiency, and promoting sustainability. Virtual try-on applications such as Beauty Genius and Style My Hair greatly improve consumer decision-making, enabling users to visualise different hairstyles and products before making a purchase. This technology reduces dissatisfaction and minimises product returns, aligning with sustainability objectives.

AI-driven personalisation further enhances the salon experience by offering customised haircare recommendations, ensuring that clients receive treatments tailored to their specific needs. Additionally, AI improves operational efficiency in salons through automated scheduling, interactive kiosks, and digital consultations, helping to reduce wait times and optimise service delivery.

However, these AI solutions are not without challenges. Algorithmic biases remain a concern, as AI recommendations may not always reflect the full diversity of hair textures, leading to unequal customer experiences. Over-personalisation in marketing can also create ethical dilemmas, as consumers may be guided towards specific products based on past behaviours, rather than being encouraged to explore genuine new options.

Furthermore, reliance on AI-driven customer service - such as chatbots and automated responses -- may reduce human interaction, potentially diminishing the personalised touch that hairstyling services traditionally offer. Addressing these limitations requires continuous improvements in AI fairness, transparency, and a balanced approach between automation and human expertise.

6.3. Limitations of the study

Despite its comprehensive exploration of AI-driven digital innovations, this study on L'Oréal's technological advancements presents several limitations. Firstly, the study primarily relies on L'Oréal's own reports, press releases, and affiliated sources, which may introduce a bias towards a positive representation of the company's AI initiatives. Independent evaluations, third-party audits, or consumer feedback studies would offer a more balanced perspective on the effectiveness and ethical implications of these innovations. Secondly, the study places significant emphasis on the technological benefits of AI without fully addressing potential consumer resistance, digital exclusion, or negative consumer experiences. While AI-powered applications such as Beauty Genius and Style My Hair enhance personalisation, they may not fully accommodate all user demographics, particularly those who lack digital literacy or access to high-tech devices. Additionally, algorithmic bias remains an underexplored issue, as AI-based beauty tools might not adequately represent diverse hair and skin types, potentially leading to exclusionary recommendations.

Finally, the study does not fully assess the long-term sustainability impacts of AI. While L'Oréal integrates AI for sustainability by optimising raw materials and reducing waste, the actual ecological footprint of AI systems, energy-intensive computing, and electronic waste from digital tools has not been critically examined. Future research should explore the full lifecycle impact of AI adoption in beauty technology, assessing whether these innovations truly align with sustainable business models.

6.4. Future Research

To address the identified limitations, future research should adopt a broader and more critical perspective on AI-driven innovations in the beauty industry. First of all, independent consumer studies should be conducted to evaluate user satisfaction, accessibility challenges, and ethical concerns surrounding AI-powered beauty tools. Surveys, focus groups, and real-world case studies would provide qualitative insights into how customers perceive AI-driven personalisation and whether it enhances or detracts from their shopping experience. Moreover, a comparative analysis across industries would be beneficial in assessing whether AI-driven personalisation, automated production, and digital engagement strategies are unique to L'Oréal, or whether they represent broader trends in digital transformation.

Also, research on the sustainability impact of AI in beauty technology should be extended beyond waste reduction in manufacturing to include the environmental costs of AI computing, cloud-based systems, and data storage. Investigating the carbon footprint of AI-powered recommendation engines, virtual try-on applications, and automated production lines would provide a more comprehensive understanding of the true sustainability impact of digital transformation in the beauty industry.

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SMART LEARNING WITH AI: DECISION FACTORS IN GENERATION Z'S ADOPTION OF CHATGPT USING THE UTAUT2 FRAMEWORK

Magdalena Kowalska[a], David Kosina[b]

[a]*University of Szczecin, Institut of Management, Szczecin, Poland*
[b]*Palacký University Olomouc, Czech Republic*

ABSTRACT

Purpose: *This study investigates the factors influencing the adoption and usage of ChatGPT among Generation Z students in higher education, utilizing the UTAUT2 framework. It explores how performance expectancy, effort expectancy, social influence, hedonic motivation, facilitating conditions, price value, and habit contribute to students' behavioral intention and actual use.*

Need for the study: *The rapid integration of AI tools in education necessitates a deeper understanding of their acceptance and sustained usage. While previous research has explored the general adoption of AI in academia, there is limited empirical evidence on how specific constructs, drive ChatGPT adoption among students. This study addresses this gap by analyzing key determinants affecting student engagement.*

Methodology: *The study employs a quantitative research design, utilizing survey data collected from university students in Poland. Structural equation modeling (SEM) was used to test the relationships between key UTAUT2 constructs and ChatGPT adoption.*

Findings: *Results indicate that performance expectancy, hedonic motivation, and habit significantly predict students' intention to use ChatGPT, while effort expectancy, social influence, and facilitating conditions were less influential. The study highlights the critical role of habitual engagement in sustained use and the importance of intrinsic motivation in AI adoption.*

Practical Implications: *The study provides actionable insights for university administrators, educators, and policymakers. Institutions should implement AI literacy programs to promote responsible and effective usage of ChatGPT. Moreover, developing AI-powered educational tools that foster habitual engagement can enhance student learning. Policymakers should establish ethical guidelines to mitigate concerns about academic integrity and critical thinking in AI-supported education.*

Keywords: ChatGPT, AI adoption, higher education, UTAUT2, student engagement, smart learning, technology acceptance

Jel codes: I23, O33, D83

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1. INTRODUCTION

The rapid advancement of artificial intelligence (AI) has significantly transformed the educational landscape, facilitated novel learning approaches and increased accessibility to knowledge. One of the most prominent AI-driven innovations in education is ChatGPT, a generative AI model capable of assisting students in their academic endeavors. Generation Z, characterized by their digital nativity and preference for technology-enhanced learning, is increasingly engaging with AI tools such as ChatGPT for knowledge acquisition, problem-solving, and academic support (Chiu et al., 2023; Kasneci et al., 2023).

The widespread adoption of ChatGPT among students underscores its growing significance in higher education. Recent studies indicate that 92% of university students in the UK use AI tools like ChatGPT, marking a substantial increase from 66% in the previous year (Freeman, 2025). Similarly, in the United States, over 40% of university students report using ChatGPT for academic tasks (Ver Mee, 2024). In Poland, a study found that 60.6% of high school students engage with AI tools, with an overwhelming 98.5% of them leveraging ChatGPT specifically for educational purposes, illustrating its dominance in the AI-assisted learning landscape (Alshammari & Alshammari, 2024). The growing role of AI in education requires investigating how cultural factors affect ChatGPT adoption. Polish university students provide a unique context to study these cultural and institutional influences.

Recent research frequently discusses AI-powered educational tools. These studies highlight their potential to improve student engagement, learning outcomes, and personalization (Chiu et al., 2023). Studies suggest that AI chatbots can provide immediate feedback, facilitate adaptive learning, and support students in self-directed learning environments (W. Huang et al., 2022). Despite these benefits, understanding the factors influencing the adoption and use of ChatGPT remains a crucial area of research, particularly within the framework of the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) (Grassini, 2023).

The concept of smart learning has emerged as a pivotal paradigm in modern education, integrating AI-driven tools with data analytics and personalized learning strategies to create a more adaptive and efficient educational experience. Smart learning environments leverage AI to provide real-time feedback, optimize learning pathways, and enhance student engagement through interactive technologies. (Dai et al., 2021; Fu, 2022). ChatGPT, as an AI-powered learning assistant, exemplifies this transformation by offering personalized recommendations, answering queries, and fostering critical thinking through dialogue-based interactions (Abas et al., 2023; Wardat et al., 2023).

Previous research on AI acceptance in education does not fully explain how Generation Z students use ChatGPT in their learning. While previous studies have primarily examined AI adoption in general educational settings, limited attention has been given to the unique motivational and behavioral factors that drive ChatGPT usage among university students (Alshammari & Alshammari, 2024). Moreover, existing research has not fully explored the moderating effects of cultural and institutional differences on ChatGPT adoption, leaving an important avenue for further investigation. This study aims to fill this gap by examining Polish university students, shedding light on how cultural and educational factors shape their engagement with ChatGPT.

This study aims to address these gaps by providing a comprehensive analysis of the determinants of ChatGPT adoption among Generation Z students through the UTAUT2 framework. By investigating a broad range of determinants influencing AI adoption, this research seeks to provide insights into the adoption patterns and potential barriers influencing students' use of AI-powered educational tools. The findings will contribute to the broader discourse on AI in education, offering recommendations for enhancing AI integration in higher education institutions and optimizing student engagement with AI-driven learning platforms. By addressing these gaps, this study aims to provide actionable insights for educators and policymakers on how to optimize AI-powered educational tools in diverse cultural settings, while also deepening the understanding of key acceptance factors that influence student engagement with AI technologies in education.

While previous studies have explored AI acceptance in general educational contexts, few have focused specifically on the behavioral drivers behind ChatGPT adoption among Generation Z students (Baidoo-Anu & Owusu Ansah, 2023; Grassini, 2023). Moreover, there is limited research on this phenomenon in non-

Western or Central European settings, where cultural and institutional factors may differ. Therefore, the aim of this study is to examine the factors influencing Generation Z students' adoption of ChatGPT in higher education using the UTAUT2 framework, addressing the gap in research on AI tool adoption in a Central European context.

LITERATURE REVIEW

2.1. Historical Development and Key Technologies in AI Education

The development of artificial intelligence (AI) in education has evolved significantly since its inception in the mid-20th century. Early systems such as PLATO (Programmed Logic for Automatic Teaching Operations) in the 1960s aimed at automating educational processes and providing personalized instruction through adaptive feedback (Bates et al., 2020).

During the 1970s and 1980s, AI-based educational technologies expanded, with systems like SCHOLAR and GUIDON employing rule-based programming and cognitive science principles to simulate human-like instructional interactions (Chu et al., 2022). The 1990s introduced increased computing capabilities, greater data storage, and advanced algorithms, leading to smart learning environments and learning analytics platforms (Almasri, 2024). Machine learning (ML) and natural language processing (NLP) emerged as pivotal technologies for understanding learner behavior (Baidoo-Anu & Owusu Ansah, 2023).

From the 2000s onward, AI education systems advanced with improved ML techniques, NLP, and big data analytics, enabling more sophisticated interactive educational experiences. Generative AI models such as ChatGPT now provide highly adaptive and personalized learning opportunities (Alafnan et al., 2023; Bin-Nashwan et al., 2023). Key AI-driven technologies shaping modern education include (Yin et al., 2021):

- Machine Learning (ML): Algorithms capable of analyzing patterns in data to adapt and tailor educational experiences to individual learner needs.
- Natural Language Processing (NLP): Technology enabling AI to understand, interpret, and generate human language, crucial for interactive education.
- Adaptive Learning Systems (ALS): Personalized learning systems dynamically adjusting content delivery according to student performance and preferences.
- Learning Analytics (LA): Tools that gather, process, and interpret data on learners' behaviors and performances to inform teaching strategies and learning interventions.
- Chatbots and Virtual Assistants: Interactive AI systems providing personalized support, immediate feedback, and enhancing learner engagement, with ChatGPT being a prominent example.

These advancements have paved the way for smart learning, an evolution of AI-driven education focused on adaptability and efficiency.

2.2. Smart learning

Smart learning integrates AI, IoT, and analytics. This creates personalized, adaptive, and interactive educational environments (Dai et al., 2021; Li et al., 2015). By utilizing AI-driven solutions, smart learning enables real-time feedback, dynamic content delivery, and enhanced student engagement (Cheung et al., 2021). A defining feature of smart learning is context-awareness, where AI-driven technologies monitor and adjust learning experiences in real time based on student performance and engagement (Mohammed et al., 2022). Adaptive feedback mechanisms within smart learning environments (SLEs) provide personalized learning pathways, allowing students to receive targeted instructional support and enhance their self-regulated learning abilities (Peng et al., 2019). Additionally, ubiquitous technology integration ensures continuous access to educational resources, fostering flexibility and enabling learning across various digital platforms (Fu, 2022; Gambo & Shakir, 2019).

Smart learning environments overcome traditional classroom constraints by incorporating immersive technologies, such as virtual reality, AI-driven tutoring, and interactive simulations, which significantly enhance student engagement and deepen learning experiences (Dai et al., 2021; Zhu et al., 2016). Moreover,

AI-powered learning analytics refine teaching methodologies by tracking learner progress, identifying gaps in understanding, and facilitating adaptive interventions that cater to individual student needs (Li & Wong, 2021).

2.3. The Role of AI in Smart Learning in Higher Education

The development of artificial intelligence (AI) in higher education plays a crucial role in teaching and learning processes, supporting students through intelligent systems tailored to their individual needs. The integration of AI into academic education is transforming traditional learning models, enabling the personalization of educational content, automating assessment processes, and fostering independent knowledge acquisition (Chiu et al., 2023). Contemporary research highlights that AI influences students' educational experiences through key functions: personalized learning, intelligent assessment systems and student progress analysis, and the provision of interactive educational content (Almogren et al., 2024; Chiu et al., 2023; Chu et al., 2022; Isiaku et al., 2024).

One of the most significant aspects of AI applications in higher education is its ability to personalize learning paths. AI-driven systems use machine learning algorithms to analyze students' academic performance, identifying their individual needs, strengths, and weaknesses in the learning process (Chiu et al., 2023; Hirankerd & Kittisunthonphisarn, 2020; Yang & Shulruf, 2019). This enables the dynamic adjustment of educational materials to students' proficiency levels, enhancing knowledge retention and increasing motivation to learn (Baidoo-Anu & Owusu Ansah, 2023). Research indicates that AI-driven personalized learning contributes to higher student engagement and improved academic outcomes, which is reflected in intelligent tutoring models and adaptive learning platforms (M. Abbas et al., 2024; N. Abbas et al., 2022).

AI in higher education personalizes learning experiences, automates assessments, and provides interactive content, significantly improving student engagement and outcomes (Almogren et al., 2024; Chu et al., 2022; Sullivan et al., 2023; Veras et al., 2023). Tools such as ChatGPT enhance learning by offering immediate responses, explanations of complex topics, and summaries of academic materials (Victor, 2024). Additionally, AI-driven smart learning fosters collaborative learning experiences, enabling real-time discussions, peer-led projects, and digital communities, which strengthen critical thinking and problem-solving skills (Hwang et al., 2015; Nikolov et al., 2016).

Smart learning environments also help higher education institutions optimize processes such as course planning, performance tracking, and student support services. AI-powered tools allow educators to personalize lesson plans, identify at-risk students, and implement data-driven interventions, improving student retention and academic success (Almasri, 2024; Almogren et al., 2024). Universities increasingly rely on predictive analytics to anticipate learning trends and improve institutional decision-making (Cotton et al., 2024; Grassini, 2023).

AI further enhances assessment methods, offering automated grading and AI-driven feedback systems that provide real-time insights into student progress (Chan & Tsi, 2023). Such systems not only evaluate correctness but also analyze cognitive approaches, allowing educators to fine-tune instructional techniques (Chiu et al., 2023). The implementation of dynamic evaluation techniques measuring critical thinking, collaboration, and creativity is an essential aspect of AI-driven education.

By aligning AI with smart learning strategies, educational institutions can harness AI-powered insights to refine pedagogical methodologies, increase student engagement, and build a responsive, learner-centric education system. Future studies should explore ethical considerations surrounding AI-driven learning and its implications for long-term educational accessibility and equity.

2.4 ChatGPT as an Educational Tool

ChatGPT, developed by OpenAI, has emerged as a transformative tool in higher education, significantly enhancing both teaching and learning experiences (Hasanein & Sobaih, 2023). Leveraging AI-driven conversation models, it provides instant access to information, supports personalized learning, and fosters interactive educational environments (Nautiyal et al., 2023).

Previous studies have extensively analyzed the role of ChatGPT in student engagement, academic integrity, and AI-driven feedback systems (Hasanein & Sobaih, 2023; Ravšelj et al., 2025). Studies highlight its influence on cognitive development, accessibility to educational materials, and self-directed learning (Elshaer et al., 2024). It also presents ethical considerations, including AI bias and its impact on pedagogical frameworks (Kavitha & Joshith, 2024b).

ChatGPT enhances personalized learning by offering tailored responses and immediate feedback, promoting independent study habits (Abas et al., 2023; Lo, 2023). Students report increased engagement and academic enrichment through AI-assisted study tools (Kanwal et al., 2023; Yilmaz et al., 2023). According to technology acceptance models, perceived usefulness significantly impacts AI adoption in education (Yilmaz et al., 2023).

A global study involving 23,218 students from 109 countries found that ChatGPT is primarily used for brainstorming, summarizing, and retrieving research materials (Ravšelj et al., 2025). However, concerns persist regarding content reliability and ethical implications, reinforcing the need for AI literacy programs. Research indicates that male students show higher performance expectancy than females, while social influence plays a role in adoption within social sciences (Elshaer et al., 2024).

Qualitative studies have identified key motivations for integrating ChatGPT into academic workflows, including efficiency in information retrieval, language learning support, and research facilitation (Hasanein & Sobaih, 2023). However, concerns such as academic dishonesty, over-reliance on AI-generated content, and critical thinking erosion necessitate institutional guidelines and AI literacy training (Hasanein & Sobaih, 2023).

Despite its advantages, ChatGPT's integration raises ethical and practical challenges. Privacy concerns, trustworthiness, and task relevance influence AI adoption (Kavitha & Joshith, 2024a). Universities must address responsible AI usage, ensuring independent thought and academic integrity (Nugroho & Wuryani, 2023; Sullivan et al., 2023).

While ChatGPT fosters learning efficiency, excessive reliance on AI may hinder peer interaction and faculty-student engagement (Wardat et al., 2023). Over-dependence on AI-generated content risks diminishing collaborative discourse and interpersonal skill development (Yan et al., 2024). Additionally, Lozano & Blanco Fontao (2023) highlight that students perceive ChatGPT as a tool that provides immediate clarification on complex topics, reducing stress and fostering engagement in challenging coursework.

Studies demonstrate improved test performance among students using ChatGPT, particularly in conceptual understanding and problem-solving (Almogren et al., 2024). Additionally, AI-powered learning platforms facilitate interactive simulations and gamified learning experiences, further enhancing knowledge retention and engagement (Chiu et al., 2023; Grassini, 2023). However, balancing AI assistance with critical engagement remains a challenge (Veras et al., 2023).

Despite extensive research, gaps remain in understanding ChatGPT's adoption determinants. The role of cultural differences in AI adoption, as well as potential disparities in accessibility among different socioeconomic groups, require further investigation (Chiva-Bartoll et al., 2020; Chu et al., 2022). While studies have examined academic performance and motivation, empirical evidence on influencing factors is limited. This study explores how performance expectancy, effort expectancy, social influence, and hedonic motivation shape ChatGPT adoption in higher education, providing insights for optimizing AI-assisted learning environments (Hasanein & Sobaih, 2023).

2.5 UTAUT2 Framework in Educational Contexts

The Unified Theory of Acceptance and Use of Technology (UTAUT2) is an extension of the original UTAUT model, tailored to better address technology acceptance in consumer contexts. It was developed to improve the prediction of technology adoption behaviors by incorporating three additional constructs: hedonic motivation (HM), price value (PV), and habit (HT). These constructs, along with the original UTAUT constructs: performance expectancy (PE), effort expectancy (EE), social influence (SI), and facilitating conditions (FC), enhance the explanation of behavioral intention (BI) and technology use among consumers (Venkatesh et al., 2003, 2012).

In the realm of higher education, the UTAUT2 model is frequently employed to investigate determinants affecting students' and educators' intentions to adopt various technological solutions, including e-learning systems (Mehta et al., 2019; Raman & Thannimalai, 2021; Raza et al., 2022), metaverse (Al-Adwan & Al-Debei, 2024), immersive virtual and augmented reality (Bower et al., 2020; Faqih & Jaradat, 2021; F.-H. Huang, 2020), mobile applications (Ameri et al., 2020; Kang et al., 2015; Muangmee et al., 2021), virtual training platforms (Zacharis & Nikolopoulou, 2022) and learning management systems (Ain et al., 2016; Alotumi, 2022; Kumar & Bervell, 2019). Recent research emphasizes how contextual factors, such as the COVID-19 pandemic, can significantly moderate these relationships, demonstrating the adaptability of UTAUT2 in dynamic educational settings (Osei et al., 2022; Zacharis & Nikolopoulou, 2022). Furthermore, the model has proven effective in guiding the design and implementation of educational technology tools, as it comprehensively integrates hedonic, economic, and habitual factors alongside traditional determinants of technology adoption, thereby improving the predictability of user intentions and actual technology use across various educational contexts (Kavitha & Joshith, 2024a).

In essence, UTAUT2 offers a robust and comprehensive framework for understanding technology acceptance by incorporating psychological, economic, and habitual determinants along with conventional acceptance factors. It is thus particularly relevant for research in education, providing detailed insights into technology use patterns among learners and educators (Kavitha & Joshith, 2024b).

Based on the reviewed literature, it is evident that a detailed investigation into the behavioral drivers of ChatGPT adoption among Generation Z students is needed. This study addresses that need by applying the UTAUT2 framework in a Central European context.

METHODOLOGY

3.1 Research Hypotheses

Given that the primary aim of this research is to examine the behavioral factors influencing Generation Z's adoption and use of ChatGPT in higher education, the UTAUT2 model emerges as an appropriate theoretical lens. This model allows for a structured analysis of key predictors of technology acceptance among digital-native students, capturing both rational and experiential motivations behind their engagement with AI tools. Generation Z, generally defined as individuals born between the mid-1990s and early 2010s, represents digital natives who have grown up immersed in digital technology (Axcell & Ellis, 2023). They demonstrate high technology proficiency, frequently accessing personalized, interactive, and visually engaging digital resources, which enhance their problem-solving skills and adaptability (Saiyed et al., 2022; Seemiller & Grace, 2017).

Generation Z students are characterized by a strong preference for immediate access to knowledge and rapid adaptation to technological advancements, making them inherently inclined to adopt and use AI-powered tools across diverse aspects of their lives. Their constant exposure to digital environments shapes distinct learning preferences and behaviors, including a predilection for multimedia-rich, interactive, and hybrid learning approaches (Seemiller & Grace, 2017). Moreover, Generation Z exhibits notable attributes, such as strong aspirations toward success, a persistent desire for self-improvement, efficiency, and adaptability, which foster quick information acquisition and effective problem-solving skills (Saiyed et al., 2022). These attributes suggest a natural alignment with innovative educational technologies like ChatGPT, which offer immediacy, personalized assistance, and interactive functionalities appealing to this specific generational cohort (Chiu et al., 2023).

Consequently, the comprehensive structure of UTAUT2, integrating intrinsic (hedonic motivation), extrinsic (performance and effort expectancy), social, and contextual elements (facilitating conditions, social influences), aligns particularly well with Generation Z's technology acceptance characteristics. The increasing relevance of interactive, personalized, and engaging technological environments further supports the applicability of UTAUT2 for analyzing Generation Z's adoption behaviors in educational contexts (Alshammari & Alshammari, 2024).

Recent research employing the UTAUT2 model to examine factors influencing students' acceptance and adoption of ChatGPT demonstrates varied findings, highlighting considerable variability across empirical results. Specifically, studies reveal differing significance levels of individual UTAUT2 constructs, indicating that the importance and strength of factors influencing behavioral intentions and actual usage may vary depending on contextual, cultural, or demographic variables. Such variability underscores the need for continued research to further validate the model's applicability and robustness, particularly in newly emerging educational contexts such as the utilization of AI-based tools like ChatGPT.

Given this variability in existing findings, the purpose of the current study is to comprehensively examine the factors influencing Generation Z students' intention and actual usage of ChatGPT within the Polish higher education context. By doing so, the study will fill the identified research gap, providing deeper insights into the specific determinants of ChatGPT acceptance among Polish students from Generation Z. Consequently, this research contributes to the existing literature by clarifying the role of UTAUT2 constructs, thus offering theoretical enrichment and practical recommendations for educational institutions aiming to integrate ChatGPT effectively into the learning process.

The Unified Theory of Acceptance and Use of Technology (UTAUT2) includes seven primary constructs: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit, which together explain users' behavioral intention and actual usage behavior of new technologies (Venkatesh et al., 2012). This document provides detailed descriptions of each construct within the educational context of ChatGPT adoption among Generation Z university students, supported by empirical findings and corresponding research hypotheses.

Performance Expectancy (PE)

Performance Expectancy is defined as "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). This implies that individuals are more likely to adopt new technology if they believe it will enable them to perform their tasks more effectively (Chakava et al., 2018). In this study, Performance Expectancy refers to the extent to which students perceive ChatGPT as a useful educational tool, enabling them to accomplish tasks more efficiently, enhance their productivity, and improve their learning performance.

Previous studies on technology adoption consistently demonstrate that Performance Expectancy significantly predicts behavioral intention (Ahmed et al., 2020; Zhou et al., 2019). Research further confirms that students are more inclined to use technology when they believe it will improve their performance (Anthony et al., 2023). Specifically, Al-Emran et al. (2024), Almahri et al. (2020), and Rahim et al. (2022) have validated the positive association between Performance Expectancy and students' behavioral intention to use chatbots for learning purposes. ChatGPT's ability to provide auto-generated text-based information relevant to study topics allows learners to reduce time spent searching across multiple sources. Additionally, its summary-based content enhances students' reading and writing skills, reinforcing their learning effectiveness. Accordingly, we propose that:

H1: Performance Expectancy positively influences Generation Z students' behavioral intention to use ChatGPT.

Effort Expectancy (EE)

Effort Expectancy is defined as the degree of ease associated with using a technology, playing a crucial role in technology adoption (Hooda et al., 2022; Venkatesh et al., 2003). When students perceive a technology as easy to use, they are more likely to adopt it. In the context of ChatGPT, studies confirm that its perceived effortlessness directly influences students' behavioral intention to engage with the platform (Al-Emran et al., 2024).

Empirical evidence highlights that ChatGPT's minimal learning curve encourages student adoption, as it allows quick and efficient access to information without requiring extensive technical skills (Mohd Rahim et al., 2022). Additionally, findings indicate that Generation Z often perceives new technologies as user-friendly, reinforcing their inclination to engage with AI-powered tools like ChatGPT (Ahmed et al., 2020).

Furthermore, research comparing various educational technologies consistently validates effort expectancy as a§ strong predictor of behavioral intention, including in mobile learning and e-learning platforms (Zhou et al., 2019). Accordingly, we propose that:

H2: Effort Expectancy positively influences Generation Z students' behavioral intention to use ChatGPT.

Social Influence (SI)

Social Influence refers to the degree to which individuals perceive that significant others, such as peers, teachers, and family members, encourage the use of a particular technology (Venkatesh et al., 2012). It affects individual behavior through mechanisms like compliance, internalization, and identification, which can shape beliefs and decision-making regarding technology adoption (Dwivedi et al., 2019).

While Social Influence has been a key determinant in the adoption of e-learning systems (Salloum & Shaalan, 2019), its impact on ChatGPT adoption appears less robust. In previous studies, conflicting findings can be observed regarding its significance. Research utilizing an extended UTAUT2 framework suggests that while Social Influence is generally important in technology adoption, its direct effect on students' behavioral intentions to use ChatGPT is not always significant (Ahmed et al., 2020). This may be due to the growing independence of Generation Z in technology adoption, where facilitating conditions and usability play a more dominant role (Mohd Rahim et al., 2022).

Contrasting perspectives exist regarding Social Influence in chatbot adoption. Some studies highlight its role in collaborative learning environments, reinforcing engagement through peer interactions (Al-Emran et al., 2024). Others argue that as technologies like ChatGPT become deeply integrated into daily student practices, their acceptance depends more on accessibility and ease of use rather than social encouragement (Lu, 2014). The divergence in findings underscores the need for continued exploration of Social Influence in the context of AI-driven educational tools. Given these perspectives, we propose the following hypothesis

H3: Social Influence positively influences Generation Z students' behavioral intention to use ChatGPT.

Facilitating Conditions (FC)

Facilitating Conditions refer to the availability of resources, support systems, and infrastructure that enable effective technology use (Venkatesh et al., 2012). These include technical support, internet access, and institutional policies (Alshammari & Alshammari, 2024; Strzelecki, 2024b).

Studies confirm that facilitating conditions significantly influence students' behavioral intention to use ChatGPT. Seamless access to devices and internet connectivity enhances adoption rates (Mohd Rahim et al., 2022). Additionally, institutional support, such as guidance from educators and technical assistance, reinforces students' confidence in using ChatGPT for learning (Al-Emran et al., 2024).

Research highlights that students who perceive strong facilitating conditions are more likely to integrate AI tools into their academic routines (Ahmed et al., 2020). Generation Z, being digital natives, expects intuitive access to technology, making institutional support crucial (Zhou et al., 2019). Based on these insights, we propose the following hypotheses:

H4: Facilitating Conditions positively influence Generation Z students' behavioral intention to use ChatGPT.
H5: Facilitating Conditions positively influence the actual use of ChatGPT among Generation Z students.

Hedonic Motivation (HM)

Hedonic Motivation is defined as the intrinsic enjoyment or pleasure individuals experience from using technology (Venkatesh et al., 2012). Generation Z students seek interactive, engaging, and enjoyable digital experiences, making Hedonic Motivation a key driver of technology adoption.

Several studies confirm that students are more inclined to use ChatGPT when they find it enjoyable. Grassini et al. (2024) highlight that hedonic motivation positively influences behavioral intention, as

students perceive ChatGPT as a fun and engaging tool in their academic activities. Similarly, Foroughi et al. (2024) found that the satisfaction students derive from using AI-powered tools enhances their willingness to adopt them. Yilmaz et al. (2023) further reinforce that intrinsic enjoyment significantly contributes to behavioral intention, suggesting that students are more likely to continue using ChatGPT when they find it engaging.

While hedonic motivation is not the sole predictor of adoption, its role remains significant, particularly in the initial engagement phase (Strzelecki, 2024). This underscores the importance of designing AI-based educational tools that maximize user enjoyment to encourage long-term adoption. Based on these insights, we propose the following hypothesis:

H6: Hedonic Motivation positively influences Generation Z students' behavioral intention to use ChatGPT.

Price Value (PV)

Price Value represents the perceived benefit-cost trade-off related to using a technology (Venkatesh et al., 2012). ChatGPT offers both free and paid versions, leading students to evaluate its value not solely in financial terms but also in its educational benefits, such as learning efficiency and time-saving (Foroughi et al., 2024).

Studies indicate that Price Value has a minimal effect on students' behavioral intention to use ChatGPT, likely due to the accessibility of a free version (Grassini, 2023). Instead of focusing on direct costs, students assess ChatGPT's utility in achieving their academic goals, making its perceived educational value a stronger determinant of usage (Foroughi et al., 2024).

Additionally, research suggests that the impact of Price Value depends on how students perceive the general utility of the technology. When students recognize tangible academic benefits, they are more inclined to engage with ChatGPT, regardless of pricing considerations (Almogren et al., 2024). However, further studies are needed to examine how Price Value influences adoption if future pricing structures change (Strzelecki, 2024b). Based on these insights, we propose the following hypothesis:

H7: Price Value positively influences Generation Z students' behavioral intention to use ChatGPT.

Habit (HT)

Habit refers to the extent to which individuals tend to perform behaviors automatically due to past experiences or repeated usage patterns (Venkatesh et al., 2012). Empirical studies consistently identify Habit as a critical determinant of both intention and actual use of educational technologies (Foroughi et al., 2024; Strzelecki, 2024b).

Several studies confirm that habit plays a crucial role in the behavioral intention to use ChatGPT. Foroughi et al. (2024) found that students who develop a routine of using ChatGPT are more likely to maintain long-term engagement with the tool. Their research highlights that habitual usage has a direct effect on user behavior, particularly in educational settings. Alshammari & Alshammari (2024) further support this finding, emphasizing that students' frequency of use contributes to the formation of habitual behavior. Regular interaction with ChatGPT fosters familiarity, leading to increased comfort and sustained use over time. Similarly, Yilmaz et al. (2023) identified habit as one of the strongest predictors of students' behavioral intentions, indicating that academic routines incorporating ChatGPT reinforce its continued use.

Additionally, Polyportis & Pahos (2025) noted that habitual engagement with ChatGPT leads to deeper integration of AI technology in academic practices. Their study found that students who developed a habit of using ChatGPT consistently relied on it for learning tasks, reinforcing its role as an educational tool. While habit may not be the sole determinant of technology adoption, its strong influence on behavioral intention suggests that as students incorporate ChatGPT into their regular study routines, they are more likely to continue using it. Based on these insights, we propose the following hypothesis:

H8: Habit positively influences Generation Z students' behavioral intention to use ChatGPT.

H9: Habit positively influences the actual use of ChatGPT by Generation Z students.

Behavioral Intention (BI)

Behavioral Intention describes individuals' willingness to adopt and utilize specific technologies (Venkatesh et al., 2012). Numerous studies confirm that BI is a strong predictor of actual technology use, directly impacting student engagement with ChatGPT (Foroughi et al., 2024; Strzelecki, 2024b).

Research highlights that students with a high intention to use ChatGPT are significantly more likely to integrate it into their academic routines (Strzelecki, 2024a). This is reinforced by findings showing that positive attitudes and strong behavioral intentions drive actual usage behavior (Bin-Nashwan et al., 2023). Furthermore, studies indicate that constructs such as Performance Expectancy and Habit strengthen this relationship, as students who find ChatGPT useful and develop habitual usage patterns tend to maintain long-term engagement (Maruszewska et al., 2024).

The application of the UTAUT2 model further supports this link, demonstrating that BI significantly explains variations in actual use behavior (Foroughi et al., 2024). These findings confirm that a strong intention to use ChatGPT translates into consistent engagement with the tool. Based on these insights, we propose the following hypothesis:

H10: Behavioral Intention positively influences the actual usage behavior of ChatGPT among Generation Z students.

The theoretical model illustrating the hypothesized relationships between the studied constructs is presented in Figure 1. Based on the UTAUT2 framework, it outlines the predictors of Behavioral Intention and Use Behavior in the context of ChatGPT adoption among Generation Z students. This model serves as the foundation for hypothesis testing in the study.

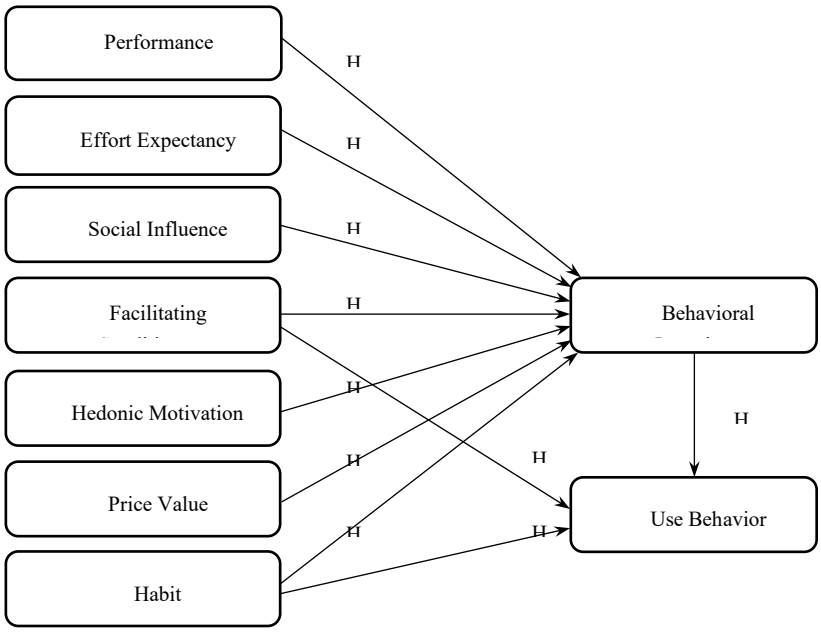


Figure 1. Theoretical framework for ChatGPT adoption and usage among Generation Z students
Source: own elaboration.

3.2 Measurement scale

The data collection method employed in this study utilized a seven-point Likert scale, where respondents were provided with options ranging from "strongly disagree" (1) to "strongly agree" (7).

This scale ensured consistency in assessing respondents' perceptions and attitudes toward ChatGPT usage. To measure Use Behavior**, a** seven-option frequency scale was employed, capturing the extent of students' engagement with ChatGPT. The response categories were structured on a scale from 1 to 7, where 1 corresponds to "Never", 2 to "Once a month" 3 to "Several times a month", 4 to "Once a week", 5 to "Several times a week", 6 to "Once a day", and 7 to "Several times a day".

Table 1. Measurement items

Construct	Item	Statement
Performance Expectancy (PE)	PE1	Using ChatGPT increases my learning efficiency.
	PE2	ChatGPT helps me achieve better results in academic tasks.
	PE3	ChatGPT allows me to find necessary information more quickly.
	PE4	I consider ChatGPT useful in my education process.
Effort Expectancy (EE)	EE1	ChatGPT is easy to use.
	EE2	Interacting with ChatGPT is clear and understandable.
	EE3	Even if technical issues arise, using ChatGPT is easy to manage.
	EE4	Learning how to use ChatGPT took me little time.
Social Influence (SI)	SI1	My friends/students think I should use ChatGPT.
	SI2	Instructors and other educational authorities encourage me to use ChatGPT.
	SI3	People important to me consider using ChatGPT a good idea.
Facilitating Conditions (FC)	FC1	I have access to the necessary tools to use ChatGPT (e.g., computer, internet).
	FC2	I know how to get help if I encounter issues with ChatGPT.
	FC3	There are resources and support available to facilitate my use of ChatGPT.
Hedonic Motivation (HM)	HM1	Using ChatGPT is enjoyable for me.
	HM2	I find ChatGPT interesting and engaging.
	HM3	Using ChatGPT makes learning more satisfying.
Habit (HT)	HT1	Using ChatGPT feels natural to me.
	HT2	I use ChatGPT frequently because I am accustomed to it.
	HT3	I feel the need to use ChatGPT in my daily learning.
	HT4	My habit of using ChatGPT helps me complete academic tasks more efficiently.
Price Value (PV)	PV1	Using ChatGPT is worth its price (if it is a paid version).
	PV2	I believe the benefits of using ChatGPT outweigh potential costs (time, money).
	PV3	Even if ChatGPT required payment, I would consider using it.
Behavioral Intention (BI)	BI1	I intend to use ChatGPT for educational purposes in the future.
	BI2	I plan to recommend ChatGPT to other students.
	BI3	I will use ChatGPT more frequently in the coming months.
Use Behavior (UB)	UB1	How often do you use ChatGPT?

Source: own elaboration.

A total of 27 items were used in the questionnaire, incorporating elements from Venkatesh et al.'s (2012, 2012) UTAUT and UTAUT2 models, along with refinements based on prior research on AI adoption in education. A detailed presentation of the measurement scale and descriptive statistics is available in Table 1**.** This approach ensures that the study adheres to best practices in technology adoption research, providing a robust framework for analyzing ChatGPT usage patterns among Generation Z students.

3.3 Sample Characteristics

In Partial Least Squares Structural Equation Modeling (PLS-SEM) research, selecting an appropriate sample size is critical for ensuring reliable and valid results. The required number of participants is influenced by multiple factors, including the complexity of the model, the number of latent variables and indicators, the strength of relationships between variables, and the statistical power needed for the analysis (Hair et al., 2013). While some scholars argue that at least 100–200 observations are sufficient (Kock, 2018), others recommend a ratio of at least 5:1 or 10:1 between the sample size and the number of indicators. Given that this study includes 27 indicators, a minimum of 280 responses was required to ensure statistical adequacy.

The data collection was conducted in February 2025 at the University of Szczecin, Poland. The questionnaire was distributed electronically via Google Forms and sent directly to students' university email addresses. A total of 346 valid responses were obtained.

The sample comprised students from various academic backgrounds and levels of study: 64.7% of respondents were female students, 32.9% were male students, 2.3% preferred not to disclose their gender. In terms of academic progression, the distribution was as follows: 77.7% undergraduate (bachelor's) students, 22.0% master's students, 0.3% PhD candidates. Regarding the mode of study: 91.3% were enrolled in full-time programs, 8.7% were part-time (extramural) students. The diversity of respondents in terms of gender, study level, and study mode ensures that the dataset is representative of Generation Z's adoption of ChatGPT in a university environment.

RESULTS

The analysis began with a descriptive statistical summary of the studied variables. Table 2 presents the means (M), standard deviations (SD), and factor loadings for each construct in the model. According to the literature, acceptable factor loadings should fall within the range of 0.5–0.7 for minimal acceptability and above 0.7 for strong indicators (Hair et al., 2013). For further analysis, the SI2 and FC1 items were removed due to their factor loadings being below the acceptability threshold, which could negatively affect model reliability. To provide an overview of the key findings, the following subsections summarize the most relevant descriptive statistics:

- The highest mean values were observed for Effort Expectancy (M = 6.27, SD = 1.30) and Facilitating Conditions (M = 6.72, SD = 0.79), indicating that students generally perceive ChatGPT as an easy-to-use tool and have access to sufficient resources supporting its utilization.

The lowest mean values were recorded for Social Influence (M = 3.28, SD = 1.72) and Price Value (M = 4.01, SD = 1.98), suggesting that social pressure is not a key factor in ChatGPT adoption, and its financial value is of moderate importance. To verify the reliability and validity of the measurement model, a construct reliability analysis was conducted. The results in Table 3 showed that all Cronbach's alpha values exceeded 0.65, indicating acceptable internal scale consistency. According to Nunnally (1994), a Cronbach's alpha above 0.70 is considered good, while values between 0.60 and 0.70 are acceptable for exploratory research. Additionally, Composite Reliability (CR) values were above 0.75, which exceeds the recommended threshold of 0.70 (Hair et al., 2019). The Average Variance Extracted (AVE) values for all constructs were greater than 0.5, which confirms the convergent validity of the model as per Fornell and Larcker (1981).

The next step involved analyzing the correlation matrix for the variables in the model (Table 4). The most notable observations include:

- The strongest correlation was found between habit and behavioral intention (r = 0.702), suggesting that users who engage with ChatGPT habitually are more likely to intend to continue using it.
- Behavioral intention showed a moderate correlation with use behavior (r = 0.476), indicating that while intention plays a role in actual usage, other factors are also influential.
- **Weak correlations** were observed for **effort expectancy and behavioral intention (r = 0.102)**, as well as **social influence and behavioral intention (r = 0.093)**, suggesting a limited effect of these variables on the adoption process.

Table 2. Measurement Items and Factor Loadings

Construct	Item	Mean	Standard Deviation	Loading
Performance	PE1	4.988	1.684	0.643
Expectancy (PE)	PE2	5.413	1.521	0.656
	PE3	6.194	1.256	0.618
	PE4	5.659	1.43	0.720
Effort Expectancy (EE)	EE1	6.399	0.988	0.717
	EE2	5.65	1.322	0.699
	EE3	5.668	1.363	0.703
	EE4	6.272	1.299	0.616
Social Influence (SI)	SI1	5.387	1.603	0.621
	SI2	***3.289***	***1.72***	***0.579***
	SI3	4.858	1.603	0.631
Facilitating Conditions	***FC1***	***6.723***	***0.79***	***0.474***
(FC)	FC2	5.009	1.849	0.612
	FC3	5.127	1.788	0.644
Hedonic Motivation	HM1	5.526	1.479	0.857
(HM)	HM2	5.509	1.527	0.871
	HM3	5.231	1.774	0.858
Habit (HT)	HT1	5.254	1.645	0.792
	HT2	4.879	1.909	0.843
	HT3	4.092	2.048	0.816
	HT4	5.153	1.781	0.796
Price Value (PV)	PV1	4.017	1.988	0.790
	PV2	4.618	1.863	0.774
	PV3	4.327	2.056	0.798
Behavioral Intention	BI1	5.714	1.473	0.825
(BI)	BI2	5.275	1.742	0.816
	BI3	5.09	1.781	0.791
Use Behavior (UB)	UB1	5.535	1.283	1.0

Source: own elaboration.

Table 3. Construct Reliability and Validity

CONSTRUCT	CRONBACH'S ALPHA	COMPOSITE RELIABILITY	RELIABILITY COEFFICIENT	AVE
PE	0.741	0.636	0.798	0.636
EE	0.766	0.657	0.810	0.657
SI	0.657	0.554	0.745	0.554
FC	0.813	0.710	0.843	0.710
HM	0.887	0.685	0.827	0.685
HT	0.916	0.644	0.802	0.644
PV	0.859	0.609	0.780	0.609
BI	0.836	0.588	0.767	0.588

Source: own elaboration.

Correlation values above 0.7 indicate strong relationships, while those between 0.3 and 0.7 suggest moderate associations, and values below 0.3 indicate weak correlations (Cohen, 1988). These results confirm that habit is the most significant driver of behavioral intention, whereas external influences such as social factors have minimal impact.

Table 4. Correlation Matrix of Constructs

	PE	EE	SI	FC	HM	HT	PV	BI	UB
PE	1.0								
EE	0.384	1.0							
SI	0.467	0.290	1.0						
FC	0.327	0.416	0.363	1.0					
HM	0.578	0.389	0.451	0.434	1.0				
HT	0.572	0.371	0.442	0.364	0.591	1.0			
PV	0.440	0.331	0.375	0.369	0.422	0.504	1.0		
BI	0.640	0.379	0.476	0.393	0.619	0.702	0.552	1.0	
UB	0.345	0.259	0.263	0.263	0.344	0.593	0.318	0.476	1.0

Source: own elaboration.

To further validate the discriminant validity of the constructs, the Fornell-Larcker Criterion Matrix was analyzed (Table 5). This method ensures that the square root of the AVE for each construct is higher than its correlation with other constructs (Fornell & Larcker, 1981). Key findings include:

- All constructs met the Fornell-Larcker criteria, confirming that each construct is distinct from the others.
- The highest AVE values were observed for Habit (AVE = 0.729) and Performance Expectancy (AVE = 0.701), indicating strong construct validity.
- The lowest AVE values were found for Social Influence (AVE = 0.512) and Facilitating Conditions (AVE = 0.524)**,** but they still met the minimum threshold of 0.5, suggesting acceptable validity.

These results support the robustness of the measurement model and confirm that each construct captures unique variance in the dataset.

Table 5. Fornell-Larcker Criterion Matrix

	PE	EE	SI	FC	HM	HT	PV	BI	UB
PE	0.797	0.384	0.467	0.327	0.578	0.572	0.440	0.640	0.345
EE	0.384	0.811	0.290	0.416	0.389	0.371	0.331	0.379	0.259
SI	0.467	0.290	0.744	0.363	0.451	0.442	0.375	0.476	0.263
FC	0.327	0.416	0.363	0.843	0.434	0.364	0.369	0.393	0.224
HM	0.578	0.389	0.451	0.434	0.828	0.591	0.422	0.619	0.344
HT	0.572	0.371	0.442	0.364	0.591	0.802	0.504	0.702	0.593
PV	0.440	0.331	0.375	0.369	0.422	0.504	0.780	0.552	0.318
BI	0.640	0.379	0.476	0.393	0.619	0.702	0.552	0.767	0.476
UB	0.345	0.259	0.263	0.224	0.344	0.593	0.318	0.476	1.0

Source: own elaboration.

The structural model path analysis provided insights into the relationships between the studied variables (Table 6 and Figure 2). The results indicate that not all hypotheses were confirmed. To determine whether a hypothesis was supported, statistical significance was assessed using p-values (<0.05 considered significant) and standardized path coefficients (β-values) to measure the strength of relationships.

The findings indicate that performance expectancy ($\beta = 0.247$, $p < 0.001$), hedonic motivation ($\beta = 0.164$, $p = 0.001$), and habit ($\beta = 0.279$, $p < 0.001$) significantly influenced behavioral intention, confirming H1, H5, and H8, respectively, suggesting that students adopt ChatGPT when they perceive it as

useful, enjoyable, and have developed a habit of using it. Among these, habit had the strongest effect on actual use behavior, supporting H9 and highlighting its critical role in technology adoption.

Conversely, effort expectancy (H2), social influence (H3), and facilitating conditions (H4) did not have a significant impact on behavioral intention, indicating that ease of use, peer influence, and external support were not key drivers of ChatGPT adoption. Additionally, the relationship between behavioral intention and use behavior was not statistically significant, implying that mere intention does not necessarily translate into sustained usage. These findings underscore the importance of intrinsic motivation and habitual engagement in technology adoption, while external influences and usability factors appear to play a lesser role.

Table 6. Path Coefficients and Hypothesis Testing

Hypothesis	Path	Coefficient	P values	f^2	Confirmed
H1	Performance Expectancy → Behavioral Intention	**0.247**	**0.000**	**0.076**	**Yes**
H2	Effort Expectancy → Behavioral Intention	0.015	0.758	0.000	No
H3	Social Influence → Behavioral Intention	0.063	0.123	0.008	No
H4	Facilitating Conditions → Behavioral Intention	0.024	0.478	0.002	No
H5	Facilitating Conditions → Use Behavior	-0.007	0.860	0.000	No
H6	**Hedonic Motivation → Behavioral Intention**	**0.164**	**0.001**	**0.037**	**Yes**
H7	**Price Value → Behavioral Intention**	**0.127**	**0.000**	**0.052**	**Yes**
H8	**Habit → Behavioral Intention**	**0.279**	**0.000**	**0.166**	**Yes**
H9	**Habit → Use Behavior**	**0.397**	**0.000**	**0.203**	**Yes**
H10	Behavioral Intention → Use Behavior	0.116	0.068	0.011	No

Source: own elaboration.

The explained variance of the model was assessed using R^2 and Q^2 values. R^2 indicates the proportion of variance explained by the independent variables, while Q^2 represents the predictive relevance of the model.

- Behavioral Intention ($R^2 = 0.631$, $Q^2 = 0.631$) → The model explains 63.1% of the variance in behavioral intention, suggesting a strong predictive capability.
- Use Behavior ($R^2 = 0.358$, $Q^2 = 0.358$) → The model accounts for 35.8% of the variance in actual use behavior, indicating a moderate explanatory power.

According to Falk and Miller (1992), R^2 values above 0.26 are considered substantial, values around 0.13 are moderate, and those below 0.02 are weak. The results suggest that the model provides a solid explanation for behavioral intention but has a more moderate ability to predict actual use behavior. The Q^2 values above zero confirm that the model has predictive relevance (Hair et al., 2013).

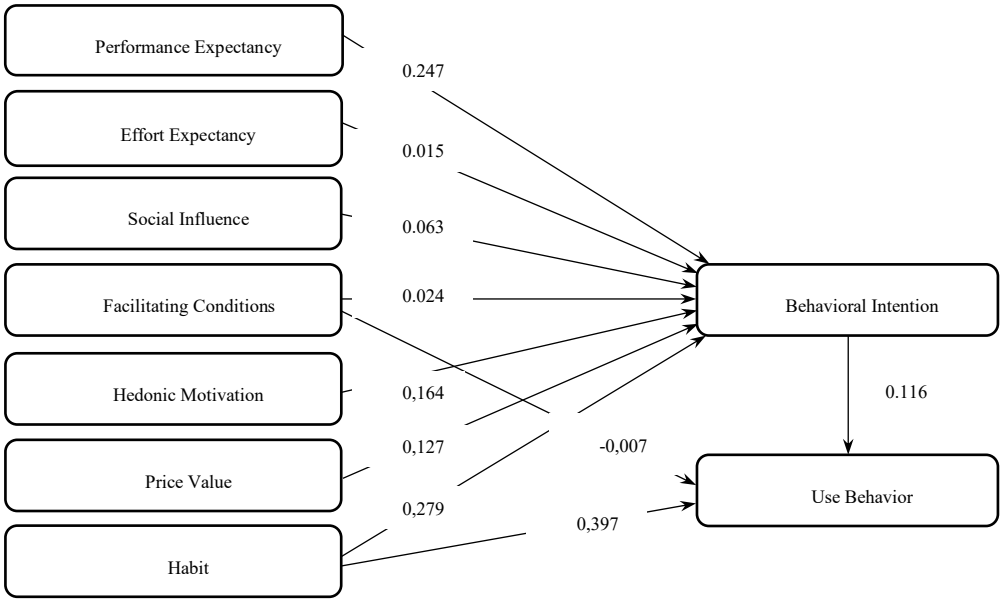


Figure 2. Final Structural Model: Path Coefficients and Hypothesis Testing
Source: own elaboration.

DISCUSSION

The findings of this study provide valuable insights into the factors influencing the adoption of ChatGPT among Generation Z students in higher education, using the UTAUT2 framework. This directly supports the aim of the study, which was to identify key predictors of ChatGPT adoption within this digital-native group. The key predictors of ChatGPT use were usefulness, enjoyment, and habit. Students view ChatGPT as a helpful and engaging tool that supports their learning. These findings align with prior research emphasizing the role of perceived usefulness and enjoyment in technology adoption (Hasanein & Sobaih, 2023; Yilmaz et al., 2023). The significance of habit also reflects earlier studies that identified routine engagement as a strong driver of sustained use of AI tools (Baidoo-Anu & Owusu Ansah, 2023; Grassini, 2023).

However, our findings contrast with those of Menon & Shilpa (2023), who found that facilitating conditions played a more dominant role in AI adoption among students in non-technical disciplines. In our study, facilitating conditions and effort expectancy were not significant, which may reflect Generation Z's high level of digital literacy and comfort with independent use of technology. These results suggest that institutions aiming to promote AI adoption among students should focus on integrating tools like ChatGPT into daily academic tasks, while emphasizing their usefulness and potential for enhancing engagement, rather than relying on peer encouragement or institutional support systems.

Effort expectancy, social influence, and facilitating conditions had little impact on behavioral intention. Generation Z students, as digital natives, easily navigate AI tools independently. Prior studies have reported similar trends, indicating that ease of use is less critical for technology adoption among highly digitalized user groups (Chu et al., 2022; Elshaer et al., 2024). However, this contradicts findings from Okonkwo & Ade-Ibijola (2021), who highlighted that social influence played a significant role in AI adoption in contexts where digital literacy was lower. This suggests that in less digitally literate environments, students may rely

more on recommendations from peers and instructors when adopting new AI tools, whereas in highly digitalized contexts, self-efficacy and habitual use become more dominant factors.

The findings also reveal a discrepancy between behavioral intention and actual use behavior**,** suggesting that while students express strong intentions to use ChatGPT, external factors may influence sustained adoption. This is particularly relevant in the context of educational policies, institutional AI guidelines, and ethical considerations surrounding AI-generated content (Nugroho & Wuryani, 2023; Sullivan et al., 2023). Similar concerns were raised by Dempere et al. (2023), who noted that faculty-imposed restrictions and concerns about academic dishonesty may prevent students from fully utilizing AI-driven learning tools.

This study confirms that habit is the strongest factor predicting actual ChatGPT use. Students who use the tool regularly are more likely to keep using it. This supports previous research highlighting that once students incorporate AI into their study routines, they are more likely to rely on it consistently (Almogren et al., 2024; Foroughi et al., 2024). Similar conclusions were drawn by Grassini et al. (2023), who emphasized that habit formation is a key determinant of technology persistence, particularly in self-directed learning environments.

The study also highlights potential socioeconomic and cultural disparities in AI adoption. The results suggest that while students generally report high levels of access to ChatGPT, their ability to effectively integrate it into their learning varies depending on institutional and contextual factors. Digital readiness and AI literacy were found to be inconsistent across different academic institutions, indicating that while students may be familiar with AI tools, their ability to leverage them for meaningful learning differs (Chiva-Bartoll et al., 2020; Chu et al., 2022). This underscores the need for universities to not only provide access to AI-driven tools but also develop structured AI adoption strategies that support skill development and equitable engagement. Vargas-Murillo et al. (2023) similarly stressed that unregulated AI adoption could widen existing educational inequalities, making AI literacy initiatives crucial for ensuring inclusive learning environments.

Additionally, the ethical implications of AI use in education remain a critical area for consideration. While ChatGPT facilitates personalized learning and academic efficiency, concerns regarding plagiarism, over-reliance on AI-generated content, and critical thinking erosion must be addressed through institutional AI literacy programs (Lozano & Blanco Fontao, 2023; Wardat et al., 2023). Victor (2024) argues that over-reliance on AI-driven tools may lead to declining problem-solving skills among students, reinforcing the necessity of policies that balance AI integration with traditional pedagogical methods.

Although the data were collected in Poland, the findings offer insights relevant to higher education institutions worldwide. The behavioral patterns observed among Generation Z students—especially the dominant role of habit, enjoyment, and perceived usefulness—are likely to be applicable in other digitally literate populations. These insights can inform global strategies for integrating AI tools like ChatGPT into academic environments by highlighting the importance of embedding them into students' daily routines and making them both useful and engaging. Furthermore, this research contributes to the broader understanding of AI adoption by students, helping international educators and policymakers anticipate how young users engage with AI-driven technologies. These findings are particularly relevant in the context of the growing global demand for scalable, AI-supported learning solutions that align with learners' preferences and behaviors.

Despite the relevance and consistency of the findings, this study has some limitations that should be acknowledged. First, the sample is limited to university students in Poland, which may affect the generalizability of the findings to other cultural or educational contexts. Future research should include comparative studies involving students from different countries or regions. Second, the data were collected through self-reported questionnaires, which can be subject to response biases such as social desirability or inaccurate self-assessment. Combining quantitative surveys with qualitative interviews or behavioral data could improve the robustness of future studies. Third, the complexity of the UTAUT2 framework and statistical techniques like PLS-SEM may pose challenges for interpretation by readers unfamiliar with these methods. Future research might explore simpler models or apply mixed-methods approaches for better accessibility. Despite these limitations, the study offers valuable insights into the behavioral factors driving ChatGPT adoption and provides a foundation for further research in AI-supported education.

Compared to prior studies, our findings reinforce the importance of intrinsic motivators such as habit and enjoyment over external conditions like peer influence or institutional support, particularly among digitally literate populations. This suggests a shift in technology adoption logic among Generation Z students, who are increasingly autonomous and goal-oriented in their use of AI tools. The added value of our study lies in applying the UTAUT2 model specifically to ChatGPT adoption in a Central European context, which has been largely underrepresented in existing research. By focusing on this emerging technology within a defined sociocultural environment, the study not only validates the UTAUT2 framework across settings but also highlights the need for locally tailored AI strategies in education.

CONCLUSION

This study contributes to the growing body of literature on AI adoption in higher education by applying the UTAUT2 framework to analyze ChatGPT usage among Generation Z students. Results show habit and perceived usefulness strongly influence students' adoption of ChatGPT. In contrast, ease of use and social influence have minimal impact. These results support the importance of habitual technology use and intrinsic motivation in AI-assisted learning environments. Our findings also highlight that AI literacy disparities and institutional policies significantly influence long-term adoption (Dikilitaş et al., 2024; Yin et al., 2021).

From a practical perspective, university administrators and educators should use these findings to develop AI-integrated learning strategies that align with students' study behaviors. This includes promoting responsible AI use, enhancing AI literacy, and ensuring equitable access to AI-driven tools. Moreover, policymakers should focus on guidelines that regulate AI use while maintaining academic integrity and encouraging critical thinking (Chan & Tsi, 2023).

Future research should explore the long-term impact of AI integration on student engagement and learning outcomes. Comparative studies across different educational systems could provide deeper insights into how institutional and cultural factors shape AI adoption patterns. Additionally, investigating the intersection of personality traits and motivation in AI use may yield new perspectives on technology acceptance models (Osei et al., 2022).

Overall, while ChatGPT presents opportunities to enhance learning, its effectiveness depends on responsible implementation, habitual engagement, and institutional support**.** By addressing these aspects, universities can optimize AI-driven education and support student success in an increasingly digital learning landscape.

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MEDIA CONSUMPTION PATTERNS OF GENERATION Z IN POLAND IN THE ERA OF AI DEVELOPMENT: A CONTENT-CENTERED ANALYSIS OF TRADITIONAL AND DIGITAL PLATFORMS

Edyta Rudawska[a], Luca Giraldi[b]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *University of Turin, Department of Law, Turin, Italy*

ABSTRACT

Purpose: *This paper examines how Generation Z (Gen Z) in Poland consumes media content, news/information, music, and entertainment amid rapid digital transformations and the growing role of artificial intelligence (AI). Unlike channel-based studies, this content-centered approach underscores Gen Z's on-demand usage patterns and the implications for traditional and digital media platforms.*

Methodology: *A quantitative survey (N=621) of Polish Gen Z respondents was conducted between January and April 2023 using a CAWI (Computer-Assisted Web Interview) technique. The study captured the frequency and mode of content consumption (news/information, music, movies/series) across various platforms, from traditional television and radio to social media, search engines, and video-on-demand (VOD) services. Descriptive statistics were used to identify consumption trends and preferences.*

Findings: *Results reveal that Gen Z predominantly relies on smartphones and digital platforms, especially social media, VOD services, and AI-driven systems (e.g., recommendation engines) for all three types of content studied. Traditional media (television and radio) emerge as complementary rather than primary sources and are used sporadically or in online/on-demand forms. Meanwhile, excessive advertising, lack of immediate availability, and minimal personalisation dampen interest in traditional outlets. Most respondents value the convenience and customisation enabled by AI-supported recommendation features, which guide their discovery of new content.*

Practical Implications: *To stay relevant, traditional media players must invest in digital presence, enhance on-demand options, and leverage AI-driven personalisation. Such steps can help reduce reliance on rigid schedules and prolonged advertising breaks—features poorly aligned with Gen Z's expectations of immediacy and customised experiences.*

Originality/Value: *By focusing on content types rather than solely on platforms, this study addresses a gap in the literature concerning Gen Z's cross-platform media consumption. The insights highlight AI's increasingly pivotal role in shaping Gen Z's media habits and underscore the need for adaptive strategies across the media industry.*

Keywords: Generation Z, Media Consumption, AI-Driven Media, Digital Transformation, Digital Innovation, Quantitative Research

Jel codes: M30; M15; D83

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1. INTRODUCTION

Contemporary consumer behaviours have undergone a swift digital transition, developing faster than anticipated (Ghosh et al., 2022). This paradigm shift is also evident in today's media consumption landscape. Contemporary media organizations must introduce a concept of intelligent management to create successful content. It means they must integrate data-driven decision-making, adaptive systems, and cognitive technologies to enhance organizational effectiveness. In the media industry, where content production, distribution, and consumption are rapidly evolving, intelligent management plays a crucial role in navigating complex market dynamics. The concept includes the use of artificial intelligence to optimize content creation and audience engagement among others (Davenport & Ronanki, 2018). For instance, recommendation algorithms on streaming platforms like Netflix or YouTube exemplify intelligent engagement by analyzing user behavior to personalize content (Gomez-Uribe & Hunt, 2016). Furthermore, media companies employ intelligent management practices to monitor real-time analytics, forecast trends, and automate content moderation (Napoli, 2014). The shift towards intelligent management is also evident in newsroom operations, where AI tools assist in news curation and fact-checking, enhancing journalistic productivity while maintaining editorial standards (Diakopoulos, 2019). Intelligent management in the media industry embodies a convergence of technological capability and strategic foresight, enabling organizations to adapt and thrive in an increasingly digital and competitive landscape.

Historically, traditional media outlets–specifically television, print, and radio—effectively provided various content. However, the proliferation of new media platforms and the ascendance of AI-driven solutions have diminished people's time on these conventional channels (Tsoy et al., 2021). Numerous scholars (Kohut et al., 2012; Elvestad & Blekesaune, 2008) have exhibited a pronounced downturn in news consumption via traditional sources over the past two decades. Disruptive technological breakthroughs have confronted established media models: on one side, artificial intelligence introduces fresh possibilities for broadening media offerings and combating misinformation; on the other, algorithmic curation and individual personalisation can enhance user experiences and potentially alleviate societal risks (Trattner et al., 2021).

The transforming media sphere has profoundly altered usage patterns, propelled by an expanding Internet user base. Recent data indicate that over 4.5 billion people worldwide use the Internet—an over 9% increase since 2019—which is forecasted to reach 4.41 billion by 2025 (Statista, 2021a). In Poland, about 28 million citizens, or 78% of the population, are Internet users (Number of Internet users, 2020). The widespread embrace of online connectivity has significantly broadened the volume and range of content available (Bachman et al., 2010). Spurred by cutting-edge developments, this expansion has ignited a shift from traditional to digital media. Technological progress, especially the rise of Web 2.0 and 3.0 applications and AI, has also accelerated the evolution of media consumption habits. Additional factors—including mobility, real-time updates, and the desire for instantaneous access—contribute to the continuing multiscreening phenomenon observed in recent years.

1.1. Media

Recent research in Poland indicates that many internet users remain relatively attached to television media, even among younger age groups (IAB Polska, 2019). Nearly 80% of individuals below the age of 34 continue to watch television, although they also seek content from significant TV channels online. In terms of media content, Polish internet users most frequently look for full-length movies and video programs (60%), followed by news and articles (54%) and short videos (53%) (IAB Polska, 2019). They primarily use laptops or desktops to access full-length movies (55%), whereas smartphones are more commonly employed for viewing short videos (49%). Each year, the number of Poles who use multiple media channels simultaneously to access their preferred content increases. Among internet users, 90% are so-called "multi-screeners," a finding consistent with global trends (IAB Polska, 2019; Intravia et al., 2017). This pattern underscores the strong interpenetration of television and internet use (Menezes et al., 2025), as both media serve similar needs related to entertainment and gathering news. Consequently, nearly 85% of Poles watch television while using the internet.

A further example of this digital transformation relates to younger audiences, who increasingly abandon traditional platforms such as television, newspapers, and radio (Ödmark, 2020). However,

older demographics like Press, Radio, and Television are also shifting toward digital consumption. Media engagement frequently occurs on social platforms (e.g., Facebook, Instagram, and YouTube) and streaming services rather than on conventional media channels. According to Statista (2021a), the global number of active social media users surpassed 3.8 billion at the beginning of 2020. In Poland, the number of monthly active social network users is expected to reach 19.81 million by 2025, representing an increase of approximately 850,000 users compared to 2020, when the figure stood at 18.96 million. These numbers are even higher for younger generations, such as Millennials and Gen Z.

Regarding the penetration rates, YouTube and Facebook are Poland's leading social networking sites. However, regarding the two platforms' engagement rate, YouTube has more than doubled online user activity levels compared to Facebook (Lipiński, 2021). Regarding media consumption, it is worth noting that Poles use social media mainly for entertainment and staying up to date on news. Those aspects were one of the most important reasons for using social media, following socialisation reasons like keeping in touch (Majerczak & Strzelecki, 2022).

Changes in media consumption are evident along two primary dimensions. The first dimension involves the evolving nature of traditional media and how content is delivered to audiences. For example, radio is no longer limited to passive listening of music and news; contemporary radio stations often enable users to "watch" broadcasts via their websites and even collaborate in content creation. The second dimension concerns the emergence of new forms and devices that facilitate media consumption. Individuals increasingly select when and where they access content rather than relying on fixed schedules or locations.

This paper addresses both of these dimensions of transformation. The expansion of the Internet, combined with the proliferation of digital media and devices, has prompted a shift in consumer preferences toward online platforms, social media, mobile applications, and streaming services. Consumers now have the flexibility to access media content of their choice at any time and in any place. This shift is particularly pronounced among younger generations, such as Gen Z, who are highly receptive to novel devices and applications that enable them to discover and engage with desired content (Chaney et al., 2017). They frequently multitask, switch between apps, and exhibit content loyalty rather than adherence to specific channels. Gen Z typically seeks out particular media content in real-time and by the most convenient means (Taneja et al., 2012). Consequently, this study focuses on Gen Z as a demographic whose emerging consumption habits compel media organisations to reconfigure their market strategies.

Artificial intelligence (AI) has also profoundly transformed media consumption patterns among Gen Z (Bunea et al., 2024). Guerra-Tamez et al. (2024) stress that as digital natives, that generation seamlessly integrates AI into their daily media interactions, influencing their preferences, trust, and engagement with content. AI represents a technology with the potential to deliver more precise, tailored, and enjoyable media content, thus enhancing Gen Z's experience. That experience will be created by combining smart sensors with AI and personal devices. AI-driven algorithms curate personalised content across social media platforms, streaming services, and news feeds, tailoring information to individual preferences and behaviours. This personalisation enhances user engagement by presenting content that aligns with their interests, thereby increasing time spent on these platforms.

As media consumption patterns and preferences evolve, especially among younger audiences, traditional media organisations must adapt their managerial approaches to remain viable. To serve as a complementary content source, such organisations require a robust online presence, supplemented by live streaming and mobile applications, to reach younger demographics. Although contemporary media platforms have become primary content sources—including news, information, movies, and music—they continue to be supplemented by traditional media.

This paper's primary goal is to investigate media consumption patterns in Gen Z, emphasising content rather than specific media channels. The following sections review the pertinent literature on new trends in the media landscape, addressing theories of competition and complementarity and the key determinants of media consumption, with particular attention to age. The research context is then presented, leading to the study's guiding research questions. Next, the quantitative methodology is described, and the findings are discussed. The paper concludes with considerations of the principal conclusions, limitations, and potential directions for future research.

1.2. Research Questions

According to the concepts discussed, the paper addresses the following research questions:

RQ.1 How do Gen Z individuals in Poland use digital platforms to consume media content, and what factors influence their preference for specific types of content (news/information, music, and movies/series)?

RQ.2 To what extent do traditional media (TV, AM/FM radio) and new media (social media, Google browser, VOD platforms) complement each other in the context of media consumption among Gen Z in Poland?

2. LITERATURE REVIEW

2.1. Media Consumption in the Light of Competition and Complementary Theory

Technological advances in communication and the steady rise in internet penetration have driven significant changes in how audiences consume media. Some scholars propose that the growing variety of platforms, websites, and streaming services has expanded consumer choice and control (Toubia et al., 2019; Allam & Dinana, 2021). As new digital channels have emerged, the extent to which they displace or coexist alongside traditional media has captured researchers' attention (Coffey & Stipp, 1997; Henke & Donohue, 1989).

Two primary frameworks shape discussions about these transformations: the first highlights continuity, positing that digital innovations will exert only a limited impact on established outlets (Coffey & Stipp, 1997; McCombs, 1972). The second predicts fundamental disruption, arguing that newer forms of media will eventually supplant older ones (Stephens, 1998; Kayany & Yelsma, 2000). Empirical studies have demonstrated that increased internet use reduces conventional media consumption (Gaskins & Jerit, 2012; Lee & Leung, 2008; Liebowitz & Zentner, 2012). At the same time, scholars have discovered overlapping content across platforms, suggesting a more complex relationship than outright replacement (Jang & Park, 2016).

Dutta-Bergman (2004) critiques competition-based theories by stressing that media users are not a monolith and often have diverse motivations. In contrast to substitution arguments, other researchers have highlighted complementarity. Norris (2001), Golding (2000), and Glynn and Huge (2014) claim that individuals frequently combine multiple platforms to satisfy different aspects of their content needs. The pattern of media multitasking also continues to grow (Jang & Park, 2016). While some consumers cancel traditional cable or betray old channels for digital ones, many still pair older and newer media in their routines. Consistent with Dutta-Bergman (2004), examining the interplay of multiple platforms around specific content categories is essential rather than viewing media use solely as time interchangeability (San-Martin et al., 2015).

2.2. Age as a Determiner of Media Content Consumption

Age strongly predicts media consumption patterns as different generations develop distinct preferences shaped by formative experiences, technological adoption, and cultural events (Glynn & Huge, 2014; Elvestad & Blekesaune, 2008). Drawing on generational cohort theory (Herrando et al., 2019; Weeks & Schaffert, 2017; Costanza & Finkelstein, 2015), researchers classify populations based on major historical factors or social trends that foster shared values within an age group (Boone-James et al., 2011).

From this perspective, Baby Boomers, Generation X, Millennials (Gen Y), and Generation Z each demonstrate varying degrees of openness to new technology, preferred media formats, and communication styles (Pandita & Singhal, 2017). For example, older segments often show more loyalty to traditional broadcasts and print outlets, while younger individuals gravitate toward digital tools, online social networks, and applications (Elareshi & Gunter, 2012; Glynn & Huge, 2014). These trends have led to a noteworthy generational gap in media usage: whereas earlier cohorts continue to rely on television or print media, younger people expect instantaneous access via smartphones or computers (Elvestad & Blekesaune, 2008; Lenhart et al., 2010; Gil de Zuniga & Valenzuela, 2009).

2.3. Generation Z as Media Consumers

Generation Z (roughly those born between 1995 and 2002) stands out for their intense engagement with digital media (Posnick-Goodwin, 2010). As 'digital natives,' they have only known a world infused with the internet and social media, making them adept at seamlessly shifting between devices and platforms (Chaney et al., 2017; Hoole & Bonnema, 2015; Loos & Ivan, 2024). They also demand quick, on-demand access to information, evidence of their short attention spans and expectations for tailored, interactive content (Babin & Harris, 2016; Gao, 2024).

Accordingly, Gen Z members value autonomy in curation (Taneja et al., 2012): they want to locate their news, music, or entertainment on flexible schedules rather than relying on fixed programming (Elvestad & Blekesaune, 2008). As newspaper readership and network TV viewing have waned, online platforms often fill the gap for younger audiences (Nie et al., 2006). The expanding myriads of digital sources challenges conventional media's relevance (Bryan University, 2016). Consequently, media firms now leverage social networks and host digital events to reach a demographic that expects interactive participation. While earlier research regarding content consumption frequently revolved around channel loyalty, Dutta-Bergman (2004) suggests younger users are more committed to the content itself; they simply seek it via whichever channel offers the greatest convenience and personalisation.

3. METHODOLOGY

3.1. Research Context

Media can be conceptualised in two distinct ways, depending on the level of categorisation. First, media may be viewed as devices like television, radio, smartphones, or the Internet. Some research has adopted this perspective, focusing on the interplay of competition and complementarity among emerging media technologies (Jang & Park, 2016; Taneja et al., 2012). Second, media can be defined as content, such as news/information or entertainment (including music and feature films/television series). This content-based perspective has received less attention and has predominantly addressed news and information consumption (Intravia et al., 2018), including political news (Bachmann et al., 2010; Holt et al., 2013; Aalberg et al., 2013), sports news (Dutta-Bergman, 2004), and finance news (Dutta-Bergman, 2004). Notably, there remains a notable gap in the literature concerning the consumption of other forms of content, particularly music and movies/television series.

Further research has examined how the Internet's consumption as a medium influences the use of traditional media channels, chiefly in terms of time spent (Aalberg et al., 2013). Moreover, most studies on media consumption have focused on analysing consumption patterns of specific media channels (e.g., television, newspapers, radio) within the general audience, exploring how these patterns evolve in response to emerging technologies (Elareshi & Gubter, 2012; Liebowitz & Zentner, 2012).

Recent scholarly concern has centered on the influence of media environment changes on younger audiences—especially Gen Z—and their tendency to move away from traditional sources of information, news, and entertainment. Research in this area has investigated the extent to which younger populations replace conventional media with online sources, particularly for news consumption (Aalberg et al., 2013). Nevertheless, no studies have assessed Gen Z's media consumption across various content types.

In Poland, declines in traditional media consumption mirror global developments, with a concurrent increase in digital media use, mainly via smartphones (Klimkiewicz, 2024; Statista, 2021b). Poland's rapid digital transformation aligns its media consumption patterns with those of Western Europe, thereby presenting a valuable setting to examine the phenomena of media complementarity and competition. Although younger generations in Poland continue to watch television, they increasingly do so through digital platforms. Social media and streaming services – for instance, YouTube and Spotify – constitute central elements of Gen Z's media habits. This intersection of digital engagement and residual traditional media consumption in Poland provides insights that are likely applicable to other regions undergoing similar transitions.

This study contributes locally and globally relevant perspectives on media consumption trends during digital transformation by concentrating on Poland.

3.2. Research Methods

Triangulation of research methods was employed to address the research questions and objectives, integrating quantitative and qualitative approaches. The primary goal was to investigate Gen Z's media consumption patterns in Poland, specifically focusing on media content rather than media channels. The quantitative phase of the study was conducted between January and April 2023, using a simple random sampling technique. According to Stat.gov.pl (2020), the target population comprises 3,126,780 individuals and 621 usable questionnaires were collected, meeting the criteria for the minimum sample size. This sample size provides a margin of error of ±4% ($\alpha = 0.04$) at a 95% confidence level. Questionnaires were scrutinised for completeness and accuracy; those with missing data were excluded. Data for this phase were gathered via the CAWI (Computer-Assisted Web Interview) method, with an average completion time of 23 minutes. To capture participants' levels of media consumption, responses were recorded on a five-point Likert scale, ranging from 0 ("never") to 4 ("always").

An exploratory phase was undertaken following rigorous scale development procedures to develop a reliable and valid measurement instrument. Secondary data sources, including a comprehensive literature review on media consumption in Poland, informed the initial conceptualisation. Qualitative data collection comprised three focus group interviews with Gen Z respondents—32 individuals in total (10–12 per group)—as well as in-depth interviews (IDIs) with five chief executives from media organisations (radio and television broadcasters). These interviews provided more profound insights into the evolving behaviours of Gen Z and their implications for media organisations. Subsequently, a pilot study assessed the questionnaire's relevance, reliability, and clarity of its terms, items, and scales. During this phase, 30 Gen Z participants completed the questionnaire and offered feedback on any ambiguities. As a result, several items were refined or eliminated to enhance the instrument's overall quality. Finally, the primary research data were analysed using basic statistical measures, including measures of central tendency (median, arithmetic mean) and measures of dispersion (standard deviation, coefficient of variation).

4. RESULTS

An examination of the results for RQ1 indicates that Gen Z wishes to access media content at any time and in any location. Nearly all respondents (98%) identified smartphones as their primary device for consuming media, followed by laptops (77%), television sets (17%), and traditional FM radio (3%). The data further reveal that this generation primarily locates preferred content on social media and through Google ($\bar{X} = 2.4$ and $\bar{X} = 2.5$, respectively). Fewer participants rely on automatic notifications from "liked" portals ($\bar{X} = 1.5$), and some occasionally watch traditional television ($\bar{X} = 1.3$). Overall, these mean values are relatively low; however, high coefficients of variation suggest that these lower averages may stem from considerable diversity among respondents' perspectives.

This study corroborates previous findings by Elvestad and Blekesaune (2008), demonstrating a significant relationship between age and traditional media consumption and a decline in newspaper readership among younger audiences. In particular, Gen Z in Poland does not perceive traditional television or AM/FM radio as essential platforms for media consumption, nor do they rely on these channels when searching for preferred content (Nurcahyo et al., 2024). Survey respondents indicated their primary reasons for not watching television or listening to the radio as excessive advertising (59.9% and 55.4%, respectively), insufficient programming of interest (54.4%), and a lack of desired music (54.8%).

Further analysis suggests that traditional media are not favoured because they do not allow users to consume content on demand, at a time and in the manner they choose. Specifically, traditional platforms do not permit the selection of specific films and shows, binge-watching of television series, selecting songs for broadcast, or sharing content with peers. These findings align with other researchers' findings, who noted that Gen Z anticipates accessing desired media content anytime and anywhere (Taneja et al., 2012).

Table 1. Places of access for content (0-4 Likert scale)

No.	Items	Always (4)	Very often (3)	Often (2)	Sometimes (1)	Never (0)	$\bar{X}$	M	S	V_s
		%								
1.	Social media	16.9	33.2	27.9	19.3	2.7	2.4	3.0	1.1	43.9%
2.	Google browser	16.3	37.7	29.1	13.7	3.2	2.5	3.0	1.0	40.8%
3.	Automatic notifications of portals liked	6.4	15.6	24.0	28.7	25.3	1.5	1.0	1.2	80.8%
4.	News portals	3.5	11.4	19.0	33.7	32.4	1.2	1.0	1.1	93.0%
5.	Radio/TV websites	2.6	8.5	16.6	32.4	39.9	1.0	1.0	1.1	105.2%
6.	Traditional newspapers	1.6	1.6	7.2	38.8	50.7	0.6	0.0	0.8	126.1%
7.	Traditional radio	2.9	8.2	17.6	42.8	28.5	1.1	1.0	1.0	88.9%
8.	Traditional TV	2.7	11.4	21.6	39.5	24.8	1.3	1.0	1.0	81.7%
9.	Devices with artificial intelligence (Hey Google, Hey Siri, Alexa)	0.5	1.9	6.6	13.0	77.9	0.3	0.0	0.7	214.3%

Source: own elaboration.

Table 2. Reasons for not using traditional media by Gen Z

Television		**Radio**	
Reasons	***%***	***Reasons***	***%***
Too many advertisements	59.9	Too many advertisements	55.4
There are little programs that interest me	54.4	Lack of my favourite music	54.8
I cannot watch the movies I want when I want	42.0	Too much talk about the amount of music played	41.4
Too much politics	33.8	Lack of choice of songs played	38.8
There are no movies that I like	26.4	There is little information that interests me	28.2
I cannot binge-watch a television series	24.0	Many politics on the air	26.7
I cannot choose the movie that I want to watch	20.3	Bad radio personalities/DJs	13.2
I cannot watch the television shows I want when I want	14.5	No influence over my music choices and the lack of sharing possibilities	0.2

Source: own elaboration.

To examine Gen Z's media content consumption patterns, the study categorises content into three primary types: news and information, music, and entertainment (movies and series). Concerning music consumption specifically, the findings indicate that smartphones are the most frequently used device among the participants, with nearly 70% reporting daily or near-daily use (i.e., at least four times per week; see Table 3). Conversely, only about 10% of respondents use stationary devices, such as AM/FM radios at home or desktop computers, daily or near-daily to access music.

Table 3. Ways of consuming music (%)

No.	Devices	Never	Up to 3 times per week	From 4 to 6 times per week	Every day
1.	AM/FM radio at home	66.3	22.4	5	6.3
2.	AM/FM radio in a car	26.1	43.4	13.6	16.9
3.	Smartphone	7.6	24.7	25	42.8
4.	Surface	94.4	3.7	0.8	1.1
5.	Laptop computer	27.9	37.3	16.1	18.7
6.	Desktop computer	83.1	7.4	3.0	6.4

Source: own elaboration.

Individuals prefer to select songs according to their immediate preferences when listening to music. As such, YouTube remains the most frequently used platform, with 74% of respondents indicating that they access it daily or at least four times per week. Additionally, approximately one-third of the respondents use Spotify daily.

Table 4. Applications used by Gen Z while consuming music (%)

No.	Devices	Never	Up to 3 times per week	From 4 to 6 times per week	Every day
1.	Spotify	52.0	12.5	8	27.4
2.	YouTube	1.9	24.2	22.7	51.2
3.	Apple Music	92.4	3.7	1.2	2.6
4.	Dezer	99.0	0.3	0.2	0.5
5.	Sound Cloud	87.6	8.3	1.7	2.6
6.	Vevo	88.7	4.6	3.3	3.2
7.	Pandora	98.6	0.8	0.4	0.3
8.	Smartphone app for my radio station	82.4	11.3	2.8	3.5
9.	Website for my radio station	85.2	11.0	2.1	1.8

Source: own elaboration.

This study examined the consumption patterns of other content types, specifically news and information. The initial aim was to investigate Gen Z's preferred news and information consumption formats. The findings reveal that these young media consumers most frequently read news and information on social media. One in five respondents acquire information this way continuously, and more than 60% do so either very often or often. Another format they actively embrace is video content: 7% of respondents stated they consume news and information via videos with subtitles and sound, and 60% reported doing so very often or often.

Regarding RQ2, given that social media emerged as the most significant channel for obtaining news and information, this study sought to analyse the role of individual social media platforms for news consumption (as opposed to socialisation). The findings indicate that Gen Z uses Facebook and YouTube most frequently when consuming news and information on social media (see Table 6). Specifically, 96% of participants use Facebook to access the news and information they seek, and 87% employ other social media platforms. Instagram is used by 70%, suggesting it is comparatively less popular. Notably, the two platforms examined—Snapchat and Twitter—were not among Gen Z's preferred news and information-gathering options.

Table 5. Format of news/information consumption (0-4 Likert scale).

No.	Items	Always (4)	Very often (3)	Often (2)	Sometimes (1)	Never (0)	$\overline{X}$	M	S	V_s
		%								
1.	Reading text on social media	18.8	37.5	26.4	14.7	2.6	2.6	3.0	1.0	40.5%
2.	Listening to the audio (e.g. podcast, radio)	2.4	14.0	22.5	43.5	17.6	1.4	1.0	1.0	71.9%
3.	Watching video with subtitles and sound	6.8	24.5	35.1	28.2	5.5	2.0	2.0	1.0	50.7%
4.	Watching video with subtitles but no sound	6.0	16.9	22.9	33.8	20.5	0.9	1.0	1.1	118.4%

Source: own elaboration.

Table 6. Social media is used for consuming news and information.

No.	Social media	Always (4)	Very often (3)	Often (2)	Sometimes (1)	Never (0)	$\overline{X}$	M	S	V_s
		%								
1.	Facebook	20.1	34.0	24.3	18.0	3.5	2.5	3.0	1.1	44.4%
2.	Instagram	12.7	19.0	18.7	20.5	29.1	1.7	2.0	1.4	84.3%
3.	Snapchat	7.1	7.9	9.5	20.8	54.8	0.9	0,0	1.3	137.3%
4.	YouTube	11.9	27.5	23.8	24.0	12.7	2.0	2,0	1.2	60.7%
5.	Twitter	3.5	5.3	5.0	8.5	77.6	0.5	0,0	1.0	215.0%

Source: own elaboration.

As shown in Table 6 Facebook emerges as the primary platform through which Gen Z consumes news and information. Consequently, it is worthwhile to investigate the sources from which Facebook content originates. Data analysis indicates that the most frequently utilised sources among the surveyed media consumers include copied links from the Internet, mass media portals (press, radio, and television), and notifications from followed profiles or websites (see Table 7).

Entertainment content – specifically movies and television series—comprised the third category of media examined. This research stage aimed to identify the most commonly used channels for viewing such content among Gen Z. The findings indicate that Polish respondents in this demographic frequently turn to social media platforms for movie and series consumption: one in ten respondents consistently uses Facebook or YouTube. At the same time, nearly 85% do so very often. Video-on-demand platforms, such as Netflix and HBO Go, also enjoy considerable popularity, with over 60% of young people regularly relying on them for entertainment.

Notably, nearly 70% of respondents reported using the recommendation functions available on VOD platforms to select which movies or series to watch (see Fig. 1). The data further suggest that Gen Z occasionally utilises traditional television for entertainment. Specifically, only 1% of respondents use television at all times, while 40% do so often or very often.

Table 7. Sources of acquiring news/information via Facebook.

No.	Sources	Always (4)	Very often (3)	Often (2)	Sometimes (1)	Never (0)	$\overline{X}$	M	S	V_s
		%								
1.	Copied links from Internet portals, press, radio, and TV portals	6.4	20.6	30.4	32.2	10.3	1.8	2.0	1.1	59.6%
2.	Direct information from participants at the event/witnesses	2.7	11.9	23.8	46.2	15.3	1.4	1.0	1.0	69.3%
3.	Directly from friends	3.2	13.8	27.5	40.9	14.5	1.5	1.0	1.0	66.8%
4.	Notifications of like profiles or websites	8.2	21.9	28.0	28.8	13.0	1.8	2.0	1.2	62.9%

Source: own elaboration.

Table 8. Channels used to watch movies & series.

No.	Channels	Always (4)	Very often (3)	Often (2)	Sometimes (1)	Never (0)	$\overline{X}$	M	S	V_s
		%								
1.	Watching traditional TV	1.1	8.5	30.8	26.1	33.5	1.1	0.5	1.4	121.7
2.	Netflix, HBO GO, Amazon, Prime, Hulu etc.	4.0	15.3	43.5	11.6	25.6	1.8	1.5	1.7	94.6
3.	Facebook, YouTube	12.1	46.1	37.5	3.0	1.0	3.4	3.5	1.7	50.3

Source: own elaboration.

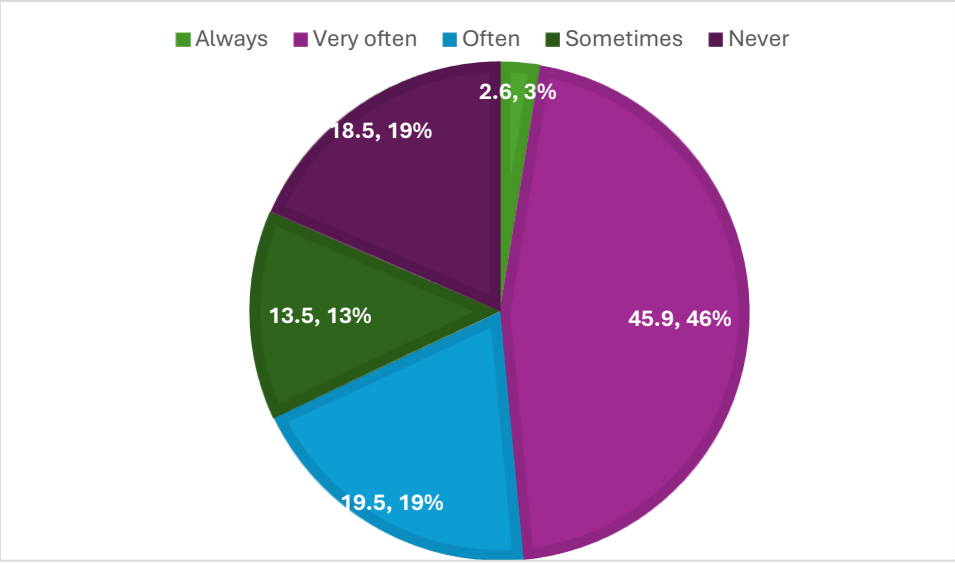


Figure 1. The frequency of using recommendation services of VOD platforms
Source: own elaboration.

5. DISCUSSION

The present study highlights how Gen Z in Poland increasingly turns to digital platforms for media consumption in an era where artificial intelligence (AI) plays a growing role in content creation, curation, and personalisation. The findings indicate a continued decline in traditional media usage—particularly television, print, and radio—while digital alternatives such as social media, search engines, and streaming services dominate Gen Z's media habits. This cohort's preference for immediate accessibility, minimal intrusive advertising, and a personalised user experience aligns with broader shifts toward data-driven algorithms that tailor content recommendations and notifications (Guerra-Tamez et al., 2024; Bunea et al., 2024).

In line with prior media complementarity theory, the study demonstrates that even as Gen Z gravitates strongly toward AI-enabled platforms (e.g., social networks and streaming services armed with recommendation engines), traditional media remain in limited use, especially in online or on-demand forms. Rather than a wholesale "replacement," most respondents treat television and radio as secondary or complementary channels. AI-driven technologies, however, increasingly facilitate the hybridisation of old and new media, enabling traditional outlets to maintain a presence through personalised online feeds, voice assistants, or mobile apps (Dutta-Bergman, 2004; Su et al., 2015). Algorithmic curation and content filtering, seen in services like Netflix, Spotify, and social media platforms, reinforce this dynamic by constantly surfacing relevant items, thus shaping entertainment and news/information consumption.

Notably, the frequent use of AI-driven recommendation systems, such as those on VOD platforms, signifies Gen Z's openness to automated, customised content delivery. Their low tolerance for interruption or off-schedule media and their desire for up-to-the-minute information underscores the importance of AI's predictive analytics. These systems offer fast, curated, and often seamless access to desired content, solidifying Gen Z's reliance on smart devices and data-driven media ecosystems. Moreover, as social media permeates news consumption, AI-based algorithms deliver information via personalised feeds and shape how Gen Z discovers, shares, and interprets events. This transformation highlights concerns about filter bubbles, content biases, and the potential spread of misinformation—topics that media organisations and policymakers must address to sustain trust and credibility (Wang et al., 2023; Trattner et al., 2021).

The findings suggest a nuanced relationship between traditional and emerging platforms mediated by AI technologies. While television, radio, and print have been supplanted in many ways, they still influence digital spheres by providing source content that is subsequently disseminated online. Yet, for Gen Z, the driving engine remains the AI-guided ecosystem that continuously refines content to match individual tastes, attention spans, and consumption contexts. Media producers and broadcasters in

Poland and beyond should adapt strategically—by integrating AI-based recommendation tools, reducing redundant advertising, and ensuring user-centric, on-demand models—in response to Gen Z's shifting sensibilities. Such measures maintain competitiveness in a saturated digital marketplace and foster media engagement in an environment increasingly shaped by algorithmic decision-making.

6. CONCLUSIONS

This study sheds new light on how Polish Generation Z engages with diverse content—news, music, and entertainment—under increasingly AI-driven conditions. While previous research has examined Gen Z's move away from traditional platforms, these findings highlight the essential role of AI-powered personalisation, algorithmic recommendations, and on-demand content in shaping media habits. Gen Z's preference for instant, tailored access via smartphones, social media, and VOD services reflects their broader expectation that advanced technologies, such as AI, curate relevant information and entertainment. This generation seeks content at the precise time and place of its choice and prefers platforms that leverage AI to reduce advertising intrusiveness and deliver highly customised user experiences.

In line with media complementarity theory, results indicate that traditional outlets have not entirely been displaced; instead, they coexist with new platforms in a "hybrid" consumption model. AI reinforces this coexistence by enabling cross-platform adaptability—such as algorithm-based recommendations for news or personalised movie and music selections. Although Gen Z continues to access some television via digital streaming services, the findings reveal that reliance on AI-assisted search engines, social feeds, and content platforms has become routine. This pattern is particularly clear in music, where streaming services (e.g., YouTube, Spotify) use recommendation algorithms to guide listeners to new artists or genres seamlessly.

Importantly, the study's content-centric approach indicates that media organisations must adopt AI-enabled strategies to remain competitive and relevant. Building robust online ecosystems with personalisation engines, recommendation algorithms, and user-friendly applications will be vital for retaining Gen Z audiences and navigating the rapidly evolving AI-centered media landscape. While these developments offer promising opportunities for increased audience engagement, they also necessitate broader considerations around data privacy, algorithm fairness, and the cultivation of media literacy skills. Overall, this research highlights the transformative power of AI in shaping media consumption patterns for Gen Z and underscores the need for media platforms to integrate adaptive technological solutions that meet the heightened expectations of an increasingly on-demand generation.

This study is not without limitations. First, the sample is confined to a small group of GenZ representatives in a single region of Poland. Consequently, whether these results are generalisable to other geographical areas is uncertain. Future research should replicate and extend the study to include broader and more diverse populations. Second, the cross-sectional nature of the data restricts inferences about causality. Longitudinal studies would offer additional insights by capturing changes in media consumption patterns over time. It would also be valuable to investigate how these three major content types (not only news but also music and movies/series) are consumed by other generational cohorts.

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MOBILE APPLICATIONS AS DIGITAL SUPPORT FOR PUBLIC TRANSPORT PASSENGERS (A POLISH EXAMPLE)

Grażyna Rosa[a], Ewa Puzio[b]

[a] *University of Szczecin, Institute of Spatial Management and Socio-Economic Geography, Szczecin, Poland*
[b] *University of Szczecin, Institute of Management, Szczecin, Poland*

ABSTRACT

Purpose: *The purpose of this study is to assess the extent to which passengers use mobile applications as digital support in planning and executing public transport trips, as well as to evaluate these applications from the users' perspective.*

Need for the study: Despite the growing role of mobile applications in public transport, there is still a research gap in Poland regarding a thorough understanding of how passengers use these technologies, particularly in the context of the changing management of transport. Transport management systems are becoming increasingly intelligent, utilizing data analytics, automation, and digital technologies to improve service quality. The use of mobile applications within the framework of intelligent transport management can significantly impact the improvement of service accessibility, efficiency, and the overall passenger experience, especially in the face of various technological barriers.

Methodology: *The study employed a nationwide survey using the Computer-Assisted Web Interview (CAWI) method, conducted in 2023. The sample included 1,117 individuals aged 18 and older, residing across Poland, ensuring broad demographic representation. One of the primary objectives of the research was to gather information on passengers' use of mobile applications as digital support in planning and executing public transport trips.*

Findings: *The results of the first part of the study showed that approximately 60% of passengers use mobile applications for ticket purchases, 80% indicated that they use maps and navigation apps, nearly 80% use location services during their trips, almost all passengers check timetables online (96.4%), over 80% check the waiting time for their chosen mode of transport online (84.6%), nearly 70% use the "Jak dojadę" app, while 30% have never used it. The second part of the study focused on the evaluation of mobile applications in railway and bus transport. About 50% of respondents rated websites, ticket purchasing applications, and passenger information apps positively.*

Practical Implications: *The obtained information provides valuable insights that transport operators need to encourage passengers to use modern technologies. It may be useful in improving individual applications, sales channels, and passenger information systems, including those for people with disabilities or limited mobility. Special attention should be given to the evaluations of mobile applications, and strategies should be developed to address the identified weaknesses.*

Keywords: mobile applications; passenger transport; public transport

Jel codes: O32; R40; R49

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1. INTRODUCTION

The early 21st century marks a period of significant change and the emergence of new phenomena in the European and global economy, leading to shifts in the perception of the transport market. The importance of transport in the economy continues to grow due to factors such as globalization, specialization and division of labor, mass consumption, economies of scale in production, cost optimization, increasing competition, shortening product life cycles, the digitalization of society, and changes in sales and customer service models. A particularly transformative period for many market trends occurred between 2019 and 2022, when the world grappled with the escalating COVID-19 pandemic (Impact of COVID-19 pandemic, 2021). These changes were reflected in the management of transport service providers, who have been intensively implementing intelligent management, understood as the integration of information technology, analytical technology, and automation to more effectively manage resources and processes within an organization (Rakhymova et al., 2024; Vredenborg et al., 2025).

These economic transformations are mirrored in changes occurring in society, exemplified by the contemporary concept of Society 5.0: "which utilizes advanced technologies to create a society based on sustainable development, social innovations, and digital transformation." This concept is also reflected in passenger transport. The development of digitalization changes how societies live, expand their knowledge, and travel. Different age groups approach the use of new information technology achievements in varying ways. A particularly important segment of consumers is Generation Z, today's 30-year-olds, who are almost addicted to mobile devices, open to technological innovations, proficient in their use, yet also impatient and impulsive, as well as seniors, often digitally excluded, relying on traditional, timeless solutions (Ilciów, 2023). Additionally, there are cultural factors that hinder the mass acceptance of Transport 5.0, including resistance to adopting technology and generally low levels of digital literacy (Atiku et al., 2024). In many cases, there is a reluctance to transition to automated systems due to a lack of trust in new technologies (Reimann et al., 2017). A low level of digital skills prevents people from using technologies such as mobile applications (Carpentiere et al., 2024; Anuar et al., 2024). Educational programs and awareness campaigns for social purposes can help overcome some of these challenges (Reimann et al., 2017; Etuk et al., 2022). To achieve the goals of Society 5.0, it is particularly important to focus on segments defined by limited digital skills and negative attitudes toward AI-based solutions, which are essential for the development and widespread adoption of these technologies.

The ongoing technological progress presents many opportunities for efficient passenger transport. It facilitates faster information flow, makes service acquisition easier, and can positively impact passengers, whose expectations are also growing. The concept of modern technologies used by passengers is broad and diversely defined. It is most often associated with the Internet (passenger information, ticket sales), mobile apps, smart boards in vehicles and at stops (Wolniak & Secuła, 2024; Ilciów, 2023). Consequently, transport providers are striving to adapt both their product offerings and distribution methods to meet consumer expectations (Chowdhury & Dewan, 2024). The issue of using mobile applications for planning and undertaking public transport trips fits squarely within this scope. In this research area, a knowledge gap exists in Poland, which required the formulation of the following research questions:

- Do passengers use mobile applications in planning and executing public transport trips? How do they evaluate the applications they use?
- Does age differentiate the population using mobile applications for trip planning (do seniors use mobile applications in public transport or are they digitally excluded)?
- Do passengers with disabilities or limited mobility use mobile applications in public transport, or are they digitally excluded?
- Does gender differentiate the population using mobile applications for trip planning?
- Does place of residence differentiate the population using mobile applications for trip planning?

Mobile applications supporting public transport are not merely technological tools but integral components of smart city and public service management. These applications are part of an ecosystem that relies on data, digitalization, and process optimization to improve the efficiency of urban services and enhance the quality of life for citizens. They bridge the gap between users and transport services,

providing real-time information, ticketing systems, and journey planning features, while contributing to the overall infrastructure of a connected and efficient city. As part of an intelligent management strategy, these applications go beyond simple transactional tools; they actively participate in the optimization of urban mobility and contribute to a city's sustainability goals (Yigitcanlar, et al., 2024).

Moreover, such mobile applications can be expanded with components of artificial intelligence (AI), allowing for the prediction of delays, analysis of user movement patterns, and the personalization of messages. AI-powered features could offer predictive analytics regarding transport capacity, and suggest optimal routes in real-time, helping to manage congestion and improve passenger experience. These capabilities would further embed mobile applications into the framework of intelligent transport management, aligning with the broader vision of smart cities, where data-driven decisions guide operational and strategic improvements (Mohsen, 2024).

From the perspective of public transport operators, mobile applications can serve as valuable sources of operational data. This data can be used to support decision-making processes, forecast demand, and manage crises. For instance, real-time data collected from users can help predict peak hours, monitor the effectiveness of specific routes, and identify areas in need of improvement. This operational intelligence supports not only day-to-day management but also long-term planning and strategic development, making mobile applications a crucial element of intelligent management systems within public transport (Abduljabbar et al., 2019). Through such systems, operators can improve efficiency, reduce costs, and provide better services to the public, which is at the core of intelligent management concepts.

The purpose of this article is to determine the level of mobile application usage as digital support by passengers in planning and executing public transport trips and to assess user evaluations of these applications.

The article includes an introduction, a literature review, a discussion of the research methods and results, as well as a discussion and conclusions.

2. LITERATURE REVIEW

The passenger transport market is highly dynamic and undergoes constant transformations, primarily driven by the changes occurring in the transport environment, especially those resulting from the concept of sustainable transport. This trend was disrupted in 2019 with the onset of the COVID-19 pandemic. Passengers, concerned about their health safety and the numerous restrictions in public transportation, increasingly opted for individual transport. The limitation of direct contact between people accelerated the development of their digital skills. Passengers, almost forced to develop digital skills during the pandemic, recognized the benefits and opportunities that these technologies provide. In the field of transport services, technology, and customer relationships (Kos et al., 2020; Kos et al., 2022; Rosa, 2024b; Oszter, 2020), the importance of innovation has increased. The ongoing digitalization process in the modern world, alongside generational changes, has had a significant impact on shaping the passenger transport services market, both for railway operators and passengers. As a result, significant changes in customer expectations have led to the emergence of new preferences alongside traditional ones (Chowdhury & Dewan, 2024). Passengers also have new expectations regarding the equipment of transport services with modern elements (Awad-Núñez et al., 2021). The modern approach to passenger expectations compels companies competing in the passenger transport market to conduct professional analyses of the market and customer preferences to implement values that are most appreciated by customers. These include, first of all, all solutions offered in the areas of innovation, as perceived in both Polish (Góra, 2021; Gontarz, 2021) (Badanie satysfakcji pasażerów – edycja I, UTK, 2020), (Sprawozdanie z funkcjonowania rynku transportu kolejowego w 2019 r., UTK, 2019) and modern technologies (Kozłowski et al., 2020; Mróz, 2021), as well as in foreign literature (Bolobonov et al., 2021; Enoch et al., 2020; Kothari et al., 2016; Zitricky et al., 2015; Chowdhury & Dewan, 2024). Special passenger requirements are also described by Brumercikova et al., 2020; Branda et al., 2020; Awad-Núñez et al., 2021), including the use of social media, Wi-Fi services in vehicles, and tracking the vehicle's current location on its route using a mobile app (Bian et al., 2022). Digital accessibility is an important and new area of accessibility in public transport

(Kamargianni, 2016; Strenitzerova & Stalmachova, 2021). Mobile applications are the most common (Górniak, 2022). Most of them enable ticket purchases and payments for parking in the city. Information is made available to passengers on passenger information boards at bus stops and stations, on the website and in a mobile application for smartphones, and on electronic information boards in buses and trains (Rosa, 2024a). The development of modern technologies and their acceptance by passengers contributes to the emergence of new forms of information and service distribution (Frederico et al., 2021; Javid et al., 2021). Moreover, such innovative solutions are intended to encourage passengers to use collective or shared forms of transport (Filippi et al., 2023; Hlavaty et al., 2021). In this context, the concept of intelligent management emerges, which not only supports these innovations but also creates more integrated and optimized transport systems. Intelligent management is a concept that goes beyond traditional transport planning and encompasses broader city management. It integrates various technological innovations, including the Internet of Things (IoT), artificial intelligence (AI), and big data analytics, to create an integrated system that optimizes resource usage, improves service delivery, and enhances the quality of life for residents. In the context of public transport, intelligent management involves real-time coordination of various modes of transport (buses, trams, trains) through mobile applications and data integration, ensuring that services are not only reactive but also predictive, eliminating problems before they arise (Patil et al., 2024). These applications play a crucial role in making transport systems more adaptive, efficient, and user-friendly, as part of the smart city concept, where each system collaborates to improve the overall functionality of the city. Mobile applications are the most widely used. Already, Stopka (Stopka, 2014) addressed the requirements of users of a mobile application supporting "door-to-door" mobility in public transport. These applications are often created by operators to coordinate timetables, synchronize arrival and departure times of different modes of transport, ticket sales, and passenger information systems (Berrgren et al., 2021; Casquero et al., 2022; Sun et al., 2021). In addition to these core functions, these applications play a crucial role in making transport systems more adaptive, efficient, and user-friendly, contributing to the concept of intelligent city management. By integrating real-time data and communication between different modes of transport, these applications enable a more coordinated and optimized transportation network, improving the overall functionality of the city. Currently, there are many incompatible applications designed to search for passenger information, and it is necessary to integrate them to provide all the relevant travel data across different transport modes (Rodriguez et al., 2021; Saputro & Futurama, 2024). Most of them allow for ticket purchasing and also include additional features, such as payment for city parking (Siyal et al., 2021; Sia et al., 2023). Since the situation during a trip may change (e.g., due to traffic disruptions or congestion), passengers should have clear access to information about their journey while using transport services. The main carriers of information are voice announcements. Additionally, vehicles are equipped with various types of boards displaying real-time travel information: static and dynamic. The variety of communication forms is particularly important when serving passengers with disabilities or limited mobility (Mogaji & Nguyen, 2021; Page & Assa, 2021).

An analysis of available studies and research, to the best knowledge of the author, has shown that there are no comprehensive studies in Poland regarding changes in the use of digital information technologies by public transport passengers and their evaluations. The only available results, in a general context and scope, are presented by the Office of Rail Transport (Jakość usług w sektorze pasażerskich przewozów kolejowych – badanie opinii pasażerów, UTK, 2025; Badanie satysfakcji pasażerów – edycja II, UTK, 2022; Sprawozdanie z funkcjonowania rynku transportu kolejowego w 2019 r., UTK, 2019). The findings presented in this article aim to fill the identified research gap.

3. METHODOLOGY

3.1. Participants

The subject of the cyclical, original research conducted as part of two projects carried out by the University of Szczecin, “Improving the Quality of Research in Economic Sciences with Particular Emphasis on the Service Sector (RID) 2019-2023 and 2024-2028,” was to study the communication behaviors of public transport passengers in Poland. One of the objectives of the research conducted

in 2023 was, among other things, to gather information on the use of mobile applications by passengers in planning and executing trips as digital support for public transport. The criterion for selecting specific applications was based on the results of studies conducted by the Office of Rail Transport and the authors' own observations (Jakość usług w sektorze pasażerskich przewozów kolejowych – badanie opinii pasażerów, UTK, 2025; Badanie satysfakcji pasażerów – edycja II, UTK, 2022). This article presents only some of the results directly related to the issue discussed.

The study population consisted of individuals aged 18 years or older, residing in Poland. A total of 1,117 interviews were conducted. The percentage basis included respondents who had traveled by public transport, with 929 respondents in total. The quantitative method and sample selection used in the study allow for generalizing the results to the entire adult population, with a margin of error of +/- 3.0% (95% confidence level).

Characteristics of the Respondents:

- Gender: women (52.4%) and men (47.6%).
- Age: between 18 and 30 years old (16.9%), between 31 and 60 years old (52.9%) and those over 60 years old (30.2%).
- Residence: About 40% of the respondents were rural residents, while one in five lived in towns with populations between 20,000 and 100,000 (19.1%). Residents of cities with over 400,000 inhabitants made up 13.6% of the sample.
- Health/ability status: 35.5% of respondents were people with disabilities and caregivers of people with disabilities and 64.5% were passengers without disabilities (able-bodied).

3.2. Research Protocol and Stimuli

The study was conducted using the CAWI method on the PBS Sp. z o.o. panel, Poznaj.to, between November and December 2023. The CAWI method was chosen by the research company selected through a competitive process, which has experience in reaching a representative sample in a short period of time. The research tool was designed by the authors and consulted with the research company PBS Sp. z o.o. The questionnaire was preceded by a brief information statement, informing respondents that questions regarding their health status would be asked, and respondents had to provide consent to participate in the study. This procedure was necessary as health status is classified as sensitive personal data under the GDPR.

3.3. Research Apparatus

The study was conducted on a random sample, using a proprietary respondent selection system and a tool for maintaining a participation delay in the research. Based on the randomly selected representative sample from the population, the obtained results were generalized. Furthermore, the sample selected for this purpose was subjected to a weighting procedure to correct the results in relation to the structure of the general population. The study control was carried out in two ways:

- Field control – During the study, the responses received were continuously monitored, which allowed for immediate intervention and the elimination of cases where the data raised doubts, such as when the time taken to complete the questionnaire was too short, or when undesirable patterns, inconsistencies, or discrepancies in responses occurred. The questionnaire script prevented respondents from skipping key questions, such as those presenting content critical to the study.
- Non-field control – A substantive analysis enabled the elimination of incomplete or unreliable data. The quality control process covered 100% of the collected material, during which the consistency of responses, response patterns, and entries for semi-open questions were analyzed.

3.4. Analysis of Measurement Data

Before the analysis began, the dataset was subjected to a weighting procedure aimed at correcting discrepancies in the empirical distribution of results relative to the structure of the general population based on gender, age, and place of residence. Iterative weighting methodology (RIM) was applied using the aforementioned characteristics. To analyze the significance of differences in responses between groups of respondents, statistical analyses were conducted using IBM SPSS Statistics 26. Chi-square tests were performed, and significant differences in column proportions – the percentage of responses

within the specified groups – were compared. A significance level of $\alpha = 0.05$ was adopted. Bonferroni correction was also applied to adjust the significance values.

4. RESULTS

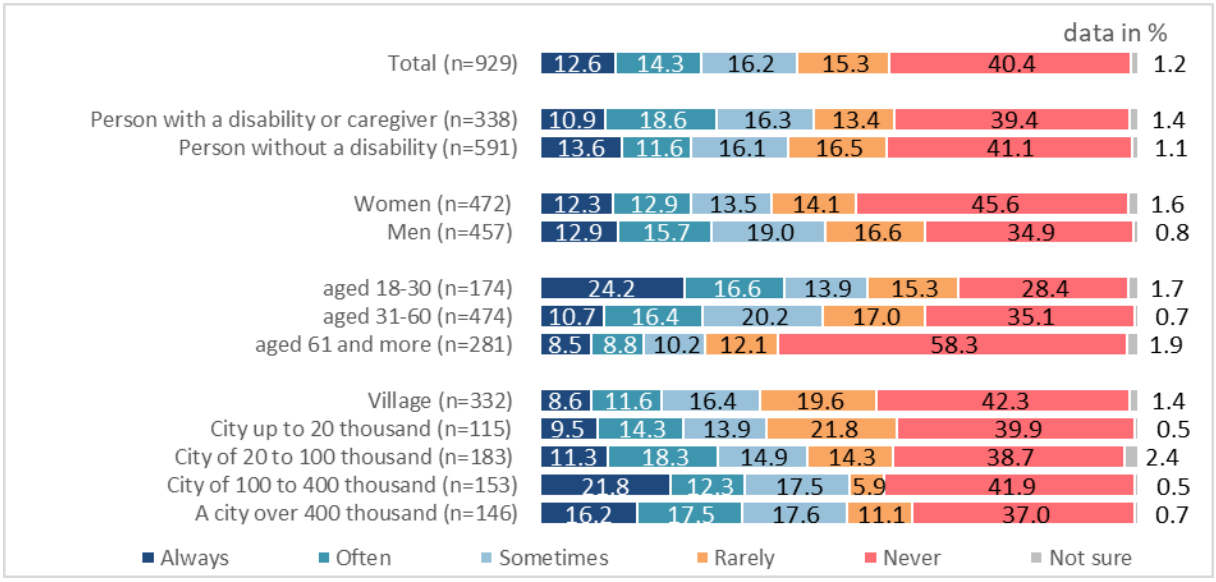
4.1. Use of Selected Mobile Applications

Respondents were asked whether they use several modern technology tools to facilitate traveling by public transport (rail and road transport) before or during their journey. One of the stages of the study involved questions about the use of specific mobile applications. The questions addressed the use of ticket purchasing applications, maps and navigation apps, location services, checking timetables online, checking the waiting time for the chosen mode of transport online, and using the "Jak dojadę" app. The responses are presented in Figures 1-6.

Figure 1 shows the frequency of using mobile applications for public transport ticket purchases. Women significantly more often than men indicated that they never use mobile ticketing apps (45.6% of women selected this answer, compared to 34.9% of men, $p < 0.05$).

This response was also more frequently chosen by individuals older than 60 years (58.3% of responses in this group) than by younger respondents. Among respondents aged 18-30, the percentage was 28.4%, and among those aged 31-60, it was 35.1%.

The size of the respondents' place of residence was also a factor that differentiated responses to this question. Rural residents (19.6% of responses in this group) and residents of towns with populations up to 20,000 (21.8% of responses in this group) significantly more often indicated that they rarely use such apps compared to residents of cities with populations ranging from 100,000 to 400,000 (5.9% of responses in this group, $p < 0.05$).



Percentage basis: respondents who have ever traveled by public transport (bus, minibus, trolleybus, tram, or train).

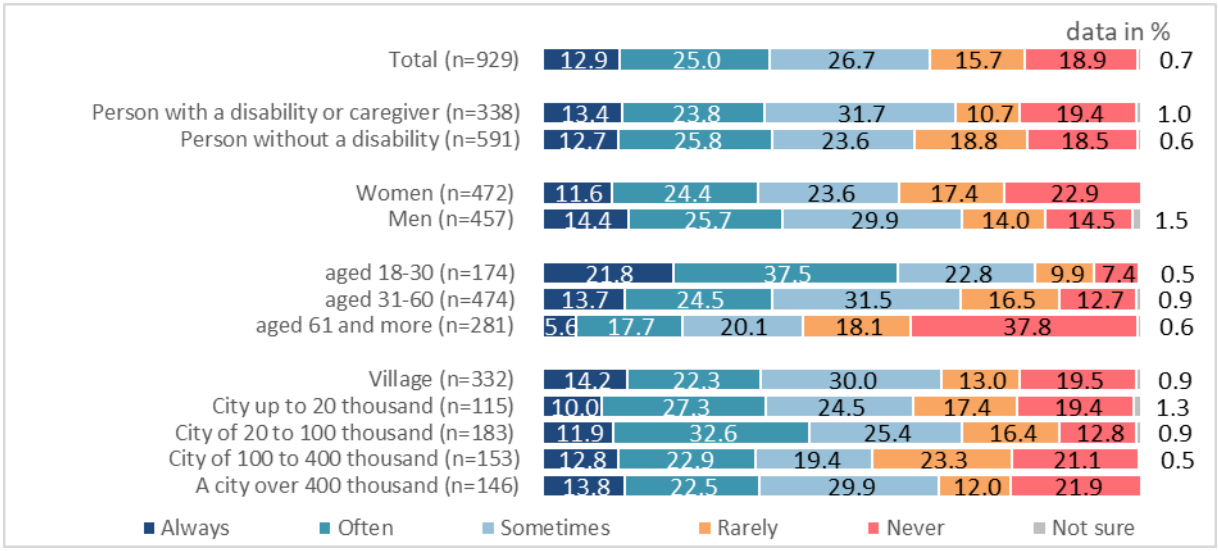
Figure 1. Use of Ticket Purchasing Applications During Travel Planning in 2023
Source: own elaboration.

Approximately 80% of respondents indicated that they use maps and navigation apps during travel planning or while traveling – 26.7% use them sometimes, 25% use them frequently, and 12.9% always use them (Fig. 2).

Individuals with disabilities statistically significantly more often than those without disabilities indicated that they sometimes use such apps (31.7% of responses in the disabled group versus 23.6% in the non-disabled group, $p < 0.05$).

Women statistically significantly more often than men indicated that they never use maps or navigation apps (22.9% of women selected this answer, compared to 14.5% of men, $p < 0.05$).

This response was also more frequently chosen by individuals older than 60 years (37.8% of responses in this group) compared to younger respondents. Among those aged 18-30, the percentage was 7.4%, and among those aged 31-60, it was 12.7%.



Percentage basis: respondents who have ever traveled by public transport (bus, minibus, trolleybus, tram, or train).

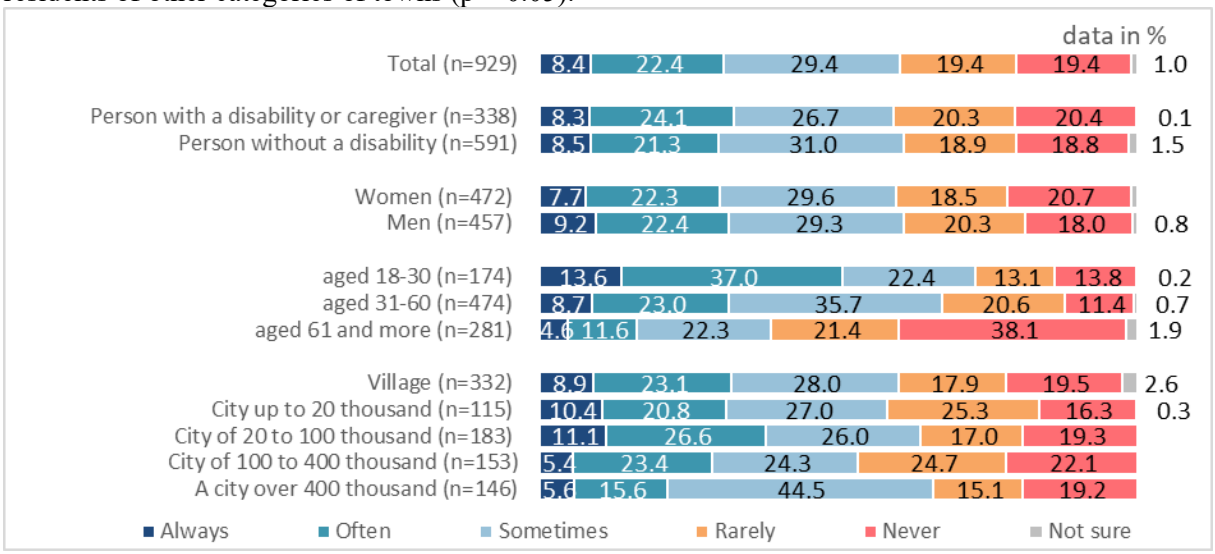
Figure 2. Use of Maps and Navigation Applications During Travel Planning or While Traveling in 2023

Source: own elaboration.

Nearly 80% of respondents indicated that they use location services during travel planning or while traveling – 29.4% use them sometimes, 22.4% use them frequently, and 8.4% always use them (Fig. 3).

Age and the size of the respondents' place of residence are variables that differentiate the distribution of responses to this question. Statistically significantly more individuals over the age of 60 (38.1% of responses in this group) indicated that they never use such applications compared to younger respondents. Among respondents aged 18-30, the percentage was 13.8%, and among those aged 31-60, it was 11.4% ($p < 0.05$).

Residents of cities with populations exceeding 400,000 were statistically significantly more likely to indicate that they rarely use such applications (44.5% of responses in this group) compared to residents of other categories of towns ($p < 0.05$).



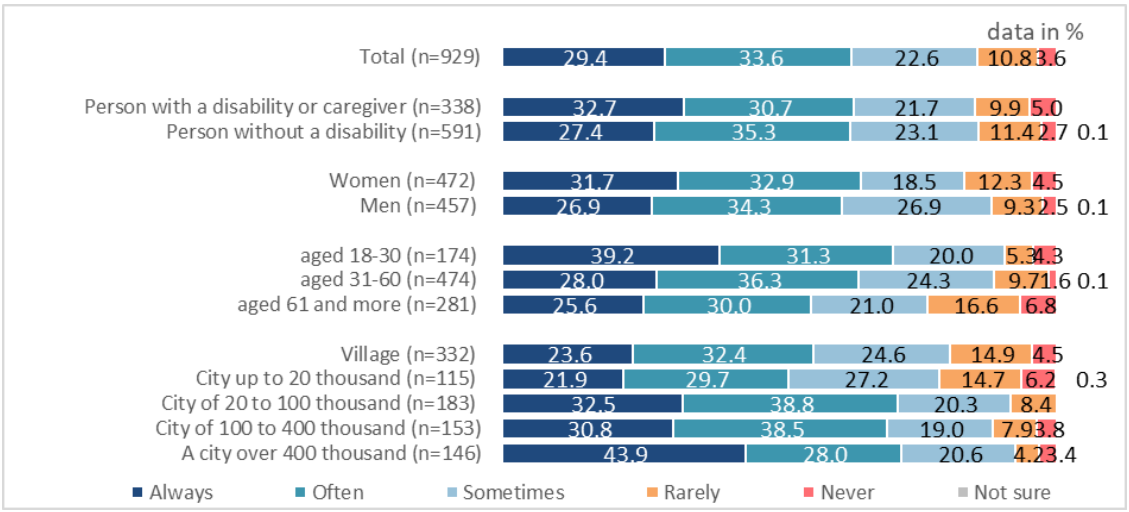
Percentage basis: respondents who have ever traveled by public transport (bus, minibus, trolleybus, tram, or train).

Figure 3. Use of Location or Position Services During Travel in 2023

Source: own elaboration.

Almost all respondents check the timetable online before their planned public transport journey (96.4%). One in five respondents checks it sometimes, one in three does so frequently, and nearly 30% always do so (Fig. 4).

Gender and age are variables that differentiate the distribution of responses to this question. Men statistically significantly more often than women indicated that they sometimes check the timetable in this way (26.9% of men selected this answer, compared to 18.5% of women, $p < 0.05$). Statistically significantly more individuals aged up to 30 years (39.2% of responses in this group) indicated that they always check the timetable online compared to older respondents. Among respondents aged 31-60, the percentage was 28%, and among those over 60, it was 25.6% ($p < 0.05$).



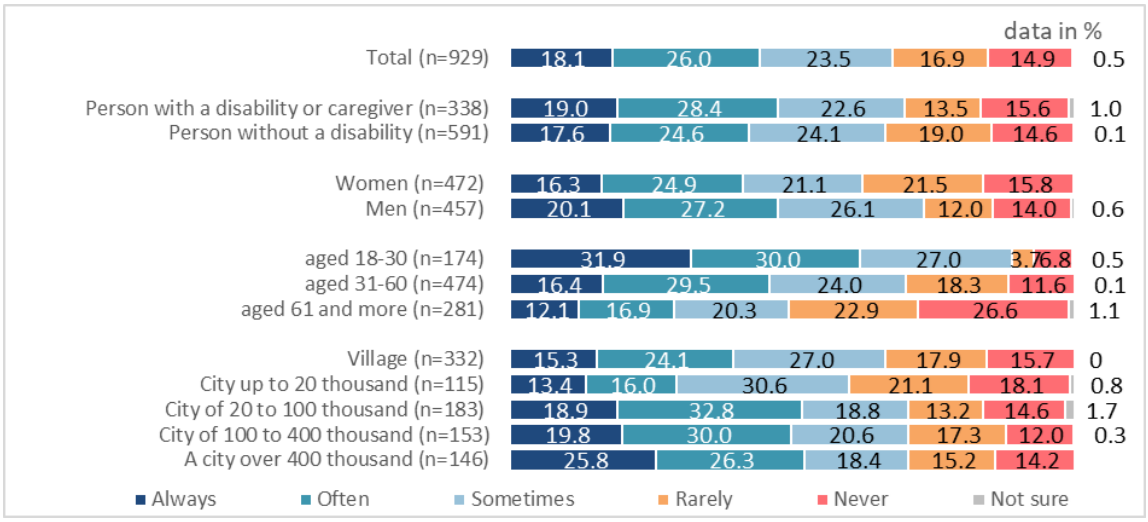
Percentage basis: respondents who have ever traveled by public transport (bus, minibus, trolleybus, tram, or train).

Figure 4. Checking Timetables Online During Travel Planning in 2023

Source: own elaboration.

Over 80% of respondents declared that they check the waiting time for their chosen mode of transport online during their public transport journey (84.6%). Of these, 23.5% do so sometimes, 26% do so frequently, and 18.1% always check the waiting time (Fig. 5).

Gender is a variable that differentiates the distribution of responses to this question. Women statistically significantly more often than men indicated that they rarely check the waiting time (21.1% of women selected this answer, compared to 26.1% of men, $p < 0.05$).



Percentage basis: respondents who have ever traveled by public transport (bus, minibus, trolleybus, tram, or train).

Figure 5. Checking the Waiting Time for the Chosen Mode of Transport Online During Travel Planning in 2023

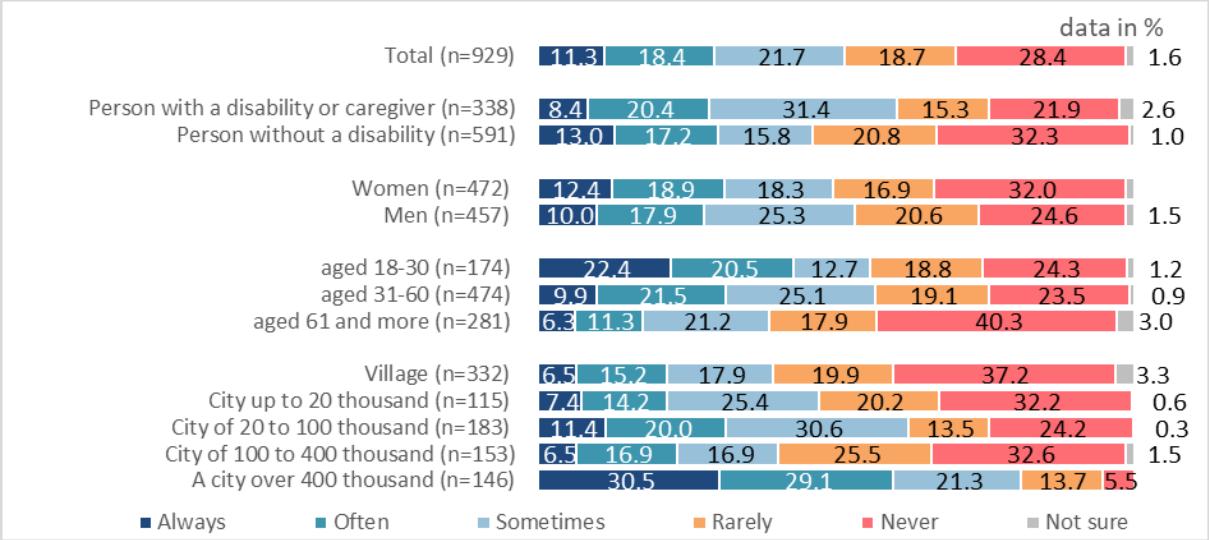
Source: own elaboration.

Nearly 30% of respondents have never used the "Jak dojadę?" app during their public transport journeys, 21% indicated that they use it sometimes, 18.4% use it frequently, and 11.3% always use it (Fig. 6).

Individuals with disabilities statistically significantly more often than those without disabilities indicated that they sometimes use this type of application (31.4% of responses in the disabled group versus 15.8% in the non-disabled group, $p < 0.05$).

Women statistically significantly more often than men indicated that they never use the "Jak dojadę?" app (32% of women selected this answer, compared to 24.6% of men, $p < 0.05$). This response was also significantly more frequent among individuals older than 60 years (40.3% of responses in this group) compared to younger respondents. Among respondents aged 18-30, the percentage was 24.3%, and among those aged 31-60, it was 23.5%.

The size of the place of residence is also a factor influencing differences between groups. Residents of cities with populations over 400,000 (30.5% of responses in this group) significantly more often indicated that they always use this app compared to residents of other town categories.



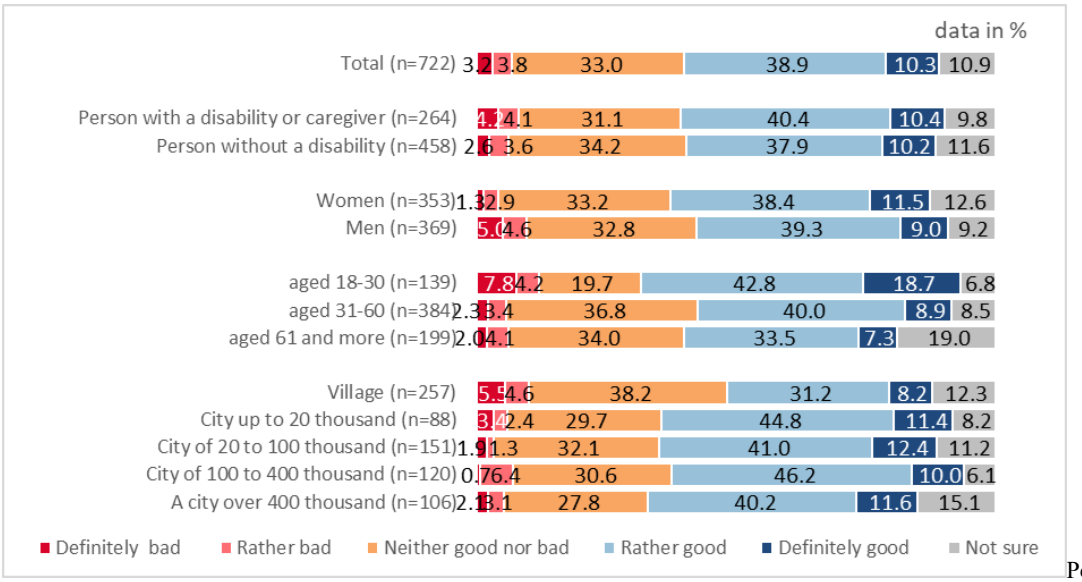
Percentage basis: respondents who have ever traveled by public transport (bus, minibus, trolleybus, tram, or train).

Figure 6. Use of the "Jak dojadę?" App During Travel Planning or While Traveling in 2023
Source: own elaboration.

4.2. Evaluation of the Website and Applications for Ticket Purchasing, Passenger Information, and Ticket Distribution

The evaluation results refer to passengers of rail transport (N = 722, Fig. 7-8) and bus transport (N = 583, Fig. 9-10). The evaluation of the website and applications for ticket purchasing and passenger information in rail transport is presented in Fig. 7. Half of the respondents rated this aspect positively, while 6.9% disagreed. Men statistically significantly more often than women rated the websites and ticket purchasing apps for trains very poorly (1.3% of women and 5% of men selected this answer, $p < 0.05$).

The results also vary based on the age of the respondents. Statistically significantly more individuals over 30 years old rated this aspect as neither good nor bad (36.8% in the 31-60 age group, 34% in the group over 60) compared to younger respondents (19.7% in this group, $p < 0.05$).



Percentage basis: respondents who traveled by train n=722

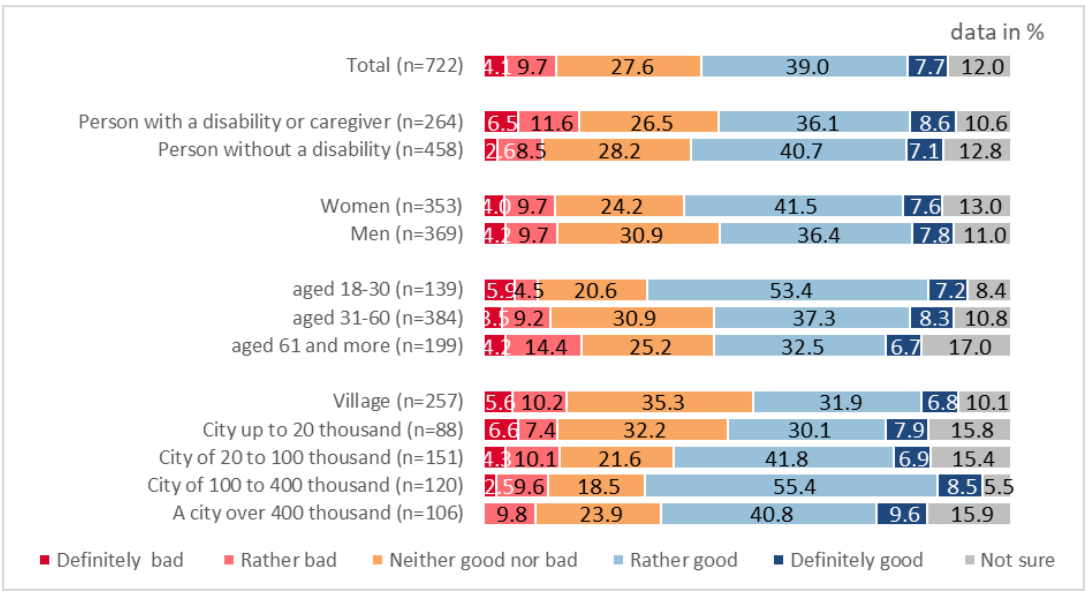
Figure 7. Evaluation of website/ticketing and passenger information applications in 2023
Source: own elaboration.

The respondents rated ticket machines in rail transport slightly worse – half of the respondents gave this aspect a positive evaluation, while only 13.8% disagreed (Fig. 8).

Individuals with disabilities statistically significantly more often than those without disabilities rated this aspect very poorly (2.6% of responses in the non-disabled group and 6.5% in the disabled group, $p < 0.05$).

The results also vary based on the age of the respondents. Statistically significantly more individuals aged up to 30 years rated this aspect rather positively (53.4% of responses in this group) compared to older respondents (37.3% in the 31-60 age group, 32.5% in the over 60 age group, $p < 0.05$).

The size of the place of residence is also a factor influencing differences between groups. Rural residents significantly more often selected the response "Neither good nor bad" (35.3% of responses in this group) compared to residents of towns with populations ranging from 20,000 to 400,000 (21.6% and 18.5% of responses in these groups, $p < 0.05$).



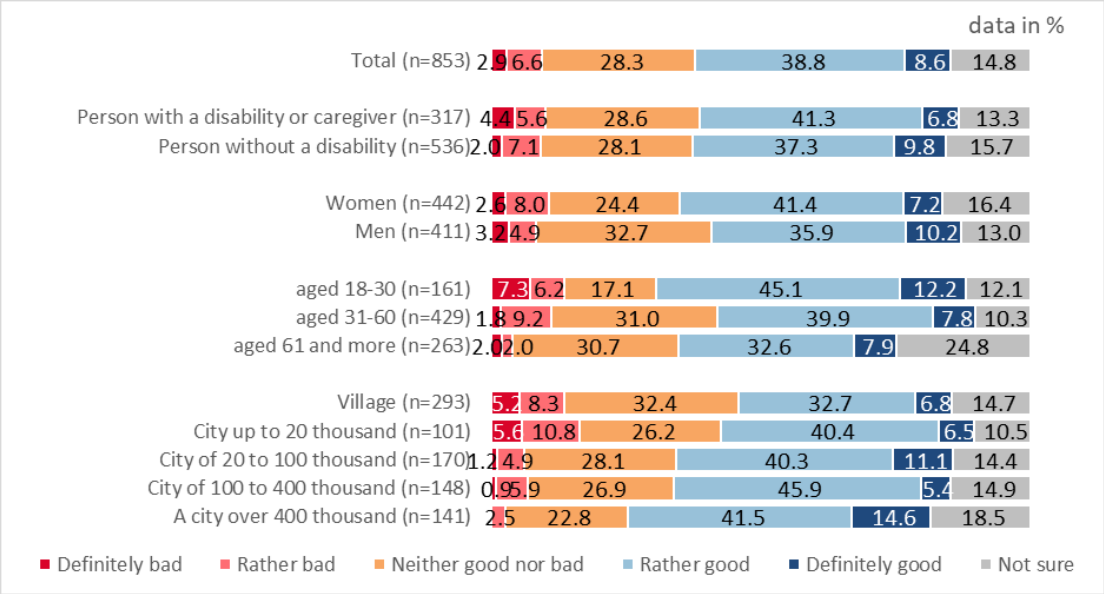
Percentage basis: respondents who traveled by train n=722

Figure 8. Evaluation of ticket machines in 2023
Source: own elaboration.

In bus transport, half of the respondents gave a positive evaluation to websites and applications for ticket purchasing and passenger information (47.4%), while one in ten disagreed (9.5%), as shown in Fig. 9.

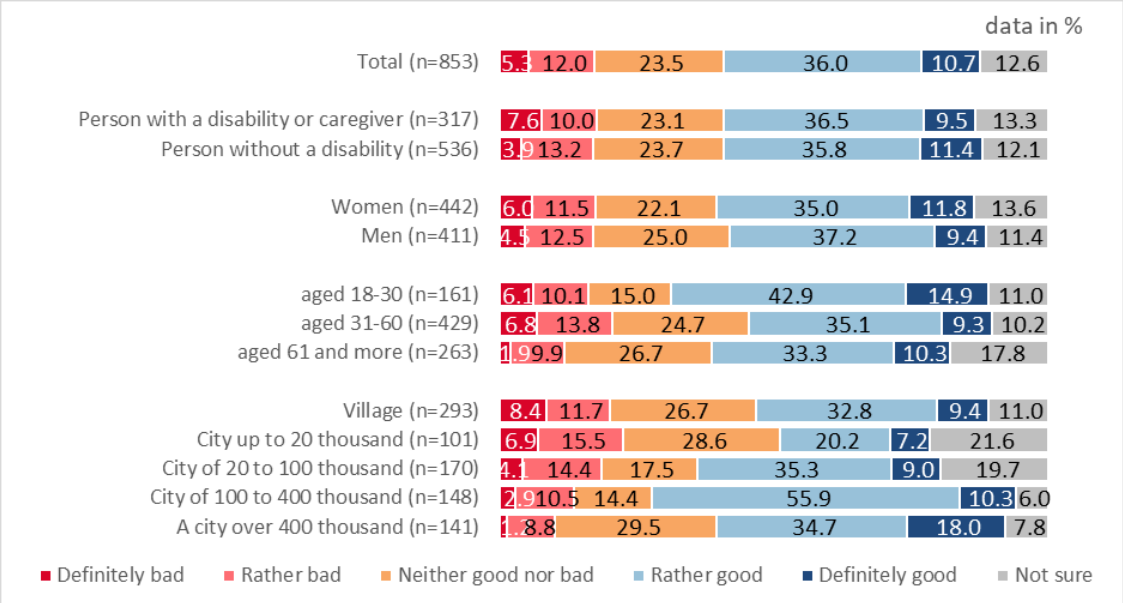
Men statistically significantly more often than women rated the websites and ticket purchasing apps for buses as neither good nor bad (24.4% of women and 32.7% of men selected this response, $p < 0.05$).

The results also vary based on the age of the respondents. Statistically significantly more individuals aged up to 30 years rated this aspect very poorly (7.3% of responses in this group) compared to older respondents (1.8% in the 31-60 age group, 2% in the over 60 age group, $p < 0.05$).



Percentage basis: respondents who have traveled by bus (N = 853).

Figure 9. Evaluation of website/ticketing and passenger information applications in 2023
Source: own elaboration.



Percentage basis: respondents who have traveled by bus (N = 853).

Figure 10. *Evaluation of ticket machines in 2023*
Source: own elaboration.

Similarly, respondents rated ticket machines in bus transport (Fig. 10) – half of the respondents gave a positive evaluation of this aspect (46.7%), while only 17.3% disagreed. Statistically significantly more individuals over 30 years old rated this aspect as neither good nor bad (24.7% in the 31-60 age group, 26.7% in the over 60 age group) compared to younger respondents (15% in this group, $p < 0.05$).

The size of the place of residence is also a factor influencing differences between groups. Residents of cities with populations ranging from 100,000 to 400,000 were statistically significantly more likely

to rate this aspect as "Rather good" (55.9% of responses in this group) compared to respondents from other categories of towns (with a maximum of 36% of responses in the other groups, $p < 0.05$).

5. DISCUSSION

In 2023, after the COVID-19 pandemic subsided, there was an observed increase in both transport services and the use of modern technologies by passengers: as many as 85% checked the waiting time for their chosen mode of transport online, 70% used mobile applications, and 96% checked timetables before their journey. However, relatively fewer passengers purchased tickets online (almost 50%), with the remaining individuals buying tickets in the traditional manner (Rosa 2024; Kos et al. 2020; Anuar 2024).

The results presented in this article from the conducted research are similar to those provided by transport operators based on their own calculations. They clearly indicate a steady increase in the use of mobile applications in planning and executing public transport journeys in Poland (Badanie satysfakcji pasażerów - edycja I; edycja II – 2019, 2022; Jakość usług w sektorze pasażerskich przewozów kolejowych – badanie opinii pasażerów, UTK, 2025).

The survey conducted in December 2019 showed that passengers were eager to use the new technological solutions offered to them (Badanie satysfakcji pasażerów – edycja I, UTK, 2020). This was indicated by the large number of individuals declaring the purchase of tickets using mobile applications and online sales systems (websites). Contributing factors include the ability to use sales services at any time and place, the increasing availability of internet access, ease, speed, and the growing security of online payments. Furthermore, the increasing number of purchases made online indicates that the trend of using mobile applications and websites to purchase tickets will continue to rise. The sample in the 2019 study consisted of 5,646 people. These results correlate with the statistics published by the Office of Rail Transport (UTK) based on annual data reports from railway operators. According to this data, the share of online channels (websites and mobile applications) in railway ticket sales has been increasing significantly year by year. A comparison of the data from 2017 and 2018 showed an annual increase in the internet share of total sales by nearly 40%. Passengers rated ticket vending machines the highest (with a combined 52.9% good and very good ratings) and online sales systems (53.7% of responses indicating a high level of satisfaction). However, the large number of respondents who expressed no opinion regarding their satisfaction with the use of mobile applications for this purpose – 38.8% of respondents – may indicate less frequent use of this ticket purchase method and also point to opportunities for development and improvement. Respondents positively evaluated the availability of passenger information from the most popular sources, particularly from the internet services of transport operators (58.6% of ratings were good or very good) (Badanie satysfakcji pasażerów – edycja I, UTK, 2020).

The Passenger Satisfaction Survey conducted in December 2021 was held in the form of an interactive questionnaire available on the website of the Office of Rail Transport (Badanie satysfakcji pasażerów – edycja II, 2022). A total of 1,516 individuals completed the survey. The results indicated that respondents most often purchased railway tickets using online sales systems (websites) – 70.2%, via mobile applications – 43.3%, or through ticket vending machines (43.1%). The largest number of respondents rated the quality of passenger information regarding available connections, train departure times, platforms, transfer opportunities, and the information provided on transport operators' websites and mobile applications as good or very good (76.3%), as well as the clarity and readability of timetables in search engines (87.4% rated this as good or very good). The most commonly used methods for checking timetables, ticket prices, or purchasing tickets included: connection search engines (75.9%), transport operators' websites (64.1%), and mobile applications (54.6%). The majority of respondents

rated the accessibility of passenger information on the most popular sources, particularly on transport operators' websites (58.6% rated it as good or very good) (Badanie satysfakcji pasażerów – edycja II, 2020).

The results of the next passenger satisfaction survey conducted by the Office of Rail Transport in December 2024 (Jakość usług w sektorze pasażerskich przewozów kolejowych – badanie opinii pasażerów, UTK, 2025) clearly show that passengers enjoy traveling by train, but they are not without criticism. With technological progress, their justified expectations are growing. Travelers expect intuitive ticket purchasing channels, fare integration, useful applications, and fast, but most importantly, reliable information – both traditional, provided by humans, and automated. The railway passenger satisfaction survey took the form of an interactive questionnaire posted on the UTK website. It was completed by a total of 2,208 people. Respondents rated the quality of passenger information about train schedules/movements on websites and in mobile applications the highest (65.4%). They rated train information provided through station megaphone announcements the lowest (43.6%). The majority of respondents rated the transparency and readability of timetables in online connection search engines as the best (87.4%), while the lowest ratings were for station posters (30.9%). The most commonly used methods for checking timetables, ticket prices, or purchasing tickets included: connection search engines (69.2%), transport operators' websites (61.2%), mobile applications (56.1%), and others (1.2%). Other sources mentioned by respondents included interactive trip planners, such as Google Maps, station displays, Network Timetable Tables (SRJP), friends, and ticket vending machines (which usually have a built-in connection search engine with timetables). The best ratings for accessibility for people with special needs were given to the websites and mobile applications of railway operators (55%) (Jakość usług w sektorze pasażerskich przewozów kolejowych – badanie opinii pasażerów, UTK, 2025).

A specific group included in the available studies consists of individuals with disabilities or limited mobility, including seniors. Many publications address similar approaches to the access and use of modern technologies, including mobile applications (Bokolo, 2023; Kos et al., 2020; Kos et al., 2022). Their importance is steadily growing among various passenger segments. A significant group that continues to grow is seniors, a segment related to the "aging societies" of many countries, who are increasingly proficient with modern technologies, particularly the use of mobile applications. This group is specifically analyzed in various studies (Jakość usług w sektorze pasażerskich przewozów kolejowych – badanie opinii pasażerów, UTK, 2025).

The main limitation of the studies conducted is the unstable period in which they were carried out, immediately following the COVID-19 pandemic. On one hand, there were growing passenger prejudices against public transport, while on the other, there was a very rapid development of societal digitalization. The access to mobile applications could be seen as a novelty, not resulting from passengers' previous experiences, thus not yet widespread. Additionally, the evaluations of the applications are based on a short period of use and do not result from long-term experiences. The period of implementation of modern technologies across various segments may vary, and their evaluation may change as users' experiences evolve.

6. CONCLUSION

In summary, the results of the presented studies, both those conducted by the author and those from organizations managing public transport, indicate that since the COVID-19 pandemic, there has been a rapid development of digitalization in society, including the use of mobile applications in public transport. Passengers in Poland generally use the available applications. The research results showed that:

- Approximately 60% of respondents use applications for ticket purchasing,
- 80% indicated that they use maps and navigation apps during travel planning or while traveling,
- Nearly 80% indicated that they use location services during travel planning or while traveling,
- 96.4%, or almost all respondents, check the timetable online before their planned public transport journey,
- Over 80% of respondents declared that they check the waiting time for their chosen mode of transport online during their public transport journey (84.6%),

- Nearly 70% use the "Jak dojadę" app, while just over 30% have never used it during their public transport journey.

Age differentiates the distribution of responses regarding the use of all the studied applications, particularly in relation to non-use. Seniors are not digitally excluded, but they use mobile applications in public transport to a lesser extent and less frequently.

Passengers with disabilities or limited mobility use mobile applications in public transport to a similar extent as those without disabilities and are not digitally excluded. Only in relation to the use of two applications can population differentiation be observed:

- Statistically significantly more individuals with disabilities than those without disabilities indicated that they sometimes use map and navigation applications (31.7% of responses from individuals with disabilities compared to 23.6% from those without disabilities, $p < 0.05$).
- Statistically significantly more individuals with disabilities than those without disabilities indicated that they sometimes use the "Jak dojadę?" app (31.4% of responses from individuals with disabilities compared to 15.8% from those without disabilities, $p < 0.05$).

Gender differentiates the population using mobile applications in travel planning. Women statistically significantly more often than men indicated that they never use mobile ticket purchasing applications (45.6% of responses from women compared to 34.9% from men, $p < 0.05$), never use maps or navigation apps (22.9% of responses from women compared to 14.5% from men, $p < 0.05$), and never use the "Jak dojadę?" app (32% of responses from women compared to 24.6% from men, $p < 0.05$).

Place of residence is a variable that differentiates the population using mobile applications in travel planning. Rural residents (19.6% of responses in this group) and residents of towns with populations up to 20,000 (21.8% of responses in this group) statistically significantly more often indicated that they rarely use ticket purchasing applications compared to residents of cities with populations ranging from 100,000 to 400,000 (5.9% of responses in this group, $p < 0.05$). Residents of cities with populations over 400,000 (30.5% of responses in this group) statistically significantly more often indicated that they always use the "Jak dojadę?" app compared to residents of other town categories.

The obtained information is a source of knowledge that transport operators need to encourage passengers who do not use modern technologies to start using them or to increase the activity of those who use them very rarely or rarely. The research results may also be useful for transport operators in improving individual applications, sales channels, and passenger information systems, including those for passengers with disabilities or limited mobility (including seniors). In the context of intelligent public transport management, the results of the presented studies indicate the significant role of digital technologies in improving the functioning of transport systems, particularly in the domain of mobile applications supporting passengers. The integration of such solutions with intelligent transport management systems has the potential to significantly enhance the efficiency and accessibility of transport services.

Intelligent public transport management relies on advanced information systems that allow for the monitoring and real-time optimization of urban transport flows. Mobile applications play a key role in this system by providing passengers with access to information on routes, delays, waiting times, as well as enabling easier travel planning and ticket purchasing. The use of such tools makes public transport more flexible, adapting to the changing needs of passengers.

The research results demonstrate that after the COVID-19 pandemic, there has been a dynamic development of digitalization, and the use of mobile applications has become more widespread, although usage varies depending on age, gender, and place of residence. The observed differences in user behavior suggest that intelligent transport management should take these variations into account in order to deliver appropriate services and information to each passenger group. For older adults and individuals with limited mobility, who use applications less frequently, it is necessary to adapt interfaces and functionalities to ensure easier access to information and services.

Furthermore, considering the research findings related to the differences in application usage depending on the place of residence, intelligent transport management should consider the development of solutions that will enable more effective outreach to passengers in rural areas or small towns who may have limited access to modern technologies.

From the perspective of public transport operators, intelligent system management should also include digital education for passengers, encouraging them to use mobile applications. This could

include informational campaigns, training programs, as well as further customization of applications to ensure they are accessible to the broadest possible group of users, including older adults and people with disabilities.

In conclusion, the application of intelligent solutions in public transport management, taking into account the diverse needs of passengers, is crucial for the future of urban mobility, enhancing both the accessibility and comfort of public transport.

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CYBER SECURITY AWARENESS AMONG CITY COUNCILORS IN THE ERA OF HYBRID WARFARE

Hubert Pachciarek[a], Maciej Drzonek[b]

[a] *University of Szczecin, Institute of Management, Szczecin, Poland*
[b] *University of Szczecin, Institute of Political Science and Security Study, Szczecin, Poland*

ABSTRACT

Purpose: *The purpose of the article is to examine the awareness of cyber security threats in the era of hybrid warfare among councillors of selected 21 medium and large Polish cities from the West Pomeranian and Subcarpathia provinces.*

Need for the study: *In the era of hybrid warfare, cyberspace is becoming another theatre of warfare. Numerous threats to society flow from cyberspace. A key aspect of defence against threats is awareness, which most often comes from knowledge of the threats.*

Methodology: *The study used methodological triangulation to fully clarify the awareness of cyber threats among city councillors. To this end, anonymous questionnaire surveys were conducted, asking people to rate the likelihood of various threats, including cyber threats. The same group of councillors was then invited to participate in in-depth interviews, during which they were asked to identify three key contemporary threats to Poland and to identify the most important concerns of the residents of the cities they represent. The results for the two provinces were compared and showed statistically significant differences.*

Findings: *The councillors indicated the presence of cyber security threats in the surveys. These threats were the second most indicated and were the fewest of all 14 threats indicated as not present. However, in qualitative research, during in-depth interviews with councillors, these threats were sporadic. This indicates a relatively low awareness of cyber security threats.*

Practical Implications: *The research methodology can be used to conduct analogous research in other regions of the world or in organizations exposed to cybersecurity threats.*

Keywords: cybersecurity, awareness of cybersecurity threats, hybrid warfare, local government, cyberspace, information technologies

1. INTRODUCTION

The hybrid war in Ukraine has been ongoing since February 2014 and has taken on a particularly ruthless character through a full-scale military conflict on February 24, 2022. This means that due to the ongoing war directly across the Polish border, Poland has become a frontline country and, at the same time,

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serves as a key logistical hub for military and humanitarian support for the fighting Ukraine. The Subcarpathia region, which borders Ukraine directly, is particularly important in this regard. Consequently, Poland has also become, to some extent, a theater of hybrid warfare waged by Russia. What is hybrid warfare? Hybrid warfare is a combination of conventional and unconventional warfare such as the use of the regular military, special forces, irregular armed groups, economic pressure, cyber-attacks, information warfare, diplomacy, and the stimulation of social conflict (Steingartner, Galinec, 2021). The dangers of stimulating internal conflicts in countries targeted by hybrid warfare by raising socioeconomic differences, including on ethnic grounds, spreading disinformation, attempting to quarrel with partner countries, and waging information warfare using mass media and electronic media require special attention (Krawczyk et al., 2024). Consequently, it is not necessary to wage war using conventional lethal weapons, a country can become a party to hybrid warfare in the information-social space, for which IT tools, the Internet and artificial intelligence will be used. Thus, information warfare is an important element of modern warfare, affecting the adversary, its information resources, information systems and computer networks (Kus, 2023). Consequently, the adversary in hybrid warfare is non-standard: a state, a state-supported organization, or a private actor, complex and fluid due to the volatile nature of the war coalitions formed, easily adapting to the situation, using advanced information technologies and spreading propaganda using the media and the Internet (Otaiku, 2018). Russia has developed a doctrine of hybrid warfare by moving away from the characteristics of traditional armed conflicts (Mumford, Carlucci, 2023), supplementing the spectrum of activities with the acquisition of direct influence, taking measures for the internal decomposition of the enemy, using irregular forces-"private armies", moving away from the traditional perception of the battlefield in physical dimensions to a multidimensional field, including cyberspace, using informational and psychological superiority, from symmetrical conflict to asymmetrical conflict using political, economic, informational, technological and ecological campaigns, and finally moving away from a limited time of conflict to a permanent state of war (Crowther, 2021).

The development of the doctrine of hybrid warfare became possible due to the emergence of cyberspace, understood as "an unlimited (in terms of reach and freedom of use) means of interpersonal communication" (Herominski, 2024, p. 187). The development of cyberspace was made possible in large part by the emergence of long-distance human communication tools. Today, cyberspace is primarily identified with the development of Internet.(Faruk et al., 2022) In fact, a distinction can be made between physical components (hardware, electronic devices), logical components (software, internet) and a network of interpersonal relations embedded in cyberspace as a non-physical element (Zdzikot, 2022; Jang-Jaccard, Nepal, 2014, Humayun et al., 2020). That is why the dangers of hybrid warfare are particularly associated with this area. This is because cyber warfare is much less visible than the use of regular military units or irregular militarized groups, and mankind has already become somewhat accustomed to the occurrence of armed conflict. In contrast, cyber threats are a new phenomenon. It should be added that engaging in traditional warfare requires entering into direct contact with the enemy; in cyberspace, the enemy can act from anywhere in the world. In traditional terms, the enemy is defined; in cyberspace, the category of the enemy is fluid and illusory, often impossible to identify. After all, we are aware of an enemy that poses a physical threat, an enemy in cyberspace we may not even notice or be aware of its existence. This is why awareness of cyber threats has become of such interest to the article's authors.

2. LITERATURE REVIEW

Hybrid warfare conditions aside, it is important to emphasize the growing risk of cyber threats. This is due to the dynamic development of the e-commerce market, the associated increase in the volume and value of electronic payments, the digitization of services and products, the widespread use of the Internet and mobile devices, and cloud solutions (Kuzior et al., 224; Ahsan et al., 2022). At every level of social life, we collide with digitization processes. Whether we are talking about public services, B2B and B2C relations, or at the individual level. In practice, most modern world citizens use mobile or online devices daily, store sensitive data in cyberspace or make electronic payments. Consequently, each such activity exposes cyber security to cyberattack or cybercrime. The development of information technology leads, on the one hand, to the simplification of everyday life for organizations and citizens. However, on the

other hand, it expands the spectrum of cybersecurity threats. Shestak and Tsyplakova attempted to create a unified classification of such threats, which are presented in Table 1.

Table 1. Classification of cybersecurity threats

Type	Characteristics
Botnet	Hackers operate some systems to coordinate attacks and dissimilate phishing, spam and malware
Organized Criminal Groups	Attacks often aim at monetary gain via spam, phishing, spying- or malware to steal personal data and e-fraud
Foreign Intelligence Service	One of the goals is information warfare and critical infrastructure decommission
Hackers (Including Hacktivists)	Applying malware or other instruments in order to cause failure and serious damage
Insiders	Disgruntled employees of an organization who do not have specific knowledge in IT, but have access to ESM. The motive is often revenge which harms not only the company's reputation, but also critical infrastructure facilities
Phishing	Persons or small groups that steal personal data or information in general in order to take advantage via spam and spy- and/or malware software
Spammers	Persons or organizations that send e-mails with hidden or false information in order to sell produce, activate phishing, spy- or malware software and attacks on the organization
The Authors of Spy- and/or Malware Software	Persons or organizations that create or dissimilate spy- or/and malware software, computer viruses and worms which damage files and hard drives
CyberTerrorism and CyberExtremism	Persons or organizations that seek to destroy, disable or use critical infrastructure to compromise national security, weaken a nation's economy and use phishing schemes or spy- and/or malware to obtain funds or gather sensitive information
Commercial Spies	More professional approach rather than insiders and the motivation is private gain

Source: Shestak, V. A., Tsyplakova, A. D. (2023). Criminological Features of the Cybersecurity Threats. The Law, State and Telecommunications Review, 15(2), 194-195.

In Poland, we can observe an increasing number of cybersecurity incidents yearly. While this is partly because citizens, institutions, and businesses are becoming more aware of this area and the introduction of simplified reporting procedures through automated reporting systems, it does not explain such a dynamic increase in identified incidents (Lisiak-Felicka, 223).In 2023, CERT Poland, a team within the national cyber-security system established to monitor cyber-security threats, handle incidents at the national level and build threat awareness, confirmed 80267 incidents. In 2020, it was still 10420 incidents (CERT, 2024). The jump in confirmed incidents shows the scale of threats to modern societies. The most important threats in the era of hybrid warfare and the growing arsenal of cyber criminals include (Wieczorek, Roszkowski, 2021):

- theft of sensitive data using information technology, not only personal data but also classified information, intellectual property, business secrets,
- cyber-terrorism- actions taken in the cyber world aimed at forcing concessions on the public or public authorities,
- cyber extortion- cyber-attacks on websites leading to their blocking in order to extort a ransom in exchange for restoring the state before the attack,
- economic espionage- the acquisition of confidential information for competitive advantage by private entities or government services. Such activities can range from stealing cutting-edge technology information about strategic decisions made to, for example, the financial health of a particular company,
- cyber warfare- attacks on enemy information systems by specialized services,

Information warfare is the use of manipulation to create social pressure, internal conflicts, and emotional reactions in response to false information or partially false information.

The spectrum of criminal activities undertaken in cyberspace is diverse, and there is still a lack of effective tools to counter cybersecurity threats. Today, we are witnessing a real cyber arms race. Therefore, awareness of cybersecurity threats and avoiding unsafe behaviour seems to play an important role in threat and incident crisis management situations (Franke, Brynielsson, 2014). To date, there have been numerous studies of cybersecurity threat awareness. Zwilling et al. conducted a comparative study of students from Turkey, Slovenia, Israel and Poland, exploring the relationship between IT knowledge, cybersecurity threats awareness and their impact on protective behaviours in cyberspace, postulating in their conclusions to conduct training programs to improve cybersecurity (Zwilling et al., 2020). Students were also studied by Muthisi and Mujinga using the SOTAM model (the student online threats awareness model), which analyzed the impact of foundational factors such as biographical data, institutional practices, and the presence of intervention programs in the form of training programs, for example, on cybersecurity threats awareness and activity in cyberspace (Mothisi, Mujinga, 2025). Research in this area, but among corporate employees, was conducted by Hadlington et al. looking for a relationship between ISA (information security awareness) and FoMO (Fear of Missing Out) (Hadlington, Binder, Stanulewicz, 2020). Their research found that measures aimed at reducing FoMO among employees can lead to more responsible behaviour in cyberspace. The human factor in dealing with cybersecurity threats was also highlighted by Georgiadou et al. by examining the relationship at two levels: individual and organizational (Georgaidou et al., 2020). At the individual level, attitudes, knowledge, awareness and competence were tested through surveys, tests, simulations and observations. In this way, it is possible to build a safety system and minimize the risks associated with risky human behaviour. In the studies analyzed by the Authors, it is clearly indicated that the key risk factor associated with cybersecurity threats is the human individual and his or her propensity for risky behaviour and vulnerability to threats emanating from cyberspace, whether they relate to exploitation of the Internet and establishment of virtual relationships, or electronic purchases and payments, use of risky network sources, or vulnerability to disinformation or even fraud created by cybercriminals. Considering the threats of hybrid warfare and specifically related cybersecurity threats, a threat awareness study was undertaken in two purposely selected regions of Poland.

3. METHODOLOGY. CHARACTERISTICS OF THE SURVEY OF LOCAL AUTHORITIES OF SUBCARPATHIA AND WESTERN POMERANIA.

The surveys described below were conducted in 2024 by the Res Publica Research Team at the University of Szczecin (res.usz.edu.pl). They are one of the elements of research conducted as part of a broader research project in 2023-2026 entitled Local Politicians vs. Patriotism and Threat Perception. A comparison of the cities of Subcarpathia and Western Pomerania.

3.1. Rationale for security and threat surveys among local government officials

In 2014. Russian Federation seized Crimea, and in 2022, the Polish public's views on its sense of security and threats may have changed as a result of the intensification of Russian aggression against Ukraine. In addition, before the full-scale kinetic war between Russia and Ukraine took place, the Russian state, with the cooperation of Belarus, implemented other hostile actions on NATO's eastern flank. These included various hybrid actions, both cyber in nature and in the form of attacks on the borders of Poland and Lithuania. In 2021, the Belarusian (and Russian) authorities from their territory massively enabled the illegal migration to Poland, Lithuania and Latvia of people coming from various African and Asian countries. Illegal transit of illegal migrants via Belarusian territory led to the need to erect barriers on the border with Belarus to impede illegal border crossings.

The 2022 Russian aggression unleashed Poland's multifaceted involvement in aid to Ukraine. The most important elements of this assistance include: political support in the international arena, military support through the provision of military equipment, as well as logistical support by making its territory available for the transit of aid to the fighting Ukraine (Rzeszow-Jasionka airport is of particular importance), and finally, providing shelter to the multi-million refugees, especially in the first months of the kinetic war. A great responsibility in both fostering patriotic attitudes and prudent perception of potential threats lies with local political elites. It is the maturity and awareness of local politicians and their willingness to engage with their local communities that determine what those local communities will be.

It is the maturity and awareness of local politicians and their willingness to engage with local communities that determine what these local communities will be. Thus, on the one hand, Russia and Belarus attempt to create an artificial migration crisis and, on the other hand, the war in the immediate vicinity of the Republic may have transformed Poles' social attitudes regarding their perception of security and threats.

It can be assumed that people holding elected positions in local government (especially councillors) have natural contact with the local communities in which they live on a daily basis and which they represent in the local government structures. It was therefore decided to check the perception of threats and security among local politicians of medium-sized cities (from 20,000 to 100,000 residents) and large cities (over 100,000 residents) in two distant provinces – Subcarpathia and Westpomeranian. The former, which is located in the Subcarpathia region, directly borders the territory of Ukraine, so it can be assumed that the threats, due to the kinetic war going on just across the border, are perceived quite clearly there. The second province, located in Western Pomerania, covers the geographically opposite area of Poland - the northwestern areas bordering Germany, at the same time, the furthest from the border with Belarus and Ukraine.

Therefore, it can be assumed that local government officials of cities in the Subcarpathia region may exhibit specific attitudes regarding various categories of threats already due to the proximity of the border with Ukraine and Subcarpathia's role as a transit corridor for multidimensional aid channelled from various parts of the world. This peculiarity is also compounded by other factors, such as political preferences with a predominance of support for political groups promoting conservative perceptions of reality, and an accompanying higher level of religiosity. On the other hand, in the cities of Western Pomerania to which many refugees were admitted after 24 II 2022, due to the distance from the military action in Ukraine, the perception of security and threats to state security may be somewhat different (although - it is worth noting at the same time that in Western Pomerania the Ukrainian diaspora already resided before 2022).

The perception of threats to state security based on a survey of respondents living and working in the local government of cities in two opposite regions of Poland is justified. This is because the attitudes of local politicians of cities from two different regions were taken for comparison: the conservative, religious Subcarpathia, which, in addition, directly borders the war zone, and the liberal, low-religious West Pomerania, distant from the immediate war threat.

3.2. Characteristics of the surveyed cities

Two categories of cities were taken for the survey: according to the methodology used by the Central Statistical Office, these are medium-sized cities, i.e. with residents between 20,000 and 100,000, and large cities, i.e. with more than 100,000 residents. This selection of cities and local government officials operating in them seems justified. Firstly, units with similar demographic structures are compared; secondly, such categories of cities are subject to systematic, periodic surveys by institutions conducting statistical research; and thirdly, in both regions studied, the number of cities in the identified categories is similar: ten in the Subcarpathian region and eleven in the West Pomeranian region.

In West Pomerania, the following medium-sized cities were singled out: Białogard, Goleniow, Gryfino, Kolobrzeg, Police, Stargard, Szczecinek, Swinoujscie and Walcz. Zachodniopomorskie has two cities in the large city category: the capital of Zachodniopomorskie, Szczecin, and Koszalin. Table 2 presents the surveyed cities with their population in 2021 and 2024.

In Subcarpathia, on the other hand, the following cities were classified as medium-sized cities, according to the criterion adopted after the Central Statistical Office (20-100 thousand inhabitants): Debica, Jaroslaw, Jaslo, Krosno, Mielec, Przemyśl, Sanok, Stalowa Wola and Tarnobrzeg. According to the accepted nomenclature in Subcarpathia, the only large city is its capital, Rzeszów. Table 3 presents the surveyed cities and their populations in 2021 and 2024.

Table 2. Studied cities of West Pomeranian and Subcarpathian province and their demographic size 2021-2024

City	Surface		Population		City	Surface		Population	
	in ha	in km²	2021	2024		in ha	in km²	2021	2024
Białogard	2573	26	23950	22418	Dębica	3383	34	45189	42986
Goleniów	1178	12	21979	21462	Jarosław	3461	35	37073	35298
Gryfino	1181	12	20923	19691	Jasło	3652	37	34542	32727
Kołobrzeg	2567	26	46198	43426	Krosno	4472	45	45948	44060
Koszalin	9834	98	106235	105540	Mielec	4689	47	60075	56972
Police	3731	37	32243	29627	Przemyśl	4617	46	59779	56050
Stargard	4808	48	67579	66604	Rzeszów	12901	129	197863	197268
Szczecin	30060	301	398255	389066	Sanok	3808	38	36999	34345
Szczecinek	4848	48	39827	37557	Stalowa Wola	8252	83	59623	55127
Świnoujście	20207	202	40948	38904	Tarnobrzeg	8540	85	46360	43712
Wałcz	3817	38	24949	23578					

Source: own compilation based on: CSO, Area and population in territorial section in 2021, Warsaw 2021, https://stat.gov.pl/obszary-tematyczne/ludnosc/ludnosc/powierzchnia-i-ludnosc-w-przekroju-terytorialnym-w-2021-roku,7,18.html; CSO, Area and population in territorial section in 2024, Warsaw 2024, https://stat.gov.pl/obszary-tematyczne/ludnosc/ludnosc/powierzchnia-i-ludnosc-w-przekroju-terytorialnym-w-2024-roku,7,21.html.

The research project "Local politicians vs. patriotism and threat perception. Comparison of the cities of Subcarpathia and Western Pomerania" in 2024 used methodological triangulation, in order to increase the ability to explain the phenomena under study. Therefore, the research was carried out in two forms. First, quantitative research was conducted in the form of an electronic survey questionnaire (CAWI) distributed to local government officials of the 21 cities under study. The second form was qualitative research implemented by conducting anonymous in-depth interviews with selected local government officials of the surveyed cities.

3.3. Characteristics of quantitative studies

The quantitative survey was a closed-ended questionnaire. It consisted of several questions, each containing a dozen statements (response options). Respondents' answers were collected on a 5-point Likert scale, with the answer "definitely no" having a value of "1" and "definitely yes" having a value of "5."

The first question was: What do you think could threaten Poland's security shortly, and to what extent? Fourteen response options were formulated for it. The remaining questions were related to separate objectives of the research project.

What do you think could threaten Poland's security shortly, and to what extent? A cafeteria of the following fourteen options was used:

1. Demographic collapse, ageing of the population.
2. Reduced standard of living, need to forgo some expenses.
3. Cyber-attack disrupting state operations, theft, cyber-security threats.
4. Social unrest and protests.
5. Increase in crime, including organized crime.
6. Threats to energy security - shortages in energy, gas supply.
7. Fear of losing jobs.
8. Increased risk of not finding a job.
9. Loss of a sense of economic security for families due to an increase in loan instalments.
10. Migration of refugees to Poland from conflict areas.

11. Spread of some infectious disease, epidemic.
12. Terrorist attack in Poland.
13. Political chaos in Poland.
14. Conflicts between ethnic and Religious groups in Poland

It is worth mentioning that the above question and the options to choose from were prepared based on nationwide surveys conducted by the Center for Public Opinion Research (CBOS). The first time CBOS conducted them was in 2014, when the National Security Office commissioned them to the President of the Republic. It was published in November 2014. In addition, the Res Publica Research Team has conducted similar surveys twice. In 2016, among councillors of ten municipalities and cities in the Lubuskie and West Pomeranian Voivodeships. These were Drawsko Pomorskie, Goleniow, Kamień Pomorski, Kobylanka, Nowogard, Stara Dąbrowa, Stargard, Strzelce Krajeńskie and Świnoujście . The 2022 survey, on the other hand, was conducted among councillors of three West Pomeranian cities with county rights (Koszalin, Szczecin, Swinoujscie).In the 2024 survey discussed here, the virtual survey questionnaire was sent to the 21 surveyed cities multiple times: more than thirty times to individuals from city council offices or city council presidents with requests to distribute to individual city councillors, plus dozens of times to individual local government officials. In the eleven surveyed cities of the West Pomeranian Voivodeship, there are 245 city councillors (see Table 3). In the Subcarpathia Voivodeship, are 220 in the ten surveyed cities (see Table 5). Despite repeatedly expressed encouragement and reminders, the return rate of survey questionnaires averaged 34.69% for eleven cities in West Pomerania and 26.36% for ten cities in Subcarpathia. The average return of questionnaires for the 21-city survey was thus 30.75%.

Table 3. Surveyed cities in the West Pomeranian and Subcarpathian region: number of councillors and percentage of survey returns

City	% return of surveys	No of councilors	City	% return of surveys	No of councilors
Szczecinek	47,62	21	Dębica	90,48	21
Stargard	39,13	23	Krosno	38,10	21
Świnoujście	42,86	21	Jasło	28,57	21
Szczecin	38,71	31	Sanok	23,81	21
Koszalin	43,48	23	Mielec	21,74	23
Gryfino	33,33	21	Stalowa W.	21,74	23
Kołobrzeg	33,33	21	Rzeszów	20,00	25
Wałcz	33,33	21	Jarosław	14,29	21
Białogard	23,81	21	Przemyśl	8,70	23
Police	23,81	21	Tarnobrzeg	0,00	21
Goleniów	19,05	21			
mean	**34,69**	**245**	**mean**	**26,36**	**220**

Source: own compilation based on quantitative research in 2024 within the framework of the project entitled Local politicians vs. patriotism and threat perception. A comparison of the cities of Subcarpathia and Western Pomerania, Project No. NdS-II/SP/0355/2023/01.

3.4. Characteristics of qualitative studies

In addition to conducting a survey questionnaire, qualitative research was conducted in anonymous in-depth interviews. They had the character of semi-structured interviews, although the people conducting them (from the Res Publica Research Team operating at the University of Szczecin) could, if necessary, change the order of the questions asked or formulate additional questions to obtain the maximum in-depth response from respondents. The questions included the perception of the most important threats

to Poland in the coming years and the concerns of the residents of their cities, i.e. their electorate, related to the future of Poland, the region, the city and themselves. These topics were addressed because councillors are directly elected and, as such, are representatives of the residents. Therefore, they should have a direct relationship with their constituents and understand their problems and concerns.

Local government officials from the surveyed cities were generally selected for interviews on a random basis. In most cases, they were local government officials serving as councillors during the interview. Often, they were current or former chairmen or vice-chairmen of city councils. In a few cases, they were individuals who had held council seats in earlier terms. Several respondents in the current term (2024-29) relinquished their councillor seats since they were simultaneously elected mayor/mayor of the city or deputies. In a few cases, local government officials sitting on the councils of the county whose seat was the surveyed city were also invited for interviews. A total of 126 interviews were held in twenty-one cities, of which 67 were held in 11 cities in the West Pomeranian Voivodeship (see Table 4), and 59 were held in 10 cities in the Subcarpathia Voivodeship (see Table 7). Counting the ratio of interviews held to the number of councillors in the surveyed cities yielded an average of 27.35% of interviews in West Pomerania and 26.82% in Subcarpathia.

Table 4. Surveyed cities in the West Pomeranian and Subcarpathia region: number of councillors and percentage of anonymous in-depth interviews conducted.

City	% of interviews	Number of councillors	City	% of interviews	Number of councillors
Białogard	23,81	21	Dębica	52,38	21
Goleniów	9,52	21	Jarosław	19,05	21
Gryfino	23,81	21	Jasło	23,81	21
Kołobrzeg	33,33	21	Krosno	38,10	21
Koszalin	30,43	23	Mielec	17,39	23
Police	23,81	21	Przemyśl	17,39	23
Stargard	21,74	23	Rzeszów	28,00	25
Szczecin	25,81	31	Sanok	33,33	21
Szczecinek	33,33	21	Stalowa Wola	17,39	23
Świnoujście	52,38	21	Tarnobrzeg	23,81	21
Wałcz	23,81	21			
mean	**27,35**	**245**	**mean**	**26,82**	**220**

Source: own compilation based on qualitative research in 2024 within the framework of the project entitled Local politicians vs. patriotism and threat perception. A comparison of the cities of Subcarpathia and Western Pomerania, Project No. NdS-II/SP/0355/2023/01.

It should be emphasized that the researchers did not suggest any choice options during the interviews with councillors regarding real threats to Poland or concerns of residents and their direct constituents. Therefore, the information obtained results from the respondents' free speech. Also, when asking these questions, respondents were asked to assess for themselves the importance and order of priority of the threats they believe exist in Poland and thus to present their reflections on their own perception of potential factors interfering with the security of the Polish state. At the same time, it was made clear to the respondents that the essence of the question about concerns occurring in the city where they held local government positions was to present what the city's residents thought about the issue, not the respondent himself. In other words, the respondent was supposed to recount, as it were, the concerns occurring among the city's residents, that is, to talk about the opinions heard about the sources underlying the concerns of the residents of the city in which the respondent served as a local government official.

A matrix was prepared to analyze respondents' answers given in the qualitative research - both for the question on the three main threats to the Polish state and what the residents of your city are concerned about. The matrix contains fifteen categories of possible responses reflecting the threats and concerns. In other words, the statements made by councillors regarding their perceived significant threats to the Polish state were classified into one of the 15 categories. The concerns respondents mentioned in the

city - that is, the perceived and heard concerns expressed by residents - were also categorized into 15 categories. This is a deliberate effort to compare within the same categories, on the one hand, the threats mentioned by local government officials and, on the other hand, the perceived concerns of residents. It should also be noted that these categories mirrored the threats assessed in the quantitative survey, with the difference that an additional category, "other", was introduced for threats not included in the quantitative survey.

Presented below is a list of categories into which city residents raised the threats identified by respondents and the concerns they believe were classified:

1. Demographic collapse.
2. Economic threats.
3. Cyber threats.
4. Threats of a social nature.
5. Conflicts of an ethnic nature.
6. Crime.
7. Energy security threats.
8. Unemployment.
9. Influx of refugees.
10. Health threats.
11. Terrorist threats.
12. Political divisions.
13. Environmental threats.
14. The threat of war, Russian aggression.
15. Other.

The quantitative and qualitative data obtained in the study were subjected to statistical analysis to determine the awareness of cyber threats among the surveyed city councillors. In addition, a comparison of awareness was made between councillors from the West Pomeranian Voivodeship (northwestern Poland) and those from the Subcarpathia Voivodeship (southeastern Poland - a region bordering Ukraine, an important logistical hub for aid to embattled Ukraine). The results obtained in the surveys and interviews were then compared. It should be noted that in the survey research, the selection of threats was supported by identifying 14 potential threats. At the same time, in the interviews, the researchers relied on the free speech of the respondents.

4. RESULTS & DISCUSSION

The reliability of the surveys was verified by measuring the reliability of the questionnaire. Table 5 presents the measurements of the Cronbach's Alpha index. The obtained value of 0.85 indicates a very high reliability of the measurement and a correct selection of variables; based on the analysis of Cronbach's Alpha index, removing any of the variables is not advisable. Thus, the list of risks was prepared correctly, and the obtained data are reliable and can be the basis for statistical analysis of the results and inference based on them.

143 responses were obtained from respondents, as summarized above. Table 6 presents the results obtained. The number of indications of cybersecurity threats is noteworthy. From the point of view of all the threats analyzed, only "demographic collapse, population ageing" (66 indications) and "migration of refugees to Poland from conflict areas" (61 indications) received more indications of YES. However, if we consider the sum of positive indications (YES +preferably yes), cyber threats are already in second place regarding the number of indications by councillors. It is noteworthy that cyber threats also received the least number of negative indications - the least number of surveyed councillors said there were no such threats. On the other hand, the mean of indications (answers were given values according to the Likert scale from NO = 1 to YES = 5) indicates a high level of awareness of cybersecurity threats among respondents. Given that these are representatives of local communities, the Polish public should be congratulated for their high level of awareness, higher than in other surveys cited in the article.

Table 5. The reliability of the questionnaire

variable	Summary.Scale: Mean=48.4196 standard deviation=9.33222 N weighted:143 (calculation_questionnaire (version 1))Cronbach's alpha: ,851488 Standardized alpha:,848912 Mean cor. between pos: ,296176				
	Mean when excluded	Value when excluded	St. dev. when excluded	Mean cor. between pos	Alfa when excluded
demographic collapse, ageing of the population	44,27273	82,28226	9,070957	0,167747	0,858970
reduced standard of living, need to forgo some expenses	45,03497	75,32046	8,678736	0,466807	0,843657
cyber-attack disrupting state operations, theft, cyber-security threats	44,41259	78,82978	8,878613	0,392505	0,847325
social unrest and protests	44,97902	76,32823	8,736603	0,494108	0,841997
increase in crime, including organized crime	45,17482	71,80859	8,473995	0,673660	0,830731
threats to energy security - shortages in energy, gas supply	44,67133	77,26960	8,790313	0,463191	0,843731
fear of losing jobs	45,36364	71,78385	8,472535	0,637647	0,832662
increased risk of not finding a job	45,50350	71,20103	8,438070	0,701889	0,828848
loss of a sense of economic security for families due to an increase in loan installments	44,93007	75,11399	8,666833	0,516687	0,840566
migration of refugees to Poland from conflict areas	44,51049	75,00513	8,660550	0,489125	0,842242
spread of some infectious disease, epidemic	45,23077	78,26143	8,846549	0,350807	0,850152
terrorist attack in Poland	45,09790	75,48692	8,688321	0,462171	0,843920
political chaos in Poland	44,67133	74,41646	8,626497	0,552708	0,838413
conflicts between ethnic and Religious groups in Poland	45,60140	72,77119	8,530603	0,542516	0,838949

Source: own study.

Table 6. The quantitative survey results

variable	yes	likely yes	neither yes nor no	likely no	no	Total yes	Total no	mean
demographic collapse, aging of the population	66	51	10	13	3	117	16	4,15
reduced standard of living, need to forgo some expenses	30	43	30	32	8	73	40	3,38
cyber-attack disrupting state operations, theft,	48	65	15	13	2	113	15	4,01

cyber-security threats								
social unrest and protests	22	55	33	30	3	77	33	3,44
increase in crime, including organized crime	23	43	30	40	7	66	47	3,24
threats to energy security - shortages in energy, gas supply	36	57	29	20	1	93	21	3,75
fear of losing jobs	19	37	37	33	17	56	50	3,06
increased risk of not finding a job	14	33	41	37	18	47	55	2,92
loss of a sense of economic security for families due to an increase in loan installments	30	47	35	25	6	77	31	3,49
migration of refugees to Poland from conflict areas	61	37	21	19	5	98	24	3,91
spread of some infectious disease, epidemic	21	35	45	34	8	56	42	3,19
terrorist attack in Poland	27	42	33	32	9	69	41	3,32
political chaos in Poland	43	51	24	20	5	94	25	3,75
conflicts between ethnic, religious groups in Poland	20	23	38	35	27	43	62	2,82

Source: own study.

A comparative analysis of the councillors' responses was also undertaken by Western Pomeranian and Subcarpathian provinces. The research assumption was that the residents of Subcarpathia, a region bordering the warfare arena, should be more concerned about the threats of hybrid warfare, including primarily cyber threats. Statistical analysis showed a statistically significant difference between the number of indications of cyber threats by councillors from both regions, with residents of West Pomerania indicating more significant concern in this regard, as shown in Table 7 and Figure 1.

Table 7. Comparison of cyber security threat assessments by councillors from the West Pomeranian and Subcarpathian provinces

Variable	Test U Manna-Whitneya									
	Rank sum SC	Rank sum WP	U	Z	p	Z corr.	p	Sample size SC	Sample size WP	p
cyber-attack disrupting state operations, theft, cyber-security threats	3560,500	6735,500	1849,500	-2,52849	0,011456	-2,71645	0,006599	58	85	0,011075

Source: own study.

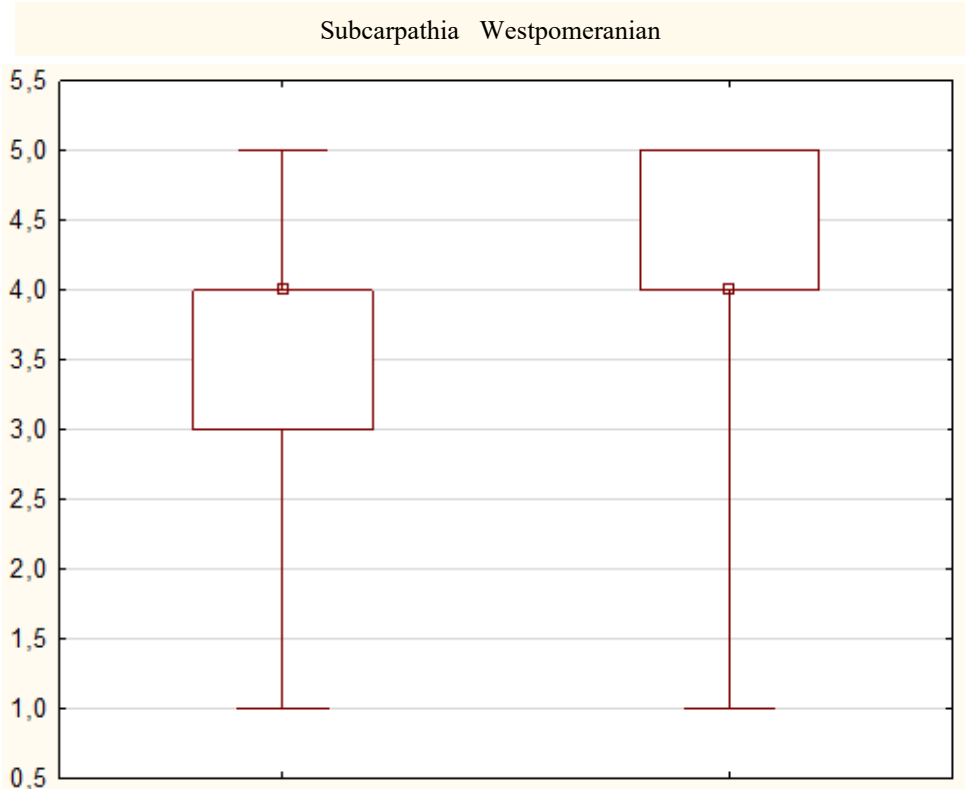


Figure 1. Comparison of cyber security threat assessments by councilors from the West Pomeranian and Subcarpathian provinces
Source: own study.

Consequently, after analyzing the data from the quantitative survey, it would be appropriate to indicate a high level of awareness of cyber threats among councillors, with a preponderance of indications on the side of West Pomeranian councillors more distant from the theatre of war. However, as noted in the research methodology, the researchers' assumption was to carry out methodological triangulation in order to obtain a complete description of the threats indicated by councillors of 21 medium-sized and large cities from two regions located at the two ends of Poland. During the interviews conducted, respondents were allowed to speak freely, so unlike in surveys, no categories of threats were

presented, but only asked to indicate the three most important ones. It would seem obvious to overlap the results of quantitative and qualitative research in the context of the perception of the most important threats and, consequently, to reflect the results of quantitative research in the results obtained during the in-depth interviews, in the free speech of respondents. It should be noted that the research group overlaps in its scope in both surveys, while very often, interview respondents also filled out questionnaires, but they did not fill out a new framework during the interview. Due to the different number of survey feedback received and interviews conducted, we expect there to be three different groups of respondents: councillors who completed the survey and participated in the interview, councillors who only completed the survey, and councillors who only participated in the interview. Based on the free declarations of the councillors who participated in the interviews, it can be expected that the first group is the most numerous, but due to the anonymity of the surveys, it is not possible to provide a detailed calculation. The results of the analysis of the interviews are presented in Table 8.

Table 8. Categories of threats identified by interview respondents

Category	Indication 1	Indication 2	Indication 3	Total no of indications
demographic collapse	5	2	3	10
economic threats	9	14	11	34
cyber threats	1	3	2	6
threats of a social nature	1	12	4	17
conflicts of an ethnic nature	1	1	0	2
crime	0	1	0	1
energy security threats	2	3	6	11
unemployment	0	0	0	0
influx of refugees	5	13	9	27
health threats	0	4	3	7
terrorist threats	0	0	1	1
political divisions	10	9	9	28
environmental threats	1	3	3	7
the threat of war, Russian aggression	64	12	5	81
other	5	17	6	28

Source: own study.

In casual statements, councillors indicated cyber security threats far less frequently than in survey statements suggesting potential threats. Only six respondents identified the area as one of the three most important to Poland, including only one who identified cyber security threats as the most important. By contrast, in terms of the number of indications, cyber-security threats ranked only 11th, a radical disparity from the survey results.

An analysis of responses to the question "What are your city's residents worried about?" yields even more serious results. None of the respondents chose to identify cyber threats as important to city residents, including those who identified cyber security as one of the most serious threats to Poland. They explained such a decision by the fact that residents do not pay enough attention to this area of security. Juxtaposing the real threat posed by hybrid warfare and the high level of indications of cybersecurity threats in the surveys with the results of the in-depth interviews, both in the area of the most important threats to Poland and the concerns of residents, it appears that cybersecurity threats awareness is more declarative than real. Given a choice between a spectrum of different threats, councillors accurately indicated the most important threats, including those related to cybersecurity. Still, the lack of indication of these threats in the free statements may indicate that this awareness is relatively low and is not a daily concern. As a result, it may lead to risky and irresponsible behaviour online by those who should serve as local leaders.

Alongside statements indifferent to the area of cybersecurity, however, there was one: x099 "I think such a big threat is the Internet and everything related to the media..., cybercrime is what is worth being afraid of today." Other councillors who identified cybersecurity threats as one of the three most important for Poland pointed primarily to disinformation and the use of fake news to cause social unrest, cyberattacks on state institutions and the media, the theft of sensitive data by cyber criminals, and risks arising from the development of artificial intelligence. The range of risks identified by the councillors is consistent with the list of the most serious cyber risks discussed in the article. So, awareness of the risks is linked to knowledge of the risks, which poses a challenge to contemporary people in raising awareness and knowledge of cyber security in society.

5. CONCLUSION

Modern times have brought the dynamic development of the virtual world, through which cyberspace has significantly expanded its scope of influence. In the era of hybrid warfare, for which the natural theatre of operations is precisely cyberspace, it is necessary to constantly improve the knowledge and awareness of societies in the field of cybersecurity threats. The research undertaken by the authors clearly indicated a very high level of declarative awareness of these threats. Surveys indicated a high frequency of indications of cyber security as a source of the most important threats. However, the results of the survey research were not confirmed in the qualitative research when the same group of councillors was asked in in-depth interviews to indicate the most important contemporary threats to Poland. The discrepancy between the second most frequently cited threat in the surveys and the 11th most frequently cited threat in the interviews leads to the conclusion that while declaratively, we do indeed understand cyber threats, they are not a daily concern and, as a result, real awareness of cyber threats is very limited. In addition, it can be assumed that a lack of awareness leads to a lack of self-restraint in online risky actions. At the same time, it should be emphasized that the councillors who pointed out cyber security risks in the interviews were very apt to give specific examples of such risks. This means that the primary path to raising awareness is to educate and promote knowledge on the subject. These words are written in a month when in Szczecin-Western Pomerania Province, at the request of the police, messages warning of the dangers of cybercrime are read in all churches during masses. It seems that any form of outreach with knowledge is important in avoiding threats.

The conducted research faces limitations due to the incomplete research sample of councillors of 21 cities in the West Pomeranian and Subcarpathian provinces. However, it should be emphasized that the analysis of the transcriptions of the conducted interviews leads to the conclusion of saturation of content and obtaining a complete description, which clearly indicates the representativeness of the research sample. In addition, the research was conducted in two marginal provinces of Poland, so extrapolating the results to the whole of Poland involves the risk of lack of representativeness.

Further research directions should extend the research to other regions in Poland and conduct a comparative analysis with other countries, both on the frontline and away from the war. In addition, an in-depth study of the attitudes and online behaviour of the surveyed councillors would be appropriate.

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ASSESSMENT OF THE USE OF MODERN ONLINE COMMUNICATION TOOLS BY UNIVERSITIES TO SHAPE THEIR IMAGE IN THE PERCEPTION OF STUDENTS

Mateusz Juźwik[a]

[a] *University of Szczecin, Institute of Management, Poland*

ABSTRACT

Purpose: *This study evaluates how internet-based communication tools shape higher-education institutions' images from students' viewpoints, identifying the most potent instruments and contrasting perceptions between public and non-public universities within intelligent management frameworks*.

Need for the study: *Accelerating digital transformation compels universities to sustain engaging online profiles. While scholarship highlights intelligent management and digital outreach, Polish studies rarely foreground student perspectives. This research addresses that gap by measuring perceived effectiveness of key online channels in university–student communication.*

Methodology: *Using Computer-Assisted Web Interviewing, we surveyed 383 students from public and non-public universities in Poland's West Pomeranian Voivodeship. Descriptive statistics and the Mann-Whitney U test compared assessments of four tools: institutional websites, social media, e-mail marketing, and SEO/SEM activities.*

Findings: *University websites were deemed the most influential image-building medium, followed by social media. Students at non-public institutions rated the visual appeal, navigability, and functionality of digital tools more highly than peers at public universities. Perceptions of e-mail marketing and search-engine visibility did not differ significantly between groups.*

Practical Implications: *Universities should professionalise and regularly refresh their digital touchpoints, prioritising content currency, mobile optimisation, and coherent branding. The greater agility of non-public institutions in adopting contemporary online solutions may confer a strategic edge, signalling to prospective students a forward-thinking, student-centred culture aligned with intelligent management principles.*

Keywords: Image management, internet communication tools, higher education institutions,

Jel codes: I23, M31, L82

1. INTRODUCTION

Intelligent management in the era of digital transformation has become a crucial element of organisational strategy, particularly in the context of shaping image and the effective use of modern communication tools. As digitalisation progresses, traditional methods of image management are

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evolving towards more advanced, data- and technology-driven approaches (Foroudi et al., 2017). Organisations, including higher education institutions, face the challenge of effectively managing their image in the minds of key stakeholders using sophisticated digital communication tools. Students are regarded as the most important stakeholders of universities, as they are not only recipients of educational services but also active participants in communication processes that influence the perception and reputation of these institutions (Carter & Yeo, 2016). Research has shown that the use of online communication tools such as social media has become an integral component of intelligent image management within organisations. Modern technologies allow not only for faster and more precise targeting of specific audiences but also enable the personalisation of content and interactive engagement, which in turn enhances user involvement. In this context, intelligent image management entails not only the implementation of appropriate tools but also their flexible adaptation to the evolving expectations of students, who increasingly assess the quality of a university through its digital presence and online communication activities (Verhoef et al., 2021). Wójcicka (2010) highlights significant differences between public and non-public universities, particularly in relation to their adopted communication strategies. Public institutions, operating within rigid regulatory frameworks and financed through public funds, may be less agile in responding to dynamic changes in the educational market. In contrast, non-public universities, functioning in highly competitive environments, tend to adopt new technologies and communication strategies more swiftly to effectively attract and retain students' attention. This greater agility among non-public institutions may support more effective implementation of intelligent management, including the use of modern internet-based communication tools, which provides an important context for further research in this area.

Considering these considerations, analysing the use of digital communication tools by higher education institutions from the perspective of students as key stakeholders is not only justified but also essential for understanding the effectiveness of communication strategies in the education sector. The present study addresses this issue, focusing on higher education institutions in the West Pomeranian Voivodeship of Poland.

2. LITERATURE REVIEW

Higher education institutions operate in a highly competitive and rapidly evolving information environment, where the effective shaping of organisational image has become one of the key elements of strategic management (Ivy, 2010). At the outset of any analysis concerning the use of online communication tools for image-building purposes, it is essential to define the concept of image itself within the context of higher education institutions. According to Lafuente-Ruiz-de-Sabando, Forcada, and Zorrilla (2019), a university's image can be understood as an evaluation formed through stakeholders' perceptions, beliefs, ideas, and impressions, which emerge over time because of consistent communication by the institution. This definition underscores the central role of communication and the temporal dimension in shaping image, highlighting its deeply rooted and evolving nature. Ivy (2010), in turn, defines image as a set of associations and expectations formed by students and other audiences based on their experiences and the communicative efforts of the institution. Meanwhile, Alessandri, Yang, and Kinsey (2006) conceptualise image as the sum of impressions a university leaves on its stakeholders through its actions, behaviours, and messaging emphasising the integrated and multi-channel character of image-building as a practical process. An intriguing aspect of image management in higher education involves the notion of a desired image, i.e. the perception that an institution actively seeks to cultivate through deliberate communication and strategic activities. Accordingly, the management of a desired image may be viewed as a process of shaping and controlling stakeholder perceptions in a manner that supports the attainment of the university's strategic goals within a competitive educational environment (Rozwadowska, 2002; Jefkins, 1998). The ongoing digitalisation of communication processes, alongside the development of internet-based tools, offers academic institutions the means not only to streamline internal management operations but also to build lasting and more personalised, engaging, and effective relationships with students (Mergel, Edelmann, & Haug, 2019). Contemporary scholarship increasingly highlights the importance of intelligent management,

which integrates modern technology with knowledge management, decision-making, and organisational communication (Davenport & Ronanki, 2018). As noted by Mergel, Edelmann, and Haug (2019), intelligent management in organisations relies on the use of digital technologies including internet communication tools to enhance decision-making processes, increase transparency, and actively engage stakeholders through interactive, multi-channel communication.

Numerous attempts have been made in academic literature to define and operationalise the concept of intelligent management within the context of higher education institutions. Researchers have explored both the conditions necessary for the implementation of modern technological solutions and the outcomes of their application across strategic, operational, and communication-related management domains. Selected studies on intelligent management in higher education institutions are summarised in Table 1.

Table 1. Selected studies on intelligent management in the higher education market

Year	Authors	Key findings
2011	Leja, K.	Identified contradictions in the management of contemporary universities, emphasising the need for intelligent management that integrates both academic tradition and modern managerial approaches.
2015	Bugaj, J., Batko, R., et al.	Analysed management models of Polish universities, highlighting the necessity of adopting intelligent management systems to improve institutional efficiency and competitiveness.
2016	Bartosiewicz, M.	Presented the concept of a "smart university" using the example of the University of Wrocław, analysing strategic development directions in the context of intelligent management and the use of modern technologies.
2024	Krivtsun, A. Lankin, A., Grinchenkov, D., Kushchiy, D.	Introduced an intelligent system for managing universities' international activities, integrating AI technologies to streamline administrative processes and foster international cooperation.
2025	Silva, W. A., Ratten, V., Cassel, G. L., Vendrametto, O., et al.	The study revealed key barriers preventing non-leading Brazilian universities from achieving effective management in the digital era. These include lack of strategic tools for institutional repositioning, insufficient knowledge of the costs and benefits of digitalisation, uncertainty regarding the future of traditional HEI models, difficulties in implementing change, and meeting stakeholders' needs.

Source: own elaboration.

The works of Leja (2011) and Bugaj, Batko, et al. (2015) focus on the systemic and organisational conditions underpinning the functioning of higher education institutions in Poland, highlighting tensions between the traditional academic model and the increasing demands of a competitive market environment. Their findings suggest the need to transform universities into more flexible and effective organisations, capable of implementing modern management solutions, including information and communication technologies. Bartosiewicz (2016) develops this issue further by introducing the concept of smart universities, which integrates intelligent management with a strategic vision for university development based on digital technologies. The author emphasises the importance of organisational innovation and the implementation of integrated systems supporting both teaching and administrative processes. From an international perspective, Krivtsun, Grinchenkov, Lankin, Kushchiy (2023) present the implementation of an intelligent management system in international university collaboration, based on the use of artificial intelligence. Their research confirms that AI technologies can effectively support universities in managing complex processes, enhancing operational performance and the quality of cooperation with external partners. A contemporary view of intelligent management is also presented by Silva et al. (2025), who identified key barriers hindering the effective implementation of dynamic management capabilities within universities. These challenges include not only a lack of strategic tools and knowledge regarding digital transformation but also limited capacity to implement change and uncertainty regarding stakeholder expectations. The authors argue that overcoming these barriers can enable universities not only to manage effectively but also to seize the opportunities afforded by digital transformation.

Considering the literature review, it is evident that intelligent management in higher education extends beyond the mere use of digital technologies; it also encompasses organisational culture, communication strategies, and the institution's capacity for adaptation and learning in a rapidly evolving environment. Within this context, the effective implementation of modern internet communication tools assumes particular significance, as these tools can play a pivotal role in shaping a university's image, strengthening stakeholder relations, and building competitive advantage in the educational market.

Table 2. Selected definitions of online communication tools

Year	Authors	Definition
2013	Wiktor, J. W.	Communication tools that utilise information and communication technologies (ICT) to effectively transmit content, foster relationships, and engage audiences in the online environment.
2014	Tiago, M. T. P. M., Veríssimo, J. M.	A set of digital technologies supporting interactivity, personalisation, and real-time automation of marketing communication with audiences.
2015	Kaczmarek-Śliwińska, M.	Platforms and applications that enable real-time communication, monitoring of public opinion, and the adjustment of message content to the preferences of Internet users.
2017	Chaffey, D., Smith, P. R.	Integrated digital means that facilitate two-way communication between an organisation and its audience through online channels, including websites, e-mail, social media, and applications.

Source: own elaboration.

All the approaches share the view that these tools are rooted in information and communication technologies (ICT), enabling effective, interactive, and individualised content delivery to audiences within the digital environment. Wiktor (2013) emphasises that the principal objective of online communication tools is to foster relationships and engage recipients through the efficient use of ICT, thereby underscoring the relational dimension of communication. Tiago and Veríssimo (2014) highlight the role of these tools in promoting interactivity and automating communication, which allows organisations to deliver real-time, tailored content that meets individual audience needs, while simultaneously streamlining communication processes. Kaczmarek-Śliwińska (2015) broadens this perspective by placing emphasis on real-time engagement, opinion monitoring, and message personalisation. Her definition draws attention to the practical use of such tools in the ongoing management of institutional image and stakeholder relations. Conversely, Chaffey and Smith (2017) adopt a broader, systemic perspective, defining online communication tools as integrated digital resources encompassing websites, e-mail marketing, social media, and applications. The core focus here lies in facilitating two-way communication, thereby strengthening interaction and dialogue between the organisation and its audience. An analysis of these definitions indicates that online communication tools not only support the dissemination of content but also serve a strategic function by enabling organisations to shape their desired image, personalise communications, and monitor stakeholder responses in real time. In view of this, it was deemed essential to identify the most relevant online communication tools used for image-building. A review of the literature was therefore undertaken, which identified key digital tools employed by higher education institutions to engage with stakeholders. The subsequent sections focus on four core areas: websites, social media, e-mail marketing, and search engine marketing (SEO/SEM).

Website

The website constitutes one of the most significant tools of online marketing, enabling institutions to present and promote their offerings, values, and unique attributes. As noted by Ciepaj, Miłaszewicz, and Wengel (2017), for many stakeholders the website serves as the first point of contact with the organisation, thereby functioning as a virtual business card. The authors emphasise that it is one of the simplest yet most effective instruments for managing organisational image in the digital sphere.

A similar view is presented by Patil, Shrirao, and Jadhav (2023), who argue that online marketing for any organisation "begins and ends with the website". However, the effectiveness of a website in image-building depends largely on its design - both in terms of content and

functionality. According to Park, Gretzel, and Sirakaya-Turk (2007), key factors influencing a website's success in shaping image include usability, content currency, responsiveness, visual appeal, and security. A failure to meet these standards may adversely affect the perception of the institution and discourage potential students (Kuzic, Giannatos & Vignjevic, 2010). Analyses of university websites in academic literature confirm their impact on institutional image-building. Lažetić (2018) observed that university websites differ depending on the characteristics of their educational markets, with institutions operating in highly competitive environments more frequently employing advanced branding techniques. Similarly, research by Saichaie and Morphew (2014) found that websites of US universities tend to promote the institution as a place for acquiring professional qualifications rather than intellectual development. Other scholars, such as Štefko, Fedorko, and Bačík (2015), highlight the importance of content currency in cultivating a positive image, while Okushova, Stakhovskaya, and Sharaev (2016) point to the role of visual presentation as a key element of stakeholder communication. Furthermore, studies on website digital accessibility (İşeri, Uyar & İlhan, 2017; Stasiak & Dzieńkowski, 2021) reveal that many universities fail to comply with basic WCAG 2.0 standards, which may negatively affect perceptions of openness and professionalism. Collectively, these findings affirm that a university website serves not only as an information source but also as a vital tool in shaping the institution's image in the minds of students.

Social media

Social media are regarded as one of the key online communication tools that enable universities to dynamically and interactively shape their institutional image. They are defined as applications based on Web 2.0 technology, which allow users to create, exchange, and share content (Kaplan & Haenlein, 2010). From an organisational perspective, social media facilitate both the analysis of stakeholder opinions and behaviours (a passive approach) and active engagement in marketing and public relations activities (Constantinides, 2014). Research indicates that these platforms contribute to enhanced brand recognition, the development of community relations, and increased trust in the institution (Budka et al., 2019; Cheung & Lee, 2010). A crucial aspect of social media utilisation is the identification of opinion leaders, whose role in interpreting and further disseminating information can significantly influence the reach and reception of communication (Dorenda-Zaborowicz, 2012). Studies examining the use of social media by higher education institutions across various countries show that these tools impact not only the promotion of educational offerings but also the effectiveness of student recruitment and the cultivation of relationships with prospective students (Alserr et al., 2011; Popa & Sasu, 2016). Research conducted in Poland demonstrates that Facebook remains the dominant communication channel; however, universities have yet to fully harness the potential of other platforms such as TikTok or Snapchat (Łuczaj et al., 2020; Kisiołek, 2021). Furthermore, barriers to effective social media management have been identified, including the absence of coherent strategy and limited understanding of these tools among staff members (Mazurek et al., 2019). Despite numerous analyses focusing on university presence on social media, the academic literature still lacks research dedicated to assessing the content of communications and their impact on students' perceptions of institutional image.

E-mail marketing

E-mail marketing is a widely used tool of online communication, valued for its convenience, the ability to personalise content, and its effectiveness in reaching target audiences. According to Melekhova (2021), it forms part of an organisation's communication strategy, based on pre-developed contact scenarios with recipients via electronic mail. Hudak, Kianickova, and Madlenak (2017) note that it is the most frequently used instrument of direct marketing on the internet, allowing for audience segmentation and the tailoring of content to specific preferences. Chaffey and Smith (2017) further highlight that a coherent and well-planned e-mail marketing strategy can strengthen stakeholder relationships and support the development of a positive organisational image. Regular, engaging communication with stakeholders through e-mail can contribute not only to the achievement of sales objectives but also to increased engagement and loyalty. Despite its widespread use, the academic literature includes limited research on the impact of e-mail marketing on the image of higher education institutions. Štefko, Fedorko, and Bačík (2015) did not confirm a

statistically significant correlation between the use of this tool and the perceived image of a university. Hartemo (2022) demonstrated that recipient engagement in the communication process enhances the effectiveness of mailing activities, a finding potentially relevant to the higher education sector. Zhytomyrska and colleagues (2022) confirmed that e-mail marketing supports the promotion of educational services and improves student engagement. Conversely, Algryani and Jardani (2023) highlighted the need to educate students in professional e-mail etiquette to improve communication standards. Research by Thomas, Chen, and Iacobucci (2022), although not focused on universities, underlines the necessity of strategically managing the frequency and content of e-mails to avoid overwhelming recipients with promotional content and to enhance message effectiveness. These findings may offer valuable insights for universities seeking to leverage the potential of e-mail marketing for both image-building and communication purposes.

Search Engine Marketing (SEO/SEM)

Search Engine Marketing (SEM) encompasses strategies aimed at increasing the visibility of websites in both organic (SEO – Search Engine Optimisation) and paid search results (PPC – Pay-Per-Click). Nabout, Skiera, Stepanchuk, and Gerstmeier (2012) define SEM as a set of activities intended to improve a website's ranking in search engines, including the identification and implementation of keywords that facilitate high positioning in search engine results pages. Tiwari (2020) confirms that effective SEO optimisation leads to increased website traffic and the attraction of new users. Rayappa (2020) highlights that most website visits originate from search engine results, thereby making SEM a crucial component of any marketing strategy. Enhanced search visibility not only drives traffic but also contributes to a positive organisational image through the "top of mind" effect users are more likely to perceive a highly ranked website as trustworthy and prestigious. Studies on the use of SEM in higher education reveal that these tools can effectively support student recruitment efforts and institutional internationalisation. Popa and Sasu (2016) demonstrated that Google advertising campaigns result in higher website traffic and increased student enrolment. Iddris (2011) noted that low positioning in Google's search results may hinder access to international students, making SEO optimisation an essential aspect of communication strategy. Isadora (2018) emphasises the need for universities to develop content aligned with user search intent and to ensure proper website structure and semantic coherence to achieve improved rankings. Killoran (2013) further adds that strategies such as keyword placement, link building, and competitive website analysis contribute to a site's credibility and reputation. Collectively, these studies indicate that search engine marketing not only enhances web traffic but also positively influences brand recognition and the perceived value of higher education institutions.

Based on a review of the relevant literature, key elements defining specific online communication tools that influence the image of higher education institutions have been identified. The aim of this development is to systematise theoretical knowledge in this field and to indicate which aspects of tools may be considered especially significant in terms of communication effectiveness and relationship-building with stakeholders. A detailed summary of these elements is presented in Table 3.

Table 3. Elements defining specific online communication tools influencing the image of higher education institutions

No.	Proposed element	Basis in the literature
	Website	
1.	Visual appeal of the university website	E. Ciepaj, B. Miłaszewicz, M. Wengel, Y. Park, U. Gretzel, E. Sirakaya-Turk, G. Okushova, Y. Stakhovskaya, P. Sharaev
2.	Currency and credibility of information on the website	E. Ciepaj, B. Miłaszewicz, M. Wengel, R. Štefko, R. Fedorko, R. Bačík,
3.	Access to student reviews and alumni success stories on the website	P. Lažetića

4.	Ease of navigation and intuitive design of the website	E. İşeri, K. Uyar, Ü. İlhan W. Stasiak i M. Dzieńkowski Y. Park, U. Gretzel i E. Sirakaya-Turk R. Štefko, R. Fedorko, R. Bačík
5.	Access to information about academic programmes and teaching staff on the website	K. Saichaie i C.C. Morphew R. Štefko, R. Fedorko, R. Bačík,
	Social media	
6.	Regular content updates on social media profiles	D. Buchnowska A. Popa, D. Sasu A. Kisiołek
7.	Visual appeal of graphic and video content on social media profiles	L. Karpenka, E. Rudiene, M. Morkunas, A. Volkov
	E-mail marketing	
8.	Regular receipt of university-related information via e-mail	D. Chaffey I P. Smith T. Zhytomyrskiej, I. Zrybnievy, N. Romaniuk, I. Havrysh i T. Gorditsy
9.	Personalisation of university e-mails (including recipient's name and surname)	A. Melekhova
	Search Engine Marketing (SEO/SEM)	
10.	High ranking in search engine results	F. Iddris N. Isadora

Source: own elaboration.

Based on the analysis of literature, it was determined that the largest number of factors defining internet communication tools concern university websites, which are widely recognised as the primary point of interaction between stakeholders and the institution, as well as serving the function of a virtual showcase (Ciepaj, Miłaszewicz, & Wengel, 2020). A central feature is the visual appeal of the website, which, as noted by Park, Gretzel, and Sirakaya-Turk (2007), has a direct bearing on stakeholders' perception of the organisation. Similar conclusions are presented by Okushova, Stakhovskaya, and Sharaev (2016), who underscore the importance of visual presentation in online communication and reputation management. Furthermore, Ciepaj et al. (2020) argue that a "visually pleasing layout" contributes positively to how an institution is received by its audience. Equally significant is the credibility and currency of the information provided, which serve to reinforce trust in the institution (Štefko, Fedorko, & Bačík, 2015). Lažetić (2018) demonstrated that providing information concerning student and alumni achievements enhances the perceived reliability of a university, particularly among prospective applicants. Another relevant dimension is the ease of navigation and intuitive structure of the website, especially in relation to digital accessibility standards. This aspect is highlighted by İşeri, Uyar, and İlhan (2017) and corroborated by Stasiak and Dzieńkowski (2021). Park et al. (2007) also note the importance of user-friendliness in shaping a favourable institutional image. In the context of social media, empirical studies confirm that the frequency of content updates strengthens engagement between universities and students (Kisiołek, 2021), while users expect access to current news and announcements via these channels (Buchnowska, 2013). Popa and Sasu (2016) establish that social media can facilitate relationship-building with potential students. Furthermore, research by Karpenka, Rudiene, Morkunas, and Volkov (2021) indicates that the visual quality of social media content, including graphics and videos, enhances user engagement and fosters trust in the institution. Regarding e-mail marketing, a well-structured communication strategy may contribute to the development of long-term relationships with stakeholders and the promotion of educational services (Chaffey & Smith, 2017; Zhytomyrska, Zrybniva, Romaniuk, Havrysh, & Gorditsa, 2022). Melekhova (2021) adds that the

personalisation of communication, for example through addressing recipients by name, may strengthen the impact of such campaigns. Finally, a university's high visibility in search engine results, achieved through effective SEO/SEM strategies, is recognised as a crucial factor influencing both traffic to the institutional website and its perceived credibility. Isadora (2018) and Iddris (2011) demonstrate that optimising search engine presence can enhance the university's online reach and support recruitment efforts, particularly on international markets. Given the foregoing findings, it was deemed appropriate to explore how these specific elements of online communication are assessed by students, who are the principal stakeholders of higher education institutions. To date, research has predominantly concentrated on institutional practices in digital communication and their measurable outcomes. However, the student perspective specifically regarding the reception and perceived effectiveness of these tools has not been sufficiently addressed. Bridging this gap is essential for a comprehensive understanding of the role online communication tools play in supporting intelligent management processes within the higher education sector.

3. METHODOLOGY

3.1. Participants

Given the substantial number of students enrolled at higher education institutions in the West Pomeranian Voivodeship (31,758 individuals), it was decided to conduct a non-exhaustive study. In line with the approach outlined by Stanimir (2005), marketing research frequently employs purposive sampling, a method based on subjective selection of units, which enables the collection of representative data while managing resource constraints. Assuming a confidence level of 95%, the minimum required sample size for representativeness was calculated at 380 respondents. Ultimately, the study encompassed 383 students enrolled in higher education institutions within the West Pomeranian region. Among the respondents, women predominated (n = 272; 71%), while men accounted for n = 111; 29% of the sample. In terms of age, the largest group comprised students aged 21–23 years (55.4%), corresponding to the typical age of those in their second and third year of study in Poland. Other age categories included: 24–26 years (18.8%), 18–20 years (17.2%), 29 years and above (7.0%), and 26–28 years (1.6%). Regarding the type of study programme, 63.4% of participants were enrolled in bachelor's degree programmes, 28.5% in master's degree programmes, 5.5% in integrated master's programmes, and 2.6% in engineering studies. Additionally, an analysis of the type of institution revealed that most students attended public universities (86.7%), while 13.3% were enrolled at non-public institutions.

3.2. Research Protocol and Stimuli

An indirect method of communication with respondents was employed in the study using a questionnaire survey, which was made available in electronic form. The CAWI technique (Computer-Assisted Web Interview) was utilised, enabling participants to complete the questionnaire independently and comfortably, without time pressure and in a setting of their choice. As noted by Mazurek-Łopacińska (2005), this approach not only enhances respondent convenience but also facilitates rapid and efficient access to the target sample. Moreover, the electronic format allows for the immediate recording of responses into a database, significantly streamlining the process of data analysis. The questionnaire was developed based on the findings of a pilot study conducted in January 2024, the purpose of which was to test the clarity of the questions and the functionality of the tool. The final version of the questionnaire used in the main study consisted of an introductory section (informing respondents of the anonymity of their participation and the study's objectives), main questions concerning the assessment of the use of online communication tools by higher education institutions, and a demographic section (gender, age, type of study, year of study, and type of institution). The questionnaire included multiple-choice questions with non-mutually exclusive options, allowing respondents to select answers based on their knowledge and experience. The predominant response format was a five-point scale, modelled on the Likert scale (ranging from "strongly disagree" to "strongly agree").

3.3. Research Apparatus

The data obtained in the study were analysed using specialised statistical software: IBM SPSS Statistics 29.0, JASP 0.18.2, and IBM AMOS 29.0. This software enabled the execution of both descriptive statistics and advanced statistical modelling, allowing for a comprehensive examination of the dataset.

To summarise respondents' answers to the questionnaire items, descriptive statistics were applied, including arithmetic mean, median, standard deviation, and confidence intervals, which facilitated the identification of overall trends within the data. For nominal variables, a frequency analysis was conducted, allowing for the characterisation of the sample structure and the distribution of responses.

3.4. Analysis of Measurement Data

Prior to commencing the main analysis, the data was verified for completeness and accuracy. No missing data were identified, and all responses were coded in accordance with the assumptions established during the questionnaire design phase. A descriptive analysis was conducted for the closed-ended questions, with particular attention given to responses based on the five-point Likert scale. Subsequently, comparative analyses were undertaken to examine the evaluations of specific elements of online communication between students from public and non-public universities. To this end, the Mann-Whitney U test was applied, enabling the verification of hypotheses regarding statistically significant differences between these groups.

4. RESULTS

The initial stage of the analysis evaluated the significance of various online communication tools in shaping a university's image from the student perspective. Guided by the literature, the author interprets the findings through a broadened conception of intelligent management - one that transcends mere technology adoption to encompass data-informed decision-making, an adaptive organisational culture, strategic communication, and an institutional capacity for continuous learning in a rapidly evolving digital environment. The aim of this phase was to identify the online communication channels that respondents perceive as having the greatest influence on the reputation of academic institutions. This, in turn, made it possible to determine which tools are most frequently used and regarded as the most effective. The results of this comparison are presented in Table 4, which provides a starting point for a more in-depth analysis of the individual components that make up these tools.

Table 4. Assessment of the significance of online communication tools in the process of shaping a university's image (respondents rated each tool on a scale from 1 to 5)

	M	*Mdn*	*SD*	*Min.*	*Max..*	*Q1*	*Q3*
Website	4,31	5	0,99	1	5	4	5
Social media	3,96	4	1,07	1	5	4	5
Search Engine Marketing (SEO/SEM)	3,83	4	1,09	1	5	3	5
E-mail marketing	3,16	3	1,31	1	5	2	4

Source: own elaboration.

Based on the collected data, it is evident that students assigned the highest significance to their university's website, with a mean score of 4.3 and a median of 5. This underscores the website's crucial role as the primary and most reliable source of information. It is perceived as an accessible and trustworthy channel for engaging with the university. Social media received a mean score of 4.0, confirming their important position within the communication process, albeit slightly lower than that of the website. Search engine marketing (SEO/SEM) was rated at 3.8, indicating moderate usefulness likely functioning as a supportive tool that enables students to quickly locate relevant information. The lowest scores were attributed to e-mail marketing, with an average rating of 3.2. This suggests that students perceive this tool as having limited utility in the student–university relationship, with a correspondingly minimal impact on communication with key stakeholders.

An additional analysis was conducted to determine whether the perceived significance of individual online communication tools differed depending on the type of university attended by respondents. This

verification aimed to identify potential discrepancies in the perceived effectiveness of communication tools between students of public and non-public institutions. The findings are presented in Table 5, enabling a comparison of respondents' views and the evaluation of any statistically significant differences.

Table 5. Assessment of the significance of online communication tools – comparison between public and non-public universities (respondents rated each tool on a scale from 1 to 5)

	Public (n = 332)			Non-public (n = 51)					
	M	*Me*	*SD*	*M*	*Me*	*SD*	*Z*	*p*	r_g
Website	4,32	5,00	0,97	4,27	5,00	1,15	-0,39	0,695	0,02
Social media	3,96	4,00	1,07	3,92	4,00	1,07	-0,29	0,771	0,01
Search Engine Marketing (SEO/SEM)	3,83	4,00	1,09	3,82	4,00	1,11	-0,04	0,969	<0,01
E-mail marketing	3,12	3,00	1,33	3,41	4,00	1,12	-1,36	0,174	0,07

Source: own elaboration.

No statistically significant differences were identified between students from public and non-public universities in their evaluation of the significance of individual online communication tools. To deepen the analysis, an assessment was also conducted regarding the application of specific elements comprising each online communication tool, considering the type of university attended by the respondents. The results are presented in Table 6.

Table 6. Assessment of the use of elements comprising individual online communication tools by universities attended by respondents (respondents assessed each element on a scale from 1 to 5)

	M	*Mdn*	*SD*	*Min.*	*Max*	*Q1*	*Q3*
Website							
Currency and credibility of information on the website	3,89	4	0,87	1	5	4	4
Ease of navigation and intuitive design of the website	3,64	4	1,08	1	5	3	4
Access to information about academic programmes and teaching staff on the website	3,67	4	1,02	1	5	3	4
Visual appeal of the university website	3,81	4	0,96	1	5	4	4
Access to student reviews and alumni success stories on the website	3,17	3	1,14	1	5	2	4
Social media							
Regular content updates on social media profiles	3,80	4	0,89	1	5	3	4
Visual appeal of graphic and video content on social media profiles	3,64	4	0,96	1	5	3	4
E-mail marketing							
Personalisation of university e-mails (including recipient's name and surname)	3,28	3	1,18	1	5	2	4
Regular receipt of university-related information via e-mail	3,49	4	1,08	1	5	3	4
Search Engine Marketing (SEO/SEM)							
High ranking in search engine results	3,46	3	0,95	1	5	3	4

Source: own elaboration.

An analysis of the evaluations concerning the use of specific elements of online communication indicates that students rated the timeliness and credibility of information published on university

websites the highest (mean score: 4.0), suggesting a high level of trust in the content provided by academic institutions. This was followed by the visual attractiveness of the website and the regular updating of content on social media platforms – both receiving a mean score of 3.8. Conversely, the lowest ratings were assigned to elements such as access to student opinions and alumni success stories on university websites (mean score: 3.2), as well as the personalisation of e-mail messages (mean score: 3.3). These findings may indicate a need for improvement in these areas of communication, which – despite their potential – do not meet student expectations. Subsequently, the study also analysed differences in the assessment of the use of individual online communication tools depending on the type of university attended by the respondents. Detailed results are presented in Table 7.

Table 7. Assessment of the use of elements constituting specific online communication tools by the university attended by respondents (respondents assessed each element on a scale from 1 to 5)

	Public (n = 332)			Non-public (n = 51)					
	M	*Me*	*SD*	*M*	*Me*	*SD*	*Z*	*p*	r_g
Website									
Currency and credibility of information on the website	3,87	4,00	0,86	4,02	4,00	0,97	-1,81	0,071	0,09
Ease of navigation and intuitive design of the website	3,58	4,00	1,11	4,08	4,00	0,72	-2,95	**0,003**	0,15
Access to information about academic programmes and teaching staff on the website	3,61	4,00	1,05	4,02	4,00	0,73	-2,46	**0,014**	0,13
Visual appeal of the university website	3,78	4,00	0,95	4,02	4,00	0,97	-2,11	**0,035**	0,11
Access to student reviews and alumni success stories on the website	3,10	3,00	1,14	3,61	4,00	1,08	-2,97	**0,003**	0,15
Social media									
Regular content updates on social media profiles	3,76	4,00	0,86	4,06	4,00	1,03	-2,93	**0,003**	0,15
Visual appeal of graphic and video content on social media profiles	3,61	4,00	0,94	3,84	4,00	1,07	-1,99	**0,047**	0,10
E-mail marketing									
Personalisation of university e-mails (including recipient's name and surname)	3,25	3,00	1,19	3,51	4,00	1,12	-1,37	0,171	0,07
Regular receipt of university-related information via e-mail	3,49	4,00	1,08	3,51	4,00	1,14	-0,19	0,852	<0,01
Search Engine Marketing (SEO/SEM)									
High ranking in search engine results	3,43	3,00	0,95	3,63	4,00	0,89	-1,18	0,240	0,06

Source: own elaboration.

The analysis revealed that the assessment of certain elements of online communication tools differed significantly depending on the type of university attended. Students from non-public higher education institutions assigned higher ratings to the following aspects: visual appeal of the university website (mean 4.0 vs. 3.8; $p < 0.035$), access to student reviews and alumni success stories (3.6 vs. 3.1; $p < 0.003$), ease of navigation and website intuitiveness (4.1 vs. 3.6; $p < 0.003$), and access to information regarding curricula and academic staff (4.0 vs. 3.6; $p < 0.014$). Higher ratings from students at non-public universities were also observed for the regularity of content updates on social media platforms (4.1 vs. 3.8; $p < 0.003$) and the visual and graphic aesthetics of materials published through these

channels (3.8 vs. 3.6; $p < 0.047$). For the remaining assessed elements of online communication - such as the frequency of receiving university-related e-mail communications, personalisation of e-mail messages, and the university's visibility in search engine results - no statistically significant differences were observed between students from public and non-public universities.

5. DISCUSSION

The objective of this study was to assessment the use of online communication tools by higher education institutions and their impact on shaping institutional image from the perspective of students. Viewed through the lens of intelligent management, comprehending how these tools strategically influence image-building is vital for universities operating in an increasingly digital and competitive environment. The findings confirm that students attach the greatest importance to the content and presentation of university websites, as reflected in the highest ratings assigned to this tool. An average score of 4.3 and a median of 5 underscore the high level of trust students place in the information provided through this channel, aligning with previous observations by Ciepaj, Miłaszewicz and Wengel (2020), who described university websites as a "virtual business card" and a primary point of contact with stakeholders. Social media and search engine marketing received slightly lower, though still high, ratings, highlighting their growing relevance in institutional communication with younger audiences. These results are consistent with the work of Buchnowska (2013) and Kisiołek (2021), who demonstrated that social media enable ongoing engagement with students, although their full potential often remains underutilised by academic institutions. In contrast, e-mail marketing received the lowest average score (3.2), corroborating trends noted by Hartemo (2022) and other researchers (Zhytomyrska et al., 2022), who observed declining interest in this channel among younger recipients, particularly when communication lacks personalisation and regularity. A significant element of the analysis involved comparing the responses of students from public and private universities. Students from private institutions assigned notably higher scores to the visual and functional aspects of websites, as well as the frequency and aesthetic quality of social media content. This finding supports Wójcicka's (2010) assertion that private universities, operating in highly competitive environments, tend to adopt modern communication strategies more rapidly and thereby implement intelligent management practices more effectively. These differences may stem from greater organisational agility and a stronger focus on achieving market advantage. The practical implications of these findings are substantial. Higher education institutions should invest in the development and optimisation of their websites, ensuring not only up-to-date content, but also visual appeal, clarity and ease of navigation. Social media may serve as a more effective relationship-building tool, provided institutions maintain regular updates and deliver engaging, visually compelling content. Meanwhile, e-mail marketing requires a more personalised approach to meet students' expectations and contribute positively to institutional image.

6. CONCLUSION

The growing importance of online communication in the operations of higher education institutions means that its quality and effectiveness have become key factors shaping students' perceptions of these institutions. The findings of the study conducted in the West Pomeranian Voivodeship confirm that online communication tools play a role in image formation, with students' assessments of these tools differing markedly depending on the type of institution. The highest ratings were given to elements related to the functioning of university websites – particularly their currency, credibility, and visual appeal. Social media also received positive evaluations, especially in terms of the regularity and quality of published content. In contrast, lower scores were assigned to e-mail marketing and SEO/SEM activities, suggesting the need to further tailor these forms of communication to the expectations of younger audiences. Moreover, comparative analysis indicated that private universities were more frequently rated highly in terms of the aesthetics and functionality of their communication channels. This may reflect greater institutional flexibility and a more rapid response to changes in the external environment. Such differences may also suggest

more effective implementation of intelligent management strategies, which consider the needs of students as key stakeholders.

Given that the research was limited to a single region of Poland, the findings should be interpreted within this context. Future research could extend to larger populations and other recipient groups. It would also be valuable to undertake a more in-depth analysis of the content communicated online by universities to obtain a fuller understanding of their strategies and their effectiveness. Moreover, embedding these insights within an intelligent-management framework requires continuously collecting data on student interactions and using analytics to iteratively refine digital strategies. Institutions that treat online communication as a dynamic, feedback-driven process – rather than a static broadcast – will be best positioned to enhance their reputations and sustain long-term competitive advantage. In conclusion, the effective use of online communication tools is no longer merely a matter of promotion but constitutes an integral component of image building and the competitive positioning of higher education institutions.

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ARTIFICIAL INTELLIGENCE AND THE TRANSFORMING SOCIO-INDUSTRIAL LANDSCAPES: A THEMATIC ANALYSIS OF STUDENT PERSPECTIVES

Olena Kulykovets [a], Malgorzata Nermend [b], Uma Shankar Singh[c], Swapnil Singh[d]

[a] *Warsaw University of Life Sciences, Institute of Management, Warsaw, Poland*
[b] *University of Szczecin, Institute of Pedagogy Szczecin, Poland*
[c] *University of Szczecin, Institute of Management, Szczecin, Poland*
[d] *Banaras Hindu University, Department of Sociology, Varanasi, India*

ABSTRACT

Purpose: *The study observes the research problem that the shift of industry due to the artificial intelligence is compelling the society to be shifted where the major effect is visible with the students, which must be addressed to establish a balanced equation in between society and industry.*

Need for the study: *The research is themed conceptually on the AI applications, where the scope is chosen the society and industry. The outcome of the study is driven methodically using thematic analysis from the secondary sources as well as the primary data has been the analysed to provide the understanding from students on the AI applications.*

Methodology: *The justification on the research is drawn from the thematic analysis providing eleven themes as Efficiency Gains, Predictive Analytics, Real-Time Tracking, Challenges, Incremental Adoption, Data Quality and Governance, Human Resource Development, Strategic Alignment, Framework of AI Measurements, Technical-Organizational-Human Factor Interface, Intervention Implementation Plan.*

Findings: *The thematic analysis provided the themes which are important to understand the shift of industry due to the artificial intelligence, which is compelling the society to be shifted. There is need to justify objectives, where the first objective is to explore the important factors of AI thematically based on the extraction from literature provided eleven themes of extreme importance for the implementation of the concept. The second objective to understand the importance of AI in the transforming socio-industrial landscapes is reached through the primary data analysis and the outcome from two parameters namely ARTIFICIAL INTELLIGENCE IN THE CONTEXT OF THEIR POSSIBLE USE IN EVERYDAY LIFE, and AI TOOLS OR APPLICATIONS IN THE CONTEXT OF THEIR USEABILITY.*

Practical Implications: *The major outcome is reached through the last objective as to measure the view of students on AI as components of socio-industrial landscapes, which is reached from RISKS RELATED TO ARTIFICIAL INTELLIGENCE EXIST. The outcomes are supportive to the idea providing the themed concept, where respondents have their positive approach towards the acceptance and implementation of AI for the better future.*

Keywords: AI, Artificial Intelligence, Industry, Society, Students, Thematic

Jel codes: I25; L86; M15; O35

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1. INTRODUCTION

The 21st century saw the advent and use of Artificial Intelligence (AI), which became one of the major transformation resources. It has impacted and reshaped the way people work and foresee the future of human and machine collaboration. The use of AI has impacted almost all the domains of human life, including the changes and transformation in the socio-economic structures (Liu et al., 2018). AI has become one of the best instruments in today's modern world to make our work easier. The systems that use artificial intelligence are basically making use of different algorithms and models, allowing them to improve with time. It is true that AI augmented technologies are continuously being created and improved to serve different human needs including entertainment, education and healthcare system among other areas. The use of AI in several domains has its own advantages and disadvantages, while in the industrial sector, the use of AI has increased the efficiency and innovation (Akhter et al., 2024).

On the other hand, the use of AI in the field of education has its own repercussions. The challenges have been met with significant improvement through the help of AI technologies. Numerous technologies are currently being applied in the transforming socio-industrial landscapes, and they include artificial intelligence such as machine learning, predictive analytics and robotics (Lucci et al., 2022). These technologies allow companies to embrace analytical decisions, forecast demand, control inventories, and use other tools to automate specific work (Toorajipour et al., 2021). Due to the capacity of AI to process large volumes of data within a short span, businesses can easily detect weaknesses that hinder the flow of goods, minimize errors and improve the flow of goods through the transforming socio-industrial landscapes. The use of AI across different industries has led to different forms of societal transformations as well. It has been observed that the innovations that are AI driven have improved the work in terms of efficiency, productivity in different sectors, which ultimately influences the economic structures and social interactions (Akhter et al., 2024). The use of AI encompasses the machine presented intelligence that has the capability to match human cognitive functions resulting into autonomous decision making and problem solving.

The autonomous decision-making capacity is a result of training on large data sets to make intelligent decisions. This training in large data set is one of the reasons which leads to personalisation and customisation of products resulting into better customer experience. The shift towards automation with the coming of AI has also sparked a great debate about the kind of job transformation that the society is going to witness (Bharati & Sandbrink, 2024). There are concerns related to the potential unemployment that it may create, and an inquisitiveness related to the adaptability of the workforce. It is to be noted that while some jobs will be rendered obsolete with the increased use of AI, it is also true that several new opportunities for skill development will be created which requires a blend of human creativity and critical thinking along with the technical expertise (Esplugas, 2023). An intelligent blend of innovation, adaptability and creativity will harness the true potential of AI driven automation in the job transformation.

As we see the evolution of AI, it is important to consider the implementation with a balanced approach. An approach that would embrace the benefits of the use of AI while mitigating the challenges associated with the overuse and unethical use of AI (Al Fraidan, 2024). It is to be seen that the public awareness and discussions on the impact of AI should be encouraged in order to promote a responsible and ethical usage of AI in order to mitigate the potential risks involved with the AI usage.Therefore, it would be a collaborative effort between different industries, government sector and different social institutions where AI and its use can be harnessed to create an efficient, equitable and technologically advanced society. Global transforming socio-industrial landscapes represent a giant web of linkages on systems and processes cutting across both industries and geographical domains (OECD, 2019). In this context, global transforming socio-industrial landscapes are continuously developing due to higher demand for execution speed, product reliability, and cost reduction, where the use of technology is one of the key factors for appropriate transforming socio-industrial landscapes management (Almeida Marques & Oliveira, 2024).

Historically, the use of conventional ways of functioning, and many of the solutions and activities were carried out manually resulting in high costs, time wastage, and human error (Kumar et al., 2024). But in the recent past ushered in by information technology, organizations have been able to make some automated, real-time tracking, and analytics in their transforming socio-industrial landscapes to help them with control. Indeed, current advanced scientific technologies like AI technology have taken the

central stage in revolutionizing transforming socio-industrial landscapes (Heesche et al., 2022). The significant factor of operating excellence has been deemed as the core competence to maintain a competitive advantage in the worldwide market area. This means getting products to the consumer at the lowest cost and therefore delivery in this case is a fundamental component of competitiveness. This has made cost efficiency into an operational strategy not only a luxury but a necessity for businesses hoping to operate in a highly competitive globalized marketplace (Demsina Sinaga & A. Hermawan, 2023).

The challenges have been met with significant improvement through the help of AI technologies. Numerous technologies are currently being applied in the transforming socio-industrial landscapes, and they include artificial intelligence such as machine learning, predictive analytics and robotics. These technologies allow companies to embrace analytical decisions, forecast demand, control inventories, and use other tools to automate specific work (Ismaeil & Lalla, 2024). Due to the capacity of AI to process large volumes of data within a short span, businesses can easily detect weaknesses that hinder the flow of goods, minimize errors and improve the flow of goods through the transforming socio-industrial landscapes. More so, with the increasingly complex and increasingly intensive global transforming socio-industrial landscapes, the AI application in the transforming experience further expansion in efficiency, visibility, and profitability (Riad et al., 2024).

The study observes the research problem that the shift of industry due to the artificial intelligence is compelling the society to be shifted where the major effect is visible with the students, which must be addressed to establish a balanced equation in between society and industry.

The research has framed the objectives to be reached as,

To explore the important factors of AI thematically based on the extraction from literature.

To understand the importance of AI in the transforming socio-industrial landscapes.

To measure the view of students on AI as components of socio-industrial landscapes.

The research is themed conceptually on the AI applications, where the scope is chosen the society and industry. The outcome of the study is driven methodically using thematic analysis from the secondary sources as well as the primary data has been the analysed to provide the understanding from students on the AI applications.

2. THEORETICAL AND CONCEPTUAL EVIDENCE

The research is crucial comparing the changing dynamics and alignments of society and industry. This is not a new phenomenon, but degree of intensity has been changed positively. Now society is more intended to be an industry driven society (Deguchi et al., 2020). It is evident looking around the world that the world population is competing to make themselves skilled to cope up with changing industry. The global market shift where every country is pushing their industrial capabilities to be a self-sustained production economy. The Chinese sustained economy driven by production seems to be the role model for the world (Stasiulis, 2017). The India, Singapore, Vietnam, Indonesia are pushing the industrial drive in Asian context. At the same time the western world is not left behind. Europe is aligning its member nations to be self-sustained in production. In this process Germany, Poland, Hungry, and Switzerland are leading the idea more aggressively than earlier.

There may be many reasons for this change, but the AI is being crucial where the industries are compelled to adopt AI support for more precision of results. The research is focused to look for the theories deriving the equations of society and industry on their coordination and conflicts. However, it undeniable that the better the coordination of society and industry the better can be the economy(Samarasinghe et al., 2024). But the changing society also not always accepts the change of industry. Now the AI and their applications are much beyond a single human skill, which is available on clicks for the industries, which is restricting and limiting human skills application in industries. The most vulnerable segment is the student groups preparing themselves to enter the job market. The usage of AI is making them ease in life and their personal affairs (European Parliament. Directorate General for Parliamentary Research Services., 2020). At the same time the professional commitments may deny the usage of AI or the AI itself may replace them.

2.1. Artificial Intelligence

Artificial intelligence has become a part of everyday life over a decade ago, having a major impact on professional life, social and family relationships (Elliott, 2019). However, the latest artificial intelligence systems are a turning point, allowing us to predict things and events or conduct conversations in a human-like way, and what's more, these possibilities are available not only to experienced users (Campo-Ruiz, 2025). The widespread use of artificial intelligence tools significantly influences users' decisions about choosing places, routes and how to experience them, shaping their perceptions through recommendations and visualizations based on selective data from previous users, which can act as reality filters and do not always reflect individual preferences.

Artificial intelligence and its rapid development have attracted great interest in various industries and disciplines (Hyder et al., 2019). According to the OECD definition, an AI system is a machine solution that, based on specific goals, makes predictions, recommendations or decisions that affect real and virtual environments, using input data, modeling and inference at various levels of autonomy (OECD, 2019). The European Commission defines AI as a machine-based system that operates with varying degrees of autonomy, can adapt after implementation, and, based on the input data received, explicitly or implicitly formulates conclusions leading to the generation of outputs, such as predictions, content, recommendations or decisions, affecting physical or virtual environments (Regulation - EU - 2024/1689 - EN - EUR-Lex, n.d.).

Artificial intelligence today, especially in its forms of machine learning and deep learning, offers users a new way of conceptualizing intelligence. Unlike human consciousness and human cognition, which is generally associated with conscious reflection and introspection, artificial intelligence bases its operations mainly on algorithmic processes, learning by analyzing large sets of data and identifying patterns (Korteling et al., 2021). The development of artificial intelligence takes place in stages, going through periods of both development and stagnation (Fui-Hoon Nah et al., 2023). In the 1950s and 1960s, successful projects such as the General Problem Solver and ELIZA (Weizenbaum, 1966) were created, but limited computing power and a decline in funding hampered progress. In recent years, however, AI has once again gained prominence, with AlphaGo (2015) and ChatGPT, which released in late 2022 to global attention.

The dynamic development of AI is primarily due to the growing number of specialists in this field as well as intensive investments, both public and private. The key role is played by the wide availability of various data in the form of images, videos, tables, location data, etc. Artificial intelligence is used in many sectors, including healthcare, conversational applications, and smart cities. It is constantly being improved in terms of architecture, integration, and optimization. Artificial intelligence is based on models that identify patterns in data, but their effectiveness can be limited by poor data quality, suboptimal learning rates, or other external factors (Majeed & Hwang, 2024).

2.2. Social Transformations

Artificial intelligence has impacted and revolutionised different aspects of our lives including business, education, healthcare system among others. The ability of AI to analyse data and make independent decisions has compelled the way we live and work. In the business world, the use of AI has impacted several processes, including cost cutting and improving the quality of products and services through automation. AI is also helping to transform how we use technology and interact. It is true that AI driven automation has led to a significant change in the global job market with both positive and negative consequences, raising a debate of job displacement versus the creation or adaptation of new roles. The existence of several platforms which are AI powered have also facilitated the rise of gig economy and remote and flexible working opportunities for different sections of the society.

The use of AI has also impacted education system with the coming of e-education and different digital platforms to enhance personalised learning experiences. The AI powered platforms not only help students and learners to access the courses from remote locations but also help teachers to ease their administrative responsibilities. AI usage in educational field has made education inclusive to a great extent. Yet another area which is heavily impacted by AI usage is of the healthcare services, where the early detection of diseases help to improve survival rates. The concept of telemedicine has again given opportunity to people from remote areas to gain access to best available medical consultation without physical visits.

It is true that every innovation and specifically technological advancements come with their own benefits and challenges. It holds true even in the case of AI and its impact on society. The transformation and reshaping of society is one of the facets of AI usage but there are ethical considerations as well as privacy concerns along with employment challenges that need to be tackled on the way. The need of the hour is to develop awareness towards responsible and ethical AI usage guided by the element of fairness and inclusivity in order to leverage the real benefits of such technology for the upliftment and empowerment of the society.

2.3. Industrial Transformations

Technologies based on artificial intelligence have become an indispensable element of the functioning of enterprises in various sectors of the economy (Majeed & Hwang, 2024). AI systems are effectively taking over tasks previously performed exclusively by humans, including driving, natural language processing, facial recognition, big data analysis, and searching the web. Just about ten years ago, no machine was able to reliably recognize images or process language at a human level (Gursoy et al., 2019). Today, artificial intelligence systems are achieving higher efficiency in these areas, surpassing humans in, among others, language recognition, image recognition, and text analysis for comprehension. In the near future, AI may also significantly improve the efficiency of handwriting recognition and prediction.

Artificial intelligence has a huge impact on various sectors today, including health, politics, public safety, research, and the economy, as well as the everyday functioning of society. Interactions with AI systems occur via smart devices, digital platforms, and applications. These technologies are widely used in city monitoring, airports, and other public spaces (Bozkurt & Gursoy, 2025). In addition, AI is also used in advanced military systems such as autonomous weapons or drone control. In the business sector, AI algorithms and machine learning support process optimization, including product design, marketing strategies and human resources management.

AI supports efficiency and innovation by offering intelligent tools to solve complex problems (Sirmacek et al., 2023). In the area of education, it enables the development of personalized teaching and the automation of assessment systems. In industry, artificial intelligence supports and increases efficiency, reduces or minimizes errors and improves quality. Artificial intelligence also finds applications in energy and sustainable development, transportation, decision-making, the entertainment industry and medicine. For example, in the hotel industry, Hilton Worldwide has hired a robot concierge, ‘Connie’, to personalize guest experiences and provide information. Aviation company KLM Airlines uses a robot named ‘Spencer’ to answer travelers' questions and reinforce their positive experiences with the airline. Retailer North Face is using an AI-powered web app to help customers choose the most appropriate product (Majeed & Hwang, 2024). AI systems not only personalize services but also reduce operating costs.

In recent decades, AI has become a key driver of transformation, imitating human intelligence through advanced technologies. AI technologies such as automation and robotics have transformed warehousing and distribution operations, increased operational efficiency, and encouraged strategic innovation. As a catalyst for innovation, its widespread implementation has become an indispensable element of contemporary technological development. Further development of AI and new technologies can help to make regulatory processes more efficient, including automated document management and algorithm-assisted reviews, allowing resources to be focused on strategic decisions and innovation.

2.4. AI on Socio-Industrial Landscapes

Generative AI models, a subset of AI systems, are characterized by their ability to synthesize new data by analyzing patterns, structures, and features observed in training sets, but their limitations include generating potentially misleading results that can lead to significant social consequences. Artificial Intelligence has a significant impact on social diversity, equality and inclusion. Social media algorithms, for example, facilitate the creation of information bubbles and can also serve to reinforce prejudices, spread false information or limit the diversity of content (Elliott, 2019). In cultural matters, AI may not meet the cultural norms of target groups, creating barriers by imposing dominant classifications, generating offensive content, violating important values, or marginalizing or simplifying history and identity.

It is worth noting that Industry 4.0 today focuses on the digitalization and automation of production, constituting the foundation for the so-called Society 5.0, which integrates these technologies in order to improve the quality of life, solve social and ecological problems and create innovative platforms supporting the professional activation of older people. Together, these two elements create an ecosystem that combines industrial efficiency with human-centric innovation. Artificial intelligence improves the process of managing resources, transportation systems, healthcare, and access to education and public services (Deguchi et al., 2020).

Artificial intelligence has enormous potential to change the shape of the global economy, especially in the area of labor markets. Developed economies will experience both the benefits and challenges of AI more quickly due to the employment structure based on tasks requiring cognitive abilities, which may deepen income inequality, especially if AI is strongly complementary to high-wage workers. To minimize the negative effects, it will be crucial to adapt regulations and invest in infrastructure and digital skills, especially in emerging economies. Technological progress, especially in the field of artificial intelligence and information processing (86%), robotics and automation (58%) and energy systems (41%), will significantly affect the labor market, leading to both an increase and a decrease in employment in various sectors (European Parliament. Directorate General for Parliamentary Research Services., 2020). Technological skills, such as artificial intelligence and big data analysis, computer networks and cybersecurity, will become key and will be among the fastest growing competences. The Future of Jobs Report 2025 underscores the profound impact of artificial intelligence on labor market dynamics, forecasting a net increase of 2 million jobs by 2030, with 11 million new positions emerging and 9 million becoming obsolete, particularly in fields such as AI specialization and data analysis. The proportion of tasks executed by human labor is projected to decline from 47% to 33% as automation increasingly assumes responsibility for routine and repetitive functions across diverse industries.

2.5. Artificial Intelligence Impact on Students

Artificial intelligence (AI) differs in the way students learn, collaborating and organizing their academic lives. The tools available on AI that are a successor to classical education, new learning opportunities available, as well as accessible. Artificial intelligence (AI) is playing an increasingly important role in students' lives, affecting various aspects of their education and daily activities. According to the "Technology through the Eyes of a Student" survey conducted by Digital Care (Survey, 2023), as many as 68% of students plan to use AI-based tools during their studies in the current academic year. The most frequently cited uses include language translation (52%), organizing work (52%), creating presentations (50%) and writing credit papers (34%). One in five students intends to use AI for thesis writing, indicating growing confidence in these technologies in the academic community. Using tools such as ChatGPT, Grammarly, DeepL or various note generators allows students to save time and focus on more challenging aspects of their studies. However, there are also challenges associated with the potential misuse of AI, which can lead to reduced self-efficacy in learning and a lower ability to think critically (Scarfe et al., 2024; Sluzek & Suppan, 2024).

Introducing AI tools into the educational process brings numerous benefits, such as increased engagement and learning satisfaction (Launonen et al., 2024). AI-based educational platforms tailor content to individual students' needs and interests, which fosters a more interactive and personalized learning experience (Navoica.co.uk - Education Platform, 2025). In addition, tools such as gamification, virtual reality and simulations make learning more enjoyable and engaging. AI also offers real-time feedback, allowing students to monitor their progress and improve quickly, increasing their sense of achievement. An example is automated grading systems for papers, which allow students to receive immediate feedback and correct their mistakes before final submission. On the other hand, the personalization of the learning process can lead to isolation, as students are increasingly less likely to use traditional group learning methods, which can negatively affect their social skills.

However, the growing use of AI tools raises questions about their impact on the development of critical thinking and creativity among students. A study conducted by sociology students under the supervision of Dr. Maja Brzozowska-Brywczynska indicates that while AI supports creative processes and learning, it also requires critical review of generated content (Janowski et al., 2024). Students recognize the potential of AI to inspire creativity but are concerned that over-reliance on technology can undermine analytical skills and independent thinking. The quality and reliability of the content generated is also an issue - artificial intelligence can make mistakes, reproduce stereotypes or provide outdated

information. Therefore, it is important to emphasize in the educational process the development of skills in the critical use of AI tools and the integration of these technologies in a way that supports, rather than replaces, traditional teaching methods. In this context, the role of lecturers and academic institutions becomes crucial - they should introduce educational programs that teach responsible use of IS, rather than banning its use altogether.

2.6. Students in the Socio-Industrial Landscapes

Today's socio-industrial landscape shapes students' lives on many levels, affecting their education, professional development and social activity. In an era of dynamic technological changes, such as automation, artificial intelligence (AI) and digitization, traditional education models are undergoing a profound transformation (University of Bialystok & Zalewska-Bochenko, 2024). Students are increasingly acquiring knowledge in a hybrid manner, combining academic learning with experience gained in industrial and business environments. Universities are introducing innovative curricula that work closely with the industrial sector, offering students access to real-world research projects and cutting-edge technological tools (Rashid et al., 2024). Artificial intelligence plays a key role here - advanced algorithms help personalize learning, analyze large data sets and support teaching processes through intelligent advisory systems (Sajja et al., 2023). AI is also being used in the automatic evaluation of papers, generation of educational content, and assisting students in organizing their learning, leading to the increasing individualization of the educational process (Kamalov et al., 2023).

In the context of changes in the labor market, the socio-industrial landscape is affecting students' expectations of their future careers. More and more young people recognize that traditional career paths are becoming less predictable, and that flexibility and the ability to adapt to new conditions are key to career success. Alternative forms of employment such as freelancing, startups and project work in the platform economy (gig economy) are gaining popularity. Many students are already engaged in entrepreneurship during their studies, creating their own companies or implementing innovative projects within business incubators. Artificial intelligence supports these processes, enabling analysis of market trends, optimization of business strategies and automation of many aspects of business(forecast,2023). AI tools such as chatbots, predictive systems or automated data management systems allow students to effectively develop their business initiatives and better prepare for professional challenges. However, access to modern technology is not equal - students from disadvantaged backgrounds may face financial barriers and limited access to advanced tools, pointing to the need to implement educational policies that support equal opportunities.

In addition to economic aspects, students in socio-industrial landscapes also play a role as active participants in social and cultural change. Awareness of global challenges such as climate change, work ethics and corporate social responsibility is shaping young people's attitudes toward industry and the economy. Student movements are increasingly playing an important role in public debates, mobilizing society and influencing corporate policy and government regulation. Artificial intelligence in this context plays an important role by facilitating data analysis, social media communication. However, it can raise concerns about the ethics of its use in surveillance and control of society. Digitization and the development of AI enable students to conduct effective digital activism so that their voices can be heard on a global scale. As technology and industry continue to evolve, it will be young people, equipped with new AI competencies and tools, who will be the key actors shaping the future of the economy and social norms, where innovation goes hand in hand with ethics and sustainability.

3. METHODOLOGY AND ANALYSIS

The methodology and analysis are the most important section of the study providing the detailed view on the chosen methodology and the process of data analysis in this context (Singh et al., 2022b). The apt methodology is the need of the chapter works as the backbone of the study. Here in this context, the section is divided in two sub sections namely dedicated for methodology and another analysis. The methodology section is broadly based on the assessment of the aforesaid problem variables with respect to identified methods. The analysis is qualitative and analytical implementation of the collected data justifying the acceptance or rejection of variables to the current context.

3.1. Methodology Adopted for the Study

This section presents the methods used in the research on the impact of artificial intelligence (AI) on the transforming socio-industrial landscapes (Singh et al., 2022a). The purpose of the study is to discover the potential of AI in changing the prospect of industrial problems, improvement in the use of resources and innovation. The work aims to strengthen the understanding of how AI can enhance the operational performance, efficiency, and accuracy throughout industries, including the results of the analyses of real-life cases of AI use in companies like Amazon.

The study makes use of an extent case study as the primary method of analysis applying a questionnaire to students to know their views on the AI applications. The case study framework pertains to such organizations as Amazon. This method allows for analyzing concrete fields, in which emergence of AI technologies has been observed, including automation of warehouses, predictive analysis, robotic systems as well as tracking systems in real time (Majeed & Hwang, 2024). Using these cases, this study examines the benchmark, critical success factors, and the reversal capabilities of AI throughout the changing industrial sphere. The case studies, and desk-based analysis, another essential data gathering method includes semi-structured interviews from a panel of experts including professionals and AI specialists. Such interviews' purpose is to gain the first-hand experience of the current field and industry, the process of the operation improvements with the help of AI applications, the most significant difficulties faced, and expected future trends.

The section also shows the methods used in analysis of the collected data. Coded data is used for thematic analysis of the case study materials using patterns identified. This entails categorizing the data collected for example into gains which include efficiency, costs, and barrier that are associated with the use of artificial intelligence. The cross-case analysis builds on the identified patterns and variations between the chosen case studies, providing an overview of AI effects throughout industries. In contrast to accidental quantitative research, which is based on the use of numbers and statistical dependencies from students, methodical qualitative is based on individual feelings and stories (Singh et al., 2022b). It makes this approach suitable for study complex and context-sensitive phenomena such as the AI adoption because it provides a detailed understanding of the benefits and drawbacks of organizations in this context. The case study as the sample size fifty investigating and discussing the difficulties stimulated by the incorporation of AI including data consolidation, the training of employees, and the expense of carrying out the procedure. Knowledge of these issues is a good starting point for outlining the prospects for AI implementation in different industries and the obstacles that may exist in this process.

The cornerstone of data analysis is the thematic analysis that will help to define the existing topics and analyze them within the collected data. The integrative method of analysis is best applied to qualitative studies as it offers an integrated approach on how data can be sorted and analyzed (Melo, 2018) . The first procedure in thematic analysis is issue coding and categorization, which entails a close look at the assessment of case analyses for obvious patterns of themes. To try and ensure a comprehensive and contextual understanding of both the content and context of each transcript these are read several times. Initial coding is then done in which texts sections are coded according to the different facets of the research. After the data has been coded, the different codes are aggregated into themes to come up with superordinate categories. For instance, codes such as automation, robotics, and predictive analytics employed as the subtopic AI-driven operational improvements. It useful in preventing the pile up of data analysis hence helps in coming up with themes that capture the outcome of the research. The final themes are also examined and changed as necessary to fully communicate the data and reiterate the research aims. The identification and analysis of these themes, thematic analysis returns useful insights on the applicative and constructive outcomes of AI in the management of industry systems and methods (Liu et al., 2018). This paper not only focuses on the benefits of applying AI in the industry but also on the problems that have occurred during the implementation of this technological solution

3.2. Analysis of the Thematic Data

The first and the most important requirement for the analysis of this study is the extraction of themes. The themes extracted through the literature are *Efficiency Gains, Predictive Analytics, Real-Time Tracking, Challenges, Incremental Adoption, Data Quality and Governance, Human Resource Development, Strategic Alignment, Framework of AI Measurements, Technical-Organizational-Human*

Factor Interface, Intervention Implementation Plan observed the most important eleven themes to be analyzed. These eleven themes further explained as it reflects from studies with a detailed view below.

Efficiency Gains: The technological advancement of warehouse automation with special reference to the availability of Kiva robots has responded positively through low order cycle times as well as accuracy in inventory (Gao & Feng, 2023). Picking, sorting, and packing have seen a lasting improvement using automation which impacts order fulfillment speeds and human oases. The incorporation of Robotics and AI in managing warehouses has pushed through rates while at the same time decreasing the expense per unit through auto operation. The following developments have helped organizations to provide customer orders processing with increased efficiency and accuracy to strengthen the market position.

Predictive Analytics: It has become now possible to identify new patterns of demand forecasting and predicting which types of resources should be assigned to a given job using predictive analytics. It also means by utilizing machine learning algorithms coupled with big data, one can accurately predict customer demand levels, hence, enable appropriate inventory to be ordered for or stocked so that cases of over stocking or stock out can be eliminated (Patrick Azuka Okeleke et al., 2024). This has brought the cost down and enhanced customer satisfaction, since the products are available where and when they are needed. Through predictive analytics, procurement scheduling, transportation routes, and storage of electronic assets have also improved. Such technologies applied by Amazon suggest the possibility of improving the total industry effectiveness and sustainability.

Real-Time Tracking: Real-time tracking has emerged as another significant AI application, which has reinvented delivery performance, industry visibility. The deployment of IoT devices with the aid of artificial intelligence makes it easy for organizations to track shipments at a go; hence give the accurate information of delivery to the clients. This visibility across the industry refines the interactivity of stakeholders, optimizes the routing of the product and guaranties on time deliveries (Campeau & Dubois, 2019). Contract transparency has not only led to the achievement of accurate delivery metrics through the application of real-time tracking but also made customers develop confidence in accented services offered by Amazon.

Challenges: The research also reveals various drawbacks connected with the application of AI in the industry field. System integration with current systems, which are still in existence, is still a major challenge that needs huge amounts of investment in IT infrastructure and skills. Another challenge is meant to be the workforce resistance; this is due to their fears that they will lose their jobs anytime due to their incapability of being trained on how to operate the new technologies. Besides, due to significant fixed costs needed to implement the AI technologies, the smaller organization will be locked out of these innovations (Groumpos, 2023). These factors present a challenge that needs strategic direction, continued enhancement of change management framework, and most importantly a direct investment on the workforce to improve AI implementation agenda.

Incremental Adoption: This is why a step-by-step approach is recommended as this will help the organization avoid risks common with AI adoption while at the same time encouraging organizational learning. Real-time tracking systems are good examples of foundational technologies that are easy to incorporate, and their implementation yields significant improvements to the operations of an organization (Hussain & Rizwan, 2024). Real-time tracking is not only a powerful tool in improving the industry transparency but also a good ground for introducing additional innovations. For example, through logistics optimization with real-time tracking of shipments and stock management more confidence can be placed in employing AI solutions.

Data Quality and Governance: The effectiveness of every AI venture depends on the quality of data as well as the policies in place for nurturing and managing such data. AI is based on effective, efficient, and complete data to make proper recommendations and support decision making. Mainly, inaccurate data inevitably degrades the performance of AI-based solutions, produces wrong forecasts, slow processing, or erodes confidence in such systems. (Reddy Desani, 2023) To these coordinates, it is crucial that organizations pay adequate attention to creating a good data governance framework for their dictionaries. This involves ensuring that data is collected systematically, using enhanced tools of data acquisition and processing, apart from ensuring that data is cleaned. In addition, organizations need to establish the mechanisms for the data usage regulation, compliance, and ethical issues of privacy and data security.

Human Resource Development: The most difficult to overcome in many organizations is employees' rejection of AI integration: it may be caused by concerns about layoffs and limited understanding of the technology. In response to these issues, business entities need to provide solutions that entail development of sufficient training and change management procedures that can enable people in the organizations to embrace the use of artificial intelligence in doing their work (Seufert & Spirgi, 2024). Training should aim to develop skills that can enable employees to complement operations of these AI systems, for instance data skills, programming and machine learning skills. These initiatives should be adaptive with the employee's levels or positions within the organization to equally empower all employees regardless of whether they work in the lower cadre or executive levels of the organization.

Strategic Alignment: That is, for these AI initiatives to unlock sustainable value for organizations, they need to fit the organizational strategy and be backed by leadership. AI adoption should not be considered as the project of its own but include it into the overall organism's development strategy. This means that, it is important for any organization to understand how AI technologies can solve problems and help in achieving organizational goals in the future ("The Impact of Artificial Intelligence on Business Strategy and Decision-Making Processes," 2023). One potential factor because of which there is a good strategic fit with AI involves leadership in translating it into actionable initiatives and providing the right resources for its realization. Leaders and managers should geta involved, embrace it, and implement it because it will contribute to the spirit of change.

Framework of AI Measurements: The theoretical implications of this study, there is a proposal to create an analytical tool for assessing AI applications in various organizations. The authors have used data collected from the case study of Amazon along with the perception of professionals to uncover crucial enablers and inhibitors of AI that form part of this examination (Guo et al., 2024). This framework takes cognizance of the fact that best practices when it comes to AI implementation may not be the same for all organizations given the size of the organization, the industry it is operating in and available resources.

Technical-Organizational-Human Factor Interface: It demonstrates how the process of AI deployment is based upon complex interactions between technical and organizational aspects, and people. Topics, including, but not limited to, predictive analytics, the automation of warehouses, and real-time tracking are proved to stimulate operational improvement and increase industry transparency (Reiterer, 1993). This research also highlights that organizational readiness, leadership encouragement and workforce improvement is vital for achieving such advantages.

Intervention Implementation Plan: The research provides a clear practical roadmap of how the concept can be implemented in a coherent, strategic and tightly controlled manner which both supports innovation and maintains operational stability (Reim et al., 2020). This framework has proposed a three-stage process of implementing AI to organizations that start off with basic levels of AI usage such as real-time tracking and move up to the higher levels of AI application like analytics and control. Step-by-step approach thereby reduces risks, strengthens AI capacities in the organization and helps to achieve the right AI integration.

3.3. Analysis of Primary Data

The primary data is collected using a structured pre used questionnaire, which has the three parameters to be assessed namely "RISKS RELATED TO ARTIFICIAL INTELLIGENCE EXIST, ARTIFICIAL INTELLIGENCE IN THE CONTEXT OF THEIR POSSIBLE USE IN EVERYDAY LIFE, and AI TOOLS OR APPLICATIONS IN THE CONTEXT OF THEIR USEABILITY". Each of the items are assessed on 1-5 Likert scale, where 1 is representing extremely disagree, 2 is disagree, 3 is neutral, 4 is agree, and 5 is strongly agree. The data is collected from students' group from the age of 18 Years to 33 Years engaged in different studies in Poland. The sample size taken is 132, which is representing the views of young students about the understanding about AI's effect to the future. The three pictures presented below is the representation of their opinion on issues (M. Nermend et al., 2022a).

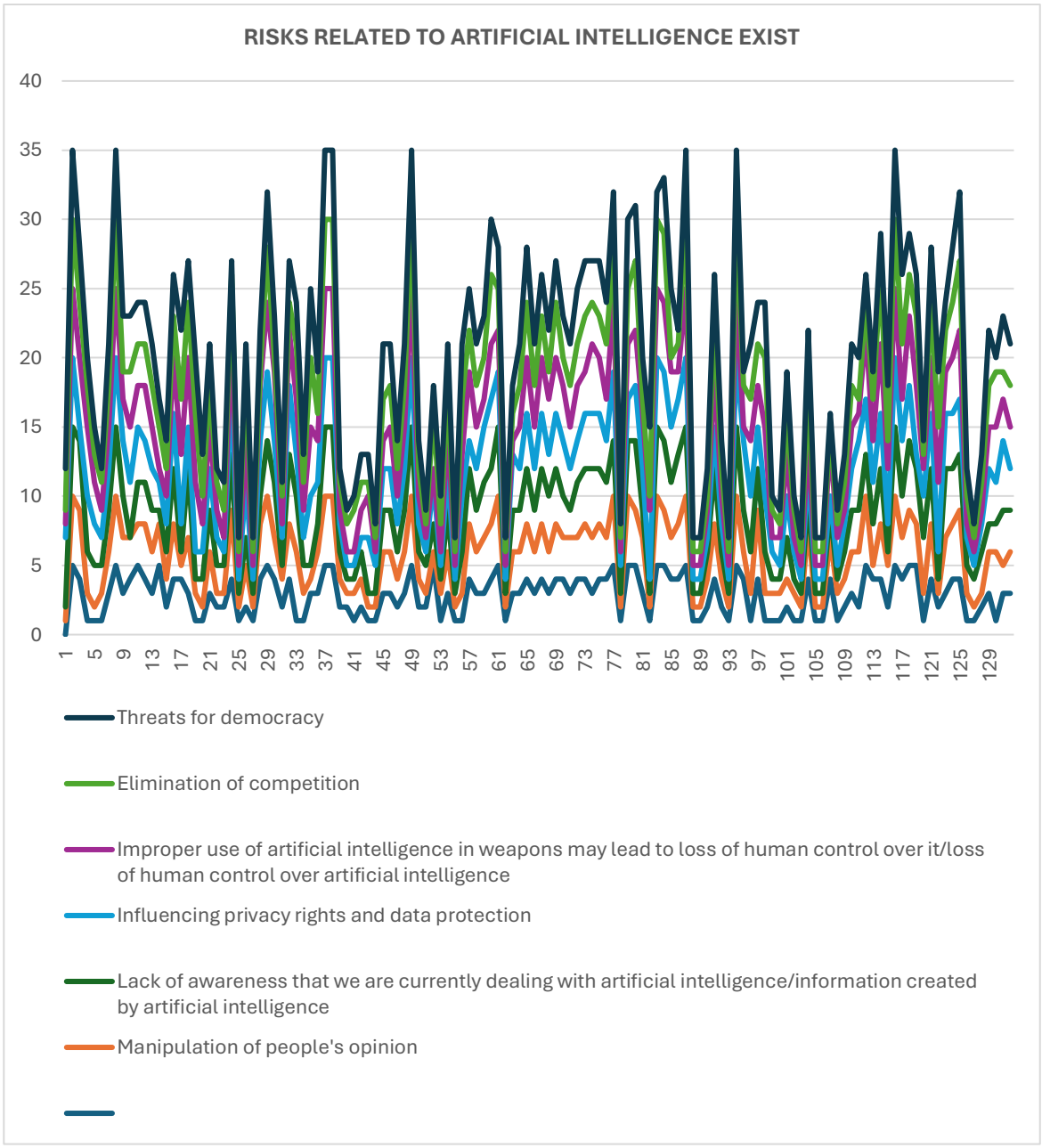


Figure 1. Risks related to artificial intelligence exist
Source: own elaboration.

The RISKS RELATED TO ARTIFICIAL INTELLIGENCE EXIST (Figure 1) is the first parameter to be assessed has seven items to be measured as Threats for democracy, Improper use of artificial intelligence in weapons may lead to loss of human control over it/loss of human control over artificial intelligence, Influencing privacy rights and data protection, Lack of awareness that we are currently dealing with artificial intelligence/information created by artificial intelligence, Elimination of competition, Manipulation of people's opinion, and Risk of job loss. The 5-point Likert scale is the measuring criteria to know the responses on the aforesaid 7 items, where the responses for all items are with mixed emotions. This shows that some of the respondents are assuming that the risk is there, though some are on the saying as no risk (K. Nermend et al., 2020).

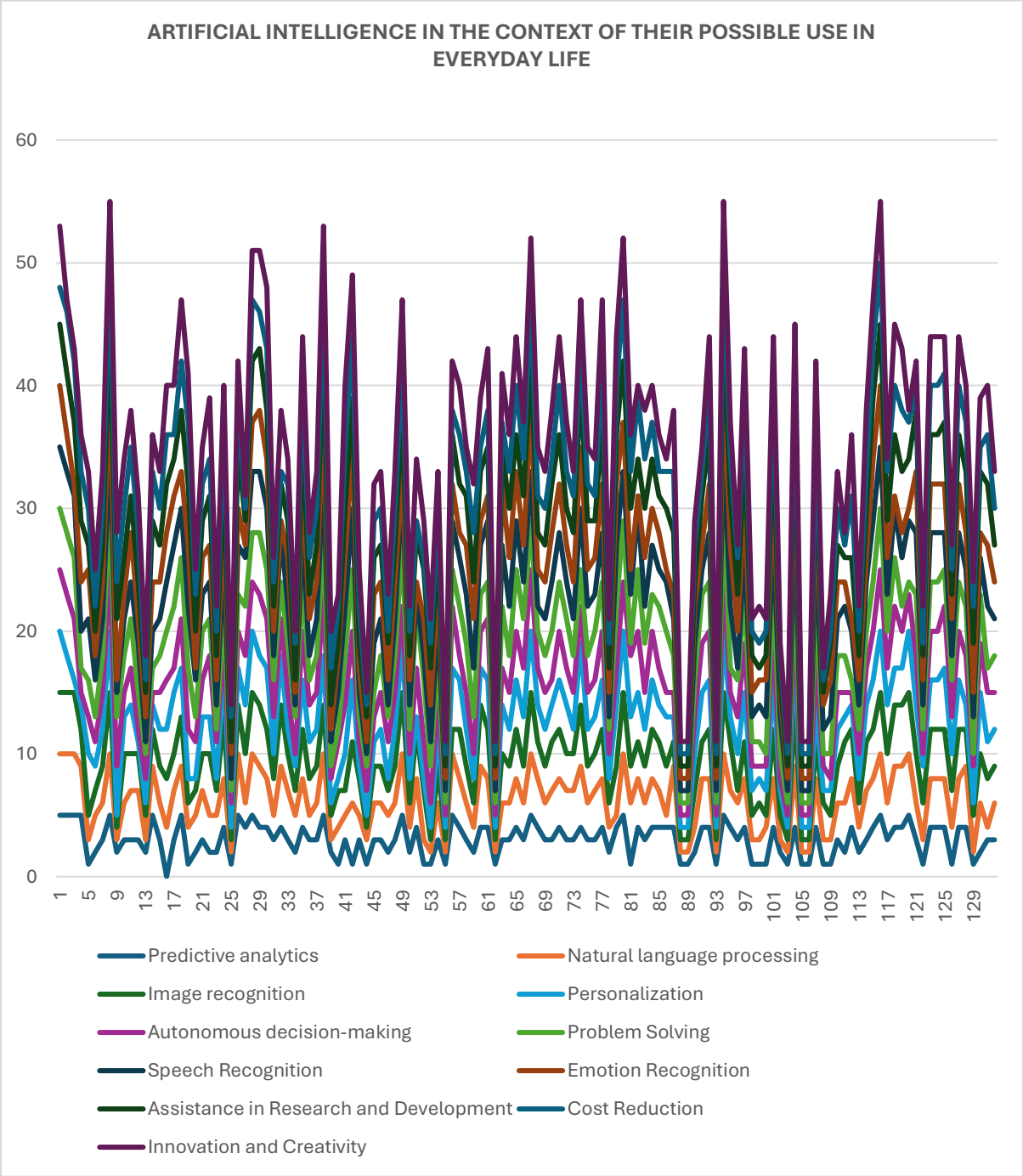


Figure 2. Artificial intelligence in the context of their possible use in everyday life
Source: own elaboration.

The parameter ARTIFICIAL INTELLIGENCE IN THE CONTEXT OF THEIR POSSIBLE USE IN EVERYDAY LIFE (Figure 2) is to be assessed has eleven items to be measured as Predictive analytics, Image recognition, Autonomous decision-making, Speech Recognition, Assistance in Research and Development, Innovation and Creativity, Natural language processing, Personalization, Problem Solving, Emotion Recognition, and Cost Reduction. The responses are measured on the 5-point Likert scale, where respondents are in favor of the Likert value 4 and 5 representing agree and strongly agree respectively. This shows a clear understanding of respondents as they see the ARTIFICIAL INTELLIGENCE IN THE CONTEXT OF THEIR POSSIBLE USE IN EVERYDAY LIFE. Young students strongly feel that the AI has the future influence and the application in day-to-day life for everyone (Bartoszczuk et al., 2022).

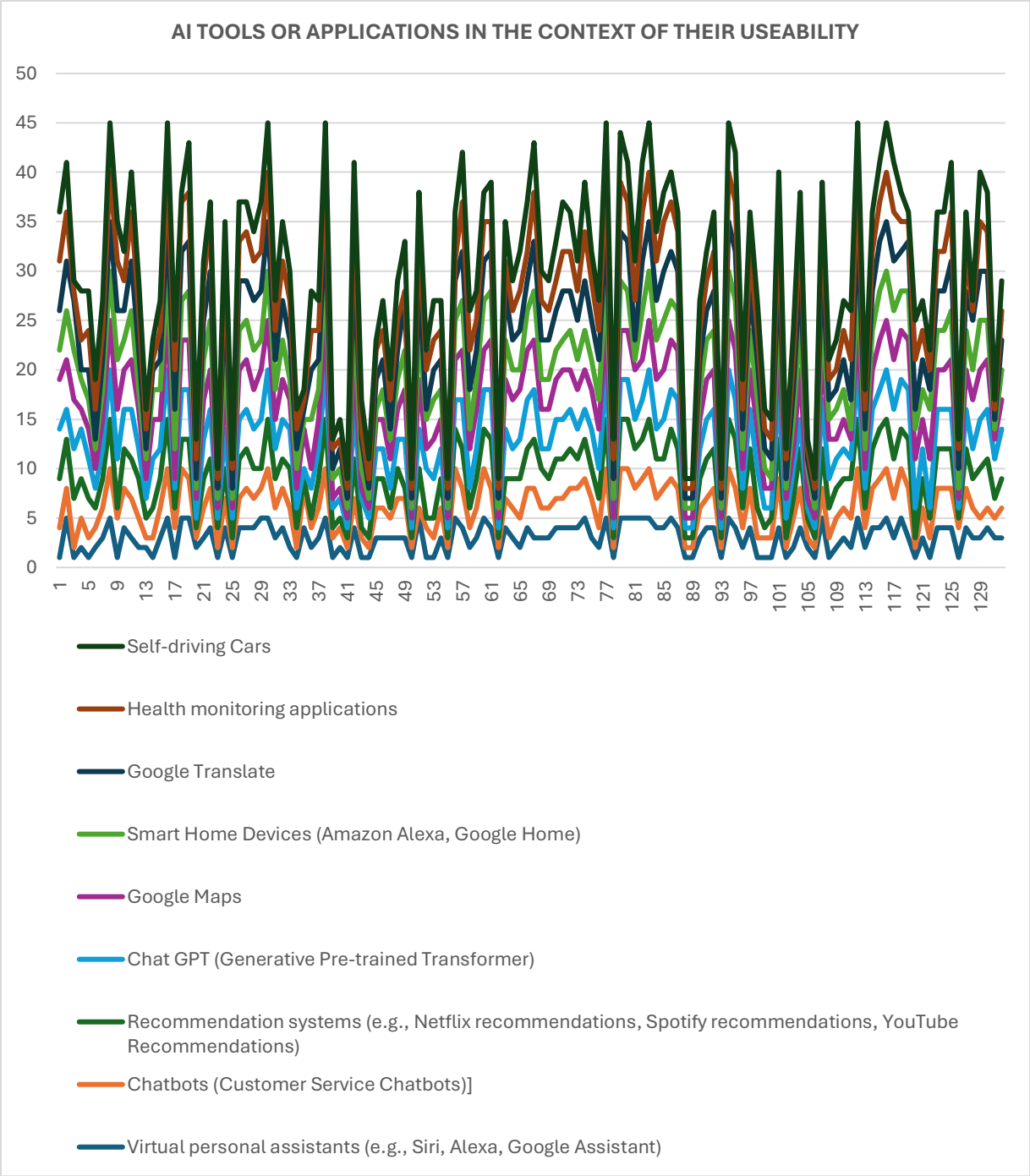


Figure 3. AI tools or applications in the context of their useability
Source: own elaboration.

The third parameter is AI TOOLS OR APPLICATIONS IN THE CONTEXT OF THEIR USEABILITY (Figure 3) is dedicated to the nine items measuring on the 5-point Likert scale. The specific items are Self-driving Cars, Health monitoring applications, Google Translate, Smart Home Devices (Amazon Alexa, Google Home), Google Maps, Chat GPT (Generative Pre-trained Transformer), Recommendation systems (e.g., Netflix recommendations, Spotify recommendations, YouTube Recommendations), Chatbots (Customer Service Chatbots), and Virtual personal assistants (e.g., Siri, Alexa, Google Assistant). The response from respondents is favoring the usage and application of AI tools with reference to the ten items. Students are sure about the future of AI tools usability in a positive sense and supporting the implementations (M. Nermend et al., 2022b).

4. RESEARCH FINDINGS AND CONCLUSION

The study conducted the extensive study through the literature to formulate the research gap, which is framed as the shift of industry due to the artificial intelligence is compelling the society to be shifted where the major effect is visible with the students, which must be addressed to establish a balanced equation in between society and industry. The theoretical base is also created for this in the introduction section. The research is themed conceptually on the AI applications, where the scope is chosen the society and industry. The outcome of the study is driven methodically using thematic analysis from the secondary sources as well as the primary data has been the analysed to provide the understanding from students on the AI applications. Further the study has the findings from thematic analysis and the primary data analysis. The justification on the research is drawn from the thematic analysis providing eleven themes as Efficiency Gains, Predictive Analytics, Real-Time Tracking, Challenges, Incremental Adoption, Data Quality and Governance, Human Resource Development, Strategic Alignment, Framework of AI Measurements, Technical-Organizational-Human Factor Interface, Intervention Implementation Plan. The thematic analysis provided the themes which are important to understand the shift of industry due to the artificial intelligence, which is compelling the society to be shifted.

There is need to justify objectives, where the first objective is to explore the important factors of AI thematically based on the extraction from literature provided eleven themes of extreme importance for the implementation of the concept. The second objective to understand the importance of AI in the transforming socio-industrial landscapes is reached through the primary data analysis and the outcome from two parameters namely ARTIFICIAL INTELLIGENCE IN THE CONTEXT OF THEIR POSSIBLE USE IN EVERYDAY LIFE, and AI TOOLS OR APPLICATIONS IN THE CONTEXT OF THEIR USEABILITY. The major outcome is reached through the last objective as to measure the view of students on AI as components of socio-industrial landscapes, which is reached from RISKS RELATED TO ARTIFICIAL INTELLIGENCE EXIST. The outcomes are supportive to the idea providing the themed concept, where respondents have their positive approach towards the acceptance and implementation of AI for the better future.

The research is practical for the understanding of the concept and stimulating the idea to get the students engagement in the exploration of thought about the AI implementations. The study can be a guide map for the practice seeking individuals in the implementation of challenging concept like AI. The secondary data provided with the thematic analysis with eleven themes and the primary data is the base to understand the current scenario based on students' opinion. This approach is providing a sound and proven track for the implementation of AI for the shifting society and social developments.

The study concludes that the AI is the most important area today for the students to be accepted as they are the future managers and the elements of society to drive with prosperity. Their understanding on the concept and implementations will decide the future of the society. There are undoubted developments and change in the technology, and especially in the AI driven devices and technologies. All technologies are the part of society and getting implemented to the human benefits and through the human hands. At this point, this is the most important to get the insolvents and positive acceptance by the society, which is considered as students for the social drive to implement developing technologies in advancing the society.

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GENERATIONAL DIFFERENCES IN THE PERCEPTION OF DISTRIBUTIVE JUSTICE IN ENTERPRISES IN THE ERA OF ARTIFICIAL INTELLIGENCE

Patrycja Zwiech[a], Magdalena M. Stuss[b]

[a] *University of Szczecin, Institite of Management, Szczecin, Poland*
[b] *Jagiellonian University, Institute of Economics, Finance and Management, Cracow, Poland*

ABSTRACT

Purpose: *The aim of this paper is to identify differences in the perception of distributive justice in enterprises by employees of Generations X, Y and Z in the era of artificial intelligence.*

Need for the study: *AI can be used to promote justice or perpetuate injustice. Perception of distributive justice by employees influences behaviours and attitudes in a workplace and these behaviours and attitudes directly translate into companies' financial results*.

Methodology: *A questionnaire survey was conducted on a group of 109 working respondents (XII 2023 – II 2024; in the West Pomeranian province in Poland). The study used the Organizational Justice Measurement Instrument (OJMI).*

Findings: *The article presents the impact of AI on HR areas in the context of distributive justice.The study also showed that differences in the perception of distributive justice are smaller between Generations X and Y than in comparisons between X and Z or Y and Z. The biggest differences were noted between Generation Z and Generations X and Y in terms of inclusion in the decision-making processes that are relevant to the work of employees and being consulted in the development of organizational policies and procedures. There were no differences between Generation X, Y and Z respondents in their perception of ethics-related issues in processes related to the implementation of the organizational strategy.*

Practical Implications: *This research allows a better understanding of human behaviour in the context of work in the era of artificial intelligence. The research shows how distributive justice is perceived by people of Generations X, Y and Z, which affects the understanding of generational differences in societies.*

Keywords: distributive justice, Artificial intelligence (AI), Generation X, Generation Y, Generation Z, human resources management (HRM)

Jel codes: D63, M54, M12, J53

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1. INTRODUCTION

Organizational justice may be broken down into the following (Warokka, Gallato & Moorthy, 2012; Colquitt, 2001; Colquitt, Conlon,Wesson, et al., 2001):

- distributive justice, which refers to justice of results of decisions and distributions made by the system;
- procedural justice, which refers to justice of processes and their elements applied in decision-making;
- interactional justice, which refers to judgments regarding justice of interpersonal reactions (including exchanges in the course of work).

This kind of justice is divided into two types: interpersonal justice, which refers to dignity and respect in the treatment of employees and informational justice, which refers to whether an employee receives adequate explanations on events at work, in particular procedures and results, thus whether communication with employees is adequate and sufficient in qualitative and quantitative terms.

Adams' Equity Theory (Adams, 1965) explains how distributive justice is perceived by employees. This theory explains the thought process an employee uses to determine the fairness of management decision making. This theory states that people assess justice (fairness) of their treatment in relation to treatment of other persons who are similarly situated in the organization. According to Adams, employees perceive a situation as fair where individuals who provide similar inputs receive similar outputs.

Artificial intelligence (AI) has become an innovative force in business and organizations, offering unprecedented opportunities. Recent advances in algorithms and AI have also become common in HR departments. Although AI is developing rapidly, its application in organizational justice research is still very low (X. Zhang, Antwi-Afari, Y. Zhang, et al., 2024). AI can serve to promote justice in organizations. But AI can also perpetuate injustices, it can lead to potentially unequal and unfair situations. Since the outcomes of HR decisions have a great impact on individuals and society, ethics should be of paramount importance. Decisions made using AI require sound reasoning because they affect employee behaviors and attitudes.

Employees pay attention to a sense of distributive justice within their organization and their perception of this justice can significantly affect various aspects such as organizational engagement, emotional engagement, job satisfaction, withdrawal behaviour, civic behaviour in the organization, entrepreneurial activities, and overall trust in the management and the organization (Zhang, Lepine, Buckman, et al., 2014; Ogwuche, Urama & Nyam, 2019; Ogwuche, Ngbede & Onah, 2023; Zwiech, 2021, 2024; Tivlumun, Onah & Ogwuche, 2024). Consequently, it affects employee performance (Rahma et al., 2024).

In an unfairness-free environment, the ability to achieve goals (both personal and organizational) through efficient use of organizational resources leads to increased employee productivity. People respond positively to work-related outputs if they receive impartial treatment from their leaders.

Given that enterprises are social actors in which employees, both individually and collectively, compete for valuable resources and power, it is unrealistic to expect employees not to use various tactics or strategies in which they seek to secure their benefits and pursue their personal interests. Distributive justice is a key internal factor affecting emotional responses and behaviours and the overall performance of human resources.

The presence of both formal and informal groups within an organization naturally leads to the development of solidarity within the institution (Sule, Amuni & Ariyo, 2015). People from different generations may perceive distributive justice differently in an organization.

An overview of different definitions and approaches to the division of population into generations is presented by Bejtkovský (2016). This study shows that not only is the year of birth important for a person's belonging to a particular generation, but also the socio-economic environment in which they grew up. Therefore, the boundaries for individual generations can be set differently depending on the country.

This study employs the division into generations offered by the Pew Research Centre. Thus, it relied on Generation X (people born in 1965-1980), Generation Y (1981-1996) and Generation Z (1997-2012). In addition to the above, the following generations can also be noted: the Silent Generation (1928-1945), Baby Boomers (1946-1964) and Generation Alpha (2013-mid 2020s).

The aim of this paper is to identify differences in the perception of distributive justice in enterprises by employees of Generations X, Y and Z in the era of artificial intelligence. The existing literature on AI's involvement in the development of distributive justice in the context of the different perceptions of distributive justice among generations X, Y, and Z has not yet been described in the literature. This paper aims to fill this research gap to provide a stronger theoretical foundation.

2. LITERATURE REVIEW

2.1. Distributive justice in the organization – input and output variables

Employees evaluate what individuals contribute to the company and what they receive in return and compare these input and output variables with their own person. According to Kalay (2016), employees' job inputs condense of such factors as education, knowledge, skills, effort, time, cognitive resources and performance. Organizational outcomes include wages, promotions, social rights, rewards, punishments, leave time, tasks, responsibilities, physical resources, and facilities for development. According to Zwiech (2024), it is important to assess the fairness of the distribution of the following outcomes: the amount of remuneration, the bonus amount, the amount and frequency of rewards, additional benefits, opportunities for promotion, the order of dismissals or the availability of training. Ledimo (2015) points out the following results: position-based salaries, bonuses, rewards, company resources (office space, computers, phones, cars), equity in the distribution of financial resources between business units/departments, promotions, performance management policy, recruitment and selection processes, participation in decision-making processes concerning the work of individuals, taking into account the opinions of employees in the development of organizational policies and procedures, clarity in the communication of the vision and mission of the organization among employees, and ethical conduct in the process of implementing the organizational strategy.

Zwiech (2024, pp. 673-674) notes that "distribution of these variables is perceived by employees as just when it is in line with selected norms of allocation. Employees compare their input-to-output ratio with other employees. They strive to remove inequalities (which emerge when proportions between employees are unequal) either by limiting input data (effort put into work) or output data (work effects). Other principles of division (based, e.g., on equality, on the moment of employment or on individuals' needs) are less frequently applied to professional work, though they also occur in selected institutions (especially the first two)".

2.2. AI's involvement in the development of distributive justice in the enterprise

As a product of the fourth industrial revolution, artificial intelligence (AI) is being applied in all aspects of life (Hamon, Junklewitz, Sanchez, 2020). Artificial intelligence (AI) has become an innovative force in business and organizations, offering unprecedented opportunities. Recent advances in algorithms and AI have also become common in human resources (HR) departments due to their alleged impact on increasing the efficiency of HR processes and practices (Prikshat, Malik & Budhwar, 2023). Although AI is developing rapidly, its application in organizational justice research is still very low (X. Zhang, Antwi-Afari, Y. Zhang, et al., 2024).

The increasing use of AI in many fields has attracted much interest in its implications and consequences. The use of AI raises additional concerns related to organizational justice and ethical and social challenges. AI compliance guidelines for HR applications are evolving, and concerns about bias, transparency, and ethical use of AI are growing. Questions are being raised about the impact of AI on individuals in an organization in terms of ethics and accountability. The need to examine the interactions between AI and perceptions of organizational justice is therefore crucial. Organizational justice is a key element of organizational functioning.

In modern organizations, justice and equality are fundamental values. AI can have a positive impact on organizational justice (Sharma, Hargreaves & Pallett, 2023). Using AI technologies, organizations can operate more fairly by reducing the influence of subjectivity and bias.

This article considers distributive justice in the context of 12 statements related to: fairness of pay, equal pay for equal work, fairness of bonuses, access to company resources and fair distribution of resources between business units, performance evaluation, promotion, recruitment and selection processes, involvement in decision-making processes, communication, employee participation in

decision-making and encouraging employees to act ethically. At the same time, the authors assumed, following Adams (1965), that employees perceive the situation as fair when units that make similar inputs receive similar results.

The first important aspect to consider in the context of AI use is **the consistent application of performance management policies to all employees**. Yu, Ding, Jia & et al. (2022) confirmed that employees' perception of organizational justice has a direct impact on work performance. Suliman & Kathairi (2012) identified a positive correlation between organizational justice and employee performance and engagement. AI technology can contribute to reducing operating costs on the one hand and improving customer experience on the other (Ismail, Muhammad, & Mosali, 2022; La Torre, Colapinto, Durosini & et al., 2023). Both of these situations lead to increased productivity.

AI systems can collect and analyse employee performance data to provide accurate and objective feedback that is not influenced by human subjective factors (Stroet, 2020). In addition, data is collected in real time based on the latest results, which significantly shortens the response time, as AI makes it easier for managers to get continuous feedback. On the other hand, companies are increasingly recognizing the need for employees to receive real-time feedback. This helps establish a fair performance appraisal system and provides employees with fair compensation and bonuses (Awan, Habib, Shoaib Akhtar & et.al, 2020). AI-based performance management shifts the focus to engagement tracking, productivity analysis, and promotion decisions.

Another important issue cannot be forgotten – reducing the administrative workload of managers. AI is also suitable for applications in the administrative area (Cappelli, Tambe & Yakubovich, 2019). AI enables people performing managerial activities to deal less with administration and paperwork and develop more in strategic functions related to people management. The self-service aspect of e-HR increases the involvement of both employees and line managers in HR practices (Baykal, 2019).

Further aspects are related to performance evaluation, but they must be considered separately in connection with organizational justice.

Another important aspect that should be considered in the context of the use of AI is **fair promotion**.

Organizations are increasingly implementing artificial intelligence to plan the career development of employees. Stored in HR IT systems or cloud systems, artificial intelligence is able to use and analyse data on, for example, personal characteristics, hours worked, and various measures of employee performance (Leicht-Deobald, Busch, Schank & et al., 2019; Wirges & Neyer, 2023), which are important predictors of career development and professional success (Ng, Eby, Sorensen & et al., 2005). Some companies also take into account the digital footprints of employees (e.g., professional profiles such as LinkedIn, and non-professional profiles such as Facebook) and analyse the content of employee or organization posts or blog content that may be of interest to gain insight into employee attitudes (Köchling, Wehner & Ruhle, 2024). AI can help not only in assessing attitudes and performance, but also provide training recommendations, personalized coaching. AI-based coaching and career paths enable personalized employee development. It can therefore help in fair promotion, in identifying and matching highly qualified and talented employees to organizational needs and strategic positions.

Another important aspect to consider in the context of AI use is the consistent application of **recruitment and selection process**. AI-based recruitment tools can balance efficiency with fairness by changing recruitment strategies. AI can automatically screen and evaluate candidates' skills based on objective criteria and data, reducing human bias in recruitment. AI can screen candidates by analyzing a large number of resumes and interview results, thus ensuring a fairer and merit-based selection process.

However, AI algorithms are increasingly being targeted at improving workforce planning, predicting skill gaps, reducing the risk of turnover and recruitment needs. This unbiased recruitment practice not only increases employee trust in the organization but also creates a better environment for diversity and inclusion.

Furthermore, the use of AI in recruitment saves managers' time while ensuring fairness. For example, data presented by Black and van Esch (2020) shows that recruitment review time was reduced by 88% with the use of AI technology.

Another two important aspects to consider in the context of the use of AI are facilitating employee **involvement in decision-making processes** that are relevant to their work and **consulting employees** when organizational policies and procedures in the enterprise are developed. For example, in the process of involvement in decision-making processes, the use of AI technologies can help analyse the impact of leadership styles and managers' skills in sharing power and delegating tasks and responsibilities on

employee behaviors, thus influencing the motivation of subordinate employees (de Oliveira, Dalla Valentina, Futami & et al., 2021; Enad Al-Qaralleh & Atan, 2022).

Another important aspect to consider in the context of AI use is **communication** in the enterprise. Particular attention should be paid to conflict resolution. Real-time advice for managers or more broadly for the entire work environment can significantly affect the atmosphere at work and increase employee satisfaction. In addition, AI can improve communication and cooperation in organizations, thus increasing organizational justice (Al-Nammari, Simsekler, Gabor & et al., 2023). With intelligent collaboration tools and automated processes, employees can more easily share information and collaborate on tasks regardless of location or time. This efficient way of working not only improves the employee experience but also ensures a fair distribution of decisions and resources.

Another important aspect to consider in the context of AI use is **encouraging** managers and employees **to act ethically**. Van der Werff, Blomqvist & Koskinen (2021) found that employee trust in AI is conditioned by perceptions of the organization's trustworthiness. Employees who have higher levels of trust in their organization and managers may be more willing to trust the AI system to evaluate its performance. Affective commitment refers specifically to an employee's emotional attachment or identification with their organization. Social exchange and psychological contract theories suggest that in return for fair treatment from their organization, an employee may reciprocate with greater trust, which in turn leads to higher affective commitment (Nguyen & Connolly, 2025).

The last five aspects that should be considered in the context of both the use of AI and the aspects described above are **the fairness of remuneration/salaries** of managers and employees in relation to their positions, **equal remuneration/rewards** for employees performing work of equal value, and **the rules for granting bonuses** to employees in relation to their performance, regardless of their position, department, or job level.

Also important are **equal access to company resources** to do their job, such as office space, computers, phones, and cars, and **financial resources fairly distributed among different business units/departments**.

With the help of algorithms and technologies, AI can fairly allocate resources according to individual skills and contributions, avoiding unequal distribution caused by perceived bias or discrimination (Grgi´c-Hla˘ca, Zafar, Gummadi, et al., 2018), which will affect emotional reactions, behaviors, and the overall performance of human resources (Zwiech, 2024).

The above is a positive approach to AI. However, it is important to be aware that the widespread use of AI can lead to potentially unequal and unfair situations (Sharma, Hargreaves & Pallett, 2023; Tjebane, Musonda & Okoro, 2022). Due to the way AI works, decisions can be made based on historical data and patterns on which the AI system was trained (Bolander, 2019; Pugna, Dutescu & Stanila, 2018). Since the outcomes of HR decisions have a large impact on individuals and society, ethics should be paramount. Such decisions require sound reasoning, and AI can be biased because it uses biased historical data to train it. For example, using AI to screen CVs during the recruitment process can lead to the spread of discriminatory biases based on gender, race, nationality, sexual orientation, and other factors (Zwiech, 2011; Zwiech, 2010).

For the same reasons, AI decision-making systems can introduce potential inequalities in the workplace in all processes related to performance evaluation and its impact on other HR functions, such as employee promotions, distribution of salaries and bonuses, distribution of additional resources.

Therefore, there is a need to delve into how AI affects organizational justice and propose solutions to ensure that the use of AI does not deepen inequality and injustice. Companies using AI technologies must ensure the accuracy, reliability, and impartiality of algorithms and data, as well as oversight and review to ensure that the use of AI technologies does not introduce new elements of injustice. A very important issue is the opacity of AI decisions, so employees must understand how decisions are made. Meaningful employee participation can contribute to a more fair perception of the introduction of AI. Organizations must be accountable for the decisions made by their AI systems (Gouba & Aallali, 2023).

3. RESEARCH METHODOLOGY

The study used the results of questionnaire surveys on organizational justice. The choice of the research method was made due to its scientifically significant features for research in social sciences

(Pinsonneault, Kraemer, 1993; Schwarz et al., 1999). The research was carried out on a sample of 109 working respondents who were at the same time studying on master's or bachelor's programmes at the University of Szczecin. The research was carried out in the period between December 2023 and February 2024, and the territorial scope covered the West Pomeranian province in Poland. The subject of the survey involved company employees. An individual company employee was a unit in the sample, while the questionnaire could be given to many employees in individual companies. The Organizational Justice Measurement Instrument (OJMI) was employed in the research. It consists of 59 statements measuring nine factors influencing justice (Ledimo, 2015).

Following the propositions of P. Salant and D. A. Dillman as the starting point, the indicator of the responses and preferred level of research precision were defined (Creswell, 2013; Salant, Dillman, 1994). The questionnaire statements were configured using a five-point Likert scale, where 1 means strong disagreement with a statement and 5 means complete agreement with a statement (Ledimo, 2015). The questionnaire also included questions about demographic characteristics. This study used part of the questionnaire relating to 12 statements concerning only one factor – distributive justice. In the distributive justice study, the following 12 statements from the Organizational Justice Measurement Instrument (OJMI) were used:

1. Managers' and employees' salaries are fair, based on their jobs [DJ01].
2. Employees in my organization have equal access to company resources to do their work, such as office space, computers, phones and cars [DJ02].
3. Employees doing the same work receive similar rewards [DJ03].
4. In my organization, bonuses are rewarded to high performing employees irrespective of their position, department or job level [DJ04].
5. Financial resources are distributed fairly to the different business units/departments in my organization [DJ05].
6. The performance management policy is applied consistently to all employees [DJ06].
7. Employees are promoted fairly, based on their skills and abilities [DJ07].
8. In our organization, the recruitment and selection processes are fair for all applicants [DJ08].
9. In my organization, all employees are involved in the decision-making processes that are relevant to their work [DJ09].
10. Employees are consulted during the development of organizational policies and procedures [DJ10].
11. The mission and vision statement of the organization is clearly communicated to all employees [DJ11].
12. Employees are encouraged to act ethically during the implementation of the organizational strategy (DJ12).

The good practices for conducting and reporting survey research, as proposed by K. Kelley, B. Clark, V. Brown, and J. Sitzia (2003) were applied.

RESULTS OF THE STUDY – PERCEPTION OF DISTRIBUTIVE JUSTICE BY RESPONDENTS FROM GENERATIONS X, Y AND Z

The survey was conducted on 109 respondents. Respondents' particulars are presented in Table 1.

Table 1. Demographic characteristics of the sample population in this study

Variables	Category	n	%
Gender	Male	50	45.9
	Female	59	54.1
Generation	X (1965-1980)	29	26.6
	Y (1981-1996)	38	34.9
	Z (1997-2012)	42	38.5
Position	Management	41	37.6
	Specialist	28	25.7
	General workers	40	36.7

Source: author's own compilation.

The average of Generation X respondents' responses to the 12 statements on distributive justice is shown in Figure 1.

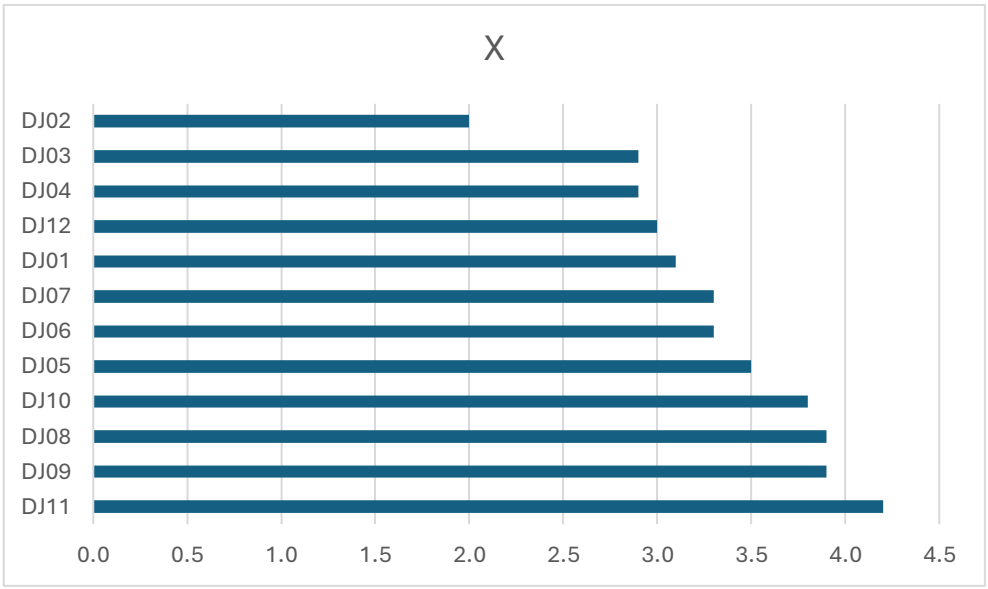


Figure 1. Average of Gen X respondents' responses to distributive justice-related statements (1-5 scale)
Source: author's own compilation.

Generation X employees mostly agree with the statement that the mission and vision statement of the organization is clearly communicated to all employees ([DJ11], 4.2). [DJ08] and [DJ09] also scored high, i.e. in the context of distributive justice, respondents rated the recruitment and selection processes and the decision-making processes (3.9) positively. Equal access to company resources to do their work, such as office space, computers, phones and cars, got the lowest scores (2.0), followed by similar rewards for employees doing the same work and awarding bonuses to high performing employees irrespective of their position, department or job level (2.9).

The average of Generation Y respondents' responses to the 12 statements on distributive justice is shown in Figure 2.

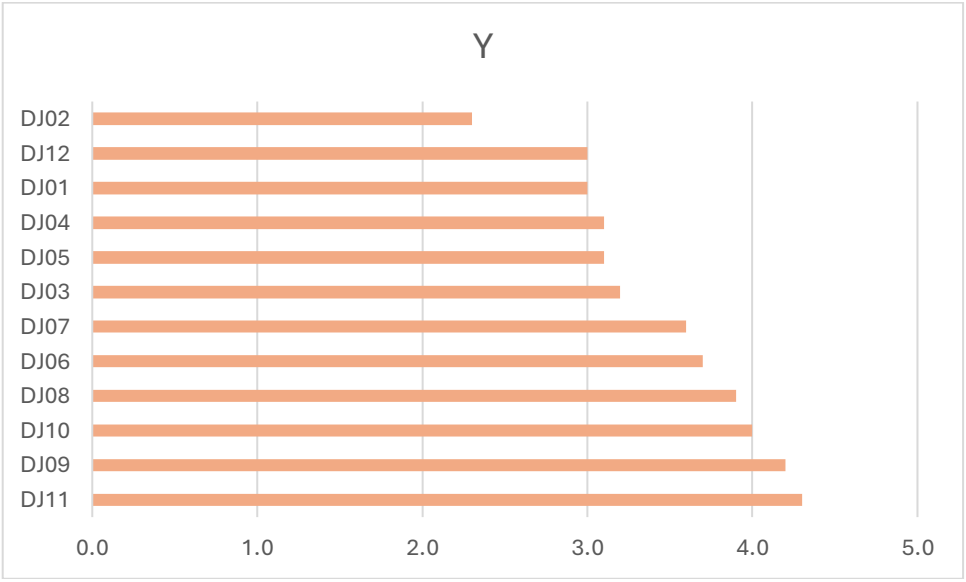


Figure 2. Average of Gen Y respondents' responses to distributive justice-related statements (1-5 scale)
Source: author's own compilation.

Similar to Generation X employees, Generation Y staff mostly agreed with the statement that the mission and vision statement of the organization was clearly communicated to all employees ([DJ11], 4.3). [DJ09] and [DJ10] also scored high, which means that in the context of distributive justice, the respondents positively assessed the decision-making processes (4.2) and the statement that employees were consulted during the development of organizational policies and procedures (4.0). Equal access to company resources to do their work, such as office space, computers, phones and cars scored the lowest (2.3), followed by the statements that employees were encouraged to act ethically during the implementation of the organizational strategy and that managers' and employees' salaries were fair, based on their jobs (both 3.0)

The average of Generation Z respondents' responses to the 12 statements on distributive justice is shown in Figure 3.

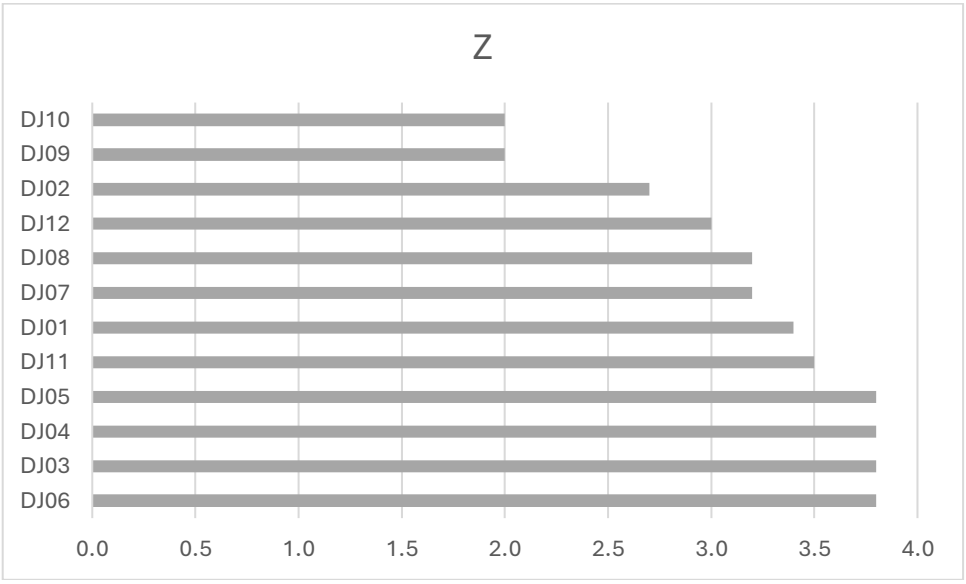


Figure 3. Average of Gen Z respondents' responses to distributive justice-related statements (1-5 scale)

Source: author's own compilation.

None of the statements got the 4.0 score among Generation Z. Respondents mostly agreed (average response 3.8) that the performance management policy was applied consistently to all employees; that bonuses were rewarded to high performing employees irrespective of their position, department or job level; that employees doing the same work received similar rewards and that financial resources were distributed fairly to the different business units/departments in their organization. The lowest rates were given to the statement that all employees were involved in the decision-making processes relevant to their work and that employees were consulted during the development of organizational policies and procedures (both were given the score of 2.0).

DIFFERENCES IN THE PERCEPTION OF DISTRIBUTIVE JUSTICE

The differences in the perception of distributive justice felt by respondents from subsequent generations are significant. These are especially noticeable when comparing Generation Z, X and Y, as illustrated in Figure 4.

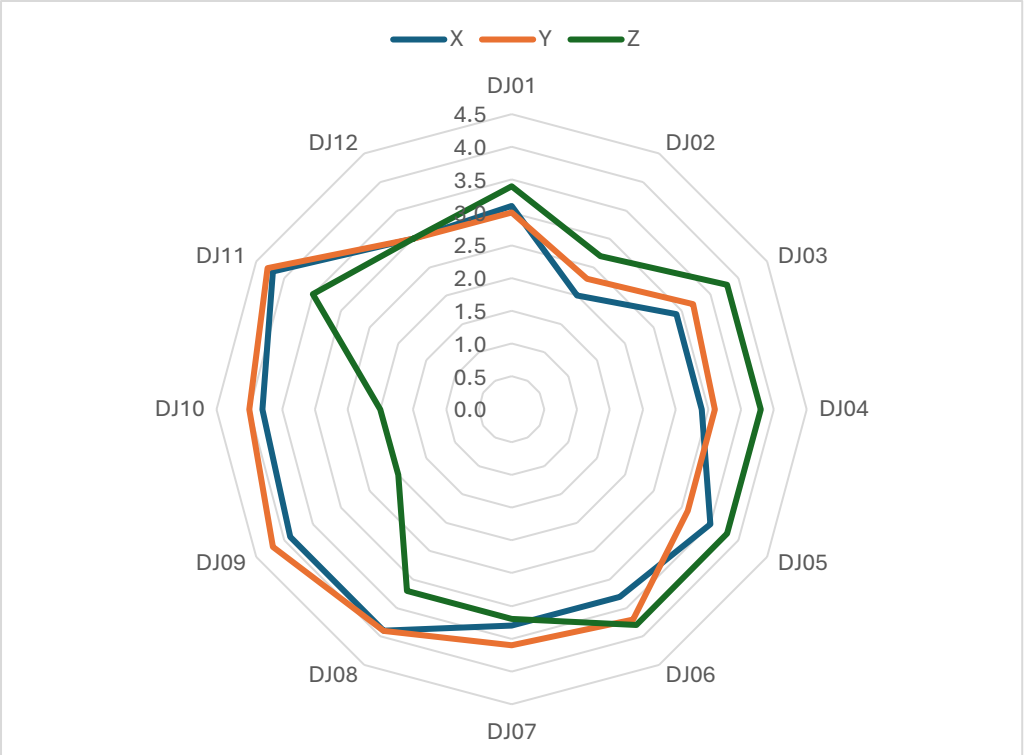


Figure 4. Differences in the perception of distributive justice between Generations X, Y and Z (scale 1-5)
Source: author's own compilation.

The highest average rating for all 12 statements was recorded for Generation Y, and the lowest for Generation Z. Differences in the perception of distributive justice were smaller between Generations X and Y than in the case of comparisons between Generations X and Z or Y and Z.

For Generations X and Y, the biggest difference (only 0.4 points) concerned the distribution of financial resources to the different business units/departments [DJ05] and the performance management policy [DJ06]. Overall, the difference in the perception of distributive justice between Generations X and Y was not significant.

In the case of Generations Y and Z, the biggest differences (exceeding 2.0 points) concerned issues related to the distribution of taking into account the opinion of the employee and the feeling of his/her importance to the organization. Gen Z employees believed that they were not involved in the decision-making processes relevant to their work and that they were not consulted during the development of organizational policies and procedures ([DJ09] and [DJ10]), unlike those of Gen Y, who rated these elements the highest of all analysed generations (employees of Generation X also rated this statement highly). This fact indicates that employers are more likely to take into account the opinions of people aged 29-44 (Y) and 45-60 (X), and to a lesser extent opinions of employees aged 28 and under. The lack of interest in the opinions of Gen Z staff may be due to employers' belief in their modest work experience, but it may also be due to a stereotypical approach to Gen Zs as people with low loyalty to employers, who change jobs quickly and have high salary requirements. On the other hand, this fact indicates that Gen Z employees notice the problem of their opinions being ignored.

For Generations X and Z, the biggest differences also applied to [DJ09] and [DJ10], although they were slightly lower than when comparing Generations Y and Z (1.9 and 1.8 points, respectively). 0.9 points differences were also noted for [DJ03] and [DJ04], referring to similar rewards and bonuses, but respondents from the Group X were more sceptical in these cases. This may be due to their better knowledge of the organization, processes taking place in it and interpersonal relations there and due to their greater professional experience.

The similar rewards aspect will become particularly relevant in the context of the European Directive on transparency of remuneration (Directive (EU) 2023/970 of the European Parliament and of the Council of 10 May 2023), which should be implemented by the member states by 2026. The EU wants

to strengthen the principle of equal pay for equal work for men and women through new EU rules on pay transparency. The Directive aims to help combat wage discrimination and close the gender pay gap in the EU. The results of this study show that as the age of an employee increases, concerns (or fewer illusions) about the functioning of the principle of receiving similar rewards for work of similar value increase.

On the other hand, there were no differences between Generation X, Y and Z respondents in their perception of ethics-related issues in the processes involved in the implementation of the organizational strategy [DJ12]. The average response in each generation was 3.0. The smallest differences between respondents from Generations X, Y and Z also occurred in the assessment of the fairness of salaries (from 3.0 to 3.4) and promotions (from 3.2 to 3.6).

CONCLUSION

Human resources management must take into account employees' perceptions of distributive justice. The perception of distributive justice affects employee performance through many aspects such as organizational engagement, emotional engagement, job satisfaction, withdrawal behaviour, civic behaviour in the organization, entrepreneurial activities, and trust in the management and the organization.

The results of this study show that the differences in the perception of distributive justice are particularly evident when comparing Generation Z with Generations X and Y.

In the case of Generations X and Y, overall, the differences in their perception of distributive justice were not significant primarily related to the assessment of the distribution of financial resources to the different business units/departments and the performance management policy.

In the case of Generations Y and Z, the biggest differences concerned issues related to the distribution of taking into account employees' opinion and the feeling of his/her importance to the organization.

For Generations X and Z, the biggest differences also concerned the distribution of financial resources to the different business units/departments and the performance management policy. Significant differences were also noted for aspects relating to similar rewards and bonuses.

On the other hand, there were no differences between Generation X, Y and Z respondents in their perception of ethics-related issues in processes involved in the implementation of the organizational strategy. The smallest differences between respondents from Generations X, Y and Z also occurred in their assessment of the fairness of salaries and promotions.

The research has shown that the perception of distributive justice varies depending on which generation the employee comes from. Differences in the perception of distributive justice are small between Generations X and Y and significant between those generations and persons of Generation Z.

The analysis also shows that AI can have a positive impact on organizational justice. By using AI technologies, organizations can operate more fairly by reducing the influence of subjectivity and bias. However, the widespread use of AI can also lead to potentially unequal and unfair situations. Since the outcomes of HR decisions have a large impact on individuals and society, ethics should be of paramount importance. Decisions made using AI require sound reasoning because they affect employee behaviors and attitudes.

This research is addressed to persons who hold managerial positions and those managing teams, to HR specialists and persons who implement human resources management systems in companies.

This study is not free from limitations. The main one is that the participants were employees of enterprises only from the West Pomeranian Voivodeship, and the size of the sample may have influenced the results, which means that the findings could not be generalized to other organizational contexts. Therefore, it is recommended that future research be conducted on a larger sample in order to gather more information. In addition, the profiles of respondents from Generations X, Y and Z were based on literature and judgments from experts. Identifying the actual profiles of all generations would require a global, representative, interdisciplinary study. As for possible directions for further research on the topic discussed in this article, focus should be given to the growing importance of organizational justice in human resource management (see, among others, Rahma, Tjahjono & Rahayu, 2024).

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28th European Conference on Artificial Intelligence (ECAI 2025)

THE DIRECTION OF CHANGES IN MARKETING MANAGEMENT, ON THE EXAMPLE OF POLISH ENTERPRISES IN THE CREATIVE SECTOR

Monika Spychalska-Wojtkiewicz[a]

[a] *University of Szczecin, Institute of Management, Poland*

ABSTRACT

Purpose: *The paper aims to clarify the direction of changes in marketing management. This analysis focused on creative sector enterprises that come from Poland. The paper is outlining COVID-19 pandemic impact on the management policy implemented in companies and what has been changed in recent years.*

Need for the study: *The study aims to expand the general information about the impact of the pandemic on creative sector companies in Poland, specifying whether and what the impact it was.*

Methodology: *The paper opted for an exploratory study using quantitative survey conducted among representatives of the creative sector in Poland. In order to maximize reaching the respondents, the CAWI technique was used. The study was enhanced with three IDI interviews with management experts cooperating with the creative sector.*

Findings: *The paper provides empirical insights about how creative sector enterprises responded to COVID-19 in the area of management and marketing. It turns out that the fact that enterprises reacted did not mean significant changes in management and marketing in recent years. Experts also confirmed that reducing operating costs was the main goal of the entities, which may be unfavourable in the longer term. Cost-cutting opportunities managers from the creative sector are also looking throughout increase the use of artificial intelligence.*

Practical Implications: *The paper includes implications for successful development of a creative sector entity. Indicates which areas were changed in entities in recent years and which could be changed to increase market competitiveness.*

Keywords: management, marketing, marketing management, creative sector, competitiveness, artificial intelligence, intelligent management

Jel codes: M10; M21; M31

1. INTRODUCTION

Contemporary discussions surrounding the current situation in business management in Poland and around the world stated that it has changed in recent years (Smith & Kowalski, 2022). It is also described that changes in management in companies are not as fast as global changes in the economic situation (McKinsey & Company, 2023). Especially in the context of the coronavirus epidemic, which appeared

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in 2019 in China but caused major economic changes in 2020, 2021 and 2022. The World Health Organization (WHO) officially called off the COVID-19 pandemic only on May 5, 2023. On that day, more than three years after the pandemic was announced in March 2020, the WHO recognized that COVID-19 no longer constitutes a global threat that would require extraordinary health measures (WHO, 2023). Therefore, enterprises have been operating in subsidized conditions without systemic restrictions for only two years so far.

During the COVID-19 pandemic, Poland experienced several lockdowns and restrictions, which were implemented in phases as the situation evolved. There were three key lockdowns:

- March 2020 - May 2020,
- October 2020 - December 2020 and
- March 2021 - May 2021.

Years 2021 and 2022 was characterised by partial lockdowns and regional restrictions (Ministry of Health of the Republic of Poland, 2022).

Thus, it is generally stated that the COVID-19 pandemic has had a significant impact on companies, their management style. Many managers set a time limit before the pandemic and after the pandemic (Smith, 2021). Despite the return to a normal lifestyle, people have changed their approach to many aspects, including what decisions they make, what kind of consumers they are. Similarly, managers are changing their approach to consumers and their needs (Johnson, 2022). This situation was define as a "new normal" to describe the changes in society, work, and daily life following the crisis (Gates, 2020).

It is commonly stated that COVID-19 has affected the creative sector. On the one hand, the creative sector tried to be very active, some entities belonging to this sector tried to be responsible for good social morale (Deloitte, 2023). A significant part of the entities benefited from state aid programs, but some had to cease their activities due to the specifics of integration with recipients. Therefore, the creative sector would have to be even more creative and evolve in its management. Thus, it is commonly said that the pandemic had a significant impact on the creative sector and its mode of operation. The pandemic also brought some good changes, accelerating the process of its digitization and improving the quality of online activities (OECD, 2020).

These necessary actions, which were very quickly forced by economic reality, had to be followed by organizational changes in entities. In this paper, the author focus more closely on:

- determining whether the COVID-19 pandemic has had an impact on the management policy implemented in companies,
- determining how the management policy has mainly changed,
- determining whether the COVID-19 pandemic has had an impact on the marketing implemented in the company,
- determining how the marketing has mostly changed,
- determining what marketing-related activities managers plan to implement in 2025.

Based on interviews with mangers as well as interviews with creative sector experts, the author contemplated potential solutions to bridge the gaps created by marketing incompatibility to market requirements.

Reducing costs can be an intense incentive to seek creative, innovative marketing solutions. Marketing activities do not always have to be expensive, what's more, campaigns that have achieved viral status were often not characterized by high expenditures but by a unique idea and exceptional authenticity that appealed to recipients. Intelligent management could be very useful in this regard. Intelligent management approach, which uses advanced technologies, including artificial intelligence, to make decisions, optimize processes and improve the efficiency of the organization can significantly support marketing management (Smith & Johnson, 2022).

Intelligent management being integration of information technologies, analytical technologies and automation in order to more effectively manage resources and processes in the organization it also has a lot in common with intelligence marketing, which will be described in the following parts of this paper.

The remainder of this paper is organized as follows. In the literature review, author identified the roles of economic, political and social changes also connected with the COVID pandemic on management in enterprises. On this basis, author formulated hypotheses that: managers are changing marketing management, not resigning from marketing expenditures but looking for different forms of

activities. Finally, author elaborate on the results, implications, limitations, and suggestions for future research.

This paper fulfils an identified need to study how entities in the creative sector should make changes in management and marketing to be competitive. Because of the chosen research approach the strong point of the article is that it focuses on the opinions of representatives of the creative sector, showing their problems. At the same time, it is a sectoral limitation, so it is worth analysing this issue in other sectors as well.

2. LITERATURE REVIEW

Economic, political and social changes also connected with the COVID-19 pandemic play a significant role in policy management in enterprises. Research indicates that COVID-19 pandemic has prompted organizations to rethink their strategies, emphasizing the need for resilience in policy management to adapt to economic, political, and social changes (Schwab & Malleret, 2020). European Union adapted its economic governance framework in response to the pandemic, highlighting the integration of the Recovery and Resilience Facility into the European Semester and its implications for enterprise policy management (European Commission, 2021).

The economic impact of COVID-19 has forced many enterprises to adjust their policy management strategies in several ways to cope with the on going challenges. The table below (Table 1.) presents how companies have had to adapt.

Table 1. Areas of policy adaptation in companies during COVID-19

Area of adaptation	Actions
Flexibility in operational strategies	Remote work and hybrid models: with the shift to remote work, many companies have adapted by implementing flexible working arrangements, adjusting HR policies, and investing in remote collaboration tools. Supply chain adjustments: the pandemic disrupted global supply chains, forcing businesses to rethink their sourcing and inventory management strategies. Many companies have become more agile and diversified their suppliers to reduce risks.
Financial risk management	Cost-cutting measures: due to economic uncertainty, many enterprises had to reassess their financial positions and implement cost-cutting measures, such as freezing hiring, reducing non-essential expenditures, or even laying off staff. Financial forecasting and cash flow management: companies have adapted their financial strategies by improving cash flow management, revising forecasting models, and seeking government subsidies or relief packages where available.
Adaptation of business models	Digital transformation: many businesses have speed up their digital transformation efforts. Traditional businesses have implemented e-commerce platforms, online services, and digital marketing strategies to stay competitive in a socially-distanced world. Pivoting offerings: some companies pivoted their products and services to meet changing customer needs (e.g., food companies offering meal kits, distilleries producing hand sanitizers, or fashion brands making face masks).
Focus on health and safety	Workplace health and safety policies: enterprises had to develop and enforce health and safety policies to protect employees and customers, including sanitation protocols, health screenings, and social distancing measures in the workplace.
Government and Policy Compliance	Adjusting to government regulations: companies had to quickly adapt to changing government regulations, including lockdown measures, social distancing rules, and changing tax or labour laws. In many cases, businesses needed to adjust their policies to comply with new regulations or benefit from relief programs.
Improving Crisis Communication	Transparent and frequent communication: policy management shifted toward clear and transparent communication strategies, both internally to employees and externally to customers, stakeholders, and the general public. This helped ensure trust and stability during uncertain times.

Employee Well-being & Mental Health	Support for mental health: recognizing the toll the pandemic took on employees' mental and emotional well-being, companies adjusted policies to offer more support for mental health, including virtual counselling, flexible schedules, and better work-life balance.
Sustainability & Resilience Plans	Building future resilience: in response to the long-term impacts of the pandemic, companies have focused on creating more resilient business models. They've reviewed their risk management strategies and invested in sustainability and long-term planning to avoid future disruptions.

Source: Reuters. (2025, March 8).

In response to the on going economic challenges, enterprises have made crucial adjustments to their policy management strategies. The focus has shifted toward flexibility, digital transformation, financial stability, and employee support. By adapting to these challenges, businesses are positioning themselves for future resilience in an unpredictable global environment.

Businesses' operations changed because economic conditions changed, but society changed as well, so their shopping habits changed. The COVID-19 pandemic has acted as a catalyst for significant societal changes, compelling enterprises to reassess and adapt their policy management strategies. By acknowledging and responding to these shifts, businesses can better navigate the complexities of the post-pandemic world and contribute to societal resilience and recovery (The Guardian, 2025).

Many companies have significantly changed their marketing strategies due to the COVID-19 pandemic. The shift was driven by changes in consumer behaviour, market conditions, and technological advancements. Digital transformation is pointed as a one of the most important. Companies has to increased focus on digital channels, with physical stores closing and in-person events being cancelled, many companies shifted their marketing efforts to online platforms. This included a heavier reliance on social media marketing, email campaigns, e-commerce, and virtual events. Investing in e-commerce was related to this. Companies had to quickly adapt to a digital-first approach. Retailers, in particular, invested in building or improving their online stores, while service-based businesses explored new models like online consultations or virtual services (The Guardian, 2025).

Creation of virtual experiences and events was also connected with digital transformation. With the inability to gather physically, many brands turned to virtual conferences, workshops, and product launches to stay connected with customers and prospects. This also resulted in a transition to experiential marketing. While traditional experiential marketing was not possible, some companies created virtual experiences, such as augmented reality (AR) ads, virtual product demos, or interactive content (Smith & Lee, 2021).

The creative sector also underwent significant transformation during the COVID-19 pandemic. The shift to digital platforms, the adoption of innovative business models, and the focus on community engagement and flexible management were essential for their survival. Creative companies had to embrace technology and data more than ever to stay connected with their audiences and ensure business continuity. Moving forward, the hybrid model combining in-person and virtual experiences is likely to remain a key feature in the creative sector's business strategies. Rapid technological change could become an opening for many entities to apply intelligent marketing which refers to the use of data, AI, and analytics to optimize marketing strategies, improve customer engagement, and maximize return on investment (ROI). It combines big data, artificial intelligence (AI), machine learning (ML), and predictive analytics to make smarter marketing decisions (Liu et al., 2022). Benefits of intelligence marketing could be:

- lower costs – AI and automation reduce manual work and optimize ad spend,
- higher engagement – Personalized marketing increases customer interaction,
- better ROI – AI-driven insights help businesses invest in high-performing campaigns,
- faster decision-making – Real-time data helps marketers act quickly.

The creative sector is very diverse, so some items from this sector have fared better, some worse during the pandemic. The creative sector refers to industries that focus on the production of goods and services that rely on creativity, culture, knowledge, and intellectual property. It includes fields such as arts, design, music, film, advertising, fashion, publishing, and digital media. This sector is driven by innovation and the creation of original content, contributing to economic growth, cultural development, and employment opportunities (UNESCO, 2013). Thus, entities that were easier to digitalize operated

more smoothly. Nevertheless, for everyone it meant a change in management to make this adaptation to the new realities possible.

In 2021 Kantor and Kubiczek wrote about creative sector in Poland during COVID-19 that: “the pandemic has contributed to a significant deterioration in the financial situation of cultural institutions because of the reduced income. Long-term effects on cultural institutions may be difficult to predict and losses may be difficult to rebuild” (Kantor & Kubiczek, 2021). It is therefore important to analyse the changes over time in this industry.

According to Szostak study from 2022 forced virtualisation and digitisation significantly affect the quality of the creative process within the aesthetic situation, depending on the form of participation in art. The creator, managing the creative process within the aesthetic situation, must take into account the new optics concerning the components of the aesthetic situation because otherwise, his work will be incomprehensible or unattainable for the recipients – not due to the low quality of the work, but because the work in new virtualised circumstances may change its properties (Szostak, 2021). This is an important analysis indicating that forced changes in management, forced digitalization may have not only a positive effect, but may also negatively affect the elements of the marketing mix, e.g. the product.

Research indicates that COVID-19 pandemic has stimulated organizations to rethink their strategies, emphasizing the need for resilience in policy management to adapt to the mix of economic, political, and social changes. This may result in interest in implementing the ESG (environmental, social, and governance) concept. In contrast, ESG requires companies to align their sustainability efforts with clear, measurable performance indicators, making them more accountable to investors and regulators (Friede et al., 2015). This transformation is shifting marketing strategies from storytelling based on values to storytelling backed by quantifiable impact. Unlike CSR, which often functioned as an add-on, ESG is integrated into a company’s governance and financial decision-making processes. ESG factors influence how businesses operate at every level, from supply chain management to leadership transparency (Kotsantonis & Serafeim, 2019). For marketers, this means that ESG is not just about branding but about demonstrating real-world impact, requiring companies to communicate sustainability in a more authentic and transparent manner (Hsu et al., 2021).

There is growing evidence that investors and consumers prioritize ESG performance over traditional CSR initiatives. Research indicates that ESG-focused companies attract more investments, as sustainable business models are perceived as less risky and more resilient (Clark et al., 2015). Additionally, Millennials and Gen Z consumers increasingly base purchasing decisions on a company’s environmental and social impact, rather than just product quality or price (Nielsen, 2018). As a result, ESG is reshaping marketing by requiring brands to demonstrate concrete sustainability commitments rather than merely promoting ethical values.

In the ESG era, authenticity and transparency are crucial. Unlike CSR, which could sometimes be used for superficial branding (i.e., "green washing"), ESG requires detailed reporting, third-party verification, and compliance with global sustainability standards (Eccles & Klimenko, 2019). The digital-first approach is evident, with social media, SEO, and AI integration leading marketing priorities.

The literature review indicates that the commonly discussed changes in management in enterprises in connection with the COVID pandemic and its consequences are a fact. Similarly, research confirms changes in marketing management. However, there is no current research examining changes in the creative sector, especially in Poland. Analyses of the situation of the creative sector in Poland in the context of the pandemic were undertaken, but these analyses were undertaken during the pandemic and often contained information that it is difficult to conclude how changes in these entities will evolve over time. For this reason, the author decided to address the topic of these changes and their direction in 2025, five years after the introduction of the pandemic and two years after its end. In most business contexts, 2 years is typically not considered as a "long term." It is generally classified as a short-term or medium-term period (Kotler & Keller, 2016). Analysing the situation in the creative sector in this period is crucial for understanding long-term recovery trends, assessing the effectiveness of adaptive strategies, and identifying on going challenges and opportunities for sustainable growth.

3. METHODOLOGY

3.1. Participants

In order to analyse the situation of the creative sector in Poland, representatives of the creative sector who are responsible for management in entities of this sector were recruited for the study. The study covered entities that have registered operations in Poland. The author had a sampling frame in the form of a list of companies in the creative sector in Poland. Invitations to participate in the study were sent to randomly selected companies. A sample of 185 entities was achieved. Due to the quality control of the answers provided, the sample was narrowed down to 150, in connection with reaching 150 correctly completed questionnaires.

These entities operate in different parts of Poland and represent different areas of the creative sector (UNESCO, 2013):

- Advertising & Marketing – Branding, digital marketing, public relations, and market research.
- Architecture – Urban design, landscape architecture, and interior design.
- Crafts – Handmade products, ceramics, jewellery, and traditional crafts.
- Design – Graphic design, product design, fashion design, and UX/UI design.
- Film, TV, Video, and Photography – Movie production, animation, streaming content, and photography.
- IT, Software, and Video Games – App development, game design, and interactive media.
- Publishing – Books, magazines, newspapers, and digital publishing.
- Music, Performing, and Visual Arts – Live performances, concerts, theatre, dance, and fine arts.
- Museums, Galleries, and Libraries – Cultural heritage preservation, exhibitions, and archives.
- Heritage & Cultural Tourism – heritage management.

Creative-sector managers were chosen for studying marketing and post-COVID-19 management policies as the study group because the creative sector is particularly interesting as it was among the industries most affected by the pandemic, requiring rapid adaptation, digital transformation, and innovative marketing strategies to survive and thrive. Creative-sector required rapid digital transformation in marketing. The pandemic accelerated the shift to digital platforms, virtual experiences, and online engagement in the creative sector. Marketing strategies evolved to emphasize social media, influencer collaborations, virtual events, and e-commerce.

3.2. Research Protocol and Stimuli

Creative sector also needed resilience and adaptive management strategies. Creative industries had to implement crisis management strategies, including hybrid business models, remote work adaptation, and new revenue streams. Understanding these strategies provides insights into agile marketing practices and business sustainability in times of crisis.

The pandemic changed consumer expectations, with increased demand for authenticity, digital content, and ethical branding. Studying creative businesses helps analyse how brands redefined their value propositions in response to shifting audience needs.

Many creative businesses pivoted to subscription-based services, crowdfunding, NFTs, and immersive marketing (AR/VR) to engage audiences that is why it is valuable to analyse in this sector role of innovation in post-COVID-19 business models. Creative sector provides also case studies on how companies use innovation to maintain relevance in changing markets.

The creative industries play a key role in economic and cultural recovery, influencing global marketing trends and government support policies. Examining marketing strategies in this sector helps understand how brands rebuild consumer trust and engagement post-pandemic. The pandemic introduced long-term changes in work environments, team management, and cross-border collaboration, which continue to impact marketing teams and content production.

Studying the creative sector's response to COVID-19 offers valuable insights into marketing resilience, innovation, consumer engagement strategies, and adaptive management practices, making it a relevant case study for post-pandemic business strategies.

3.3. Research Apparatus

The study was conducted using the quantitative research method. The selected technique for collecting questionnaires was the Computer –Assisted Web Interviewing (CAWI) technique, considering the fact of wide access to respondents and maximization of the response rate.

The CAWI technique proved effective in collecting data from a specific group of respondents at a specific time and place, and at the same time giving them the opportunity to think about their answers. The CAWI technique is particularly appropriate for surveys targeting managers in the creative sector for several compelling reasons. CAWI's digital nature aligns with the tech-savvy habits of young people and creative people. The combination of technology-driven efficiency, flexibility, and engaging design makes CAWI an appropriate choice for conducting surveys among creative entities managers. By aligning with their preferences and expectations, this method can give authentic responses, leading to insightful results.

In order to enhance the results obtained from the quantitative study, triangulation of methods was used and qualitative research was conducted in the form of individual in-depth interviews (IDI). In-depth interviews were conducted with three experts from the creative industry. Adding IDI to a CAWI approach significantly enhanced the depth of the data collected, providing valuable insights that might not be captured through surveys alone. Combining IDI with CAWI offered the benefits of both quantitative and qualitative research, allowing to gain broader, statistically significant insights from the CAWI survey while also exploring deeper, more personal insights through IDI. This integrated approach led to a richer, more nuanced understanding of the research topic.

4. RESULTS

This study aims to reduce the gaps between research and practice that arise as a result of the lack of analyses of changes in entities' management or the incompatibility of their marketing activities to market requirements. Drawing insights from interviews with both managers and experts in the creative sector, the author explored potential solutions to address the gaps arising from the misalignment between marketing strategies and market demands.

According to respondents from the creative sector, the COVID-19 pandemic has had an impact on their management (Figure 1). More than half of the respondents (58,7%) stated this. The group that stated that COVID-19 has not changed the management of companies is about one third of the respondents (34%). 7,3% of the respondents find it difficult to assess whether a change in management related to COVID-19 has taken place.

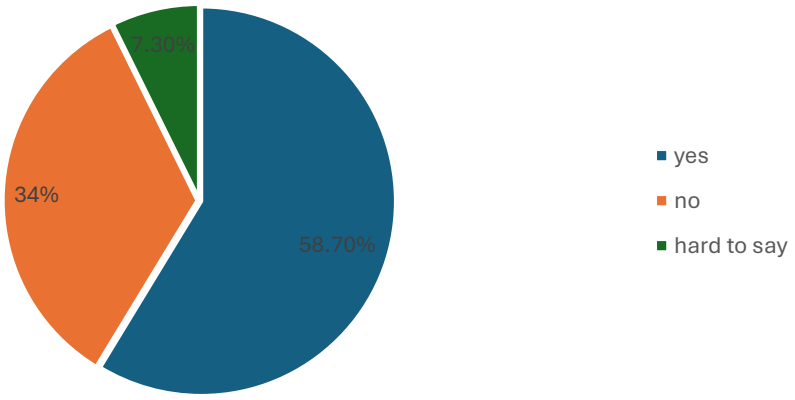


Figure 1. Please specify whether the COVID-19 pandemic has had an impact on the management policy implemented in your company?

Source: own elaboration.

The results suggest that COVID-19 had a significant impact on management practices in the creative sector, with a majority (58,7%) recognizing changes, while a substantial minority (34%) saw no impact and 7,3% were uncertain align with broader trends observed in various industries, where the pandemic forced businesses to adapt their management approaches, accelerate digital transformation, and rethink operational strategies.

This majority response is consistent with research showing that the pandemic led to shifts in remote work policies, digitalization, crisis management strategies, and organizational flexibility (OECD, 2021, Kniffin et al., 2021). In the creative sector specifically, restrictions on physical interactions likely pushed businesses to adopt digital tools, virtual collaboration, and new business models.

The fact that one-third of respondents saw no impact suggests that some companies were either already operating in flexible, digital environments before COVID-19 or that their business models were not significantly disrupted. This is comparable to findings from sectors that already had remote work infrastructure or minimal reliance on in-person operations (Eurofound, 2021).

According to creative sector experts: the respondents who were unsure about changes in management could indicate that:

- the shifts were subtle and gradual, making them harder to perceive,
- sometimes employees might not have been directly involved in managerial decision-making, affecting their ability to assess the impact,
- some companies may have returned to pre-pandemic management styles, making the changes seem temporary.

When describing how the management policy has changed the most, among the companies that declared changes in management, the respondents could indicate only one leading option (Figure 2). As many as 70,9% of respondents stated that this change concerned reducing production costs. 15,30% declared changes towards pro-ecological activities, sustainable production. Slightly fewer entities declared that they focused on social issues (12,80%). One percent of respondents are mainly focused on finding new ways of managing their business that will be appropriate for them in such uncertain times.

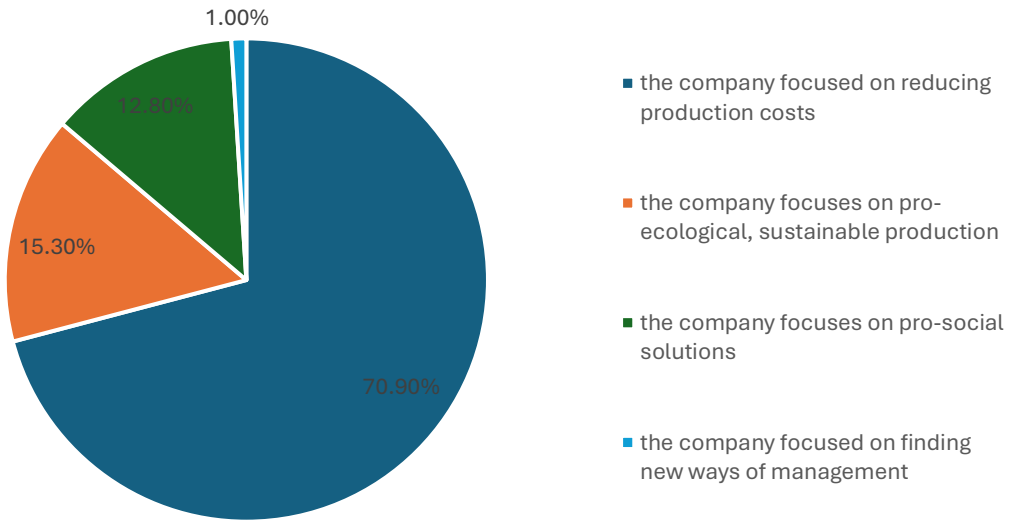


Figure 2. Please indicate how the management policy has changed the most
Source: own elaboration.

A significant majority of respondents (70,9%) indicated that their main focus was on reducing production costs. This suggests that many businesses are still prioritizing efficiency and profitability in uncertain times, likely as a response to economic pressures and market unpredictability. Nevertheless according to experts downsizing measures could include streamlining operations, optimizing supply chains and as well investing in automation.

A smaller group of respondents (15,3%) have focused on pro-ecological activities and sustainable production. Although this is a smaller percentage, it still points to a growing awareness of environmental issues and aspects connected with circular economy. Those operating in this area can also generate savings. Companies are increasingly seeing sustainability not only as a social responsibility but also as a way to appeal to conscious consumers and meet regulatory demands. The fact that 12,8% of respondents are focused on social issues is interesting as it highlights a shift in priorities towards for example corporate social responsibility (CSR). While this is a smaller group, it reflects growing attention to employee well-being, diversity, and community engagement, which are becoming more important for long-term business success.

Analysing changes connected with marketing more than half (60%) of the creative sector respondents declared that the COVID-19 pandemic had an impact on marketing in their company (Figure 3). The result is slightly greater than in the case of declarations that COVID-19 would affect management policy in general (58,7%). Only 13,3% of the respondents stated that there was no impact. On the other hand, 26,7% stated that it is difficult for them to determine whether COVID-19 had affected marketing in their company or not. In the case of influence on management, only 7,3% of respondents had such doubts.

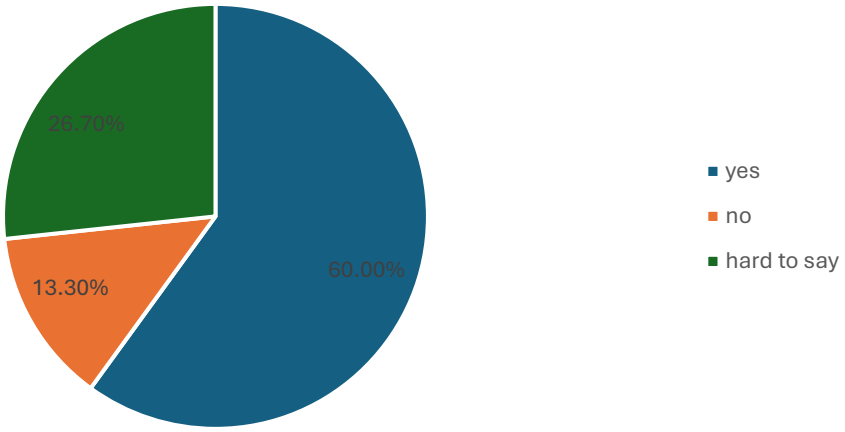


Figure 3. Please specify whether the COVID-19 pandemic has had an impact on the marketing activities carried out in your company?
Source: own elaboration.

More than half of the respondents indicated changes in marketing could reflect several factors, such as the shift to digital channels as in-person events, traditional advertising, and physical experiences were disrupted. The creative sector, which often relies on live events, performances, exhibitions, and physical interactions, likely had to pivot to virtual events, online content, and social media campaigns. This shift required quick adaptation and rethinking of how to connect with audiences.

The pandemic accelerated the digital transformation in many industries, including the creative sector. With physical venues closed or limited, companies may have turned to online platforms, social media, digital content creation, and streaming services to stay connected with customers. Creative firms may have adopted innovative marketing methods, such as virtual exhibitions, digital performances, or influencer partnerships, to replace traditional marketing approaches.

The pandemic likely led to shifts in consumer behaviour, including changes in spending habits and preferences. This could have forced creative sector companies to re-evaluate their target audience, redefine brand messaging, or adapt their marketing channels to align with a more digitally focused audience. The need to maintain engagement with consumers during lockdowns and restrictions would have further driven this shift toward digital-first strategies.

Marketing teams in the creative sector would have had to be more flexible and innovative, possibly focusing on creating digital content, enhancing e-commerce platforms, or shifting advertising efforts toward platforms that saw increased activity during the pandemic (e.g., social media, streaming

services). Creative companies that were able to innovate with their marketing strategies during this time may have gained an advantage by adapting quickly to the new normal and capitalizing on the increased demand for digital content. Thus, the sources of change had many different bases. Sometimes these changes could be wanted by managers and sometimes they had to implement projects and activities that they did not intend at all.

The managers from the creative sector in Poland who took part in interviews when they were asked how they would describe the marketing changes they were introducing three main areas (Figure 4). When describing how the marketing has changed the most, among the companies that declared changes in marketing actions, the respondents could indicate only one leading option. Most entities focused on reducing costs related to marketing activities (71%). This result is similar to the one in the case of changes in management policy (70,90%).

Further entities pointed to the circularity aspect of implementing issues related to sustainable marketing (17%). Sustainability issues also appeared in the next response, as 12% of respondents indicated that they implement ESG policy issues. ESG (Environmental, Social, and Governance) is often viewed as an evolution of CSR (Corporate Social Responsibility). Both ESG and CSR share a focus on social good, ESG brings a more structured, measurable, and investor-focused approach. ESG can be considered a new iteration of CSR for marketing. For marketers, this shift means being prepared to communicate not just corporate values but real, actionable outcomes tied to environmental, social, and governance criteria. ESG is rapidly becoming a cornerstone of brand identity and marketing, especially as consumers and investors increasingly demand responsible business practices (Eccles, Ioannou, & Serafeim, 2020).

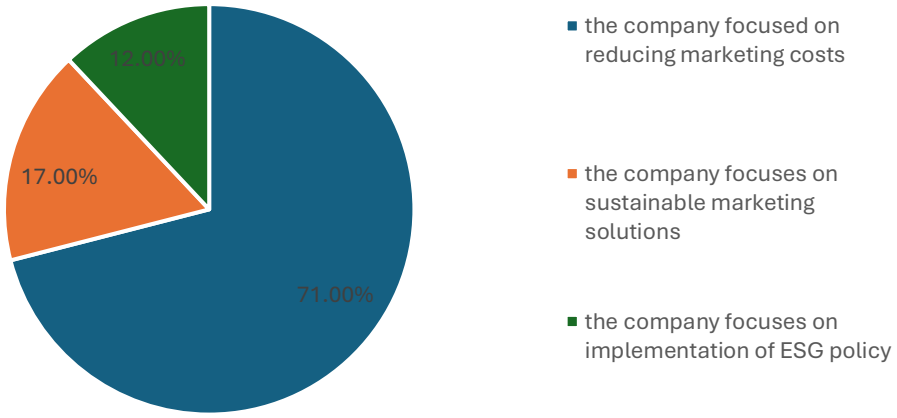


Figure 4. Please indicate how marketing has changed the most
Source: own elaboration.

In response to the question: What marketing-related activities do you plan to implement in 2025? The studies indicated many different answers, but it can be noticed that actions related to cost reduction are indicated more often (Figure 5).

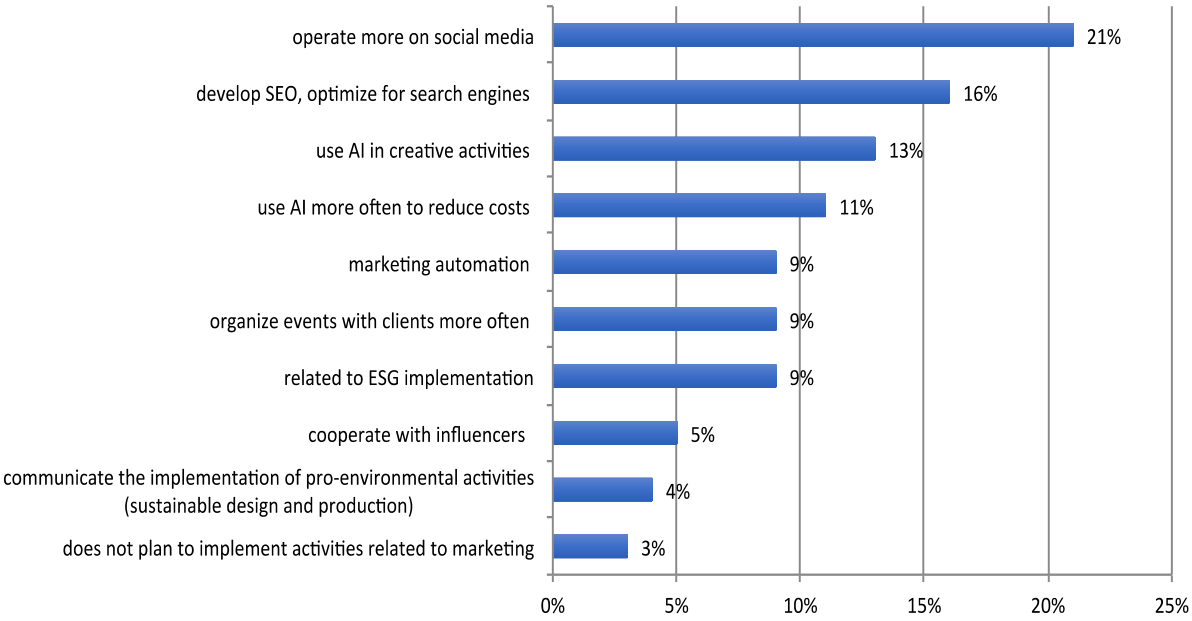


Figure 5. What marketing-related activities do you plan to implement in 2025?
Source: own elaboration.

The respondents mainly plan to operate more often in social media (21%), which in itself is not a high-cost activity. SEO optimization (16%) came next, so it is really an expansion of actions already taken. Optimization usually aims to reduce costs.

Using AI in creative activities (13%) can also reduce costs. The respondents also stated that they intend to use AI more often to reduce costs (11%).

Marketing automation activities (9%) can be an investment in the initial phase, but in the long term they are also aimed at reducing costs. The respondents less often indicated organizing events with clients more often (9%), actions related to ESG implementation (9%).

As a separate category of activities, apart from activities in social media, the issue of cooperation with influencers (5%) appeared.

4% of respondents plan to communicate the implementation of pro-environmental activities (sustainable design and production). However, 3% declared that they do not plan to implement activities related to marketing.

Key observations apart of the will decrease costs can be social media dominance (21% and 5%). This suggests that companies recognize the growing importance of digital presence, audience engagement, and social media-driven marketing strategies. Only 5% of respondents plan to collaborate with influencers, despite the rise of influencer marketing. This might indicate a shift toward more owned and organic digital marketing efforts rather than relying on third-party endorsements.

The second-highest priority is SEO development (16%). This indicates that businesses are focusing on organic visibility, recognizing the need to optimize websites and content for search engines to improve reach and customer acquisition.

Responses indicate the growing role of AI in marketing (13% and 11%). 13% of respondents plan to use AI in creative activities, which reflects the increasing role of AI in content creation, design, and personalized marketing campaigns. 11% aim to use AI to reduce costs, highlighting an interest in automation, efficiency, and data-driven decision-making to optimize marketing expenditures.

9% plan to implement marketing automation, which suggests a focus on streamlining campaigns, email marketing, and customer segmentation. Another 9% plan to organize events more often, possibly indicating a shift back to in-person marketing efforts or hybrid models post-pandemic.

ESG and Sustainability Considerations (9% & 4%) is important trend which is constantly shifting. Especially since Poland's 2025 introduces mandatory ESG reporting. 9% of companies are aligning marketing strategies with ESG initiatives, which may be in response to increasing consumer and

regulatory pressure. A smaller 4% plan to specifically communicate their pro-environmental activities, such as sustainable design and production. This suggests that while sustainability is gaining attention, it is not yet a primary marketing focus.

Only small group (3%) does not plan to implement any marketing-related activities. According to experts this could include businesses that either do not rely heavily on marketing or have already established sufficient brand recognition.

5. DISCUSSION

This study indicates the changes that have taken place in creative sector companies in Poland in recent years in terms of management and marketing. After analysing the respondents' answers and the experts' interpretations, it can be stated that the hypothesis was correct verified positively. Managers are changing marketing management, not moving away from marketing expenditures but looking for different forms of activities. The common opinion that entrepreneurs change management policy to reduce costs and thus give up marketing activities is not true. Marketing activities are strongly present in creative entities and are not eliminated. Managers change marketing management to reduce costs by looking for other forms of activities.

Research conducted in 20216 indicated a slow pace of change in the creative sector entities. In study by Joanna Kubicka (2016) investigated the implementation of management changes in cultural and creative organizations in response to environmental shifts. The findings indicated that only a portion of respondents fully recognized the scope and impact of management changes on their organizations, and the overall state of implementing these changes was still low. While Kubicka's research highlights a low implementation rate of management changes, it does not specifically address the relationship between cost reduction and marketing activities. Therefore, the assertion that managers in Poland's creative sector are maintaining or adapting marketing efforts despite cost-reduction pressures appears to be a relatively unexplored area, suggesting a potential gap in existing literature.

However, there is little data on the creative sector in Poland that would provide a picture of the changes taking place in this sector in recent years. The size of the sector and the fact that the entities in it are very often very different are not without significance here.

Results obtain during this study align with global trends, highlighting how COVID-19 influenced management adaptation in varying degrees. The majority of creative sector companies recognized a shift, but a significant minority either maintained previous management approaches or were uncertain about changes. Further research could explore specific areas of management transformation, such as leadership styles, work arrangements, and innovation strategies.

The COVID-19 pandemic has significantly influenced management practices across various sectors, including the creative industries. While many companies have adapted to new challenges and new reality, others have maintained traditional approaches or remain uncertain about necessary changes. This aligns with global trends observed during the pandemic. For instance, the UK's TV production sector faced substantial financial challenges due to decreased spending on program commissions by British broadcasters. Despite a record income of nearly £4 billion in 2022, the abrupt downturn left many small independent producers at risk of closure, with over 70% facing possible shutdowns by May 2025 if conditions did not improve (The Guardian, 2024). Similar, the 2015-founded events company Creation showed resiliency throughout the pandemic by reorienting services and continuing to run without laying off employees. The business, which prioritizes tenacity, prompt decision-making, and team values, has extended its operations internationally and intends to join the US market (The Times, 2024). These illustrations show how different levels of managerial adjustment occurred in the creative industry throughout the pandemic. While some businesses acknowledged the necessity of major changes, others held to their previous management styles or were hesitant to make the necessary adjustments. Further research could explore specific areas of management transformation, such as leadership styles, work arrangements, and innovation strategies, to understand better how organizations can navigate such unprecedented challenges.

An important direction of changes are activities within the ESG framework. ESG which stand for Environmental, Social, and Governance *(*MSCI, 2023) and is often viewed as an evolution of CSR (Corporate Social Responsibility), but it’s not exactly the same thing. While both ESG and CSR share

a focus on social good, ESG brings a more structured, measurable, and investor-focused approach. The compatibility of certain areas may indicate the fact that ESG can be considered a new iteration of CSR for marketing. CSR has traditionally been seen as a company's voluntary commitment to social good, often focusing on philanthropy, community engagement, and sustainability projects. ESG, on the other hand, is more data-driven and involves clear metrics that can be evaluated, reported, and assessed by investors, stakeholders, and consumers. ESG focuses on:

- Environmental (e.g., carbon emissions, waste reduction).
- Social (e.g., employee diversity, human rights).
- Governance (e.g., board diversity, ethical business practices).

For marketing, this means that brands must not only perform with good approach but also prove their efforts through measurable results and transparency (CFA Institute, 2022).

CSR initiatives, while impactful, were often treated as separate from the core business model, mostly driven by marketing and PR teams. ESG, however, is becoming deeply integrated into a company's core strategy, influencing decisions at every level—from operations to supply chains to executive leadership. This integration makes ESG a more strategic focus for marketing, as it's now part of the company's overall value proposition and reputation management (Carroll & Shabana, 2010).

The literature on the subject indicates that ESG goes beyond CSR by answering the growing demand from investors and consumers for more accountability. While CSR was about enhancing a company's image, ESG adds a layer of credibility and risk management, which appeals to both ethical consumers and investors looking for sustainable, long-term business models. Companies that effectively market their ESG efforts attract consumers who care about sustainability and social responsibility, as well as investors who want transparency and ethical practices (Eccles & Klimenko, 2019).

With ESG, marketing plays a crucial role in storytelling - but it's storytelling based on hard data. Rather than just positioning CSR initiatives as optimistic marketing, ESG pushes companies to share quantifiable impact (Hsu, Ko, & Chung, 2021). Authenticity and transparency are key to marketing ESG effectively - if the claims don't align with the company's actions, consumers and investors are quick to call it out as "green washing".

CSR typically focused on social causes such as charitable donations or employee volunteer programs. ESG is more comprehensive, considering environmental, social, and governance factors across the entire business model. This holistic focus means that companies need to engage with all stakeholders, including employees, suppliers, investors, and consumers, in a more cohesive way.

ESG could be seen as the "new CSR" in the sense that it's a broader, more measurable, and more integrated approach to corporate responsibility. While CSR emphasized good intentions and community involvement, ESG places a stronger emphasis on impact, data transparency, and long-term sustainability - all of which are key elements in modern marketing strategies.

For marketers, this shift means being prepared to communicate not just corporate values, but real, actionable outcomes tied to environmental, social, and governance criteria. ESG is rapidly becoming a cornerstone of brand identity and marketing, especially as consumers and investors increasingly demand responsible business practices.

Mention very often by mangers during the study social media is a powerful tool for promoting a company's also ESG efforts. To engage consumers, investors, and stakeholders, companies must authentically communicate their ESG initiatives in a way that builds trust and transparency. While ESG builds upon CSR principles, it represents a more rigorous, accountable, and strategic approach to corporate sustainability. For marketing, this means shifting from value-based branding to data-driven transparency, ensuring that corporate sustainability efforts are credible, measurable, and aligned with stakeholder expectations. In this sense, ESG is not just the "new CSR" - it is a more evolved, integrated, and market-driven approach to responsible business practices. Companies should leverage storytelling to showcase ESG Impact. For creative sector entities creative approach can be very useful and should allow you to reduce your marketing costs.

Respondents pointed out that reducing costs is important to them but still they want to act according to market needs and trends. Experts pointed out, however, that various elements related to marketing activities do not have to mean high costs, but can, in the long term, translate into savings. Such issues may be, for example, the increasing use of artificial intelligence in creative work indicated by the respondents, as well as focusing on achieving a sustainable business.

Implication for further research and practice is combining activities around intelligent management with marketing and ESG in one business model and testing this model. Merging intelligent management with marketing and ESG in companies involves integrating data-driven decision-making, sustainability initiatives, and ethical business practices into a cohesive strategy. Creative sector companies can effectively merge these three elements in areas describe in the Table 2.

Table 2. Merging areas between Intelligent management, ESG and marketing

Merging areas	Actions
1. Intelligent Management: leveraging data & technology	Intelligent management refers to using AI, big data, and analytics to enhance decision-making. Furthermore using AI for creative purposes is also respondents goal. Companies can use: - AI and machine learning: analyse consumer behaviour and predict ESG trends. - Automation: streamline sustainable supply chains and reduce environmental impact. - Real-time monitoring: track ESG performance metrics (carbon footprint, diversity, ethical sourcing).
2. ESG Integration: aligning with business strategy and finance	- Sustainable supply chains: use intelligent management to optimize logistics, reduce waste, and ensure ethical sourcing. - Governance & compliance: AI can assist in monitoring regulatory requirements and avoiding ESG-related risks. - Corporate social responsibility: develop meaningful community engagement programs based on consumer insights.
3. Marketing: communicating ESG Value to Consumers	- Data-Driven Personalization: Use intelligent management tools to tailor ESG messaging for different customer segments. - Transparency & Trust: Showcase ESG efforts through real-time dashboards, interactive reports, and blockchain-backed verification. - Brand Storytelling: Use ESG initiatives to differentiate the brand and appeal to conscious consumers.

Source: own elaboration.

Combining those elements can mean building the synergy of intelligent, ethical, and market-driven growth. By integrating intelligent management with marketing and ESG companies make smarter, more ethical decisions based on real-time insights. Marketing can become more authentic by leveraging ESG initiatives and then ESG becomes a competitive advantage rather than just compliance. Those merged areas will apply intelligent marketing that refers to the use of data, AI, and analytics to optimize marketing strategies, improve customer engagement, and maximize ROI.

6. CONCLUSION

The study examines recent changes in management and marketing within Poland's creative sector, concluding that while managers are adapting their marketing strategies, they are not completely reducing marketing expenditures but rather exploring different forms of activities. This challenges the common belief that cost-reduction efforts lead to diminished marketing efforts; instead, marketing remains integral to creative entities.

The creative sector experienced both extreme disruptions e.g., live event cancellations and rapid innovations e.g., digital content expansion, virtual exhibitions (UNESCO, 2021). Therefore, the search for new management policies is strongly justified.

In conclusion author would like to indicate two key directions of changes in marketing management that companies have adjusted their marketing in response to COVID-19:

- Strategic planning: understanding the broader societal shifts resulting from the pandemic is crucial for enterprises to align their strategies with changing societal expectations and contribute positively to societal well-being.

- Policy adaptation: enterprises have had to adapt policies to address the evolving needs of their workforce, including implementing remote work arrangements and supporting mental health initiatives.

The research results show not only the desire to reduce costs but also openness to new technologies and solutions. Implementation of AI and intelligent management in companies can significantly lower marketing costs while improving efficiency and effectiveness. AI-driven tools like chatbots, email automation, and AI-generated content reduce the need for large marketing teams, lowering labour costs. AI-driven analytics tools can improve customer segmentation and targeting, ensuring marketing budgets are spent effectively. AI tools can also create social media posts, ad copy, and even videos, reducing creative costs. AI-powered dashboards and decision-making tools can help businesses analyse performance and adjust marketing strategies in real time. By automating processes, optimizing spendings and improving personalization, AI and intelligent management can significantly reduce marketing costs while improving effectiveness. Due to its specific nature and adaptation experiences from recent years, the creative sector may be particularly prepared for these innovative changes.

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ETHICAL CONTEXT OF THE USE OF ARTIFICIAL INTELLIGENCE IN POLISH ORGANISATIONS - EXPERIENCES AND OPINIONS OF GENERATION Z REPRESENTATIVES

Agnieszka Kwarcińska[a]

[a] *University of Szczecin, Institute of Management, Poland*

ABSTRACT

Purpose: *This article aims to explore the opinions and experiences of Generation Z representatives regarding the use of AI in the organisations in which they work and their consideration of the ethical context when using AI, together with an indication of future application challenges.*

Need for the study: *The impetus for the present research was three basic research questions. What are the opinions and experiences of Generation Z representatives regarding using artificial intelligence in organisations and their workplaces? What is the status quo regarding training on the use of AI in their workplaces and the use of AI codes of ethics? What are the desired directions of challenges in this area?*

Methodology: *The research methodology in the article is based on two coherent parts: theoretical and empirical. In the first part, an analysis of the literature on the subject was carried out, pointing out, above all, the importance of the topic under consideration and the observed research gap. The second part presents the results of primary research conducted on a purposively selected group representing people from Generation Z. The research, in terms of subject matter, was related to the presented aim of the article and was conducted in the year 2025 using an electronic questionnaire containing 17 questions from the indicated area.*

Findings: *The research made it possible to establish the actual state of affairs in several areas: knowledge of the concept of artificial intelligence by the surveyed representatives of generation Z, the degree and scope of use of such systems in organisations where the surveyed persons work, determination of the advancement of training in the area of the use of artificial intelligence by the indicated organisations, determination of the advancement of implementation of ethical codes of conduct by the indicated organisations with the use of AI, the respondents' sense of trust in the use of AI systems and indication of concerns related to this. In addition, the survey results indicated the direction of desirable actions related to the need to organise relevant training in the use of AI and the implementation of codes of ethics for the use of AI in organisations.*

Practical Implications: *The article indicates the state of the art in using artificial intelligence systems in organisations and the related ethical and training issues. It also provides specific recommendations for both future research and management practitioners.*

Keywords: artificial intelligence system; AI; modern technology; organization management; business ethics; generation Z

Jel codes: M19; M29; O33

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1. INTRODUCTION

The dynamic development of artificial intelligence systems, or, for a shorter time, 'artificial intelligence' or AI (as an abbreviation for Artificial Intelligence), is causing an intensification of discussions, including scientific ones, concerning various aspects of its activation. This includes the issue of developing AI itself and the context of its practical application. There are more and more threads and problems associated with it, and often they only emerge when specific phenomena and undesirable behaviour occur. This means that the new, not yet fully recognised nature of high-tech AI solutions generates, on the one hand, a beneficial and desirable direction for the development of humanity and, on the other hand, especially when, for example, there are signs of abuse or the need for accountability of AI, prompts a parallel reflection on issues related to the ethics of artificial intelligence, the ethical use of solutions using AI systems and the tools that can be used in this area. This also applies to the functioning of the business world, which, seeing above all the benefits of implementing intelligent solutions, is applying them increasingly intensively and, therefore, drawing attention to the already emerging threads of ethical problems. It is worth undertaking a discourse dedicated to this. In addition, paying attention to the initial phase of development and application of AI, it seems that it is mainly the representatives of the youngest generation present on the labour market - generation Z - who will primarily be confronted in the future with the already indispensable presence of artificial intelligence in the workplace and the consequences of such coexistence.

It is for this reason that this article focuses attention firstly on the problems of AI ethics in the context of its functioning in various organisations, above all, however, enterprises; secondly, it refers to the applicability of an ethics-relevant tool such as AI codes of ethics; and thirdly, the empirical research is subject-centred on representatives of generation Z.

2. LITERATURE REVIEW

For the purpose of this article, a review of the literature on the subject was conducted, noting the definition of the category of 'artificial intelligence', the increasing dynamics of AI development and application possibilities, the legitimacy of undertaking a discourse on ethical aspects related to both the development of AI itself and its use, and the need to develop codes of ethics for the use of AI and regular training in this area.

According to an analysis of the literature, the term 'artificial intelligence' (AI) was proposed in 1955 by John McCarthy (Siyah, https://www.kaggle...). Since then, many definitions of artificial intelligence have been coined and are being coined. According to John McCarthy's original formulation, artificial intelligence is the science and engineering of creating intelligent machines, brilliant computer programmes (McCarthy, 2007). This succinct and rather general notation is the basis for further definitions of this category found in the literature, which often develop and detail the answer to the question of what artificial intelligence is (Warszycki, 2019). An interesting definition of artificial intelligence has been proposed by, among others, the UK's Institute of Business Ethics, emphasising that it is 'a term generally used to describe the simulation of elements of human intelligence processes by machines and computer systems. AI is characterised by three main features: learning - this is the ability to acquire relevant information and rules to use it; reasoning - this is the ability to apply acquired rules and use them to reach approximate or finite conclusions; and iteration - this is the ability to change a process based on new information acquired' (Business Ethics & Artificial Intelligence, 2018).

The OECD, on the other hand, defined an AI system by stating that it is 'a system built from machines that can, for a given set of human-defined goals, make predictions, recommendations or decisions affecting real or virtual environments' adding that 'AI systems are designed to operate with different levels of autonomy' (OECD, 2019). The OECD also noted that 'it is a general-purpose technology that has the potential to improve human well-being and prosperity, positively sustainable global economic activity, increase innovation and productivity, and help respond to key global challenges. It is being deployed in various sectors, from manufacturing, finance and transport to healthcare and security' (OECD, 2019). It is worth noting, therefore, that the primary distinction in

terms of artificial intelligence is the machine and the use of various parts that mimic human intelligence in the broadest sense. It is important to note that applying such solutions in practice can have a vast dimension and applies to business functioning and its environment.

Currently, it can be assumed that around 35%[3] (http://www.ifirma...) of organisations use artificial intelligence. This probably varies territorially and regarding the types of AI solutions used. According to a Eurostat study (https://businessinsider ..., 11.03.2025), the percentage of companies using at least one of the AI technologies, such as machine learning, natural language generation, speech and image recognition, is 13.5 % for the European Union, and is highest in the north-west (Benelux, Scandinavia and Germany) and lowest in the south (Portugal, Italy, Greece) and east (Poland, Hungary, Romania, Bulgaria). In Poland, this percentage is 5.9 per cent. A report by KMPG and Microsoft indicates that 'there is a dynamic increase in the number of companies in Poland that use artificial intelligence tools. 28 per cent of surveyed companies declared the implementation of AI-based solutions, which is as much as a 13 percentage point increase compared to 2023. Additionally, of the companies not yet using this technology, 30 per cent want to use AI-based business tools soon. The automotive (47 per cent) and financial (40 per cent) industries show the most extraordinary sophistication in the use of AI (https://businessinsider ..., 13.03.2025).

It therefore appears that an increasing number of entities are incorporating and will continue to incorporate artificial intelligence systems into executing processes and tasks within their operations. It should be stressed, however, that in addition to the opportunities and positive aspects associated with this, certain dangers must be recognised. Among the main dangers of artificial intelligence are the following: incomplete use and abuse of artificial intelligence, liability aspects, threats to fundamental rights and democracy, impact on jobs, distortion of competition, security threats (https://www.europarl...). They also often touch on moral issues. This is pointed out, among others, by R. Sroka, who states that '... the work on artificial intelligence carried out by companies seems beyond any social control from the side of ethical evaluation' (Sroka, 2019, p. 272).

It is worth adding that this is one of the contexts of ethical problems related to the progressive development of AI. Therefore, arguably, for a long time now, one has noticed a growing discourse in the literature covering the topic of the ethics of artificial intelligence in the broadest sense (Gasparski, 2019; Sroka, 2019; Niezgoda, 2019; Ryan, Stahl, 2021; Siau, Wang, 2020; Brendel, Mirbabaie, Lembcke, Hofeditz, 2021; Kosiak, 2023; Sypniewska, Gołębiowski, 2023; Sroka, 2024), which, according to the Guidelines of the High-Level Expert Group on Artificial Intelligence (HLG). Artificial Intelligence, which the European Commission set up, focuses on normative issues related to the design, development, implementation, and use of AI (Wytyczne w zakresie...). As M. Chojnowski (2022) points out, the ethics of artificial intelligence can be framed in various ways:

1. 'Legalistic (principled, code) approach – static, focuses on formulating rules and norms and confirming compliance with them. In this view, AI ethics resembles a soft version of law. It is primarily associated with the codification stage, but can also develop into an overarching approach due to the over-representation of lawyers among AI ethics experts.

2 The operational (pragmatic) approach – active, seeks to apply general norms and principles in practice, i.e. to operationalise values. It involves the methodical integration of ethics into designing, implementing and using AI.

3. critical (contextual) approach – dynamic, recognises the variety and variability of situations in which principles and norms are applied. Related to the contextualisation stage. Here, ethics is a tool for critical reflection on the shape of the social and political reality in which AI operates' (Chojnowski, 2022, p. 16-17).

This author adds that 'the legalistic approach is currently the most widespread. It can take the shape of recommendations or guidelines - either general (such as EU or OECD guidelines) or aimed at specific stakeholders (such as IEEE guidelines). It also includes corporate codes of ethics (Chojnowski, 2022, p. 17). It is worth noting at this point, as pointed out by M. Ryan, and B. C. Stahl (2021), to the multitude of existing AI ethical guidelines. In this regard, they recognise the problems of, firstly, that many guidelines are very broad in scope, meaning that they provide guidance for different stakeholder groups,

[3] According to IBM's 2022 Global AI Adoption Index report, compiled from a survey of more than 3,000 companies across 22 industries and 53 countries, up to 35% of organisations are now using artificial intelligence. (http://www.ifirma...).

and secondly, that there are currently so many guidelines that it is very difficult to navigate through them and understand which ones exist, and what specific practical guidance exists, for those who develop and use AI systems. To date, guidelines of a universal nature and international relevance have emerged. However, some provisions specifically refer to principles and standards detailing the specifics of the development and use of AI systems in specific countries, organisations or even companies.

One example of international guidelines is the principles prepared by the OECD promoting innovative and trustworthy AI use and respecting human rights and democratic values (https://www.oecd...). These principles include:

1. 'Inclusive growth, sustainable development and prosperity.' This principle highlights the potential of trustworthy AI to contribute to overall growth and prosperity for all - individuals, society, and the planet - and achieve global development goals.
2. Respect the rule of law, human rights and democratic values, including integrity and privacy. AI systems should be designed to respect the rule of law, human rights, democratic values and diversity. They should include appropriate safeguards to ensure a fair and just society.
3. Transparency and explainability. This principle concerns transparency and responsible disclosure of AI systems to ensure that people understand when they interact with them and can question the results.
4. Robustness, safety and security. AI systems must operate robustly, safely and securely throughout their lifecycle, and potential risks should be continually assessed and managed.
5. Accountability. Organisations and individuals developing, implementing or operating AI systems should be held accountable for their proper functioning in accordance with the value-based OECD Principles for AI' (https://www.oecd...).

At the European Union level, the Ethics Guidelines for Trustworthy Artificial Intelligence, which were prepared by an independent high-level group of experts on artificial intelligence appointed by the European Commission (2019), first emerged. The aim of the guidelines 'is to promote trustworthy artificial intelligence. Trustworthy artificial intelligence has three characteristics that must characterise the system equipped with it throughout its life cycle: a) it should be lawful, i.e. comply with all applicable laws and regulations, b) it should be ethical, ensuring compliance with ethical principles and values, and c) it should be robust from both a technical and societal point of view, as AI systems can cause unintended harm even when used in good faith' (Wytyczne w zakresie...).

Subsequently, an Artificial Intelligence Act was drafted establishing a common framework for the use and provision of AI systems in the EU, with a classification of AI systems with various requirements and obligations aligned to a 'risk-based approach'. According to the provisions in the AI Act, 'certain AI systems posing 'unacceptable' risks are prohibited. A wide range of 'high-risk' AI systems that may harm health, safety or their fundamental rights are allowed, but are subject to a set of requirements and obligations to gain access to the EU market.' AI systems posing limited risk due to a lack of transparency will be subject to information and transparency requirements. AI systems posing only minimal risk to humans will not be subject to further obligations (http://www.europarl...).

In Poland, the AI Policy (Uchwała nr 196 Rady Ministrów…) was enacted in 2020, taking into account 'actions that Poland should implement and goals that it should achieve in the short term (until 2023), medium term (until 2027) and long term (after 2027), aimed at the development of Polish society, Polish economy and Polish science in the field of artificial intelligence. All objectives and tools are divided into six areas: AI and society (...), AI and innovative companies (...), AI and science (...), AI and education (...), AI and international cooperation (...), AI and the public sector (...)"(Uchwała nr 196 Rady Ministrów…).

Besides, it is worth emphasising that, in application terms, peculiar codes of ethical use of artificial intelligence of various organisations are emerging. An example is the 'Warsaw Principles', which were developed by The International Communications Consultancy Organisation (ICCO) and adapted to the Polish market by the Association of Public Relations Firms. They are intended to be helpful in 'organising processes and resolving ethical dilemmas that arise when PR practitioners use AI solutions' (Powstały zasady...). They take into account the following rules (Powstały zasady...): Transparency, Openness and Authenticity; Integrity, Fact-Checking and Combating Misinformation; Privacy, Data Protection and Responsible Sharing; Bias Detection, Mitigation and Inclusivity; Intellectual Property, Copyright Compliance and Media Literacy; Human Oversight, Intervention and Collaboration; Context Understanding, Adaptation and Personalisation; Responsible Automation and Efficiency; Continuous

Monitoring, Evaluation and Feedback; Ethical Professional Development, Education and Promotion of AI.

The direction to create codes of ethics more 'dedicated' to the specific ways and specificities of using artificial intelligence systems seems correct. According to the provisions of the 'Independent Expert Guidance' (Wytyczne w zakresie..., 2019) on codes of conduct, 'organisations and stakeholders can use these guidelines and adapt their corporate social responsibility code, key performance indicators, codes of conduct or internal policy documents to include the drive to implement trustworthy artificial intelligence' (Wytyczne w zakresie..., 2019). It is therefore worth emphasising the legitimacy of the otherwise voluntary efforts of specific organisations, companies to develop codes and detailed provisions for artificial intelligence systems specific only to them, particularly in their modes and scopes of use. General guidelines may not always be sufficient in view of the various problems and risks generated by artificial intelligence systems.

It is important to bear in mind that AI systems are constantly evolving, finding new uses and can generate previously unseen harms. Implementing AI codes of ethics by various organisations, including companies, also shows their awareness of responsibility. Companies can apply AI codes of ethics to their business, which has many more benefits. As K. Sobków emphasises, this allows companies to (Sobków, Przykłady...): better adapt to the changing regulatory environment, define standards of responsibility for the consequences of AI decisions and establish control mechanisms, build the trust of customers and business partners, prevent AI-related discrimination and abuse, support the sustainable and ethical development of technology.

It is worth emphasising that the very fact of drawing the company's attention in just such a way, i.e. using code provisions, to the possible risks related to the use of artificial systems, analysing them and indicating the chances of controlling the potential negative effects of its operation, influences the sense of security in the broad sense. Arguably, any code should be governed by basic, universal principles, among which we can distinguish (Sobków, Przykłady...): the priority of humans over algorithms, ensuring the security and reliability of technology, privacy protection and data management, non-discrimination and equal treatment, social and ecological well-being, or issues of accountability and oversight mechanisms. However, just as each application of artificial intelligence systems may differ, AI codes of ethics should address this specific application and refer to the possible risks and hazards involved. They should also be confirmed by the values recognised and respected at the level of each organisation. Therefore, the integrity of the provisions on using AI with the organisation's strategy for shaping social responsibility, or directly with its code of ethics or code of conduct, seems legitimate.

Another, separate issue, remains the adherence of individual members of companies and organisations to the principles and rules of conduct enshrined in AI codes of ethics. This is because it often turns out that the provisions do not fully convey the understanding of directly bearing responsibility for using AI. Therefore, the ongoing need for training and awareness-raising in this area is worth noting. Cyclical meetings and lively discussions are of particular value, as they often result in awareness-raising on the one hand and, on the other hand, can provide information about problems that have not yet occurred and can thus be a reason to amend or supplement existing code provisions.

Although there is a significant number of publications in the literature on definitional issues of AI ethics and analyses of normative documents in its scope, one can notice a research gap and a paucity of publications addressing the theme of applied problems related to the ethical use of AI in various organisations. In this dimension, this article fills the gap, as it refers to the presentation of the experiences and opinions of Generation Z representatives about using artificial intelligence systems in their workplaces.

3. METHODOLOGY

The subject scope of the study was the opinions and experiences related to the use of artificial intelligence in Polish organizations, workplaces of the people surveyed, and the use of normative solutions and training in the field of artificial intelligence ethics. For this purpose, a 17-question questionnaire was prepared electronically using the MS Forms application. Four questions from the

questionnaire were so-called metric questions, in which the respondents were asked to specify their gender, age, type of study, and field of study. Two questions concerned the category of "artificial intelligence", another two the use of artificial intelligence systems in the workplace, and three further training in AI. The next three questions referred to normative solutions in the field of the use of artificial intelligence, and the last three took into account opinions on trust in artificial intelligence and concerns related to it.

The scope of the study included Generation Z from the group of students studying at the University of Szczecin as part of full-time and part-time studies in the following fields of study: Management of Public Institutions and Public Relations, Logistics, Logistics Engineering, Entrepreneurship and Investments, and Management. The sample selection was purposeful, considering the largest possible group of Generation Z people, assuming that primarily representatives of this generation will be most closely associated with work using artificial intelligence systems. Since it is commonly assumed that Generation Z people are born in the years 1997-2012 (Wojtoszek, 2023, p. 174; Pokolenie Z na rynku pracy..., 2023, p. 3), and these boundaries are conventional and quite flexible, attention was paid to ensure that the study included primarily people under the age of 30. Of the students surveyed, only about 5% were people over 30. The survey was conducted in March 2025.

4. RESULTS

The study involved 186 people, including 111 women and 75 men. The respondents were 60 percent full-time students and 40 percent part-time students. The structure of their answers to individual questions is presented in the latter part of the article, considering the division into individual parts concerning the broad context of using artificial intelligence in organisations where the respondents work or have worked. The survey's first question referred to the respondents' familiarity with the category of artificial intelligence or artificial intelligence systems, and where they first encountered these concepts. The structure of answers to these questions is presented in Table 1.

Table 1. Answers to questions about the category of ‘artificial intelligence’

Questions	**Percentage of respondents' answers**				
Have you encountered the term ‘artificial intelligence’ or ‘artificial intelligence system’?	Yes			No	
	99			1	
Where did you first encounter the term ‘artificial intelligence’?	at school	at university	at work	on the Internet	somewhere else
	22	18	2	57	1

Source: own study based on the results of primary research.

When analysing the data from Table 1, it is worth emphasising that almost every Generation Z person surveyed has encountered the term “artificial intelligence” or an artificial intelligence system. The relatively most significant percentage of respondents indicated the Internet as the place where they first encountered this term. The next two questions in the survey concerned the use of artificial intelligence in the workplace of the surveyed people and the areas in which the organisation uses it. The answers to these questions are presented in Table 2.

The results of the answers to the questions about the use of artificial intelligence in the workplace suggest that a significant minority of the surveyed people work or have worked in an organisation that uses such solutions. However, they indicate a relatively significant scope of use of artificial intelligence in organizations. The following three questions in the questionnaire were related to implementing training in the workplace on the use of artificial intelligence. The answers to these questions are presented in Table 3.

Table 2. Answers to questions about the use of artificial intelligence systems in the workplace

Questions	Percentage of respondents' answers	
Do you work or have you worked in an organization that uses artificial intelligence?	Yes	No
	11	89
If so, to what extent (area) does/did the organization use artificial intelligence? (please indicate the department, tasks, products, activities, etc.)	creating text content - marketing, emails, to create a marketing strategy and marketing materials, creating strategies, text optimization, content creation, activities supporting programmers, marketing department, master data department, BI department, creating reports, tables and creative content, customer service, query analysis, assignment, queries to the appropriate department, answering simple customer questions, in hearing aids, data analysis, translating data between Excel templates, using chats and AI assistants to search for information, creating presentations and summaries, designing, searching for thematic information, IT department, writing articles, mathematics department	

Source: own study based on the results of primary research.

Table 3. Answers to questions about AI training.

Questions	Percentage of respondents' answers	
Was/is there any training on using artificial intelligence in your workplace?	Yes	No
	4	96
If so, to what extent?	data security, protection of sensitive data when using such tools, data privacy and safe use, and how it works in hearing aids	
Do you think that training on using artificial intelligence should be carried out in every organization?	Yes	No
	68	32

Source: own study based on the results of primary research.

The analysis of the responses in Table 3 shows that only 4% of respondents confirmed that they had conducted training in the workplace on the use of artificial intelligence, and most of it concerned safety issues. At the same time, most respondents believe that training in using artificial intelligence should be conducted in every organization. In the next part of the study, respondents were asked three questions about normative solutions in the field of the use of artificial intelligence used in the workplace. The structure of the responses to these questions is presented in Table 4.

Table 4. Answers to questions about normative solutions for the use of artificial intelligence in the workplace.

Questions	Percentage of respondents' answers		
Does your organisation have a separate code of ethics/code of conduct regarding artificial intelligence?	Yes	No	I don't know
	11	49	40
Does your organisation have specific provisions regarding artificial intelligence in its code of ethics / code of conduct?	5	53	42
Do you think that a code of ethics/conduct regarding AI should be implemented in every organization that uses AI?	82	18	x

Source: own study based on the results of primary research.

As can be seen from the data presented in Table 4, 11% of respondents indicated that their organization has a separate code of ethics or code of conduct regarding artificial intelligence, 5% indicated that the organization has specific provisions regarding artificial intelligence in the code of ethics or code of conduct. It is also worth noting that in the case of answers to these two questions, a relatively large number of respondents did not know whether such solutions were used in the organization. In addition, it can be stated that the vast majority of people surveyed believe that a code of ethics or code of conduct regarding artificial intelligence should be implemented in every organization that uses artificial intelligence. The last questions in the survey concerned the respondents ' opinions on their trust in artificial intelligence and concerns related to its use. In response to the question "To what extent do you trust the use of artificial intelligence in the workplace?" with the option to select a rating on a scale from 1 to 5, where 1 meant very little trust and 5 meant very much trust, the calculated average rating was 3. The distribution of answers to the last two questions regarding the respondents' concerns and the indication of the types of concerns are presented in Table 5.

Table 5. Answers to questions about opinions on trust in and concerns about artificial intelligence.

Questions	**Percentage of respondents' answers**	
Do you have concerns about the use of artificial intelligence in the workplace?	Yes	No
	28	72
If so, what are these concerns? (Please indicate at least one, maximum three)	replacing an employee with artificial intelligence, people do not know how to use it and do not verify information, and not everything is always true, loss of jobs for many people, often makes mistakes, fewer jobs for people, unreliable information, false information, plagiarism, complete replacement of human work, opens the door to "shirking" work, leakage of sensitive data due to a system error, irregularities in understanding customer needs, lack of data security, too much reliance on artificial intelligence, lack of human development, loss of control over artificial intelligence, erroneous understanding of the problem = incorrect solution, need to check answers - frequent errors, use of old databases, lack of 100% certainty regarding the knowledge of artificial intelligence, data leak, improper use of data made available to artificial intelligence, poor assessment of the situation by artificial intelligence or failure to take all aspects into account, it can obtain our private information without our knowledge and consent, the problem is the substantive knowledge of AI based on the Internet and its verification, it is not accurate, reliable, poor effectiveness, people will stop thinking independently and will trust blindly artificial intelligence, does not take into account all aspects when making decisions, is not "intelligent" enough at the current stage of development to have a free hand in making decisions, does not respect copyrights and spreads disinformation	

Source: own study based on the results of primary research.

Based on the analysis of the data presented in Table 5, almost 30% of respondents have concerns about the use of artificial intelligence in the workplace, and the list of concerns indicated is relatively long.

5. DISCUSSION

The development of artificial intelligence systems and the constantly expanding scope of application of such solutions, also in business, have been a source of both previously unseen problems and threats as well as various scientific discourses, including managerial and ethical ones (Siau, Wang, 2020; Brendel, Mirbabaie, Lembcke, Hofeditz, 2021; Kosiak, 2023; Sypniewska, Gołębiowski, 2023; Sroka, 2024). The research carried out in this article is a contribution to the discussion on the need to draw the attention of both scientists dealing primarily with business ethics and practitioners of managing and managing organizations to the ethical context of using artificial intelligence systems and the need to promote awareness of accepting responsibility in this area.

It is worth emphasising that existing normative solutions in the form of guidelines and principles of international application, which are subject to various analyses by researchers (Ryan, Stahl, 2021), seem to be the primary and universal determinants of the basic rules relating to the use of AI. First of all, they allow for the maintenance of the primacy of human rights when using AI systems, as well as to make AI users aware of the types of risks and threats, i.e. to address the topic of security and emphasise issues related to specific consequences, and thus consider the aspect of responsibility. However, given the variety of ways of using AI systems and the heterogeneity of stakeholder groups, this general nature of the guidelines' provisions often seems insufficient. It encourages reflection on creating more detailed rules, considering the specificity of their application to specific entities. These rules can be included in various normative documents already functioning in organizations or may take the form of completely separate ethical codes of AI use (Guidelines on...). It should be noted that, as stated by R. Sroka (2024), "The process of intentional and at the same time spontaneous shaping of institutions for business ethics, using AI in each of the above-mentioned aspects of institutional economy, i.e. in the scope of informal institutions, formal institutions and institutions-organizations, has only been underway for several years." Therefore, this is related to the initial stage of forming appropriate regulations and requires special attention and involvement of practitioners and scientists. The fields of discussion and implementation of research in this field must be consistent with the needs emerging with the expanding contexts of using artificial intelligence systems. Additionally, it is worth pointing out the need to shape awareness of the opportunities and threats that AI solutions bring, as well as the special role in this area of training at various levels of education, carried out by employers, also covering ethical aspects.

6. CONCLUSION

In this broad context of the development and use of AI systems and the related ethical issue, the empirical research results presented in the article first allowed us to establish a specific status quo in terms of:

- familiarity with the concept of artificial intelligence among the surveyed representatives of Generation Z; it turned out that almost all of the surveyed people know this concept, and they indicated the Internet as the source of their first encounter with this category; this probably means that there is great interest in this topic among young people and at the same time indicates the need for conscious education in this area;
- degree and scope of use of such systems in the organizations in which the surveyed people work; according to the research results, only 11% of respondents confirmed working in an organization that uses artificial intelligence; the scope of AI application was diverse and included, among others: creating text content, marketing strategy and marketing materials, and activities supporting programmers; this indicates primarily the initial phase of using such solutions by the organizations in which the surveyed people work;
- determining the level of advancement in conducting training in the area of the use of artificial intelligence by the indicated organizations; based on the conducted research, one can see a complete lack of satisfaction related to conducting training on the use of AI, and thus also drawing attention, apart from safety itself, to the issues of responsibility related to it and the variety of problems and threats;
- determining the level of advancement in the implementation of codes of ethics by the indicated organizations about the use of AI; a relatively small percentage of people indicating the implementation of codes of ethics or specific provisions in existing documents related to the use

of AI in organizations may mean that we are dealing with the initial phase of shaping awareness of the importance of ethical issues when using AI;

- the sense of trust of respondents in the use of artificial intelligence systems and indication of concerns related to it; a relatively low level of trust of the surveyed people in the use of AI in the workplace and a relatively high percentage of indications of existing concerns and their numerous and diverse set may mean a high sense of awareness of problems related to the use of AI.

Secondly, the survey results helped to determine the direction of desirable actions related to the need to organise relevant training on the use of AI and the implementation of codes of ethics/conduct on the use of AI in organisations. The answers of the surveyed people concerning these issues argue such a conclusion. Their indications of "yes" in the questions about the need to organise training on the use of AI and implement codes of ethics for the use of AI are further presented in Figure 1.

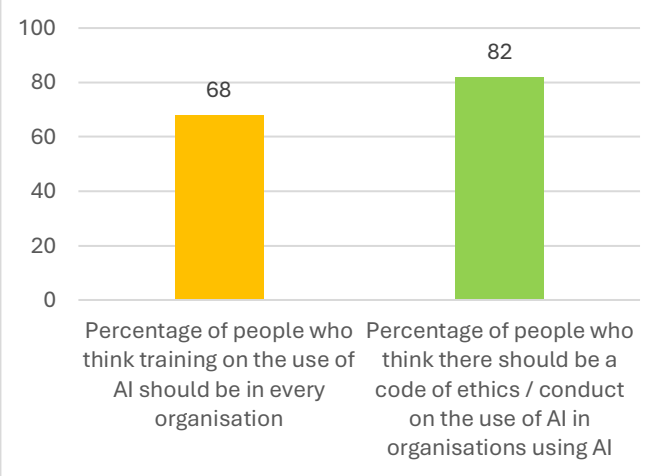


Figure 1. Percentage of people confirming the need for training and the implementation of codes of ethics / conduct on the use of AI in organisations using AI systems
Source: own study based on the results of primary research.

As seen from Figure 1, it is worth noting again that the vast 68% of respondents highlighted the need for training by organisations that use AI. In addition, the vast majority of respondents - 82% - indicated the need to implement a code of ethics or code of conduct on AI in any organisation that uses AI. This may mean that those surveyed recognise the importance of the problems and risks associated with using AI. This is why they indicate as legitimate the provision of training and the creation of codes of ethical conduct for using AI.

To sum up, as the research shows, the processes related to the use of solutions using artificial intelligence in Polish organizations, as well as those related to ethical issues, can be treated as initiated, but in the initial phase of development. This is perhaps related to the still negligible adoption of intelligent solutions by Polish companies, especially micro, small and medium-sized ones. It seems, therefore, that the preparation of the relatively young part of the community - people from generation Z and beyond - for the standards of working with AI remains at the stage of the need for broad education and awareness-raising, taking into account both the benefits and risks associated with it. The role of employers, who are interested in the development and use of AI, as well as schools and universities, is therefore significant.

In the context of further research, analyses and application activities, in view of the awareness of the constantly growing scope of AI use and dynamic changes in conditions, risks and threats, it is also important, in addition to constructive discussions and scientific publications and activities shaping the basic rules of broadly understood responsibility, to create code provisions by individual organizations, including enterprises, their simultaneous constant monitoring and possible improvement. Additionally, it is worth noting that the mere existence of codes or specific provisions may prove insufficient. It is also worth paying attention to various procedures and control systems related to both the use of artificial intelligence in the organization itself and the application of established rules of conduct. Therefore, the

issues of enforcement (Sobków, Przykłady...) of these provisions and possible sanctions related to their violation also require attention. Therefore, it is worth expanding the research threads to include further issues related to the research conducted in this article and, due to the intensive development of this subject, taking into account the cyclical nature of this type of research.

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THE PROBLEM OF DISCRIMINATION IN THE APPLICATION OF AI IN PUBLIC SERVICE MANAGEMENT

Kinga Flaga-Gieruszyńska[a]

[a]*University of Szczecin, Faculty of Law and Administration, Poland*

ABSTRACT

Purpose: *The aim of the study is to identify and analyse the mechanisms leading to discrimination as a result of the use of AI systems in public service management, as well as to identify possible solutions to reduce these phenomena.*

Need for the study: *With the rapid development of AI technologies, they are increasingly being used by public institutions to make decisions in areas such as welfare, education, security or employment. However, the lack of transparency of algorithms, biased input data and insufficient oversight mechanisms can lead to the reproduction and exacerbation of existing social inequalities, resulting in discrimination against specific groups of citizens.*

Methodology: *The analysis was based on a literature review, reports from public institutions, case studies and current examples of AI implementation in the public sector. Ethical and legal aspects were also taken into account, based on regulatory documents and recommendations on the use of AI in public administration.*

Findings: *The use of AI without proper oversight and awareness of risks can lead to the automation of discriminatory practices, especially towards ethnic minorities, people with low socio-economic status or people with disabilities. In practice, there is also often a lack of clear procedures regarding accountability for decisions made by algorithms and mechanisms for audit and correction.*

Practical Implications: *The results of the study point to the need to create a transparent and ethical regulatory framework, to ensure diversity in training data, and to implement algorithmic audits and accountability mechanisms. It also recommends public participation in the design and implementation of AI systems in public services to ensure fairness and equity.*

Keywords: AI, public service management, anti-discrimination, equality before the law, automated decision-making process

Jel codes: K23; K38; K41

1. INTRODUCTION

Recent years have witnessed the dynamic development of technologies based on artificial intelligence (AI), which are increasingly being applied in the public sector. Public administrations and public institutions are implementing algorithms to optimise decision-making processes, improve administrative efficiency and increase the availability of public services. AI-based systems are being used, for example,

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to assess eligibility for social benefits, manage urban traffic, predict health needs, and for recruitment and selection in education systems. However, the implementation of such technologies is also associated with several risks, including the particularly serious problem of discrimination - both conscious and unconscious - against specific social groups.

A growing number of examples from different countries indicate that improperly applied algorithms can reinforce existing social inequalities rather than redress them. This is mainly due to imperfect training data, which reflects historical biases, and a lack of transparency in the operation of AI systems (the so-called 'black box'). The lack of clarified institutional accountability for erroneous algorithmic decisions and the limited possibility for a citizen to appeal a decision made by an AI system are also often a problem. As a result, artificial intelligence, which was supposed to serve as a tool to promote fairness and equality, can lead to systemic exclusion of those who are already socially and economically disadvantaged.

The main theses under scrutiny focus on three issues. First, AI systems used in the management of public services can reproduce and exacerbate existing social inequalities. Second, the lack of appropriate regulatory frameworks, oversight mechanisms and transparency of algorithmic decisions fosters the perpetuation of discriminatory practices. Third, both the design and implementation of AI in the public sector should be based on ethical principles, transparency and public participation.

The presentation uses as its main research method a critical analysis of the literature on the subject, including both academic publications in the social sciences and reports from public institutions. In addition, case studies illustrating concrete examples of AI applications in public institutions that led to discriminatory situations were included.

The paper is interdisciplinary and combines a technological and legal perspective with social analysis. The aim of the paper is not only to identify problems but also to formulate recommendations for the design and implementation of fair, inclusive and accountable AI systems in the public sector.

2. LITERATURE REVIEW

The application of AI in the public sector has been the subject of intense scrutiny in both the information technology and social science literature. Research indicates that while AI can bring significant benefits in terms of efficiency and precision to public institutions (Eubanks, 2018; OECD, 2021), it also carries the risk of reproducing social biases and inequalities (O'Neil, 2016; Noble, 2018).

One of the key problems discussed in the literature is the bias in training data. Authors such as Barocas and Selbst (2016) and Binns (2018) highlight that algorithms 'learn' from historical data, which often contain structural biases (e.g. race, class or gender), leading decision-making systems to replicate these inequalities. For example, Eubanks (2018) analyses cases from the US where AI systems used to assess social needs led to disproportionate surveillance of the poor and ethnic minorities. The literature also criticises the lack of transparency (the 'black box problem') and the difficulty of auditing algorithmic decisions. Pasquale (2015) points out that many AI systems used by public institutions operate in a non-transparent manner, making it difficult for citizens to understand decision-making mechanisms and to assert their rights in the event of erroneous or hurtful decisions.

In the context of public governance, there is also the issue of a lack of legal and ethical accountability for AI actions. Yeung (2018) and Veale and Brass (2019) highlight the legal gap regarding accountability for decisions made by algorithmic systems. They point to the need for regulatory frameworks and the implementation of ethical guidelines for the design of AI systems in public services. European literature (e.g. Floridi et al., 2018; European Commission, 2020) emphasises the need to implement AI ethical principles such as fairness, transparency, accountability and inclusivity. It is noted that the implementation of technologies should be done with the participation of citizens and experts from different fields, based on a participatory and intersectional approach.

There are also empirical studies analysing specific use cases of AI in the public sector. Among the most cited are the COMPAS system used in the US to predict the risk of recidivism (Angwin et al., 2016), Amazon's recruitment algorithm that excluded women (Dastin, 2018), and the SyRI system in

the Netherlands that automatically classified benefit recipients as potential fraudsters, leading to a court ruling declaring the practice a human rights violation (UN Special Rapporteur, 2020).

In conclusion, the literature unanimously points to the need for critical reflection and regulation of the use of AI in the public sector. A consensus is emerging that technological innovations alone do not guarantee social justice - on the contrary, in uncontrolled conditions, they can perpetuate and exacerbate discrimination. It is, therefore, necessary to develop interdisciplinary research that takes into account technological as well as social, legal and ethical aspects.

3. METHODOLOGY

This paper is based on a qualitative method to analyse in depth the phenomenon of discrimination related to the use of artificial intelligence in public service management. An interdisciplinary approach was used, combining the perspectives of the social sciences, legal sciences and information technology, with a particular focus on the ethics of technology and public management.

The primary research method was a critical review of the literature on the subject. Both academic texts - monographs, articles and peer-reviewed publications - and reports from public organisations were analysed. The selection of sources was purposive - the focus was on works that relate directly to the application of algorithmic systems in the context of public administration, with a particular focus on ethical and social aspects. It was also important to include publications critical of the unreflective implementation of AI, which point to its discriminatory and anti-social potential.

In the following part of the study, case studies were used as a complementary method. Known and well-documented examples of AI systems that have in the past led to practices considered discriminatory or violative of human rights were analysed. For detailed analysis, the case of the EPV-R (Evaluation of Partner Violence Risk) tool, implemented in the courts of the Basque Country (Spain) to support the operation in domestic violence cases, was used. This predictive tool supports the decisions of judges and law enforcement officers in domestic violence cases. A study by Valdivia at al. (2024) found that a lack of adequate user training and limited algorithm transparency led to mechanisms for automatic profiling of female victims and influenced decisions to apply protection and supervision measures. The second case was the SyRI system used in the Netherlands to type people suspected of defrauding social security benefits - its operation was found by the court to violate the right to privacy and the principles of non-discrimination. The third was Amazon's internal recruitment system, which, although developed in the private sector, revealed mechanisms of bias against women, a good illustration of the risk of historical bias being transferred to technology.

The research also analysed selected normative documents and regulatory guidelines on the use of artificial intelligence in public administration. Among others, the European Commission's AI White Paper, the OECD Principles for Responsible Artificial Intelligence and the guidelines developed by the European Commission's independent AI expert group were taken into account. The aim of this part of the analysis was to determine to what extent the existing ethical and legal frameworks respond to the challenges of algorithmic discrimination and to what extent they are applied in practice.

It is worth noting that due to the fact that the work covers issues in legal sciences, the study is exploratory and based on secondary sources only. No in-house empirical research or technical testing of algorithmic systems was carried out due to the dissimilarity of the analysis in the field of legal sciences. It is also limited by the fact that many AI systems used in administration operate in a non-transparent (black box) manner, which makes it difficult to fully evaluate them. Nevertheless, the collected material allows a thorough analysis of the phenomenon of discrimination and the formulation of conclusions and recommendations of a general nature, useful for further research and legislative work.

4. RESULTS

The results of the analyses conducted confirm that the use of AI in the management of public services can lead to unintentional but systemic forms of discrimination. Although AI is often seen as a neutral and objective tool, in reality, it embodies and reproduces the biases contained in the data on which it is trained. The case studies of EPV-R, SyRI and Amazon confirm that the lack of transparency of

algorithmic, historical data biases and limited end-user awareness can result in socially unjust and legally controversial decisions.

The EPV-R system (Evaluación del Riesgo de Violencia de Pareja - Revisada) was implemented in the civil judiciary of the Basque Country as a tool to support the assessment of domestic violence risk. Its aim was to support judges and law enforcement agencies in deciding whether to grant protection to women at risk of partner violence. However, research by Valdivia, Hyde-Vaamonde and García-Marcos (2024) found that the algorithm often classified serious cases as low risk - even in situations where violence later escalated to violence or homicide. The system was based on a limited set of characteristics, without taking into account relevant cultural and social factors, and its users were not trained to interpret the results (Valdivia et al., 2024). The process ran in parallel with the forensic investigation. The police had their own protocol for assigning protection measures to victims, even if the case had not yet been decided by a judge, and the case was handled by the police depending on the risk assessment assigned to each person. The assessment could change if the police managed to collect more information from the victim, the perpetrator or the neighbourhood, but the EPV-R was always involved in the process. The results of the questionnaire were, in all cases, included as evidence in the report received by the judges, which did not happen in other similar systems. This meant, in practice, that judges could face a dichotomy between their own opinion of the level of risk and that given by the algorithm.

It was also controversial that the EPV-R ranked risk higher for women from other cultures - indicating the algorithm's potentially biased approach to ethnicity. The system was accepted by judges as 'scientific' and reliable, limiting the possibility of critical evaluation in practice. The questions asked of victims of violence in the questionnaire are not necessarily asked in numerical order. The first question on the list is only worth one point but refers to whether the victims themselves or the perpetrators are 'foreigners' - except that the word used does not refer to all foreigners. In fact, this question is about people of a non-Western culture. According to the assumptions of the developers of this system, this would only apply to all cases where there is a non-European cultural understanding in relation to couples. Significantly, however, neither a specific methodology nor a list of referenced countries is used when completing the questionnaire and the selection of officers is subjective. (Bellio, 2023).

The SyRI system (Systeem Risico Indicatie), used in the Netherlands to detect abuses in the social benefit system, was officially banned in 2020 after a court ruling in The Hague. SyRI analysed residents' social and financial data in order to target people 'suspected' of defrauding benefits. In practice, however, the system focused almost exclusively on low socio-economic neighbourhoods with a high proportion of migrants, resulting in biased profiling of entire communities (Zuiderveen Borgesius, 2020). The court found that SyRI violated fundamental human rights - including the right to privacy and protection of personal data - and did not meet the standards of transparency and proportionality required by European law. This was one of the first cases in which the court directly invoked human rights principles to prohibit the use of an algorithm in the public sector (Hussain, 2020).

Another relevant example of the use of artificial intelligence in the management of public services, which has led to discriminatory situations, is the case of an automatic fraud detection system in the Swedish social security system. The state-run Försäkringskassan (Social Insurance Agency) started to use an algorithmic risk assessment model to identify individuals who might be taking unfair advantage of public benefits (Molén, 2024).

This system assigned a so-called 'risk score' to each applicant, based on a range of demographic and socio-economic data, such as migration status, education level, income level or age. Those with the highest scores were sent to a special screening department, which automatically triggered a screening process, often without the applicant's knowledge. These individuals were subjected to invasive vetting, involving, among other things, social media analysis, contact with educational institutions or banks, and even community interviews (Molén, 2024; Skelton, 2024).

As a result, there were situations in which people with low social status, women, people with so-called 'foreign backgrounds', and people with disabilities were significantly more likely to be flagged as 'risky' by the algorithm - despite the lack of objective reasons for such assessments. A journalistic investigation by Lighthouse Reports, conducted in collaboration with the daily Svenska Dagbladet, found that the system operated in a systemically biased way, reinforcing stereotypes and social inequalities (Molén, 2024).

Amnesty International, which investigated the case in a human rights context, unequivocally found the operation of the algorithm to be discriminatory and incompatible with international law. The organisation called on the Swedish authorities to immediately halt the system, pointing out that it violates fundamental rights, including the rights to equal treatment, privacy and social security (Amnesty International, 2024). Despite previous warnings, including from the Inspectorate for Social Security (ISF), which already in 2018 drew attention to the unequal impact of the algorithm, the system continued to be used without significant modifications (AIAAIC, 2025). From a regulatory perspective, it is worth highlighting that the system - used in a non-transparent manner and without audit mechanisms - may not be compliant with the new EU legal framework. According to the EU AI Act regulation, systems used in the public sector to profile citizens must be subject to strict requirements of transparency, risk assessment and protection against discrimination. The absence of these elements in the Swedish model makes its continued use highly problematic both ethically and legally (Babl.ai, 2024).

The case of Sweden, a country commonly associated with high levels of transparency and protection of citizens' rights, clearly demonstrates that even in the most advanced democracies, algorithms can operate in an oppressive manner if they are not properly designed, supervised and controlled. At the same time, it demonstrates the need to create independent auditing mechanisms and provide citizens with real opportunities to challenge decisions made by automated systems.

This kind of situation is also happening in the private sector. In 2018, it was revealed that Amazon was internally testing an algorithmic recruitment system to automate the assessment of job candidates. The problem was in the training data: the system learned from CVs sent to Amazon over the past 10 years, which reflected the company's dominant culture of hiring men in technical departments. As a result, the algorithm 'drew' the erroneous conclusion that men were a desirable profile and women a less desirable one (Vincent, 2018). In practice, this meant that the system downgraded CVs containing words such as 'women's' (e.g. 'women's chess club captain' or 'women's college'), while upgrading candidates who used technical language typical of male work environments, such as the terms 'executed', 'captured', 'driven' (Goodman, 2018). Furthermore, the tool ignored neutral competency data and favoured a particular style of expression that correlated with gender (Dastin, 2018; Vincent, 2018). Although the system was withdrawn before full implementation, this case perfectly demonstrates how easily artificial intelligence can transform existing social biases into automated, 'technical' discriminations. The 'garbage in, garbage out' mechanism was particularly evident here - the system not only mapped historical managerial preferences but systematised and reproduced them.

Each of the cases analysed highlights a different aspect of this phenomenon. The EPV-R system in the Basque Country shows how an inadequately implemented predictive tool can lead to a misjudgement of risk and expose victims of violence to further danger. The case of SyRI in the Netherlands reveals how the combination of big data and covert scoring can violate basic civil rights, leading to profiling and discrimination against entire communities. The Swedish model of welfare fraud detection, on the other hand, shows that even in countries with developed institutional mechanisms, AI can serve as a tool for systemic exclusion if it is not subject to independent oversight and transparency. The Amazon example points to the fundamental importance of input and shows how easily past patterns of inequality can be automated and made credible by an 'intelligent' system.

All these cases have a few key problems in common. The first is a lack of transparency and auditability, as the algorithms used in the public sector are often 'black boxes' whose operation is not understood by citizens or even by those implementing them. There is a lack of mechanisms for independent scrutiny, fairness and equity compliance tests (Binns, 2018; Veale & Brass, 2019). Also not insignificant is flawed or biased training data - the data used to train AI systems reflects existing social inequalities, historical institutional biases and lack of representation of marginalised groups (Barocas & Selbst, 2016; Noble, 2018). Consequently, even seemingly neutral algorithms can lead to systematic exclusion. This leads to the fundamental problem of a lack of institutional accountability - in the cases studied, there were no clear procedures in place to challenge the algorithm's decisions or assign responsibility for their consequences. As a result, affected citizens often had no real possibility to defend their rights. Moreover, the technocratisation of public decisions is an important threat. There is a tendency in public services to fetishise 'intelligent' systems, which are treated as more reliable than human judgment, even if they are based on incomplete data and models that do not fit the social context. Public administrations mistakenly treat the outcome of an algorithm as a 'neutral fact', undermining citizen scrutiny and democratic accountability of the administration (Pasquale, 2015; Eubanks, 2018).

From the above, it follows that technology in itself is not neutral. Designing and implementing AI systems in public administration requires not only technical competence but, above all, social and ethical awareness. Data-driven decision-making systems should be developed in a participatory manner, involving representatives of different social groups, human rights experts, as well as NGOs. Moreover, there is an urgent need for a clear and enforceable regulatory framework. The AI Act Regulation, adopted at the European Union level, is an important step in this direction, but its effectiveness will depend on the implementation mechanisms at the national level. It will be crucial not only to classify systems as high-risk, but also to ensure that they can be realistically controlled, suspended or banned in the event of a breach of citizens' rights.

5. DISCUSSION

The introduction of artificial intelligence into the public service sector has spawned a new quality in the functioning of public institutions - more automated, 'objectifying' and data-driven. However, at the same time, it has brought to light phenomena that have hitherto occurred mainly in social and institutional relations but have now been perpetuated and amplified by algorithmic decision-making mechanisms. Discrimination that might previously have been incidental becomes, thanks to AI, systematic, difficult to detect and - most importantly - difficult to challenge.

However, the discussion of the problem of algorithmic discrimination should not end with its identification. The key issue relates to what action should be taken to ensure that technology does not serve to exacerbate social inequalities, but to redress them. One of the most important lessons to emerge from the analysis of past cases is the need to change the approach to the design and implementation of technology in public institutions. Currently, many AI implementations in the public sector follow a logic of 'technocratic efficiency': the system is supposed to work faster, cheaper and without 'human error'. Meanwhile, many algorithmic errors are not due to accidental mistakes, but to a systemic lack of control, context and ethical imagination. In this sense, a paradigm shift is required - from human-dominant technology to human-serving technology. To achieve this, multi-level action is required. At the institutional level, this means the need to create sustainable procedures for assessing risks and social impacts even before AI systems are deployed. Instead of testing tools on citizens, public administrations should adopt a preemptive model, in which any decision to implement a new system is preceded by stakeholder consultations, legal and ethical analysis, and a forecast of possible impacts on different social groups.

The next step is to create structures of accountability - not only legal, but also organisational and political. It must be made clear who is responsible for the decision that the algorithm takes, as this strengthens citizens' sense of legal security. In this regard, it is also important that there is a possibility to appeal against this decision and that citizens are given insight into the mechanism that evaluates, assigns and classifies them. These issues are too often ignored or left unaddressed today. Meanwhile, every action of an AI system should have a 'face' - a specific person or organisational unit that is responsible for its effects and makes the decision to continue or stop it.

Public scrutiny of the technology can play an important role in this process. Independent audits of algorithms, the availability of technical documentation, citizen reporting of errors or whistleblower mechanisms can all build the resilience of democratic institutions to technological errors and abuse. At the same time, it helps counteract the loss of public trust, which can be exacerbated when administrative decisions become illegible, irrevocable and depersonalised.

Citizen participation in the system design process is also extremely important. Including representatives of community organisations, minority groups, academia and end-users in consultations can help identify weaknesses in a system before its operation leads to irreversible damage. In many countries, 'data democratisation' and 'participatory AI' initiatives are emerging, which involve the co-creation of technology policies with the participation of a broad spectrum of civil society. In this way, it becomes possible not only to increase the effectiveness of digital tools, but above all, their social legitimacy.

Finally, it is worth noting that technology alone will not solve problems that are deeply embedded in social structures. Even the best-designed algorithmic system can act discriminatorily if it is based on data from an unjust social order. This means that the fight against algorithmic discrimination cannot be

separated from the broader fight for social equality. AI cannot be treated as a neutral technology - it is a political tool that shapes the relationship between citizens and institutions, affects access to resources and participation in public life.

Therefore, corrective action must be carried out in parallel at several levels: technological, institutional, legal and cultural. We must learn to think of algorithms not just as technical products, but as social decisions encoded in the language of computer science. Only then will it be possible to create public systems that not only 'work' but also work fairly.

6. CONCLUSIONS

The analyses carried out clearly show that the use of artificial intelligence systems in the management of public services can lead to serious social consequences if these technologies are not properly supervised and embedded in a legal and ethical context. In each of the cases described - from benefit selection algorithms in Sweden to abuse detection tools in the Netherlands - the risk of replicating and reinforcing inequalities that previously operated as implicit patterns of social treatment became apparent.

Based on the data collected, the key problem is not the technology itself, but the way it is implemented. The main mistakes made by public institutions are the lack of transparency, insufficient control over data quality and the unavailability of viable redress mechanisms for citizens. As a result, decisions made by algorithms become virtually unassailable - violating the basic principles of procedural fairness and trust in the state.

To counter these phenomena, public administrations should deploy AI based on clear criteria: any technological solution should undergo a formal risk assessment, include built-in audit mechanisms and allow the system's operation to be explained to the individual concerned. Furthermore, key decisions - such as granting a benefit, classifying a citizen or interfering with his or her life situation - should not be made solely by a machine. It is necessary to ensure that a human retains ultimate control over the decision-making process ('human in the loop').

In light of planned and already implemented European regulations, such as the AI Act, Member States will be required to identify so-called high-risk systems, implement codes of conduct and conduct oversight of algorithmic systems used in the public sector. However, the experiences described in the study show that legislation is not enough - what is also needed is a change in institutional practices, greater involvement of ethics and human rights experts and, above all, the inclusion of citizens in the evaluation and consultation of technological solutions.

The most important conclusion of this analysis, then, is that technological justice will not emerge spontaneously because of AI development. It requires deliberate action - responsible design, informed management and consistent enforcement of equal treatment. Otherwise, rather than fostering the development of public services, AI may deepen social divisions and undermine trust in democratic institutions. The responsibility to counter these effects lies with technology designers as well as policy makers, regulators and civil society. What is at stake in this debate is not just the efficiency of digital government, but the quality of life of citizens and the shape of the relationship between the state and the individual in an era of digital transformation.

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ETHICS AND GOVERNANCE IN AI MANAGEMENT

Aleksandra Klich[a], Bartosz Brożyński[b], Yuliia Khvatsik[c], Marcin Białecki[d]

[a] *University of Szczecin, Institute of Legal Sciences, Poland*
[b] *University of Szczecin, Institute of Management, Poland*
[c] *Jönköping University, Business School, Sweden*
[d] *Cardinal Stefan Wyszyński University, Institute of Legal Sciences, Poland*

ABSTRACT

Purpose: *The publication aims to analyse ethics and governance in artificial intelligence (AI) management within organisations. It examines how ethical principles and governance mechanisms facilitate the responsible use of AI, taking into account both legal obligations and social expectations.*

Need for the study: *The study addresses the growing significance of AI in various sectors and the challenges it presents to society, the economy, and individual rights.*

Methodology: *An interdisciplinary approach is used, combining a literature review, legal analysis, and case studies. The study integrates legal, ethical, and technological perspectives to provide a comprehensive view of AI governance.*

Findings: *Three governance models are examined: regulatory, self-regulatory, and hybrid. The regulatory model offers legal certainty but limited adaptability. The self-regulatory model allows innovation and flexibility but may lack consistency in ethical norms. The hybrid model, which combines both approaches, is the most effective, striking a balance between structure and flexibility, and sharing responsibility.*

Practical Implications: *The article discusses the implementation of effective oversight mechanisms tailored to industry-specific needs and technological maturity. It emphasizes the need for a dynamic regulatory framework that adapts to technological advancements, while promoting self-regulation and private sector accountability. A balanced governance model—combining formal legal controls with voluntary industry standards—is essential for promoting safety, transparency, and ethical compliance in AI use.*

Keywords: Artificial Intelligence; Governance; Ethical; Management; Legal Rules

Jel codes: K23, Regulated Industries and Administrative Law; K30, General; K49, Other

1. INTRODUCTION

Artificial intelligence (AI) is becoming an increasingly common tool in organisational management, supporting decision-making, data analysis, process automation, and resource optimisation. It is becoming a key element of modern management, transforming decision-making processes, optimising organisational activities, and redefining corporate structures. AI systems are

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used in finance, healthcare, public administration, and human resource management, which opens up a wide range of possibilities, but at the same time raises serious ethical and legal challenges. AI encompasses a set of technological capabilities that provide new resources, opportunities, and applications for organisations and society (Berente et al., 2021). However, significant ethical and regulatory challenges arise with AI systems' increasing autonomy and influence. However, the rapid spread of artificial intelligence systems has given rise to risks associated with algorithmic opacity, unethical behaviour, and unintended consequences (Kroll et al., 2017). These concerns also relate to the potential of generative artificial intelligence to replace humans in the workforce, including issues such as technostress, bias in artificial intelligence algorithms, lack of transparency, and potential misuse of artificial intelligence technologies (Korzyński et al., 2024). The key issue, therefore, is to create supervisory mechanisms that will ensure the responsible implementation of AI, combining innovation with transparency and efficiency with responsibility. This involves establishing ethical, technical, social, and legal requirements to ensure that algorithms and data comply with standards, while also establishing ethical principles, acceptable practices, and regulations (LaBrie et al., 2019).

On the one hand, AI contributes to increased efficiency and precision in management by eliminating subjective human errors. On the other hand, its functioning can lead to a lack of transparency in decisions, algorithmic discrimination, violations of employee rights, and threats to privacy protection. The increase in AI autonomy raises key questions regarding legal responsibility for erroneous decisions made by algorithms. These issues require appropriate regulations and oversight mechanisms to control the technology and ensure its legality. The literature on the subject expresses the view that the expected increase in digital reliability and security incidents will exceed 1,000 cases per month by 2030. Incidents related to transparency, explainability, and accountability will also increase steadily, emphasising the need for a governance framework that prioritises these principles (Cebrian et al., 2025).

Currently, AI systems are subject to various regulations, depending on the jurisdiction and sector in which they are used. In the European Union, the AI Act Regulation plays a key role in artificial intelligence regarding risk and ensuring its compliance with fundamental rights. Other critical legal acts are: a) General Data Protection Regulation (GDPR) (Regulation (EU) 2016/679) – imposing an obligation to protect personal data processed by AI; b) The Directive on Liability for Defective Products (Directive (EU) 2024/2853), which may apply to erroneous decisions made by AI that lead to damages; c) European Charter of Digital Rights (European Declaration on Digital Rights and Principles for the Digital Decade), which defines the rights of users about digital technologies, including AI. Work is underway at the global level to harmonise regulations. The Organisation for Economic Co-operation and Development (OECD) and the United Nations (UN) are developing guidelines for the ethical use of AI. In the USA and China, regulatory approaches differ - the USA focuses on self-regulation of the sector, while China is introducing strict control over AI, especially in the context of its use in administration and national security.

The publication aims to analyse the challenges of AI governance, focusing on legal and regulatory aspects. In particular, the article focuses on identifying key legal and ethical issues related to AI, such as legal liability and compliance with data protection and human rights regulations. The authors analyse current legal regulations concerning AI, including the EU AI Act, GDPR, and national rules in selected countries. The aim is also to assess the effectiveness and impact of existing supervisory mechanisms on organisations' management practice. It also aims to formulate recommendations for effective legal solutions and governance models that can ensure the responsible implementation of AI in management. The basic research hypothesis is that current legal regulations concerning AI are insufficient, leading to the risk of abuse and a lack of responsibility for algorithm decisions. At the same time, in the authors' opinion, the lack of transparency of AI algorithms hinders effective governance and enforcement of regulations, which can lead to violations of human rights and business ethics. In contrast, implementing comprehensive AI audit and governance mechanisms can improve the quality of management and limit the risk of discrimination and abuse. Undoubtedly, EU regulations, such as the AI Act, can become a global model for AI regulation, influencing the shaping of technology policy worldwide.

AI governance is one of the key challenges of the 21st century. The lack of effective regulation can lead to serious legal and reputational consequences for organisations, such as sanctions for GDPR violations, lawsuits regarding algorithmic discrimination, or liability for AI decisions resulting in financial losses. Regulations such as the AI Act attempt to balance innovation and protecting

fundamental rights. Still, their effectiveness depends on implementing appropriate enforcement and auditing mechanisms. Organisations must therefore invest not only in AI development, but also in legal and ethical compliance systems to ensure the responsible management of this technology. The rest of this paper will analyse specific cases of AI use in management, assess the effectiveness of regulation, and present solutions for improving AI governance.

2. LITERATURE REVIEW

The issue of using artificial intelligence to improve decision-making processes and increase productivity is increasingly being addressed in the literature. Research focuses on using AI to identify patterns, analyse scenarios based on forecasts, learn from historical data, and recommend actions to optimise performance (Akerkar, 2019). The growing number of publications in this area reflects the increasing interest in the theoretical aspects of this technology and its practical applications in various sectors. The ever-increasing number of publications aligns with the growing number of publications analysing how artificial intelligence affects business models and corporate strategies. The academic study aims to investigate the role of artificial intelligence in transforming business models, emphasising the interaction between technological innovation and business strategy. The authors emphasise the long-term consequences of technological innovation for the economy and market competitiveness, and in the area of necessary legal changes (Oluwatoyin et al., 2023).

The topicality of artificial intelligence in various sectors is also determined by the fact that this issue is increasingly becoming the subject of scientific publications. This is in response to practice, as this field is dynamically developing. J. Laine, M. Minkkinen, and M. Mantymaki (Laine et al., 2024) review the literature by analysing and synthesising various approaches to ethical principles in the context of AI auditing and present relevant information for key beneficiaries of this process. Thanks to the publication, it is possible to identify the importance of such features as fairness, transparency, non-maleficence, responsibility, privacy, trust, beneficence, and freedom and autonomy in AI systems. In the authors' opinion, it is possible to distinguish three basic types of knowledge, i.e., guidelines, methods, tools, and frameworks for action, as well as awareness and increased capacity for action. Publications that address issues related to the use of AI contribute to the literature review by combining an analysis of the impact of artificial intelligence on education and the service market in the context of digitalisation and dynamic technological progress. Publications such as D. Badulescu et al. (Badulescu et al., 2025) provide theoretical justification and empirical evidence for adapting educational competencies to the requirements of the AI-driven labour market.

In literature, there is a trend towards analysing AI management methods from the perspective of specific sectors (e.g., medical, banking, agricultural, etc.). This is because each industry has unique needs, challenges, and regulations. This emphasises the fact that AI does not work in isolation. Its application in healthcare differs from its use in agriculture or law. For example, R. Dara, F. S. M. Hazrati, and J. Kaur (Dara et al., 2022) highlight the growing role of AI in digital agriculture, emphasising both its benefits and the ethical challenges it poses. The authors emphasise that AI can improve the efficiency of agricultural operations and support decision-making. On the other hand, they emphasise that its improper implementation can lead to negative consequences, such as violation of farmers' privacy, threat to animal welfare, or lack of responsibility for the effects of AI systems. Specific considerations complement the general considerations regarding AI's ethical aspects, transparency principles, and personal data protection.

3. METHODOLOGY

Studying ethics and governance in AI management requires a multifaceted methodological approach, including legal perspectives and ethical and managerial aspects. During the work on this publication, a multidimensional research approach was applied, combining the analysis of legal regulations, scientific achievements, and practical challenges related to the implementation of AI systems. The following research methods were used. Firstly, the dogmatic-legal method analyzes current legal norms, their interpretation, and application in practice. It focuses on the

systematisation of regulations and their interpretation. This method was used to analyse existing legal regulations, the understanding of standards concerning ethical and legal AI governance (e.g., the principle of transparency, algorithmic accountability, the right to explain AI decisions), as well as to examine the relationship between regulations and AI management practice in regulated sectors. Analytical methods were also applied to logically explore legal and ethical concepts, principles, and structures. Applying this method, the authors thoroughly reviewed the literature on the subject. This method was used to analyse ethical concepts applied in AI, verify the effectiveness of AI governance supervision, identify the risks associated with using AI systems, and analyse the risks associated with the lack of appropriate governance models.

The comparative law method was applied to a basic extent due to the lack of final regulations at the level of national legislators. In this respect, its use refers to comparing bare legal acts at the international, EU, and, in some cases, national level. This analysis aimed to identify similarities, differences, best practices, and the consistency of different legal acts regulating identical issues. Using this method, the authors compared EU regulations on AI with solutions used in the USA, China, or the UK, and analysed AI governance models. The result of this analysis was the identification of three models of AI governance, i.e., regulatory, self-regulatory, and hybrid, with an indication of their effectiveness in the areas studied. To a minimal extent, an empirical method was applied by observing real challenges related to the regulation and implementation of AI, which was possible thanks to the Authors' professional experience in the legal and management fields. The experiences of practitioners and cases of AI application in various sectors, such as healthcare, the financial industry, and the judiciary, were analysed.

The applied research approach allowed for a comprehensive assessment of the ethical and regulatory challenges in managing artificial intelligence. The integration of legal analysis, literature review, and observation of practical experiences made it possible to formulate conclusions relevant to both the academic community and entities involved in implementing and regulating AI systems.

4. AI MANAGEMENT GOVERNANCE

The dynamic development of AI is associated with both enormous innovative potential and risks to individual rights, public safety, and economic stability. In response to these challenges, various AI governance models have been developed to ensure that AI systems comply with legal, ethical, and technological standards. For this study, governance models have been distinguished based on the degree of state interference and AI implementers' autonomy level. As a result, three basic governance models have been identified: regulatory, self-regulatory, and hybrid. The rationale for adopting the above classification of AI governance model is primarily based on analyzing the degree of state interference (from centralised in the case of the regulatory model, through strong in the self-regulatory model, to mixed in the hybrid model). The level of autonomy of the entities implementing AI is also necessary, as the degree of freedom left to entrepreneurs and organisations in shaping the principles of responsible implementation of AI-related mechanisms is a crucial factor. In addition, different governance models have been noted in practice, depending on a given industry's risk and regulatory needs. As a result, the classification adopted allows for an analysis of the advantages and disadvantages of each model, their impact on innovation, security, and the development of AI.

4.1. Regulatory governance

The first of these, regulatory oversight, is based on strict legal regulations and enforcement mechanisms at the international, European, and national levels. This oversight model is based de facto on rules set at a higher level, obliging national legislators to implement them through state institutions and market governance bodies. This model can be described as centralised or direct. Under this model, the state legislates the rules for designing, implementing, and using AI, imposing obligations on entities regarding compliance, reporting, and auditing. An example of this approach is the EU AI Act, which classifies AI systems according to risk level and imposes different legal requirements. It is worth emphasising that despite the significant development of artificial intelligence and the large increase in its users worldwide, there was still no comprehensive legislation governing the situation of AI and its users until mid-2024. This situation changed on 1 August 2024 when the AI Act, published on 12 July 2024, came into force. It is the world's first

act to regulate artificial intelligence in such a comprehensive manner. The document in the form of a Regulation regulates safety, transparency, and compliance, the observance of which is to ensure the development and application of AI following the values of the European community. Due to the broad subject matter regulated in the AI Act, most provisions will come into force 24 months after its announcement. However, individual regulations will gradually come into force after 6, 12, or even 36 months. For example, rules banning the use of dangerous systems throughout the EU came into force in February 2025, and AI governance regulations will come into force in August 2025. The impetus for adopting the above act was the desire to harmonise rules on digital services in EU member states, thus avoiding fragmentation of the internal market. This harmonisation covers intermediary services in the internal market. It aims to ensure a safe, predictable, and trusted online environment, to counter the dissemination of illegal content online, and to address the social threats that the dissemination of disinformation or other content may pose (recital 9 of the AI Act). The Digital Services Act aims to build a safe and fair digital environment (Urbanowicz, 2025). Among intermediary services, the EU legislator in Article 3(g) of the AI Act distinguishes the service of: a) 'mere conduit' (transmission in a telecommunications network of information provided by a recipient of the service, or the provision of access to a telecommunications network); b) 'caching' (transmission in a telecommunications network of information provided by a recipient of the service, including the automatic, intermediate and temporary storage of that information, carried out solely to facilitate the subsequent transmission of the information upon request by other recipients); c) 'hosting' (storage on the information provided by a recipient of the service and at their request).

The wording of recital 153 of the AI Act is crucial from the perspective of the regulatory model, in which the EU legislator stipulates that the Member States play a key role in the application and enforcement of the regulation. In each national legal system, at least one notifying authority and at least one market surveillance authority should be designated as the national competent authority to supervise the application and enforcement of the AI Act. The EU legislator authorises Member States to establish any public entity to perform the tasks of national competent authorities, which, according to Article 3(38) of the AI Act, are notifying authorities or market surveillance authorities. By the regulation mentioned above, concerning AI systems put into use or used by EU institutions, bodies, and organisational units, the references to national competent authorities and market surveillance authorities contained in the AI Act should be read as references to the European Data Protection Supervisor. It is worth emphasising here that the AI Act and other EU data protection regulations (in particular the GDPR (Regulation (EU) 2016/679, 2016), EUDPR (Regulation (EU) 2018/1725, 2018) i LED (Directive (EU) 2016/680, 2016), and the e-Privacy Directive (Directive 2002/58/EC, 2002) must, in principle, be treated (and interpreted consistently) as complementary and mutually reinforcing instruments. The EU data protection regulations apply to processing personal data throughout the entire life cycle of AI systems, as explicitly stated in Article 2(7) and recitals 9 and 10 of the AI Act.

According to recital 10 of the AI Act, this regulation does not affect or modify the existing European Union regulations on protecting personal data, including the competences of independent governance bodies responsible for monitoring compliance with these regulations. It also does not change the obligations of providers and users of artificial intelligence systems who act as controllers or processors under national or EU law on protecting personal data if AI systems' design, development, or use involves processing such data. In addition, the AI Act does not limit the rights and safeguards of data subjects under EU law, including those related to decisions made solely by automated means, including profiling. According to Article 2(1) of the AI Act, this regulation applies to intermediary services offered to service recipients established or located in the EU, regardless of the place of establishment of the providers of these intermediary services. The EU legislator has not defined a closed list of purposes that a digital service must fulfil from the user's perspective to be considered an intermediary service. For this reason, it is worth emphasising at the outset that, in principle, any digital service that enables the transmission and storage of data will be considered an intermediary service, provided that it meets the criteria defined in the DSA (Urbanowicz, 2025). An intermediary service provider is any entrepreneur who offers these services on the European market. This means that the provider's activity consists of directing the services they provide to people in the EU, regardless of the country in which the provider operates.

Another characteristic of the regulatory model is that the EU legislator recommends that Member States designate, following national law, one or more authorities and entrust them with supervising the

application and enforcement of the AI Act. The recommendations of the AI Act, as expressed in recital 109, give EU countries flexibility in the extent to which they can assign tasks and competences to existing bodies in specific sectors. Consequently, various legal forms of governance bodies are permissible, meaning they can function within already existing administrative structures. This sectoral approach allows for the assignment of specific competences to bodies already operating in the relevant areas, e.g., electronic communications authorities if the regulation concerns telecommunications, media regulatory authorities if it concerns the governance of media content, or consumer protection authorities if the regulation relates to the protection of consumer rights. It can therefore be assumed that the EU legislator, in creating a general framework for governance in AI management, respects the diversity of constitutional and administrative structures in the Member States, leaving them free to organise governance. As a result, this can lead to different governance models in individual countries, e.g., centralised, where one body supervises the entire regulation, or decentralised, where competences are distributed among several institutions. However, coordination between the various authorities is crucial to avoid confusion over competences and the dispersion of responsibilities. In practice, this may require the creation of a framework for cooperation and information exchange between authorities, e.g., through the conclusion of inter-agency agreements, or the creation of joint supervisory and sanctioning procedures. Thus, the EU legislator focuses on flexibility and adaptation to national realities, while requiring effective governance. The key challenges are ensuring consistency in enforcement and effective coordination between the various authorities, especially in countries that divide competencies.

It is also worth noting that in recital 113 of the AI Act, the EU legislator gives EU countries the option of designating an existing national authority to act as a Digital Services Coordinator or to perform specific tasks to oversee the application and enforcement of the AI Act. This is conditional on such a body meeting the requirements set out in the regulation, including, in particular, its independence. This may require an adjustment of the body's competences, e.g., by strengthening its operational and financial autonomy. The regulation allows Member States to combine different regulatory functions in a single body, if compatible with EU law. For example, the governance functions over digital platforms can be assigned to a body that governs media, telecommunications, or consumer protection. However, as mentioned above, the recital clearly states that it must not weaken their independence if the state decides to reorganise the governance bodies. The EU legislator specifies in this respect that the chair or board members of a collegial body cannot be dismissed before the end of their term of office solely because of an administrative reform if there are no guarantees of their continued independence. This regulation aims to protect against a situation in which the government could interfere with the composition of the bodies to increase political influence on their activities. When analysing the above recommendations and principles created by the EU legislator, it is reasonable to assume that Member States are given flexibility while maintaining the independence of governance bodies. This is particularly important in digital services, where effective governance of online platforms requires autonomy from political pressure and market interests. Member States may therefore reform their governance structures, but they must do so in a way that does not undermine regulatory effectiveness or public trust. This provision allows flexibility in the governance of digital services but sets precise requirements for the independence of governance authorities. Institutional reforms must not be used to remove inconvenient regulators or weaken law enforcement.

Consequently, it should be emphasised that Member States are required to designate or establish three types of authorities in the implementation of the EU AI Act, i.e.:

a) Market Surveillance Authority (MSA), whose task will be to implement the measures provided for in Regulation (EU) 2019/1020 on market surveillance and product compliance; this institution is based on the already existing and well-established concept of market surveillance authorities in EU law, and its main task will be to ensure that only products that meet EU legal requirements are on the EU market (Art. 3 No. 26 AI Act);
b) Notifying Authority (NA), i.e. the national authority whose task will be to establish and implement a procedure for the assessment, designation and notification of conformity assessment bodies, as well as for their governance (Article 3(19) and Article 28(1) AI Act); in this group of entities, ‘Conformity assessment bodies’ should also be distinguished. Entities performing third-party conformity assessment activities, including testing, certification, and inspection (Article 3(21) AI Act). According to Article 3(48) of the AI Act, the notifying and market surveillance authorities are jointly referred to as National

Competent Authorities (NCAs). Consequently, they must function independently, impartially, and without bias, have adequate technical, financial, and human resources and infrastructure to effectively perform their tasks by the Artificial Intelligence Act, as confirmed by the wording of Article 70(1) and (3) of the AI Act.

c) National Public Authorities (NPAs), which will be responsible for enforcing the obligation to respect fundamental rights in the Member States in the context of high-risk AI systems; they should have the power to request and access any documentation drawn up or stored under the AI Act, if this is necessary for the effective fulfilment of their mandate within their jurisdiction (Art. 77 (2) AI Act).

Transferring the above considerations to the practical aspects of implementing the AI Act in member states, it is worth noting that the European Commission established the European Artificial Intelligence Authority in February 2024. This authority supervises the enforcement and implementation of the act on artificial intelligence in EU member states. Some EU countries have already taken steps towards establishing governance authorities responsible for their implementation. According to the AI Act, Member States are required to designate market surveillance authorities at the national level by 2 August 2025. Legislators in the Member States are working on creating appropriate mechanisms and governance bodies to supervise the application and implementation of the AI Act. Each Member State must designate the appropriate authorities and publish a list.

In September 2023, Spain, by Royal Decree No. 729/2023 (Real Decreto 729/2023, 2023), established an AI governance agency (esp. *Agencia Española de Supervisión de Inteligencia Artificial,* AESIA) based in A Coruña. AESIA is a specialised body responsible for governance, advice, awareness raising, and training related to the development and use of artificial intelligence at the national level. Its tasks include ensuring compliance with national and EU regulations on AI, coordinating the implementation and application of the regulation's provisions, and cooperating with the EU AI Office and market surveillance authorities from other Member States. In addition, AESIA promotes AI innovation in the public and private sectors by creating regulatory sandboxes and developing best practices. In other EU member states, discussions are taking place on the designation of appropriate governance authorities for the AI Act. The position of the European Data Protection Board (Statement 3/2024 on data protection authorities' role in the Artificial Intelligence Act framework, 2024) is worth mentioning, according to which data protection authorities should play an essential role in enforcing the AI Act. In this context, these bodies are recommended to act as market regulators, especially for high-risk AI systems used in law enforcement, border management, and the judiciary (Statement 3/2024). The justification for this position is that the data protection authorities, in connection with the EU General Data Protection Regulation, have experience and knowledge of the impact of AI on fundamental rights. As of today, 23 EU countries, i.e. Austria, Belgium, Bulgaria, Croatia, Cyprus, the Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Romania, Slovakia, Slovenia, Spain and Sweden have appointed the relevant authorities and published a list of tchem (Artificial intelligence act management and enforcement). When analysing the overall status of National Authorities, it should be emphasised that as of 8 November 2024, the unclear status of authorities concerned 16 MSAs and NCAs and 12 NPAs, partial clarity was identified for 10 MSAs and no NCAs, and clarity concerns 1 MSA and 15 NCAs (Overview of all AI Act National Implementation Plans, 2024). This data clearly shows the ongoing work of national legislators. The Polish legislator is also developing rules for implementing the AI Act. During the pre-consultation organised by the Ministry of Digital Affairs, most participants favored creating a new market governance body instead of transferring these powers to existing institutions, such as the President of the Office for Personal Data Protection. In response to these demands, the Ministry of Digital Affairs announced the creation of an AI governance committee, which is reflected in the draft law on artificial intelligence systems (Draft Polish law on artificial intelligence systems, 2024, October 17, No. UC71, 2024). The Commission for the Development and Security of Artificial Intelligence (KRiBSI) is intended to be the market governance authority for artificial intelligence systems within the meaning of Section 70 (1) of the AI Act. It will act as a single point of contact. According to the will of the initiator, KRiBSI is to cooperate with several existing authorities and ministries. In addition to its governance activities, the Commission's role is primarily to strengthen the artificial intelligence industry and act as an expert entity cooperating with other public institutions in AI.

In conclusion, it seems reasonable to assume that the regulatory model for AI management governance created by the EU legislator is quite demanding, while at the same time giving Member States freedom to shape the structure of entities equipped with governance competences. The AI Act defines a general legal framework, but leaves room for national legislators to clarify the regulations. There is no doubt that, despite the ongoing technological process, many EU countries do not yet have sufficient technical and human resources to analyse and supervise AI systems effectively. National legislators in EU countries face numerous challenges in implementing the AI Act, including legal, organisational, and technological aspects. A lack of adequate human and financial resources can slow the process, and differences in approach between EU countries can lead to market fragmentation. However, it is clear that in Poland and other EU countries, the implementation of the AI Act is in progress, with varying degrees of progress and challenges. However, there is no doubt that each Member State faces the challenge of implementing the AI Act in a way that, on the one hand, provides adequate protection against AI-related risks and, on the other hand, prevents the inhibition of innovation.

4.2. Self-regulatory governance

The second AI governance model distinguished for this study is self-regulatory governance. It includes all internal standards that establish artificial intelligence standards in the activities of entities using AI systems. Legislative measures taken at the EU level have therefore given private sector companies an incentive to get involved in developing and implementing artificial intelligence (Taebi, 2019), and international efforts are currently being made to achieve this goal. It must be admitted that China was the first country to regulate AI. However, due to the two divergent objectives of China and the European Union, it is considered that the AI Act is the world's first act regulating issues related to artificial intelligence. China has chosen to strengthen state control over the content provided to citizens, while the EU has set itself the goal of minimising the damage caused by the use of AI by European citizens (Maciążka, 2025). Other non-EU countries also recognise the need to regulate AI. The UK is one such country. However, in this case, it was decided that the regulations should support the development of artificial intelligence rather than restrict it. Therefore, the rules adopted are selective, more flexible, and certainly not comprehensive. In the USA, there are currently no federal regulations on AI. However, there are regulations in individual states; bills in this context have been passed in 45 states. The legislative situation regarding artificial intelligence is also influenced by political decisions leading to the repeal of the executive order on the safe and reliable development and use of artificial intelligence. President Donald Trump has already announced that he will begin work on AI regulations. Still, they will be aimed primarily at strengthening the American AI industry, which may mean he will not continue with the concept proposed by Joe Biden.

Significantly, since 2 February 2024, suppliers and AI system users have been obliged to ensure that their employees have the appropriate AI knowledge and skills necessary to perform their tasks. This obligation covers the area of AI competence, so-called AI Literacy (Article 4 AI Act). According to the regulation mentioned above, providers and users of artificial intelligence systems should ensure adequate knowledge and skills in AI among their personnel and persons responsible for the operation and use of these systems. The level of required competences should take into account: the level of technical knowledge, professional experience, level of education and training, the specifics of the context in which AI will be used, as well as the characteristics of individuals or groups to whom AI systems will be applied. Thus, the EU legislator emphasises the need to ensure adequate competence among persons and entities responsible for implementing artificial intelligence systems. This is crucial from the perspective of minimising the risk of errors, as a lack of technical knowledge can lead to the misuse of AI systems. This, in turn, can result in violations of personal rights, discrimination, or incorrect algorithm decisions. It is also essential to ensure the safe and ethical use of AI. Proper personnel training helps to consciously implement and supervise AI systems by legal and ethical standards. It is worth noting here that doubts about industry self-regulation also characterise the current debate on the ethics of AI. Dealing with the moral challenges of artificial intelligence has become a priority for legislators worldwide. This issue is analysed later in this paper. Ensuring that those who manage and use AI have the right skills is essential to adapt skills to the context and audience. EU legislators emphasise that knowledge requirements should consider the specific nature of the situation in which AI is used; for example, different skills will be required in healthcare than in the financial

sector. The obligation to ensure employee competence means that organisations cannot use a lack of knowledge as an excuse for AI errors or malfunctions, which positively strengthens the responsibility of both AI providers and users. The self-regulatory model means that those who use and manage AI must determine what educational and training measures are necessary for implementation and what promotes self-regulatory governance mechanisms in AI management. The justification for creating internal regulations for AI management in a broad sense is therefore the pursuit of responsible and ethical use of this technology.

Regarding the text of the AI Act, recital 88 of the aforementioned legal act is also of significant importance, in which the EU legislator obliges providers of huge online platforms and substantial online search engines to exercise due diligence in the measures taken for testing. It is recommended that they adapt their algorithmic systems, particularly their recommendation systems, if necessary. The aim of implementing self-regulatory solutions is to ensure that AI systems are developed and implemented ethically, safely, and in accordance with applicable laws and social standards. As indicated, the AI Act has broad application for companies in various industries, not only those related to IT or artificial intelligence. The new regulations cover suppliers, distributors, and importers from all EU member states. This, in turn, generates several obligations for them. Suppliers of AI systems, especially those considered high-risk, must carry out a risk assessment, submit technical documentation, and guarantee the system's highest level of security and transparency. In addition, they must systematically audit compliance and adapt subsequent technologies to the requirements specified in the AI Act. This means these entities must develop a clear and systematic approach to regulatory compliance, affecting their internal structure and day-to-day operations.

This means that processes must be implemented to identify, assess, and minimise the risks associated with artificial intelligence. This will be reflected in the creation of risk management procedures. Each new version of an AI system should be evaluated for potential risks (e.g., discrimination, unforeseen decisions). Artificial intelligence system providers should also monitor whether AI systems cause unintended consequences (e.g., misjudgment of customers in credit systems). Within this area of self-regulation, it seems reasonable to establish and adopt procedures to be followed if irregularities are detected, including the possibility of immediate intervention in the event of AI malfunctioning. It is also important to create methods to control the technical documentation of AI systems, which should undoubtedly be created and updated. This documentation should include descriptions of the system's operation and algorithms, testing and validation methods, and measures to ensure compliance with regulations, including the AI Act. Simply creating internal regulations without regularly reviewing them will be pointless. For this reason, it is essential to regulate the conduct of compliance audits and AI quality control. In practice, AI compliance teams should be separated in the organisational structure of AI system providers responsible for monitoring and controlling processes. In this context, these entities may be required to adopt external certifications confirming the compliance of their systems with EU regulations.

Distributors and importers, on the other hand, are responsible for verifying that the AI systems they place on the market comply with the legal regulations in the AI Act. In the event of violations, they may bear similar liability to suppliers. As for users, their situation is also regulated in the AI Act. Their responsibilities include monitoring AI systems, reporting problems, and confirming that the technologies provided are being used for their intended purpose and in accordance with the supplier's instructions (Naron-Grochalska, 2024). In light of the above, it is possible to assume that the AI Act places great emphasis on self-regulation by obliging entities to create internal regulations and procedures to ensure compliance with new legal requirements and the ethical and responsible use of artificial intelligence. However, it is still necessary to continue researching the moral management of artificial intelligence and how companies can create value that benefits both business and society (Naron-Grochalska, 2024).

The self-regulatory governance model assumes that AI system providers are responsible for developing and implementing internal regulatory compliance oversight systems, including risk assessments, risk mitigation strategies, and specific countermeasures. The EU legislator's call for creating codes of conduct is intended to facilitate the independent monitoring of and response to potential law violations. It can therefore be assumed that internal supervision is de facto based on the organisation's independent commitment to creating and implementing ethical and legal standards. Suppliers are obliged to ensure transparency of their activities and to provide mechanisms to assess the

effectiveness of their governance systems. It is worth emphasising, however, that the self-regulatory governance model, although more flexible than regulatory governance, carries the risk of inconsistent application of standards and difficulties in ensuring complete transparency and accountability.

4.3. Hybrid governance

The third and final supervision model is a hybrid model, which combines public and private elements. In this case, we are talking about recommendations and guidelines constituting so-called soft law, addressed primarily to AI system providers regarding desirable solutions in internally created procedures and standards. Soft law guidelines are voluntary measures regulating the ethical development and implementation of artificial intelligence (Bietti, 2020). Cooperation between public governance and self-regulatory systems is crucial in the hybrid governance model. This applies to both the exchange of information, the assessment of risks, and the conduct of audits. In the former case, the legislator will define the rules for managing specific areas, and suppliers must provide information on their activities. In the case of risk assessment and auditing, both external (regulatory) and internal (self-regulatory) governance should cooperate in conducting risk assessments and audits to identify potential sector-specific risks (e.g., in the case of advertising, this concerns manipulation and disinformation). In this model, the EU or national legislator suggests the necessary measures, but the final decision-maker in this context is the entity managing the AI system. It is up to these entities to decide whether the recommended solutions will be introduced into the supervision. Recital 21 of the AI Act emphasises that the European Commission and the Member States, cooperating with relevant stakeholders, should facilitate the development of voluntary codes of conduct to improve AI competence among those involved in developing, operating, and using AI. This is a direct manifestation of the hybrid model of AI governance and AI management.

This requirement is expressed in recital 117 of the AI Act, as the EU legislator stipulates that codes of practice should be one of the main tools for properly fulfilling the obligations under the AI Act for providers of general-purpose AI models. Suppliers should be able to rely on codes of practice to demonstrate compliance with these obligations. The EU legislator indicates that codes of practice are the primary tool enabling providers of general-purpose AI models to demonstrate compliance with the obligations under the AI Act. This mechanism is crucial for self-regulation because it allows AI providers to develop compliance rules. Looking at the codes of good practice in personal data protection in individual sectors created in connection with the GDPR, it is possible that the codes of practice are not rigid regulations imposed by law. They are industry standards that can be developed by AI providers themselves or sector organisations. Due to the diversity of AI systems and the sectors for which they are implemented, codes of practice will enable a differentiated approach depending on the type of AI model. This means that AI system providers can adapt risk assessment, testing, transparency, and security procedures to the specifics of their systems.

Despite the wide range of freedom in the actions taken by AI system providers, the fundamental rule that codes of good practice must be in line with the general objectives of the AI Act should not be overlooked. Importantly, self-regulatory governance can occur under the supervision of the European Commission and the AI Office, as the AI Act provides in recital 117 that the EC can endorse codes of practice, giving them general validity in the Union. However, if the codes are not created or prove insufficient, the EC can introduce implementing acts, which means the possibility of regulatory interference in the event of ineffective self-regulation. However, if the code of practice is approved, its application implies a presumption of compliance with the AI Act, which limits the risk of sanctions and regulatory controls. However, AI suppliers can also use alternative means of demonstrating compliance, giving them freedom of choice within the self-regulation framework.

One example of an area where such recommendations would be justified is the advertising sector. As indicated in recital 95 of the Digital Service Act (DSA) (Regulation (EU) 2022/2065, 2022), the use of AI systems in advertising, especially in the case of extensive online platforms (e.g. Google, Facebook) and search engines, is based on advanced algorithms that analyse vast amounts of user data to target advertising. The aim is to tailor advertising content to individual user preferences, often based on their previous interactions with the platform, online behaviour, and demographic data. These systems create the risk of information manipulation, privacy violations, or insufficient oversight. Advertisements can be used to spread misinformation, which can negatively affect public health, security, or civil discourse.

In turn, using users' data without complete transparency about what data is collected and how it is used can lead to a breach of privacy. In Article 22(3) of the GDPR, the EU legislator establishes that every user should have the right to obtain explanations and challenge AI decisions. Despite the use of advanced technology, these systems often operate in a problematic way to monitor, which minimizes the possibility of ensuring full accountability for their operation. For this reason, the necessity of public supervision over these systems is emphasised. The measures provided for by the EU legislator include advertising repositories. It is assumed that extensive online platforms and search engines should provide access to advertising repositories to facilitate public supervision. These repositories are intended to contain the content of advertisements (name of the product, service, brand), information about the advertisers and entities that paid for the ad, the targeting criteria of the advertisements, and data about the audience, including details about the targeting of vulnerable groups (e.g., minors). The repositories aim to increase transparency and enable regulators and the public to monitor and investigate the risks associated with the distribution of advertisements, including disinformation and manipulation. The hybrid governance model is a response to the challenges of AI governance in advertising, which combines elements of external (regulatory and governmental) and internal (service providers such as online platforms) governance. In this case, the regulatory model will manifest in public repositories of advertisements and regulatory control. In contrast, the self-regulatory model will manifest itself in risk management, defining the principles of corrective action and creating codes of practice.

When discussing other areas where the hybrid AI governance model can be applied, it is worth considering the labour sector. AI systems used in recruitment processes, employee performance analysis, and team management can lead to risks related to discrimination, breach of privacy, and lack of transparency in decision-making processes. For example, the Swedish system, Swedish Public Employment Services (PES), is worth mentioning. Its goal is to connect job seekers and employers effectively and contribute to long-term employment. Labour market policy evaluations are no longer carried out manually by employees, but mainly using a statistical profiling tool (Berman, 2024). The hybrid model in the labour sector means that, in regulatory terms, data protection authorities and employment agencies are authorised to supervise compliance with privacy and equality regulations in recruitment processes and employee management to prevent discrimination based on race, gender, age, or other characteristics. The self-regulatory model in this context means that companies using AI in recruitment must introduce procedures to control recruitment algorithms to ensure fairness and transparency. They should also provide accountability for decisions made by AI, including the ability to explain them to candidates.

Another example is the transport sector, including aviation. In Europe, the European Union Aviation Safety Agency is responsible for certifying and approving aviation systems (The Agency." European Union Aviation Safety Agency, 2024). For certification, EASA defines the regulations that the system developer must meet. Therefore, to enable the use of AI-based systems in aviation, EASA, in cooperation with other stakeholders, is currently developing a framework of guidelines to ensure the reliability of AI-based systems (Artificial Intelligence Roadmap 2.0, Human-centric approach to AI in aviation, 2023). As emphasised in the literature, the human factors framework for AI considers the human factors associated with its use, and the framework for mitigating the security risks of artificial intelligence introduces steps to deal with the uncertainty of artificial intelligence (EASA Concept Paper: Guidance for Level 1 &2machine learning applications, A deliverable of the EASA AI Roadmap, 2024). In this case, external (regulatory) supervision is carried out by government agencies and road safety authorities, such as the European Aviation Safety Agency (EASA) or national transport agencies. They will approve new technologies and monitor their performance in real-world conditions. In the case of self-regulatory governance, for example, manufacturers of autonomous vehicles must conduct their safety tests and audits, develop procedures for liability in the event of accidents, and apply transparency rules regarding decisions made by the AI systems in these vehicles.

A further sector worth noting is digital agriculture. Artificial intelligence can help ensure sustainable production in agriculture by streamlining farming operations and decision-making. However, improper design and configuration of intelligent systems can result in damage and unintended consequences for digital agriculture. Examples of challenges in digital agriculture include: violation of farmers'privacy, destruction of animal welfare due to robotic technology, and lack of responsibility for issues arising from the use of AI tools (Dara et al., 2022).

The hybrid supervision model is applicable in many areas where AI systems significantly impact people's lives and society. These include health, finance, transport, education, work, and agriculture. A key element in these cases is a combination of external (regulatory) and internal (self-regulatory) governance, which ensures more comprehensive risk management and compliance with applicable regulations and social values. In conclusion, it seems reasonable to assume that codes of practice are a self-regulatory model's primary form of governance. They ensure flexibility by allowing AI suppliers to determine how they will meet regulatory obligations. They can also be created by AI sector organisations, which will encourage the development of industry standards. This self-regulation can occur under EU supervision, which can determine the dissemination and development of good practices in individual sectors. Consequently, it is possible to assume that the self-regulatory governance model is based on an industry initiative, but with an EU control mechanism. This means that tech companies have the opportunity to remain autonomous in their activities, but they must act responsibly to avoid regulatory interference.

5. CORE AREAS OF GOVERNANCE IN AI

Given the subject of this study, it is essential to emphasize that issues concerning supervision in AI management encompass both internal and external areas. Regarding internal regulation, it is crucial to establish mechanisms that ensure the implementation of AI systems in compliance with rules at both the European and national levels. In the external area, on the other hand, AI system providers have a responsibility to ensure transparency, explainability, and accountability, as well as to strive to limit algorithmic bias and ensure the security of personal data. This, in turn, requires the development of information policies, e.g., indicating how users can assert their rights in the event of erroneous decisions by the AI system. This area is primarily addressed to users of the AI systems offered. In the AI Act, the EU legislator employs terminology commonly used in the scientific literature on XAI, such as transparency, opacity, and comprehensibility. In practice, this means that AI systems must be developed to ensure sufficient transparency and enable users to interpret their results correctly (Panigutti, 2023). When analysing the area related to ensuring transparency and explainability, it is essential to emphasise the obligation to provide users with clear information and rules of AI system functioning, as well as mechanisms for explaining decisions made by the AI system. Providing remedies for entities affected by AI decisions (e.g., in banking or recruitment systems) is also necessary. AI systems must be interpretable, showing how decisions are made and what factors are considered (Ausloos, 2020). With the development of autonomy and learning capabilities, modern artificial intelligence is increasingly developing algorithmic models. It generates results that are only understandable to a narrow group of specialists, remaining opaque to others, and in some cases, even impossible for society to interpret. The complexity concerns the algorithms responsible for autonomy and machine learning, as well as the contexts of their application, which are characterized by increasing diversity and complexity (Berente et al., 2021).

Transparency is therefore a key principle of ethical AI, which plays a vital role in building trust. It should be equated with openness in policies, actions, and regulations, which fosters better communication, common understanding, and cooperation. This is a foundation present in many frameworks for AI ethics. For example, according to the OECD's transparency principle (Ryan, 2020), Individuals should be informed about their data collection, participation in automated AI-based decision-making processes, and the decisions made about them resulting from the use of this data. The inability to interpret and understand the results of an AI model constitutes a violation of the principle of transparency (Jobin, 2019). Transparency means that AI systems are designed and used in a way that ensures they are traceable and explainable. This includes informing users that they are dealing with AI and providing relevant information to those who use these technologies about their capabilities and limitations. Furthermore, those affected by the AI should be aware of their rights in this context (recital 27 of the AI Act).

The term 'interpretable artificial intelligence' refers to the extent to which humans can understand the functioning and results of AI algorithms (Slack, 2019). Consequently, the transparency of AI systems should be equated with the availability of information, the rules for its provision, and how this information can practically or epistemically support the user's decision-making process (Mittelstadt,

2016). Transparency ensures that the artificial intelligence system provides information about its decision-making processes, allowing its beneficiaries and users to understand its performance and limitations by explaining, interpreting, and reproducing its decisions (Mohseni, 2021). Methods for making artificial intelligence systems transparent and comprehensible can be divided into three categories: pre-modelling (explaining data sets), internal modelling (creating models that can be interpreted), and post-modelling (building surrogate models) (Kaur, Uslu et al., 2022). Increasing transparency in AI management is intended not only to improve user confidence but also to enable the identification and elimination of potential errors or unethical activities. An important aspect is ensuring accountability and monitoring, including verifying compliance with applicable regulations, which may involve self-regulation by organisations and external oversight mechanisms established by the EU or national legislators. In conclusion, it is worth emphasising that transparency plays a fundamental role in the development of AI technology, especially in the face of the growing autonomy of systems and their applications in many fields, such as medicine, finance, and law, where errors in decision-making can have serious legal and social consequences.

The issue of explainability is closely related to the XAI mechanism. It is worth noting that in recent years, the scientific community has addressed the topic of black-box AI models (i.e. models that are too large or too complex from a technical point of view to be understood by humans), focusing on developing techniques to explain the decision-making processes of these models in a way that is understandable to humans, creating the field of eXplainable AI (XAI) (Doshi-Velez, Kim, 2017). The term 'black-box AI' refers to artificial intelligence systems whose mode of operation is difficult or impossible for humans to fully understand. This concerns advanced models that process vast amounts of data and make decisions based on complex patterns and relationships. Due to their complexity, users cannot trace the logic behind a given result, which raises challenges related to explainability, accountability, and potential algorithmic biases (Panigutti, 2023). These systems are characterised by a lack of complete transparency, which makes it difficult to analyse their operation. In technical literature, the terms 'explainability' and 'interpretability' are often used interchangeably. However, it is worth noting that their meanings may vary depending on the context (Adadi & Berrada, 2018). They refer to the extent to which it is possible to comprehend the structure of the AI model, its results, and the decision-making processes it employs. The High-Level Expert Group on Artificial Intelligence (HLEG), appointed by the European Commission, developed guidelines on the ethics of artificial intelligence in April 2019 (High Level Expert Group on Artificial Intelligence, 2019), according to which explainability means 'the ability to explain both the technical processes in the AI system and the decisions made by humans in the context of its applications'. However, it is worth noting that the question of what constitutes a 'good explanation' that is understandable to humans remains the subject of scientific debate (Miller, 2019). This is mainly due to the fact that there is no clear, generally accepted definition of a 'good explanation' in the context of AI. This is important because different fields may have different expectations regarding transparency and how AI decisions are presented. In the regulatory and ethical context, the lack of a clear definition can hinder the implementation of appropriate legal and technological standards, which is why this topic remains a key area of research and discussion.

Another area of supervision in AI management is data protection and user privacy (Okonkwo, 2020). According to recital 27 of the AI Act, privacy protection and data management involve developing and using AI systems in accordance with data protection regulations, while ensuring that information processing processes meet stringent quality and integrity standards. This issue is crucial for oversight in AI management, primarily because AI system operations require data, often including personal data. The large datasets collected in the systems can compromise the privacy of individuals whose data is disclosed. Data privacy protects individuals from being identified or linked to specific information, as automated decision-making systems can risk violating the privacy of data subjects by exposing their information to potential unauthorised disclosure or use (Mökander, Morley et al., 2021). The obligation to maintain privacy guarantees against unauthorised transfer of information, which would constitute data processing contrary to the purpose for which it was collected. From the perspective of this study, it should be emphasised that privacy issues include the challenges and values associated with data protection and the safeguarding of private and personal information (Jobin et al., 2019). Data privacy should be considered to protect individuals from being identified or linked to specific pieces of information. Automated decision-making systems can expose decision-makers to violations of the decision (Mökander & Morley, 2019; Weder et al., 2022). Privacy protects the data, including sensitive

data, provided by an individual or collected by an artificial intelligence system, safeguarding it from unjustified or illegal collection and use (Kaur, 2022). According to Article 22 of the GDPR, everyone has the right to protection against automated decision-making, including profiling. The AI Act develops and supplements these principles by introducing more detailed regulations for AI systems, particularly those with high risk. For this reason, it should be emphasised that using AI in terms of privacy requires the assumption that privacy ensures that sensitive data provided by an individual or collected by an AI system is protected from unjustified or illegal data collection and use. This is because they can be misused and have harmful consequences. Furthermore, according to Article 22 (4) GDPR, making decisions based on special categories of personal data (e.g., racial origin, political opinions, biometric data) is prohibited unless certain conditions are met. The AI Act supplements this provision by specifying additional data protection safeguards for the use of AI.

When assessing the relationship between the AI Act and the GDPR, it is crucial to recognise the complementary nature of the two acts. The AI Act expands and clarifies the principles outlined in Article 22 of the GDPR, particularly regarding the transparency of AI systems, human oversight, and the possibility of appealing decisions made by algorithms. Together, they form a legal basis that limits the use of black-box AI and ensures greater control over the impact of artificial intelligence on the lives of citizens. Other countries are also taking steps to regulate the use of black-box AI. For example, the United States has published the Blueprint for an AI Bill of Rights (Blueprint for an AI Bill of Rights), emphasizing the importance of transparency and explainability of AI systems. However, it is not a binding legal act. China, on the other hand, has introduced regulations requiring AI systems to be auditable and subject to evaluation before implementation, aiming to increase transparency.

In summary, EU legislators aim to limit the use of non-transparent AI models by designing the AI Act and the GDPR. To achieve this goal, it imposes obligations related to transparency and explainability. There is no doubt that these measures aim to ensure that AI systems operate in a way that is understandable to users and are subject to appropriate control.

6. THE IMPORTANCE OF ETHICAL PRINCIPLES FOR EFFECTIVE GOVERNANCE IN AI

As indicated, the rapid development of AI has motivated many social groups to debate its ethics. This topic is very popular among philosophers, engineers, politicians, and lawyers today. The conclusions that follow from these deliberations reach ordinary users who utilize the ever-evolving possibilities of digital tools every day (Rudnicka et al., 2020). Various organisations and institutions are increasingly addressing the issue of ethics in AI. These include national and international organisations, governmental and non-governmental organisations, as well as representatives from the commercial sector. By April 2020, these entities had issued 167 guidelines in this context. The proposed guidelines, on the one hand, are the result of the rapidly developing and ubiquitous AI. On the other hand, they carry many errors, risks, and limitations. They result from AI not creating intelligent behaviour, but only imitating it (McAfee, 2016).

The dynamic development of artificial intelligence creates enormous opportunities for many areas of life. However, rapid growth also brings ethical challenges. Effective management of emerging challenges will protect humanity, particularly in the areas of privacy and data protection. Any data obtained by AI must be processed securely to prevent unauthorized access and the unethical or illegal use of the data (Skrzecz, 2024). Therefore, standardising and regulating international ethical principles is necessary for proper and adequate supervision in AI management. This includes both the creation of a regulatory framework for AI and the implementation of audit and compliance systems, including ethical tests. Outsourcing tasks to AI can generate several abuses, the elimination of which will be a moral challenge (Taddeo and Floridi, 2016). To meet these challenges, it will be necessary to conduct an audit procedure based on ethics, i.e., capAI (Mökander & Axente, 2016). It enables the most precise compliance assessment by identifying abuses and modifying unethical behaviour. In addition, it provides in-depth knowledge of ethical considerations when designing similar systems. Importantly, the AI Act outlines the principles for conducting an audit (Mökander, Axende et al., 2021). Large-scale, ethically based audits of this kind will make it possible to avoid AI failures or improve the chances of successful system repair. In addition, they will clearly explain the causes of the failure. A correctly

performed CAI audit will enable organisations to design better, less failure-prone artificial intelligence systems. The functioning of capAI is straightforward and very effective. Thanks to the control, it is possible to eliminate the most common failure modes.

When analyzing the issue of ethics in effective AI management, it is crucial to emphasize that building public trust in AI is essential. As indicated, the Ethics Guidelines for Trustworthy Artificial Intelligence were published in April 2019. This study presents the desired perspective for developing and applying artificial intelligence in EU countries. In brief, it seeks to ensure that the development of AI in Europe respects democracy, the rule of law, and fundamental rights. Citizens should feel confident that they can safely use AI tools without risk of harm from the system (Chojnowski, 2025). The trustworthy AI has three characteristics that must be present simultaneously throughout the system's entire life. These are: legality, ethics, and reliability.

As far as legality is concerned, as the name suggests, AI should comply with generally applicable law, i.e., legislation and implementing acts. There is also no doubt about ethics; in this case, the functioning of AI should always follow ethical principles and values. The third characteristic – reliability – may raise doubts. This characteristic should be interpreted in two dimensions, both technical and social. After all, abuse can also occur when AI is used in good trust (Ethics guidelines for trustworthy artificial intelligence, 2019). So, it remains to be seen how to strengthen public confidence in AI. The answer to this question is clear – the regulatory framework for AI still needs to be strengthened. Regulations should always prioritise the safety of AI users and should be comprehensive and uniform. A milestone in this direction has already been achieved, namely with the entry into force of the AI Act.

At this point, it is also worth mentioning the Organisation for Economic Co-operation and Development (OECD) again, which laid the foundations for AI governance in 2019. According to the OECD, artificial intelligence can address challenges in education, healthcare, science, and climate action. At the same time, the organisation believes that AI poses several risks, especially to its users. These risks can be mitigated through effective governance that is based on legal regulations. In addition, the International Organization for Standardization has published ISO/IEC 42001:2023, a document designed to support organizations in using artificial intelligence systems. The document outlines principles and values to ensure that AI is developed and deployed in the best interest of society (ISO/IEC 42001:2023, 2023). The accepted standards promote the ethical and lawful use of AI through: transparency and explainability, fairness and non-discrimination, privacy and data security, responsibility and accountability, stakeholder engagement, continuous improvement, and learning. Artificial intelligence offers numerous benefits, including increased efficiency, task automation, enhanced decision-making, and support for data review. However, misused AI can cause numerous problems, including incorrect decisions, privacy breaches, bias, fraud, and cyber threats. Knowledge of the most common mistakes and the use of proven methods make it possible to limit or avoid the risks involved altogether.

The use of AI carries the risk of undesirable events. These include: a) incorrectly formulated prompts; b) data security; c) the source of the application; d) incorrect answers; and e) deepfakes and fraud.

Promptly, the questions that the user enters into the system are. The more precisely the question is asked, the greater the chance the AI will answer correctly. When using free AI systems, it is also important to remember that users pay for access with the data they enter into them, which directly leads to the risk of data security breaches. This data can be leaked and used by artificial intelligence for learning. In the context of the application's source, it is essential to emphasize that its originality should be verified each time. The justification for this practice is that there are many counterfeit platforms on the web, the use of which can pose a significant threat to their users. Fake applications are usually free and deceptively similar to the original. Therefore, the source of the application and the opinions of other users should be verified each time.

Additionally, incorrect answers are a significant risk. Applications that utilize artificial intelligence typically leverage open data sources. Therefore, the answers provided may lead to bias, prejudice, or preconceptions. As a result, the answers may be based on stereotypes that have no basis in reliable knowledge. Ultimately, AI-based applications offer numerous benefits. They support learning, work, and entertainment. However, it is essential to remember that they are often a source of misinformation or cyberattacks. The level of security in the world of AI will be significantly higher if users of artificial intelligence take the initiative to educate and train themselves. They should also be careful and verify

the displayed content, especially when the decisions have financial consequences. The role of artificial intelligence is to support and assist people, but it can never replace thinking. The careless use of artificial intelligence can lead to data leaks that pose serious risks to individuals and businesses.

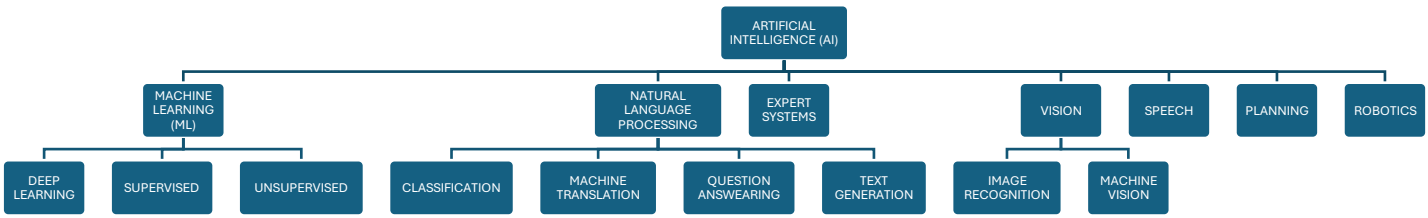
7. CHALLENGES IN COMPLIANCE AND AUDIT IN AI MANAGEMENT

The development of artificial intelligence continues to accelerate. New and more advanced tools are being developed, and existing systems on the market are continually evolving. Rapid development opens up new possibilities but also causes many risks. Therefore, today's times require constant adaptation to technology and its skilful and safe use. In addition, it is necessary to verify all legal regulations, especially those concerning personal data protection. Hence, the rapid development of AI poses a significant challenge to compliance in its broadest sense. Compliance specialists will be forced to develop new internal procedures. And to do so, they must demonstrate extensive knowledge of artificial intelligence and creativity. Verifying whether AI tools constantly comply with the law will be necessary.

On the other hand, internal practices and procedures should be continually adapted to the evolving legal environment and kept pace with the rapid development of AI. Only then will compliance officers be able to meet this challenge. At the same time, the AI audit should be kept in mind, which will enable verification of whether artificial intelligence tools function properly and whether they are unbiased and do not discriminate.

AI is the most transformative technology of our time. And it is not a single technology, but a complex set of technologies that can be combined to perform a wide range of tasks, from understanding language to helping you plan your holidays. Due to the limited scope of this study, it would be tough to discuss all technologies in an accessible and understandable way. For this reason, three basic types of AI will be analysed.

Firstly, narrow artificial intelligence only performs specific, simple tasks or sets of functions that can be found in everyday applications. It is called narrow AI because its scope of activity is limited and does not go beyond the indicated domain. Examples are facial recognition and voice assistants, which many companies and institutions already use. Secondly, there is general artificial intelligence. Its wide



range of possible actions characterises this. In principle, it can master any difficult intellectual task and perform better than a human being.

Furthermore, it can learn from experience and patterns. General AI remains a subject of ongoing research. Thirdly, there is super-intelligent AI. If it were to be developed, it would far exceed human intelligence. It could improve itself and make decisions based on data analysis. Super-intelligent AI would undoubtedly change the world. It would be able to replace humans in most processes. The following image illustrates the complexity of AI technology.

Figure 1. Artificial Intelligence (AI) Structure and Sub-Areas
Source: Raport Eurofound (2020), Game–changing technologies: Transforming production and employment in Europe, Publications Office of the European Union, Luxembourg.

European Commission documents indicate that AI as a scientific discipline has many techniques at its disposal, such as machine learning (deep and reinforcement learning), machine reasoning (planning,

reasoning, searching and optimising), robotics (control, perception, integration of other techniques) (Artificial intelligence act management and enforcement). On the other hand, OECD documents suggest that artificial intelligence can impact the environment by providing recommendations or predictions in this context. To this end, it uses machine and human input data, which enables: 1) perceiving real or virtual environments, 2) summarising such perceptions in models manually or automatically, 3) using model interpretations to formulate result options. OECD documents indicate that artificial intelligence can interfere with the environment by presenting recommendations or predictions in this context. To this end, it uses machine and human input data, which enables: 1) the perception of real or virtual environments, 2) the summarisation of such perception in models, either manually or automatically, and 3) the use of model interpretation to formulate result options.

AI is on a rapid development path and is finding applications in an increasing number of areas of life, including education, transportation, medicine, and industry. Artificial intelligence will undoubtedly play a key role in process optimisation and decision-making. It will also make it easier to diagnose diseases. These are just a few examples of the areas of life that AI will affect, and there will be many more. All this is thanks to advancements in machine learning, an area of AI that is experiencing rapid growth. This will enable even more accurate data analysis and decision-making. Artificial intelligence also brings great opportunities for the country's development. Therefore, in 2020, Poland adopted its AI development policy. The document focuses on actions and objectives in the short term (until 2023), medium term (until 2027), and long term (after 2027). They are based on six areas: society, innovative companies, science, education, international cooperation, and the public sector. This division was argued on the basis that AI permeates many areas of life; hence, the need for policy to cover all social groups as widely as possible.

With the development of artificial intelligence and its increasing use in various organisations and institutions, the need has arisen to regulate AI management standards. The ISO/IEC 42001 standard was developed in December 2024 in response to this need. It is an international standard specifying the requirements to be met when designing, implementing, maintaining, and improving an AI management system. It is intended for organisations that provide or use AI-based products and services. It is the world's first standard to regulate the management of artificial intelligence. It contains essential recommendations for the rapidly developing AI, which support organisations in managing risks and opportunities in artificial intelligence (ISO/IEC 42001:2023, 2023). It is part of a broader set of standards for implementing and improving AI. Information security management is regulated by ISO 27001, and risk management is addressed in ISO 27005 (Wygodny, 2024).

In addition, in 2024, the National Institute of Standards and Technology in the United States issued the AI RMF Generative AI Profile (NIST AI 600) under Executive Order (EO) 14110, aimed at promoting safe and trustworthy artificial intelligence to support organisations in risk management. However, on 20 January 2025, President D. Trump issued two executive orders on artificial intelligence after taking office. One of them, entitled ‘Initial Rescissions of Harmful Executive Orders and Actions’, revoked the aforementioned Executive Order (EO) 14110 (Trump Administration, 2025). It is therefore questionable whether the NIST AI 600 document will continue to be respected or whether the Trump administration will propose new solutions. These activities confirm that, despite the dynamic development of artificial intelligence, risk management is still regulated in various documents with standards that differ significantly from one another. The lack of uniform standards for AI management can lead to unforeseen risks and complications that could be eliminated by a sound management system based on uniform guidelines.

Regarding the balance between innovation and regulation in AI management, it is worth noting that the world's largest economies are vying for primacy in AI. This means that Europe must remain an active player in this field. Therefore, despite lagging behind the United States and China in technological development, the European Union has undertaken the challenging task of establishing a regulatory framework for AI. These efforts are now showing promising progress. The AI Act is the world's first comprehensive document to regulate issues related to artificial intelligence. However, it is a significant challenge to maintain innovation in mind, despite extensive regulation, and not to lose balance between the two. There is no shortage of concerns in this context. Organisations indicate that EU regulations could hamper artificial intelligence development, exceptionally if restrictions on technical stability and liability for damage caused by artificial intelligence providers are maintained.

8. CONCLUSIONS

Modern artificial intelligence systems are playing an increasingly important role in various sectors, which necessitates the implementation of appropriate supervisory mechanisms and adherence to ethical principles. Key areas of AI governance include ensuring transparency and accountability, minimising algorithmic bias, protecting privacy and personal data, and auditing and certifying AI systems. From a regulatory perspective, global initiatives such as the European Union's AI Act, the Blueprint for an AI Bill of Rights developed in the USA, and the restrictive AI regulations in China are significant. Technical solutions that support an ethical approach to artificial intelligence, such as Explainable AI (XAI), and mechanisms that eliminate so-called 'black boxes' in AI models, also play an essential role. Scientific discussions continue to focus on the issues of explainability and interpretability of AI systems, which are crucial for building public trust and the successful implementation of artificial intelligence in critical areas such as healthcare, the financial sector, and the justice system. The regulations governing this area are designed to ensure that AI functions adhere to the principles of ethics, human rights protection, and algorithmic justice.

Creating effective legal regulations regarding ethics and governance in AI management is crucial. For this reason, it is necessary to distinguish among three governance models in this publication: regulatory, self-regulatory, and hybrid. Legal regulations created at the EU and national levels (regulatory supervision model) are of fundamental importance in ensuring compliance with the law of their creation and use, as well as in protecting fundamental rights. The use of AI systems in various sectors of everyday life has a direct impact on human rights. Artificial intelligence can affect the fundamental rights and freedoms of individuals, including a) the right to privacy and the protection of personal data (AI is often based on the processing of vast amounts of data, which carries the risk of misuse, profiling of users or violation of the GDPR); b) the right to equal treatment (algorithms learn from historical data, which may reflect existing prejudices in society; AI systems not covered by any regulations may perpetuate or even exacerbate inequalities, e.g. in recruitment processes or credit decisions); c) the right to a fair trial (AI is increasingly used in justice systems, e.g. for simple organisational and technical activities). Given the above, it is reasonable to assume that the legal framework governing the operation of AI should ensure that decisions made using AI are transparent and subject to human oversight and control. In addition, creating clear regulations ensures that AI systems operate according to democratic values and fundamental rights.

The second area of importance from the perspective of regulating the ethics and governance of AI management is security. Numerous risks associated with the use of AI-based systems are being identified today. With the systematic implementation of AI in key sectors such as healthcare, justice, and finance, the need for regulation regarding responsibility for decisions made by algorithms is growing. In this context, the main risks are, for example, wrong medical decisions when using AI in the diagnosis and treatment of patients. A lack of regulation can lead to a situation where it is unclear who is responsible for an incorrect diagnosis generated by an algorithm.

Another example is autonomous emergency systems, as autonomous vehicles or robots can cause accidents for which liability is not clearly assigned (i.e., manufacturer, operator, or user?). Additionally, cybersecurity issues must be considered, as AI systems are increasingly vulnerable to hacking. This, in turn, can lead to data leaks or the manipulation of decisions made by algorithms.

An analysis of current and proposed legal regulations on ethics and governance in AI management has led to the conclusion that transparency in AI is essential. Therefore, citizens, users, and institutions must be able to trust that decisions made by AI are comprehensible, open to challenge, and subject to human oversight and control. This means that the system's users should be aware of the basis on which the algorithm made a decision (e.g., when assessing creditworthiness), and regulations should ensure the right to appeal against AI decisions, especially in cases involving important issues. Importantly, AI cannot act completely autonomously in situations affecting citizens' rights. The introduction of legal regulations at the EU level, obliging member states to create internal rules and AI system providers to establish their own internal procedures, currently favours ensuring an adequate level of AI transparency. The development of their own ethical codes for AI by providers will minimise legal risk, build trust among customers and employees, and increase the credibility of organisations through transparency. These measures are complemented by so-called soft law acts, which support the regulatory and self-regulatory governance model. The coherence of regulations at the EU level is noticeable, as exemplified

by the principles formulated by the EU legislator in the GDPR, particularly the principle of explainability, which affords everyone the right to information about how algorithms that affect their lives operate. The AI Act also imposes a transparency obligation on high-risk systems.

The analysis of the current legal regulations shows that the European Union is currently the leader in AI regulation. The creation of a uniform AI regulation system at the EU level is crucial. First of all, it prevents legal fragmentation. In the absence of harmonised regulations, different regulations in individual countries could hinder the functioning of entrepreneurs and institutions in the single market. Secondly, it facilitates business activities, as it is possible to comply with a single EU standard instead of having to adapt to different national regulations. Thirdly, it is about protecting democratic values. The activity of the EU legislator ensures that AI regulations reflect the European approach to protecting human rights and promoting technological ethics.

In summary, well-designed regulations should not limit the development of AI but provide a legal framework for innovation. In an era of leveling geographical barriers and shifting a significant portion of activity to the online sphere, it is essential to maintain interoperability standards. This facilitates cooperation between different AI systems in Europe and worldwide. Regulations on artificial intelligence are necessary to ensure security, transparency, and the protection of citizens' rights. At the same time, well-designed laws can promote innovation and competitiveness. For this reason, the process of harmonizing regulations at the EU level, adapting them at the national level, and implementing ethical principles within organizations should be assessed as unequivocally positive.

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THE GOVERNMENTAL HAND IN THE ALGORITHMIC AGE: POLICY LEVERS, CHALLENGES, AND IMPLICATIONS IN SHAPING ARTIFICIAL INTELLIGENCE SKILLS

Monika Rozkrut[a], Adam Kucharski[b] , Kesra Nermend[c], Jarosław Waśniewski [d]

[a] *University of Szczecin, Institute of Economics and Finance, Poland*
[b] *University of Szczecin, Institute of Psychology, Szczecin, Poland.*
[c] *University of Szczecin, Institute of Management, Szczecin Poland*
[c] *University of Gdansk, Faculty of Management, Gdańsk, Poland*

ABSTRACT

Purpose: *This paper examines how national governments use policy levers to shape the supply of AI-related competences, distinguishing clearly between skills for AI development (advanced R&D, engineering) and skills for AI adoption (work-force and citizen literacy). It synthesises theory and practice to propose a multi-level framework that links human-capital investment, innovation-ecosystem coordination and inclusion goals to concrete skill outcomes.*

Need for the study: *Global surveys show acute shortages of AI specialists and low baseline AI literacy among workers; yet most national strategies still treat "AI skills" as a single policy target. Little academic work has analysed how different policy mixes map onto these two distinct gaps or what constitutes a balanced, equitable skill strategy.*

Methodology: *The study conducts a structured review of recent research, international guidelines and national AI strategies. It integrates insights through comparative thematic coding and builds a conceptual model—the Nested AI-Skill Ecosystem—that explicates causal links between policy instruments (education reform, R&D subsidies, PPPs, immigration, ethics standards) and the twin skill domains.*

Findings: *The "AI skills gap" is dual: specialist shortages impede frontier innovation, while weak adoption skills limit productivity diffusion. Policy effectiveness hinges on coherent bundles: regulation or funding alone is insufficient without ecosystem coordination. Three archetypal government approaches emerge—development-led, adoption-led and balanced—each traceable to different strategic narratives and institutional capacities. Public–private partnerships and lifelong-learning infrastructures are critical cross-cutting enablers; ethical-AI guidelines indirectly create new training demand.*

Practical Implications: *Policymakers should set dual, measurable targets for developer talent and broad AI literacy; embed AI ethics across all curricula; align R&D grants with mandatory up-/re-skilling components; and establish governance bodies that integrate education, labour and innovation portfolios. The proposed typology offers a diagnostic tool for auditing existing national strategies and designing adaptive, inclusive skill ecosystems for the algorithmic age.*

Keywords: artificial intelligence skills, human capital development, public policy & governance, AI adoption vs. AI development, workforce upskilling and reskilling, skills gap, digital inclusion

JEL codes: J24; O33; O38; I28; H52

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1. INTRODUCTION: THE NEXUS OF GOVERNMENT POLICY AND AI SKILLS

Artificial intelligence (AI) is a key tool for accelerating civilization development, affecting employment, society, and the economy. Its proper implementation requires strategies and regulations from governments and international organizations that should invest in education and user protection. In today's world, artificial intelligence and its development are becoming the main tools for gaining an advantage and obtaining a dominant position in international competition. Systematically and intensively developing on a global scale, artificial intelligence significantly impacts employment, society, and the economy. More fields of science, such as medicine, industry, logistics, transport, finance, education, entertainment, and work, are opening to new AI solutions (Szpilko et al., 2023a, 2023b). Progress in the field of artificial intelligence is continuous, leading to groundbreaking technological and innovative achievements. Spending by governments and companies on the development of Industry 4.0 is growing rapidly.

A properly constructed strategy for artificial intelligence modernizes the economy and elevates citizens' lives. States and international organizations are increasingly taking action to develop strategies for AI advancement. They are involved in creating specific recommendations and guidelines for implementing AI solutions. Artificial intelligence is a tool that can bring great benefits, but it requires understanding and a proper approach. It is impossible to stop technological progress; therefore, the application and implementation of AI must be approached responsibly. It is the responsibility of governments and international organizations to develop specific practices in the field of AI development. Work on appropriate regulations should aim to both invest in educating society about artificial intelligence and create conditions for developing new skills in its use, while also protecting users and preventing abuse. Technology companies should consider ethical principles in their AI projects, act transparently, and safeguard user privacy. In the current phase of continuous implementation of intelligent solutions across various sectors, primarily in the private industry, the burden of educating society falls on both state institutions and enterprises.

1.1. Defining the Core Research Problem

The rapid integration of Artificial Intelligence – broadly defined as machines imitating human intelligence functions like perception, learning, reasoning, and problem-solving – into nearly every facet of society presents profound opportunities and complex challenges. As AI technologies evolve at an unprecedented pace, governments worldwide grapple with how to steer their development and deployment towards societal benefit while mitigating inherent risks (Taeihagh, 2021). Central to this endeavor is the cultivation of AI-related skills within the populace and workforce. This research investigates the multifaceted ways in which national and regional governments, through deliberate policy interventions and strategic frameworks, influence the development, diffusion, and equitable distribution of AI skills.

Artificial Intelligence is transforming economies and job markets at an unprecedented pace, creating an urgent need for new skills across societies. A significant skills gap has emerged: many organizations report that shortages of AI-related talent are a major barrier to adopting AI technologies. Governments around the world recognize that without deliberate policy intervention, the workforce may lack the competencies required to develop and to effectively use AI, risking lost economic opportunities and widened inequalities (European Commission, 2021). The problem is twofold – we need highly skilled experts to create AI systems, and a broader base of users and managers who can adopt and leverage AI responsibly in all sectors. This research is relevant because closing these skill gaps is critical for innovation, productivity, and inclusive growth in the age of AI.

The core problem lies in understanding the effectiveness, efficiency, and equity implications of diverse governmental approaches in navigating these AI-driven technological shifts. Governments are increasingly formulating national AI strategies and policies, recognizing AI's potential to enhance economic competitiveness and transform societal structures (UNESCO IESALC 2025). However, these policies operate within a context of significant uncertainty regarding AI's trajectory and impact. A critical aspect of this challenge is bridging the perceived and growing gap between the accelerating demand for AI competencies in the labor market and the current supply within the workforce.

This study addresses the fundamental question: *To what extent and through which mechanisms can government policy effectively shape a nation's AI skills landscape to foster economic growth, ensure*

social equity, and prepare the workforce for the future of work? It moves beyond simply documenting policy initiatives to critically analyze the interplay between government actions and the complex ecosystem of AI skill formation. The way this "problem" is diagnosed – whether primarily as an economic competitiveness race, a workforce transition imperative, or an ethical governance challenge – significantly influences the types of policies governments prioritize. An economic framing might focus on elite talent and R&D, a workforce framing towards broad reskilling, and an ethical framing towards regulation and safeguards. A truly comprehensive approach likely requires integrating all three perspectives.

1.2. Relevance and Significance

The role of government policy in shaping AI skills is critically relevant for several interconnected reasons. Firstly, AI holds transformative potential across economic, social, and geopolitical domains. AI skills are increasingly viewed as central determinants of national competitiveness, innovation capacity, productivity growth, and even military superiority. Governments perceive AI development as crucial for economic prosperity and strategic positioning in the global order.

Secondly, the rapid advancement and deployment of AI systems pose significant risks that necessitate proactive governance. These include the potential exacerbation of social and economic inequalities (National Institute of Standards and Technology, 2023), the displacement of workers in specific sectors as tasks become automated, and a host of ethical dilemmas concerning bias, fairness, privacy, transparency, and accountability. AI systems can amplify existing societal biases present in training data, leading to discriminatory outcomes. Furthermore, the potential for AI misuse, such as the spread of misinformation or the development of autonomous weapons, raises profound security and societal concerns (Taeihagh, 2021). Effective government policy is therefore crucial not only to harness AI's benefits but also to navigate these complex challenges and ensure AI development aligns with societal values and human rights (UNESCO IESALC, 2025).

Thirdly, understanding the effectiveness of different policy interventions is vital for evidence-based decision-making. Governments, educational institutions, industry stakeholders, and civil society require insights into which policies are most likely to succeed in fostering the necessary skills, promoting equitable access, and adapting to the dynamic nature of AI. Evaluating policy impact, however challenging, is essential for optimizing resource allocation and achieving desired outcomes.

1.3. Research Objectives and Scope

This research pursues to critically review and synthesize existing frameworks for defining and categorizing AI skills relevant to policy intervention, identifying commonalities, divergences, and gaps; to identify and analyze the primary policy instruments (levers) employed by governments globally to influence AI skill development across education, R&D, labor markets, and collaborative initiatives; to comparatively evaluate the AI skills strategies of key nations and regions, assessing their distinct approaches, underlying rationales, and last but not the least to synthesize findings and propose actionable policy recommendations for fostering effective, equitable, and adaptable AI skill ecosystems that support both economic prosperity and social well-being.

This paper contributes to the existing literature by providing a structured analysis that explicitly differentiates between policy approaches for AI development skills and AI adoption skills. While many studies address digital skills or national AI strategies broadly, few delve into the specific policy mechanisms targeting these distinct skill sets and critically assess their effectiveness (Hong, Wang, Fu, & Li, 2024). Often, policy discussions tend to conflate different types of AI skills or lack rigorous evaluation of intervention impacts. By offering a comparative framework and synthesizing characteristics of potentially effective policies, this research aims to provide valuable insights for policymakers, researchers, and educators grappling with the challenge of preparing society for the AI revolution.

2. LITERATURE REVIEW

To ground this study, we review three relevant bodies of literature: digital transformation, public policy in skill formation, and emerging work on AI skills. This situates our inquiry in a broader theoretical context.

The digital transformation era has repeatedly shown that technology adoption goes hand-in-hand with workforce skills. Research on digital innovation highlights that lacking the right skills is a major obstacle to successful transformation in organizations and the public sector (Mettler, Miscione, Jacobs, & Guenduez, 2024). Governments increasingly view digital skills as a foundation for economic competitiveness and public service delivery in the 21st century. For instance, Mettler *et al.* (2024) note that governments, as strategic actors, actively shape digital transformation by investing in infrastructure and skills, framing a national vision for change. High failure rates of IT modernization projects have been attributed in part to insufficient understanding of technology and inadequate skill preparedness within organizations. Thus, a consensus in the literature is that continuous upskilling and reskilling are required to keep pace with rapid technological change (often summarized in concepts like the need for "lifelong learning" in the digital age). AI represents the latest, and perhaps most profound, wave of this digital disruption, intensifying the spotlight on skill formation.

There is a rich tradition of scholarship on the role of the state in developing human capital. Classic human capital theory holds that education and training yield broad social benefits beyond the private gains to individuals, justifying government investment in skills. Public policy in many countries has long encompassed education systems, vocational training programs, and labor market interventions to develop workforce skills and enhance employability. Modern skill formation literature (including studies in political economy and labor economics) emphasizes how governments can correct market failures in training: for example, firms may under-invest in employee training because some benefits "spill over" to other firms or to society (Organisation for Economic Co-operation and Development, 2023). Indeed, OECD analyses find that employers often do not provide enough AI-related training on their own – partly due to information gaps about AI and partly because the returns on training may extend beyond the individual firm. This gap opens space for government action. Additionally, policy scholars discuss how different institutional models (e.g. education systems, apprenticeship schemes, public-private partnerships) affect skill development outcomes. The notion of "skills ecosystems" has emerged, viewing skill formation as a coordinated effort among government, industry, and educational institutions. In summary, the literature suggests that proactive public policies are crucial to build the skills base needed for new technologies, especially when the pace of change is too rapid for traditional education alone to keep up (Organisation for Economic Co-operation and Development).

Specific research on AI and skills is relatively nascent but growing quickly since around 2018. Early studies and policy reports identify AI as a general-purpose technology that will significantly alter skill demands. One key finding is that AI does not only affect technical occupations – its impact is broad-based, requiring adaptations across many roles. AI skills discourse often highlights a dual need: cultivating AI specialists and promoting AI literacy for all. For example, the OECD Employment Outlook 2023 finds that as AI adoption expands, there will be growing demand for both advanced AI expertise and basic digital/AI literacy, along with higher demand for cognitive skills that complement AI. At the same time, skills that AI can automate (routine cognitive or manual tasks) may decline in importance. This aligns with broader future-of-work literature (e.g. World Economic Forum's Future of Jobs reports) which project increasing importance of complex problem-solving, creativity, and social intelligence skills by 2025 as automation spreads. Recent policy analyses by institutions like the European Union and OECD consistently flag the 'AI skills gap' as a strategic challenge. The EU's Coordinated Plan on AI (2021) explicitly calls out the persistent ICT and AI specialist shortage as a key hurdle to AI development in Europe and equally stresses the need for 'AI for all' through broad digital skill initiatives to avoid societal inequalities (European Commission, 2021). In sum, current literature converges on the view that AI is reshaping skill needs on two fronts – deep technical expertise and widespread user capabilities – and that public policy must evolve to foster both.

2.1. The Strategic Imperative of AI Skills

Artificial Intelligence (AI) stands as a transformative general-purpose technology (GPT), fundamentally reshaping economies and societies across the globe. Its potential extends far beyond incremental improvements, offering pathways to tackle complex global challenges. The capacity of AI to automate tasks, augment human capabilities, and drive innovation positions it as a critical engine for productivity growth. Consequently, national capabilities in AI are increasingly viewed as central determinants of international competitiveness, economic prosperity, and overall societal well-being. However, realizing the profound benefits of AI requires more than technological advancement alone; it necessitates a

population equipped with the requisite skills to develop, deploy, and interact with these powerful systems effectively.

Governments worldwide play an indispensable role in navigating the complexities of digital transformation. This role becomes even more critical in the context of AI, where strategic policy interventions are needed to cultivate the human capital essential for the AI era. Recognizing this imperative, numerous nations are formulating and implementing comprehensive national AI strategies, often placing skills development at the core of their agendas.

These strategies acknowledge that fostering an AI-ready populace is not merely an economic goal but also a societal necessity. The urgency for government action is amplified by the dual nature of AI: while it presents immense opportunities, it also introduces significant risks, including potential job displacement, the amplification of bias and inequality, and threats to privacy and security. Skills gaps exacerbate these risks; a workforce unable to adapt may face heightened insecurity, and a society lacking critical AI literacy may struggle to ensure responsible and ethical deployment. Therefore, government policies focused narrowly on cultivating elite AI development talent, while neglecting the broader societal adjustments and skills needed for widespread, responsible adoption, may inadvertently widen societal divides even as they pursue technological leadership.

2.2. The Dual Nature of the AI Skills Gap (Development vs. Adoption)

The central challenge hindering the full realization of AI's potential is a significant and multifaceted skills gap (Wu & Lin, 2025). This gap manifests in two distinct but interconnected domains, a distinction crucial for effective policy formulation:

- AI Development Skills,
- AI Adoption Skills.

AI Development Skills encompass the specialized expertise required to design, build, train, test, and advance AI systems. It includes deep knowledge in areas such as machine learning (ML) engineering, data science, AI research, algorithm development, and related technical fields. Shortages in these high-level skills directly constrain a nation's capacity for innovation, limiting its ability to create novel AI solutions and compete at the technological frontier.

AI Adoption Skills is a broader set of competencies is required by the wider workforce and citizenry to effectively and responsibly utilize AI tools, interpret AI-generated outputs, collaborate with AI systems, and navigate the ethical considerations inherent in their use. Key skills include AI literacy (a basic understanding of AI), data interpretation, critical evaluation of AI outputs, ethical reasoning, effective human-AI collaboration, and prompt engineering. Deficiencies in these adoption skills limit the diffusion of AI benefits across the economy, hindering productivity gains and increasing the risk of misuse or unintended negative consequences.

A fundamental premise of this paper is that government policies must strategically address *both* the AI development skills gap and the AI adoption skills gap. These two challenges often necessitate different policy instruments, target populations, and timelines, requiring a nuanced and differentiated approach from policymakers.

3. ARTIFICIAL INTELLIGENCE

We are currently in the era of the fourth industrial revolution, also known as Industry 4.0. Its foundations were laid during the third revolution, which occurred in the 1960s. At that time, technology and information began to determine the development of the economy, leading to the creation of the information society. The first IT systems appeared, enabling production planning and control, which in turn contributed to the increase in automation. The rapid development of technology at the beginning of the 21st century initiated the fourth industrial revolution. It is associated with the development and dissemination of information and communication technologies, intelligent network technologies, mutually communicating objects, and artificial intelligence. As a result of these changes, the modern physical world began to intermingle with the digital world rapidly. A swift pace of change, considerable force, and significant impact on all sectors of the economy characterize the fourth revolution. A key element of the current and future era of civilization development is artificial intelligence, which has permeated various areas of our lives. Despite the widespread use of the term artificial intelligence, it is not easy to define this concept clearly. There are currently many different approaches to this term.

One of the most frequently cited definitions is that used by J. McCarthy, the creator of this term: "the science and engineering of creating intelligent machines", a fundamental and still relevant concept that emphasizes the creation of machines capable of intelligent action. Kaplan and Haenlein (2019) define artificial intelligence as the ability of a system to correctly interpret external data, learn from it, and use this knowledge to perform specific tasks and achieve goals through flexible adaptation. Definitions of artificial intelligence usually assert that it is an area of computer science dealing with the construction of machines and algorithms that exhibit characteristics of intelligent action. As a field of science, artificial intelligence analyzes and defines the principles underlying human intelligent behavior and then implements these principles in the form of computer programs and algorithms. Artificial intelligence uses computational methods to analyze and perform intelligent actions (Duch, 1997, after Gałat, 2019). In the context of artificial intelligence, two approaches are often mentioned. The first one, strong artificial intelligence, refers to a system with intelligence comparable to human intelligence that is capable of independent thinking and reasoning. It assumes that a properly programmed computer can reach the level of human intelligence or even surpass it. In this context, creating self-learning programs, such as neural networks, that can solve abstract and conceptual problems through machine learning is considered. The goal is to create a system with intelligence comparable to or higher than human intelligence, capable of independent thinking and development.

Currently, scientists strive to construct machines and programs that imitate the functions of the human mind and senses, going beyond the possibilities of algorithmization. The second approach, referred to as weak artificial intelligence, emphasizes its various limitations and lower position in relation to the human mind (Różanowski, 2007). According to its proponents, the greatest achievement of artificial intelligence is imitating the human brain, creating advanced mathematical models, and implementing them in computer programs for specific applications. Weak AI systems operate intelligently in the real world, but only to a limited extent, focusing on individual tasks that they perform efficiently. Today, narrow AI is widely present in our environment. We encounter it in chatbots that help us online, in voice assistants on our mobile devices, and in systems that recognize faces on social media. It is also used to analyze city traffic, allowing for better management of taxis. In turn, the essence of strong AI is to perceive a properly programmed computer as having elements of human intelligence, in some way equivalent to the brain. On this basis, it is considered possible to create self-learning programs and structures – models of neural networks – and develop procedures for solving conceptual and even abstract problems by teaching machines and obtaining answers to questions posed to them (Różanowski, 2007).

To sum up the considerations in this area, it should be stated that for over 60 years of research devoted to this issue, a uniform, coherent, and complementary definition of artificial intelligence has not yet been developed. This is primarily due to its interdisciplinary nature and the multitude of diverse issues discussed within it. Nevertheless, as part of the conducted research, attempts are made to define its essence descriptively. In general, artificial intelligence is understood as a field of knowledge that includes, in particular, neural networks, the creation of models of intelligent behavior, and computer programs capable of simulating these behaviors.

The continual modeling and development of algorithms facilitate their autonomous self–improvement, enabling predictions of future behaviors through data analysis and inter-system interactions. Artificial intelligence, as a subfield of computer science, focuses on developing algorithms and systems endowed with intelligent attributes, such as adaptability, learning (including machine learning and reinforcement learning), and the capacity for abstract reasoning and decision-making. A prevailing consensus in defining AI adopts a systemic perspective, recognizing it as a system capable of influencing its environment by generating recommendations, predictions, or decisions based on specific objectives. Thus, AI uses input data–whether from machines or humans—to interpret the environment, constructing models based on these observations and subsequently deriving actionable outcomes such as decisions, behaviors, or recommendations. In advancing intelligent solutions for machines and systems, AI research aims to identify and implement rules governing human-like intelligent behavior into computer programs and algorithms. A prerequisite for the effective and responsible advancement of AI innovations is education, which involves elucidating AI mechanisms, addressing ambiguous issues, and objectively presenting both the potential and challenges associated with AI, thereby demystifying it as knowledge traditionally regarded as arcane or accessible to a select few.

4. THE ROLE OF POLICIES AND GOVERNMENTS IN SHAPING ARTIFICIAL INTELLIGENCE

Overarching national and supranational AI strategies serve as crucial high-level policy levers. These documents articulate a government's vision, priorities, and commitment regarding AI development and adoption. They often include specific goals and action plans related to talent cultivation and skills development, such as targets for AI researchers, plans for educational reform, priorities for R&D investment in AI, and strategies for managing workforce transitions. These strategies play a signaling role, indicating government priorities to industry, academia, and the public, and aim to coordinate actions across different ministries and agencies. However, the level of detail, specific targets, timeframes, and implementation frameworks vary considerably across countries. Some strategies may lack concrete outcome measures or detailed implementation plans, potentially limiting their effectiveness as coordination tools (National Audit Office, 2024).

4.1. International Initiatives on Artificial Intelligence

To initiate a meaningful discourse on the topic, it is essential to examine various examples of global or supranational strategies. The United Nations, through its specialized agencies, including the United Nations Educational, Scientific and Cultural Organization (UNESCO), the United Nations Development Programme (UNDP), and the International Telecommunication Union (ITU), actively engages in numerous initiatives that address the ethical, social, and legal dimensions associated with the development and implementation of artificial intelligence (AI). A noteworthy example of this commitment is the UNESCO Recommendation on the Ethics of AI, which was formally adopted in November 2021. This landmark document represents the first comprehensive global framework dedicated to the promotion of human rights, social equality, and sustainable development in the context of AI applications. Such initiatives highlight the necessity for collaborative approaches in navigating the complexities and challenges posed by AI technologies globally. The UNDP also uses AI to enhance the Rapid Integrated Assessment (RIA), enabling governments to evaluate their national development plans against the 169 Sustainable Development Goals (SDGs), assessing readiness for the global development agenda. Meanwhile, the ITU focuses on responsible AI development with the AI for Good platform, aimed at identifying and scaling practical AI applications aligned with the SDGs through a year-long program and an annual Global Summit.

The Organisation for Economic Co-operation and Development (OECD) has launched various initiatives to facilitate responsible AI development, including conferences, standards publication, and the establishment of the AI Policy Observatory and the ONE AI Advisory Group. These efforts aim to enhance technological trust and promote international cooperation. Since initiating its AI work at the Technology Foresight Forum in 2016 and the Intelligent Machines, Smart Policies conference in 2017, the OECD has published numerous reports assessing modern technologies' impacts on economies and societies at both national and international levels.

In May 2019, OECD released its first intergovernmental standards for AI development, emphasizing responsible management aligned with human rights and democratic values. The guidelines target all stakeholders in AI design and implementation, divided into two sections: one for developers and the other for policymakers (Organisation for Economic Co-operation and Development, 2019). The former outlines five principles for responsible AI management: fostering prosperity and sustainable development; prioritizing values and human consideration; ensuring transparency; guaranteeing user safety; and maintaining responsibility. The second section addresses policymakers, advocating for principles such as investing in AI R&D, nurturing the AI ecosystem, shaping conducive political environments, enhancing workforce competencies, and fostering international collaboration for ethical AI development.

Established in 2020, the AI Policy Observatory provides a framework to assist countries in leveraging AI benefits while mitigating associated risks. The OECD AI platform offers guidelines for effective AI tool development. The informal ONE AI Advisory Group advises the OECD on AI-related policy and technical issues, comprising diverse experts from government, civil society, and academia. It reports to the Digital Economy Policy Committee, which formulates recommendations on digital policies, including those related to AI, privacy, and digital security. The OECD also established the Digital Policy Committee (CDEP) to support sustainable development and technological innovation in

partnership with organizations like UNESCO and the Council of Europe, aligning its initiatives with European Parliament and European Commission activities.

The European Commission's Digital Decade is an initiative. The Commission has developed this program to accelerate Europe's digital transformation by 2030, setting specific goals and actions in areas such as digital skills, the digital transformation of enterprises, digital infrastructure and the digitalisation of public services. Artificial intelligence is a key element of this transformation. One of the programme's goals is for 75% of EU businesses to use cloud technologies, artificial intelligence or big data by 2030. AI is seen as a tool that can significantly improve the operational efficiency and innovation of enterprises. The program envisages increased investment in AI research and development, so that Europe can become a leader in this field.

The European Parliament is taking several actions regarding artificial intelligence, including publishing draft regulations, establishing special committees, adopting the AI Act, and working on the protection of citizens' rights as well as the application of AI in various sectors. In 2020, the European Parliament's Legal Affairs Committee published a draft report with recommendations to the Commission on a civil liability regime for artificial intelligence containing a draft resolution regulating liability for the operation of AI systems (European Parliament, 2020). In February 2024 EU Artificial Intelligence Act (AI Act) was adopted. It is considered the first legislative text concerning artificial intelligence in the world.

The European strategy for artificial intelligence development posits that AI can positively transform modern society by enhancing daily life and supporting sustainable development. It aims to improve healthcare, reduce energy consumption, increase communication and transport safety, and optimize the use of natural resources. Furthermore, AI can aid in environmental forecasting, financial risk management, fraud detection, and law enforcement. It is anticipated that AI will significantly advance public service digitization, ensuring that by 2030, all major public services are accessible online, promoting effective management and citizen accessibility (European Commission, 2018).

4.2. Implementation of AI Strategies Across Countries

The development and application of AI extend beyond international organizations and technology corporations; many countries are now formulating national AI strategies, reflecting a growing interest in AI within the public sector. Governments and local authorities are persuading citizens that technological advancements, particularly AI, will offer new opportunities for development. However, it is crucial to acknowledge the accompanying threats. Key components of an effective AI development strategy include: a thorough assessment of the current landscape, identifying the primary drivers for AI development, setting goals with a timeline, outlining key industries and applications, creating an implementation plan, delineating the strategy's role in government functions, designating a leading research center for national AI efforts, planning research sector development, recognizing barriers and challenges, fostering collaboration between business and science, establishing principles for international cooperation, and defining funding and support mechanisms alongside progress indicators.

The analysis of AI implementation strategies in OECD countries shows that most of them recognize the strategic importance of AI for economic growth and innovation. They emphasize ethical development, investment in R&D, education, and international cooperation. Regulative approaches and priorities vary depending on the specifics of the economy and challenges of the individual countries.

The analysis of AI implementation strategies in OECD countries reveals several common themes and differences in the approaches used. Almost all countries recognize the strategic importance of AI for future economic growth, innovation, and social well-being. The need for ethical and responsible AI development is widely emphasized, often with references to the OECD Ethical Principles and, in the case of European countries, to the upcoming European Union AI Act. Most strategies highlight investment in AI research and development, as well as fostering talents and skills in this area through education and training programs.

At the same time, strategic priorities and goals vary based on the specifics of each economy and the individual challenges faced by countries. For example, South Korea and Japan are setting ambitious goals for their positions in global AI rankings and AI-driven economic growth. In contrast, countries such as New Zealand and Canada seem to focus on responsibly implementing AI in the public sector and building public trust in the technology.

Approaches to AI regulation also vary. Some countries, such as Australia and Japan, prefer light regulation and the use of existing legal frameworks, intervening only when serious risks arise. Others, particularly in Europe, are actively involved in the development and implementation of more comprehensive regulations, such as the EU AI Act, seeking to ensure safety and protect fundamental rights while supporting innovation. Ethics is widely recognized as an integral part of AI strategies, and many countries have adopted or are developing their own AI ethics principles, often based on OECD recommendations.

Talent development and infrastructure are regarded as essential for successful AI implementation. Most strategies encompass initiatives to enhance AI education at all levels, from primary schools to universities, along with training and retraining programs for the current workforce. Investment in digital infrastructure, which includes computing power, data centers, and high-speed telecommunications networks, is also considered crucial for supporting the development and deployment of advanced AI systems. International cooperation is another vital aspect of many OECD countries' AI strategies. AI is perceived as a global challenge and opportunity, emphasizing the importance of knowledge exchange, best practice sharing, and participation in international initiatives such as the Global Partnership for Artificial Intelligence (GPAI) and the OECD's work on AI.

5. THE NATURE AND CATEGORIZATION OF AI SKILLS

Artificial intelligence and the development of information and communication technologies accelerate civilizational progress, requiring society to acquire new digital competences that are necessary for the effective use of AI in work and everyday life. In today's world, artificial intelligence is becoming the main tool for accelerating civilization, gaining an advantage, and obtaining a position in international competition. A properly constructed strategy regarding artificial intelligence makes the economy more modern and the lives of citizens reach a higher level.

Contemporary society is subject to constant change. Technological intensity is accompanied by an accelerated pace of life and exceptionally rapid changes. Among the many consequences of these ongoing processes, acquiring new skills and deepening existing ones, especially in the realm of ICT, is of particular importance. Achieving an appropriate level of competence is essential, both in the micro dimension – the spheres of work and everyday life of individuals – and in the macro dimension, as it conditions stable and systematic socio-economic development.

In the information society, an important role, in addition to access to ICT, is also played by using modern technologies, which is inextricably linked to establishing and enhancing appropriate competencies referred to as digital. The rapid development of technology and artificial intelligence is transforming the way we learn and work. In contrast, the need to interact with technology and collaborate with AI necessitates unique skills that are essential in the realm of modern technologies. These skills encompass not only basic knowledge of digital tools but also a deeper understanding of the operational principles of AI and other advanced technologies. Employees must be able to cooperate effectively with AI systems and comprehend their capabilities and limitations. Skills related to data analysis, programming, and management of technological projects are increasingly crucial. In the context of AI, the ability to interpret results generated by algorithms and make business decisions based on these results is invaluable. Nowadays, everyone should possess a foundational understanding of artificial intelligence to consciously and safely utilize its potential. (Luckin, George, & Cukurova, 2022).

5.1. Skills and Competences as a Key Element of AI Strategy

The lack of appropriate digital competencies in society is a significant barrier to the effective implementation and use of artificial intelligence. This is why OECD countries emphasize education and raising awareness of AI at all levels of education and through continuing education programs.

The lack of appropriate competences is becoming a serious obstacle to using AI tools. In the strategies for implementing artificial intelligence in OECD countries, the issue of society's digital competences is treated as a key element enabling the effective use of AI's potential and adaptation to changes in the labor market. Many countries emphasize the need to raise awareness and understanding of AI among citizens at all levels of education, from primary schools to universities, as well as through continuing education programs and vocational training. For example, in Poland, the AI strategy assumes actions aimed at making the country one of the primary beneficiaries of the data-based economy and

increasing the digital competences of Polish society. Similar goals for raising awareness and digital competences can be found in the strategies of Lithuania, Luxembourg, the Czech Republic, Finland, Germany, Sweden, Slovenia, Latvia, and Denmark. The strategies often include specific educational initiatives, such as integrating AI topics into curricula at various levels, creating specialized AI-related courses and study programmes, and supporting training and retraining for people whose jobs may change due to AI developments.

An example is Finland, which promotes initiatives such as free online courses 'Elements of AI' to raise general awareness of AI, a free online course created by the University of Helsinki, aimed at introducing the subject of artificial intelligence to a broad audience. The course does not require advanced mathematical knowledge or programming skills, making it accessible to anyone who wants to understand what AI is, what its capabilities and limitations are, and how it affects our lives. The main goal of the initiative is to increase awareness and understanding of AI among the public. It has gained tremendous popularity, with over a million registered users from over 110 countries. It is worth adding that the Finnish government actively supports and promotes "Elements of AI" as part of its AI development strategy in the country, aiming to raise the level of digital competence of citizens. The course has been translated into many languages.

AI. Estonia plans to develop a similar online course based on the Finnish model. OECD countries recognize that raising the level of digital literacy in society is essential not only for economic development and innovation but also to ensure that AI is used ethically and responsibly, respecting human rights and democratic values. As such, investment in education and digital literacy is an essential element of many national AI strategies.

5.2. Frameworks of AI Skills

Defining and categorizing the skills required in the age of AI is a complex and evolving task, crucial for designing effective educational programs and policies. The discourse has moved beyond simple digital literacy towards a more nuanced understanding of AI-specific competencies. AI literacy involves a basic understanding of AI concepts, capabilities, limitations, and societal implications, enabling individuals to interact critically and effectively with AI systems. Competencies represent a broader set of skills, knowledge, attitudes, and abilities needed to perform specific tasks or roles in an AI-influenced environment.

Several frameworks attempt to structure the diverse range of AI-related skills. UNESCO has developed separate competency frameworks for students (UNESCO, 2024) and teachers (UNESCO, 2025). The student framework emphasizes four interlinked aspects: human-centred mindset, ethics of AI, AI techniques and applications, and AI system design, each with progression levels (understand, apply, create). The teacher framework outlines 15 competencies across five dimensions: human-centred mindset, ethics of AI, AI foundations and applications, AI pedagogy, and AI for professional learning, also with progression levels (acquire, deepen, create).

WEF (World Economic Forum, 2025a) global skills taxonomy aims to provide a structured, shared language for skills to align businesses, governments, and education providers. It categorizes skills broadly into Skills/Knowledge/Abilities and Attitudes. While not exclusively focused on AI, it explicitly includes "Artificial intelligence and big data" as a key skill area, alongside related competencies like technological literacy. Its value lies in facilitating communication and alignment across different sectors regarding skill requirements.

US Office of Personnel Management (OPM) AI Competency Model**,** developed specifically for US federal government AI roles, distinguishes between 43 general competencies (e.g., critical thinking, problem-solving, accountability, teamwork, ethical reasoning) and 14 technical competencies (e.g., AI/ML, data analysis, modeling and simulation, software engineering). It emphasizes a shift towards skills-based hiring, prioritizing demonstrated proficiency over traditional credentials.

The OECD has developed frameworks for classifying AI *systems* based on dimensions like context, data, model, and task, which indirectly inform the skills needed to develop, deploy, and govern such systems. Academic and library-specific frameworks also exist, often categorizing skills into areas like knowledge and understanding, analysis and evaluation, use and application, and ethical considerations. The NIST AI Risk Management Framework, while focused on risk, outlines characteristics of trustworthy AI (e.g., valid, reliable, safe, fair, transparent, accountable) that imply necessary skills for

developers and users (National Institute of Standards and Technology, 2023). Table 1 provides the overview of selected frameworks.

Table 1. Comparative analysis of major AI skill/competency frameworks

Framework	Primary Target Audience	Key Skill Categories/Dimensions	Emphasis
UNESCO Student Framework	Students (K-12/Higher Ed)	Human-centred mindset, Ethics of AI, AI techniques & applications, AI system design	Foundational Literacy, Ethical Use, Human-Centricity, Progression Levels
UNESCO Teacher Framework	Teachers	Human-centred mindset, Ethics of AI, AI foundations & applications, AI pedagogy, AI for professional learning	Teacher Training, Ethical Pedagogy, Classroom Integration
WEF Global Skills Taxonomy	Businesses, Govts, Education	Skills/Knowledge/Abilities (incl. AI & Big Data, Tech Literacy), Attitudes	Workforce Readiness, Shared Language, Alignment Across Sectors
US OPM AI Competency Model	US Federal Workforce	General Competencies (Cognitive, Soft, Foundational), Technical Competencies (AI/ML, Data, Modeling, Systems Design, Ethics)	Government Workforce Needs, Skills-Based Hiring, Technical & General Mix
ALA Academic Library	Library Professionals	Knowledge & Understanding, Analysis & Evaluation, Use & Application, Ethical Considerations, Dispositions (e.g., Adaptability)	Domain-Specific Application (Libraries), Information Literacy Context
NIST AI RMF	AI Developers, Deployers	Implied by Trustworthiness Characteristics: Valid, Reliable, Safe, Secure, Fair, Transparent, Accountable, Privacy-Enhanced	Risk Management, Trustworthy AI Development

Source: own elaboration.

Synthesizing across these diverse frameworks reveals recurring and essential dimensions of AI skills: technical, application and domain, cognitive and soft, ethical and societal. Technical skills cover foundational understanding of AI concepts (machine learning, natural language processing, deep learning), data literacy (collection, processing, analysis), programming proficiency, algorithm development, AI system design and architecture, and the practical ability to use various AI tools and platforms. Cognitive and soft skills relate to higher-order thinking skills such as critical analysis, complex problem-solving, creativity, and strategic thinking. Also crucial are adaptability, flexibility, learning agility (lifelong learning), collaboration, communication, emotional intelligence, and interpersonal skills. These are often highlighted as increasingly important human skills that complement AI's capabilities. Application and domain skills represent ability to effectively identify opportunities for AI application and integrate AI tools into specific workflows, tasks, and professional domains (e.g., using AI for medical diagnosis, educational personalization, financial modeling, or scientific research). This requires combining AI knowledge with domain-specific expertise. Ethical and societal skills Critical understanding of ethical principles related to AI (fairness, accountability, transparency), awareness of potential biases in data and algorithms, knowledge of data privacy regulations, ability to assess the societal impacts of AI deployment, and commitment to responsible AI development and use (National Institute of Standards and Technology, 2023).

While these frameworks offer valuable perspectives and categorizations, a significant challenge remains: the lack of a universally adopted, standardized taxonomy specifically designed for policy purposes that consistently and clearly distinguishes between AI development and AI adoption skills. The existence of multiple, overlapping, yet distinct frameworks highlight a significant challenge: the lack of a single, universally accepted, detailed taxonomy for AI skills. Terminology varies (literacy, competency, skills), and categorizations differ (levels, themes, roles). Some focus broadly on digital skills, while others are AI-specific. This ambiguity and fragmentation can hinder the design of precisely

targeted government interventions and make comparative evaluation difficult. Establishing a more common policy language remains an important goal for effective national and international strategy development.

5.3. The AI Skills Gap and Workforce Development Needs

A significant body of evidence points towards a growing gap between the demand for AI-related skills and the supply available in the workforce, often referred to as the 'AI skills gap'. Surveys consistently indicate that employers perceive a significant skills gap within their organizations, hindering their ability to adopt and leverage AI technologies effectively. The World Economic Forum's Future of Jobs Report 2025, for instance, highlights that skill gaps remain a primary barrier to business transformation, with a large percentage of employers citing this challenge. Executives estimate that a substantial portion of their workforce, potentially up to 40%, will require reskilling in the near future due to AI implementation (Frank Hawkins Kenan Institute of Private Enterprise, 2025a). This perceived gap fuels calls for a 'reskilling revolution'.

The potential impact of AI on employment is a subject of intense debate and analysis. While some fear widespread job losses due to automation, the dominant view suggests a more nuanced picture involving both task automation and job augmentation. AI is demonstrating capability in automating routine cognitive and non-routine tasks previously thought immune, potentially affecting professions ranging from clerical work to programming and analysis. Estimates suggest a significant percentage of workers will see at least some tasks affected by AI, with a smaller but notable portion facing substantial task automation. However, complete job displacement is considered less likely for many roles than a transformation of tasks within those roles. AI is expected to complement human workers, taking over routine elements and freeing up time for more complex, creative, or interpersonal activities, thereby potentially enhancing productivity (Frank Hawkins Kenan Institute of Private Enterprise, 2025a). This augmentation effect, coupled with economic growth spurred by AI, is also projected to create new jobs, particularly in AI development, data science, cybersecurity, and roles requiring human-AI collaboration. The net effect on employment remains uncertain and likely varies significantly across industries and occupations.

The AI-driven transformation inevitably alters the demand for specific skills. Technical skills related to AI and big data are consistently identified as the fastest-growing and most in-demand competencies. Technological literacy, network and cybersecurity skills are also projected to rise sharply in importance. Conversely, demand for skills associated with routine manual and administrative tasks is expected to decline due to automation. Interestingly, OECD research suggests that for many non-specialist roles highly exposed to AI, the most demanded skills initially were management and business skills (project management, finance, administration), although recent data hints at a potential decline in demand even for these, suggesting a complex and dynamic shift. Crucially, alongside technical skills, there is a growing emphasis on human-centric, cognitive, and socio-emotional skills. Analytical and creative thinking, problem-solving, resilience, flexibility, agility, curiosity, emotional intelligence, communication, and lifelong learning are frequently cited as critical competencies for navigating the future of work. This 'soft skills paradox' arises because as AI handles more technical and analytical tasks, the unique value humans bring lies increasingly in areas like complex judgment, ethical reasoning, creativity, and interpersonal interaction.

The existing workforce and general population often exhibit low levels of AI literacy and data literacy (Sidhu et al., 2024). Many individuals lack a basic understanding of AI concepts, how these systems work, or their potential implications. This limits their ability to use AI tools or critically engage with AI-driven information effectively. Nontraditional educational pathways, such as online courses (MOOCs), coding boot camps, industry certifications, and micro-credentials, are playing an increasingly important role in bridging the skills gap. These often offer more flexible, targeted, and rapidly updated training options than traditional degrees. However, questions may remain regarding the quality, recognition, and accessibility of these alternative credentials.

The AI skills gap also has significant global and regional dimensions. Developed economies generally exhibit higher demand for AI skills and possess greater capacity for AI development and training, though they still face shortages. Developing countries often lag significantly behind due to inadequate digital infrastructure, limited investment in education and R&D, and fewer resources for workforce reskilling. This disparity creates a risk of a widening 'AI divide', where the benefits of AI

are concentrated in a few leading nations and corporations, while others fall further behind, potentially exacerbating global inequalities. Paradoxically, while a smaller percentage of jobs in developing countries may be currently exposed to automation, these nations may be less equipped to manage the transition or leverage AI for productivity gains due to these underlying gaps.

The identified skills gap and the transformative nature of AI necessitate urgent and large-scale workforce development efforts. This includes significant investment in reskilling and upskilling programs for the existing workforce, fostering a culture of lifelong learning, and adapting formal education systems (primary, secondary, tertiary, and vocational) to equip future generations with relevant competencies. AI itself can play a role in enhancing workforce development through personalized learning platforms and predictive analytics to identify emerging skill needs.

5.4. Distinction Between AI Development and AI Adoption Skills Gaps

Understanding the nature and scale of the AI skills gap is fundamental to designing effective policy responses. This gap is not uniform; it varies significantly between the specialized skills needed for AI development and the broader competencies required for AI adoption.

Evidence consistently points to a high and rapidly growing demand for individuals possessing AI development skills. Job postings for roles such as AI specialists, machine learning engineers, data scientists, and AI researchers have surged globally across numerous industries. Reports from organizations like the World Economic Forum and LinkedIn, as well as labor market data, indicate significant annual growth rates for these specialized roles, often outpacing overall job growth (World Economic Forum, 2025b). For example, one analysis found that for every AI job posting in 2012, there were seven in 2024, with postings requiring AI skills growing 3.5 times faster than all job postings since 2016 (PricewaterhouseCoopers, 2024).

The mismatch between demand and supply results in critical talent shortages, particularly for high-end AI development roles. Numerous reports document the difficulty organizations face in recruiting and retaining qualified ML engineers, data scientists, and AI researchers. Some estimates suggest only a small fraction of data scientists possess the specialized skills needed for advanced AI work. This acute shortage acts as a bottleneck for innovation and AI deployment.

Initially concentrated in the technology sector, the demand for AI development talent is broadening as AI adoption diffuses across the economy. Sectors such as financial services, healthcare, information technology, professional services, manufacturing, and even agriculture are increasingly seeking professionals who can build and deploy AI solutions. The specific technical skills most sought after by employers align closely with the development competencies outlined previously, particularly proficiency in Python and key ML libraries, cloud platforms (like AWS and Azure), deep learning frameworks, and data engineering capabilities. This intense demand translates into significant wage premiums for workers possessing these specialized AI skills, reported to be up to 25% on average in some markets, and even higher within specific professions like law or finance.

Simultaneously, there exists a potentially larger, though less precisely measured, gap in AI adoption skills across the broader workforce. Surveys of employers and employees reveal a growing expectation that workers in nearly all roles will need some level of AI literacy and the ability to interact effectively with AI tools. A significant majority of students expect their educational institutions to equip them with relevant AI skills, and workers express willingness to retrain for AI-related competencies.

While the shortage of AI specialists receives significant attention, the lack of widespread AI literacy, critical evaluation skills, and ethical awareness may pose a more pervasive barrier to realizing the full economic and societal benefits of AI. If most of the workforce cannot effectively and responsibly use AI tools, productivity gains will be limited, and the risks of misuse or negative societal impacts increase. This highlights a crucial point: the AI skills gap is not monolithic. Policy interventions focusing solely on producing elite AI developers risk neglecting the vast need for foundational and applied AI competencies across the entire population, thereby failing to prepare society adequately for AI integration.

This demand is driven by the way AI is reshaping work. Rather than simply automating jobs wholesale, AI is often augmenting tasks, requiring humans to work alongside AI systems. This human-AI collaboration necessitates new skills. Employees need to understand how to prompt Generative Artificial Intelligence tools to get desired outputs effectively (prompt engineering), critically evaluate

the information AI provides (checking for bias, accuracy, and relevance), understand the ethical implications of using AI in their work, and adapt their workflows to incorporate AI-driven insights.

Furthermore, as AI handles more routine analytical and operational tasks, there is an increasing emphasis on complementary "human skills" (Strietska-Ilina et al., 2021). Skills such as critical thinking, complex problem-solving, creativity, communication, collaboration, leadership, and emotional intelligence are becoming more valuable as they represent areas where humans currently maintain an advantage over AI and are essential for navigating the complexities of an AI-augmented workplace (Sidhu et al., 2024). Table 2 highlights the differences between AI development and AI adoption across key categories.

Table 2. Estimated AI skills gap dimensions (development vs. adoption)

Categories	AI Development	AI Adoption
Specific Skill Examples	Machine Learning Engineer, Data Scientist, AI Researcher, Algorithm Developer.	AI Literacy, Data Interpretation, Critical Evaluation, Ethical Use, Prompt Engineering, Human-AI Collaboration.
Evidence of Demand	High job posting growth.	Growing demand across *all* sectors; High employee/student interest; Need for skills complementary to AI (critical thinking, communication).
Evidence of Supply/Shortage	Widely reported shortages; Difficulties in recruiting; High wage premiums.	Generally low existing literacy in workforce/public; Potential insufficiency of training supply for general literacy; Education lag.
Key Affected Sectors	Technology, Finance, Healthcare, Professional Services, Information & Communication.	All sectors undergoing digital transformation; Knowledge work, Customer service, HR, Marketing, Healthcare, Education.
Regional Variations	Concentrated demand in developed economies; Global competition for limited talent pool.	Significant gaps in developing countries due to infrastructure/education deficits; Risk of AI Divide/Exclusion.

Source: own elaboration.

Accurately quantifying these gaps remains challenging. Measuring specialized technical skills through job postings or degree completions is relatively straightforward, but assessing broader competencies like AI literacy or ethical reasoning across diverse populations requires more complex and standardized assessment tools, which are still under development (Strietska-Ilina et al., 2021). The dynamic nature of AI further complicates the picture. The skills required today may differ significantly from those needed in a few years. This suggests a feedback loop: a lack of adoption skills can dampen demand signals for specialized AI development relevant to specific sectors. At the same time, a shortage of developers slows the creation of user-friendly tools that could facilitate broader adoption. Government policy must recognize and address this interplay between the development and adoption skills gaps to foster a virtuous cycle of innovation and effective utilization.

5.4. Conceptualizing AI Skills in the Policy Context

The rationale for government intervention in workforce skills development is well-established in economic and policy theory. Market failures often lead to underinvestment in training, particularly for general skills that are transferable across firms. Employers may be reluctant to invest heavily in training if competitors can easily poach skilled workers, while individuals may face credit constraints or lack information about future skill demands (Glover & King, 2010). Furthermore, a skilled workforce generates positive externalities, benefiting society beyond the direct returns to individuals and firms through increased innovation, productivity, and adaptability (Lopes, Sargento, & Farto, 2023). Human capital theory posits that investments in education and skills are crucial drivers of economic growth. In contrast, endogenous growth theory highlights the synergistic relationship between human capital, technological advancement, and economic progress.

In the context of rapid technological change, such as the current digital and AI transformation, these justifications for government intervention become even more salient. The pace of change often outstrips

the ability of individuals and firms to adapt, creating skills mismatches and potential labor market disruptions (Strietska-Ilina et al., 2021). Governments, therefore, have a legitimate role in steering skill development to align with emerging technological paradigms and national strategic goals, ensuring both economic competitiveness and inclusive growth (Hong, Wang, Fu, & Li, 2024). Policies targeting digital and AI skills are increasingly seen as essential components of national innovation systems, aimed at correcting market inefficiencies, fostering the necessary human capital for technological absorption, and guiding development towards societal priorities (Digital Regulation Platform, 2023).

AI is widely recognized not just as another technology but as a general purpose technology, with the potential to alter most economic processes and activities fundamentally. Its impact is expected to be pervasive, driving significant productivity gains, enabling the creation of new industries and business models, and transforming labor markets and the delivery of public services. This transformative potential creates powerful incentives for governments to shape the development and deployment of AI actively.

A dual imperative drives policy interventions: harnessing the immense opportunities AI presents while simultaneously mitigating its inherent risks. On the one hand, governments seek to leverage AI for economic growth, scientific advancement, improved public sector efficiency, and solutions to societal challenges. On the other hand, they must address significant concerns regarding potential negative consequences, including widespread job displacement due to automation, the exacerbation of income inequality, risks to privacy and data security, and the potential misuse of AI for malicious purposes. Developing appropriate skills across the population is central to achieving this delicate balance. A workforce equipped with relevant AI skills is better positioned to adapt to labor market changes, utilize AI tools productively, and contribute to innovation. Simultaneously, broad AI literacy and ethical awareness are crucial for ensuring responsible deployment, fostering public trust, and enabling informed societal debate about AI governance.

6. GOVERNMENT STRATEGIES AND POLICIES FOR CULTIVATING AI SKILLS

Governments have long intervened in markets related to technology, education, and labor, based on various theoretical justifications. Understanding these established paradigms provides context for analyzing government actions aimed explicitly at shaping AI skills. Standard economic theory justifies government intervention primarily to address market failures or achieve equity goals. Market failures relevant to AI skills include externalities, information asymmetries, coordination failures, and public good.

The societal benefits of a skilled workforce (e.g., innovation, productivity spillovers, informed citizenry) may exceed the private benefits accruing to individuals or firms, leading to underinvestment in skills without intervention (Poterba, 1996). AI development itself can generate positive externalities (knowledge spillovers) or negative ones (e.g., societal disruption, security risks), (Taeihagh, 2021). Information asymmetries mean that individuals may lack information about future skill demands or the quality of training providers. Employers may struggle to assess the skills of potential hires accurately (World Economic Forum, 2025a). Aligning the actions of diverse stakeholders towards a common goal like developing a national AI skills base may require government coordination. Beyond market failures, governments intervene to promote equity, reduce inequality, and ensure social protection, for instance, by ensuring access to education, providing safety nets for displaced workers, or enacting anti-discrimination measures. The specific context of AI, characterized by rapid, potentially disruptive change, high uncertainty, network effects, significant ethical considerations, and strategic geopolitical importance, arguably strengthens the rationale for proactive government involvement. Public good in the form of foundational research in AI, like other basic science (non-rivalrous, non-excludable), also potentially requires public support (Howell, 2024). General AI literacy might also be considered a public good necessary for democratic participation in the AI age.

Governments employ various tools to foster technological advancement, including direct funding of R&D (especially basic research in universities and public labs), tax incentives for private R&D, subsidies for technology adoption, government procurement policies that create demand for new technologies, intellectual property protection, and the setting of technical standards. The focus is often on supporting "failure-tolerant, open-ended research" that yields breakthroughs.

The government's role in education is pervasive, encompassing funding (primary, secondary, tertiary), curriculum setting or guidance, teacher training and certification, quality assurance and accreditation, provision of public education, financial aid to students, and policies aimed at ensuring equitable access and outcomes (UNESCO IESALC, 2025). A key function is linking the education system to the needs of the labor market, although this alignment is often challenging, particularly with rapid technological change. AI introduces specific challenges, such as the need to update curricula rapidly, train educators, ensure ethical use of AI tools in classrooms, and address potential impacts on academic integrity and equity (Global Solutions Initiative, 2024).

Governments influence labor markets through a wide range of policies, including setting minimum wages, regulating working hours and conditions, providing unemployment insurance and social assistance, enacting employment protection legislation (hiring/firing rules), supporting collective bargaining and unionization, implementing anti-discrimination laws, funding active labor market policies like job search assistance and training programs, and managing migration policies. These policies interact significantly with technological change; for example, strong employment protection might slow down labor reallocation in response to automation, while robust training programs and social safety nets can ease worker transitions. Some argue that strengthening worker power through labor policy is itself a crucial form of technology policy, enabling workers to shape technology adoption in the workplace (Economic Policy Institute, 2024).

The historical tendency for policymaking to react to technological disruption rather than proactively shape it presents a particular challenge in the context of AI. The unprecedented speed of AI development strains the capacity of traditional policy cycles and educational institutions to adapt, potentially leading to persistent skills gaps and reactive, rather than strategic, policy responses (Frank Hawkins Kenan Institute of Private Enterprise, 2025a).

6.1. Policy Rationale and Objectives for AI Skills Development

Why should governments support AI skill development? This section articulates the motivations and goals behind policy interventions, distinguishing between objectives related to *AI Development Skills* and those related to *AI Adoption Skills*. While overlapping, each has a somewhat different policy rationale.

The major rationale behind supporting AI Development Skills is that these are crucial for national competitiveness and technological sovereignty. Advanced AI skills enable domestic innovation, startup creation, and productivity gains in the economy. Nations with more AI researchers and engineers are better positioned to create cutting-edge AI products and intellectual property. Public policy thus aims to expand the supply of AI specialists to fuel the innovation ecosystem. For example, the EU explicitly notes that to remain globally competitive, Europe needs more professionals with specialized AI skills who can contribute to AI research and the rollout of AI systems (European Commission, 2021). A larger AI talent pool can accelerate technological breakthroughs and economic growth.

Many governments view AI talent as a strategic resource in the global race for technology leadership. Cultivating domestic AI expertise is seen as essential to reducing reliance on foreign technology and talent. This has national security and industrial policy dimensions. By supporting AI education, governments aim to secure a seat at the table in defining the future of AI. Ensuring a self-sufficient talent base in critical areas like AI can be part of maintaining technological sovereignty.

Fostering AI development skills is also about job creation in high-value sectors. Policymakers encourage the growth of AI expertise to attract investments and create high-paying jobs for citizens. Regions with strong pools of AI specialists can become hubs for tech industry growth, as shown by how skilled labor availability has driven clustering in past tech booms. Thus, one policy goal is to create a virtuous cycle: more skilled AI workers lead to more AI companies and projects, fostering more innovation and jobs.

In practice, these rationales translate into concrete targets in policy agendas: for example, aiming to double the number of AI graduates or researchers over a decade, or to have world-class AI research institutions. Achieving these goals typically involves both short-term measures (like attracting existing talent via immigration or industry partnerships) and long-term measures (educational reforms). Ultimately, supporting AI development skills is about building capacity at the frontier of technology, ensuring the country can invent and not just import AI solutions. The theoretical benefit is a higher national absorptive capacity for new innovations and a stronger hand in shaping AI's trajectory globally.

Equally important is the rationale for developing AI Adoption Skills across the general workforce and society. AI's promise of productivity gains will only be realized if businesses and workers can effectively *use* AI tools. A core rationale is to prepare the current workforce to work alongside AI, thereby boosting productivity in all sectors, not just tech. This means upskilling workers so they can integrate AI into manufacturing, healthcare, finance, public services, etc. Governments support broad AI literacy and reskilling programs to ensure that AI-driven innovations diffuse widely through the economy (avoiding a scenario where only a few firms or sectors benefit). In policy terms, this is about technological diffusion, enabling small and medium-sized enterprises (SMEs) and traditional industries, especially, to adopt AI by having employees and managers who understand it.

As AI automates certain tasks, workers need to adapt by moving to tasks that are complementary to AI. Public policy has a protective rationale here: to prevent unemployment or skills mismatch, governments invest in training programs that help workers transition into new roles where AI is a tool rather than a threat. One goal is to future-proof the workforce by fostering adaptability – teaching not only specific tools, but learning-to-learn, digital agility, and foundational data skills so workers can continuously evolve alongside AI advances (Organisation for Economic Co-operation and Development, 2023. By doing so, policymakers aim to reduce the risk of technological unemployment and ensure a smoother adjustment to AI's labor market impacts.

Governments also want to ensure all groups can participate in the AI-driven economy to prevent divides. Raising digital and AI literacy helps workers utilize AI tools and avoid job market polarization. Inclusive policies, like community workshops and targeted programs for underrepresented groups (e.g., women in AI) or rural areas, foster equitable access to AI-related skills.

Beyond the private sector, adoption skills are needed in government and among citizens for AI-enabled public services (e.g. healthcare AI systems used by doctors, AI in education used by teachers, etc.). A policy goal is to improve public sector innovation capacity by training civil servants in digital and data competencies (Mettler, Miscione, Jacobs, & Guenduez, 2024). Likewise, an informed citizenry that understands AI can better navigate issues like data privacy, algorithmic decisions in daily life, and civic debates on AI ethics. In this sense, promoting AI literacy for the public also has a democratic rationale – empowering citizens to engage with the societal implications of AI.

An important goal is fostering ethical AI use by training experts, end-users, and managers on AI bias, fairness, transparency, and safety to build public trust. Educating users on AI ethics helps them make informed decisions and encourages acceptance of AI. Policies highlight the need for understanding AI's limitations, promoting skills like recognizing algorithmic biases through guidelines and training.

In summary, the policy rationale for AI adoption skills revolves around empowering the broader population to work with AI, thus amplifying economic benefits while safeguarding employment and social cohesion. The ultimate goal is an AI-ready workforce and informed society, capable of leveraging AI in a way that enhances productivity and well-being. These rationales complement the innovation-centric goals for development skills: together, they ensure that AI's creation and diffusion are both supported by an enabling skill base.

6.2. Conceptual Frameworks for Government Intervention in AI Skill Formation

Building on the above, different conceptual frameworks can be used to analyze how governments can intervene to shape AI skills. These frameworks offer theoretical lenses for understanding policy action in this domain. We propose here to distinguish between:

1. Human capital investment and market failure framework.
2. Innovation ecosystem and triple helix framework.
3. Social inclusion and public value framework.

From an economic perspective, government intervention in AI skills can be seen as an investment in human capital to correct market failures. In this framework, AI-related skills (both high-end development skills and general digital abilities) are treated as a form of capital that yields social returns – fueling innovation, productivity, and employment. Left alone, markets may underproduce these skills: individual workers may under-invest in expensive training, and firms may poach skilled employees rather than train their own, leading to overall shortages. The role of government, then, is to ensure an adequate supply of AI skills by funding education and training, providing incentives for lifelong learning, and sharing information about skill needs. Policies are justified on efficiency and equity grounds. In short, the government acts as an investor in the nation's AI talent, stepping in where private

actors underinvest, to maximize public value and avoid skill gaps that could hamper AI adoption or exacerbate inequality.

A second framework situates AI skill development within the broader *innovation ecosystem*, emphasizing the interplay between government, industry, and academia (often described by the 'triple helix' model). Here, the government's role transcends funding and includes strategic coordination and vision-setting. Public policy is viewed as a catalyst that brings together universities (which supply education and research), businesses (which demand skills and provide practical training), and government agencies (which regulate and often employ AI talent) to create a robust pipeline of AI competencies. The focus is on systemic capacity-building – for example, establishing research centers of excellence that double as training grounds for AI scientists, or curriculum co-design between industry and educational institutions to keep skills aligned with fast-moving AI advances. This approach also stresses agility and foresight: government continuously scans emerging technology trends and adapts skill programs proactively.

A third framework emphasizes the normative goals of skill policy, viewing government as a steward of inclusive growth and ethical technology use. In this perspective, beyond economic calculus, public policy on AI skills is driven by the mandate to empower citizens to participate in the digital society and to mitigate the social risks of AI (like unemployment or digital divides). Government interventions are framed by concepts of digital inclusion, equity, and public value creation. This means ensuring that AI skills initiatives reach diverse groups, including underrepresented communities in tech, older workers, and those in regions or sectors at risk of being left behind (European Commission, 2021).

Together, these conceptual frameworks provide a multi-dimensional understanding of why and how governments intervene in AI skill formation. They are not mutually exclusive; an effective national strategy may draw on all three – investing in human capital, coordinating the innovation ecosystem, and pursuing inclusion – as we will explore in the policy recommendations.

6.3. Proposed National AI Strategy Archetypes

Recognizing the strategic importance of AI skills, governments globally are implementing a wide array of policies and initiatives. The focus and combination of these interventions vary significantly, reflecting different national priorities, economic contexts, and institutional capacities. However, analyzing these strategies reveals distinct approaches to tackling the dual challenges of fostering AI development and enabling widespread AI adoption.

While nearly every national AI strategy acknowledges the importance of skills (Futurium, 2025), the specific emphasis and policy mix often align with broader strategic goals, leading to discernible archetypes (CIFAR, 2018). Comparative analyses, such as the Brookings Institution (2025) cluster analysis and reviews by organizations like CIFAR and OECD (Galindo, Perset, & Sheeka, 2021), help illustrate these patterns.

The first category may be characterized as development-led. These strategies prioritize building national capacity to create and innovate in AI. They focus heavily on funding fundamental and applied R&D, establishing elite research centers, and attracting/retaining top-tier international talent (PhD researchers, experienced engineers). Early strategies in countries like Canada, as well as the stated ambitions of China, often exhibit elements of this approach, aiming for global leadership in AI creation (CIFAR, 2018).

The second group, adoption-led strategies**,** emphasizes preparing the broader society and economy to utilize AI effectively and responsibly. Policies may focus on nationwide digital literacy programs, extensive workforce reskilling initiatives, promoting AI adoption in the public sector, and establishing robust ethical and governance frameworks. Aspects of the EU's approach, focusing on trustworthy AI and digital single market integration (Futurium, 2025), and Singapore's strategy emphasizing deployment across all sectors (Civil Service College Singapore, 2025), align with this archetype.

The third broad type of strategies may be characterized as balanced, comprehensive approaches**.** These strategies attempt a more holistic approach, simultaneously investing in high-end talent and R&D while also implementing programs for widespread digital literacy and workforce adaptation. Later iterations of national strategies, and potentially the multi-faceted approach seen in the US (combining R&D funding, STEM education pushes, and workforce initiatives), may fall into this category. Cluster 1 in the Brookings analysis (including India, Mexico, US) planned to use various capability development sources (Brookings Institution, 2025).

These archetypes are not mutually exclusive, and national strategies evolve over time. However, they highlight a potential tension: allocating finite resources and policy attention between cultivating a small pool of elite AI creators versus equipping the entire population with the skills to navigate an AI-driven world. (Brookings Institution, 2025). The optimal balance likely depends on a nation's specific context, including its existing industrial base, educational system, and strategic goals.

6.4. Policy Instruments and Mechanisms for AI Skill Formation

Having identified the *why*, we now explore *how* governments can achieve these goals – the policy tools and mechanisms available to support AI skill development and adoption. In theory, governments have a broad toolkit, ranging from education system reforms to labor market incentives. We categorize these instruments into several key types:

- Educational curriculum reform (pre-university) as one of the foundational levers, to integrate digital and AI-related content into general education. Governments can update school curricula to include computational thinking, coding, and basic AI concepts at earlier stages (primary and secondary education. The aim is to build strong STEM foundations and digital literacy for all students, creating a talent pipeline and a populace comfortable with technology. This policy category ensures the next generation enters the workforce with significantly higher baseline digital competencies than previous ones – a long-term strategy for closing skill gaps.
- Higher education and research initiatives, to expand the capacity of universities and research institutes to produce AI experts. This includes funding new AI degree programs, centers of excellence, and scholarships. Such initiatives increase the output of qualified AI graduates and often incorporate industry partnerships for real-world experience. Another tool is updating university curricula to be interdisciplinary – combining computer science with ethics, business, or domain fields – so that graduates have well-rounded skills for AI development and deployment.
- Vocational training and lifelong learning programs to upskill and reskill adults for AI and digital tasks. This can include government-sponsored training courses, tech bootcamps, online learning subsidies, or expansion of vocational education to cover data analytics and AI. A particular emphasis should be placed on vulnerable groups, low-skilled workers, those in declining occupations, or older workers who get targeted training to adapt to AI changes (Organisation for Economic Co-operation and Development, 2023). Lifelong learning mechanisms also include public employment services providing counseling
- Incentives for employer-led training. Tools here include tax incentives or credits for training expenditures, grants or co-funding for corporate training programs, and recognition awards for companies that excel in workforce development (Organisation for Economic Co-operation and Development, 2025). Some governments set up public-private partnerships where the public sector matches training investments by industry in critical areas (for example, a government might co-finance an AI apprenticeship program run by a consortium of tech companies and universities). Another mechanism is incorporating training requirements or skills development plans into broader innovation grants. Governments may also mandate specific industries to ensure staff are trained in AI ethics or data handling (Organisation for Economic Co-operation and Development, 2023). By lowering the cost or sharing the burden of training, these incentives align private sector behavior with the public goal of a more AI-skilled workforce.
- National skills strategies and coordination bodies that serve as umbrella frameworks aligning various policies. Within these, governments often establish dedicated bodies or task forces (for example, a national AI skills council) to coordinate efforts across ministries (education, labor, industry) and with stakeholders (tech companies, academia, training providers). This ensures coherence, linking education reforms with industry needs and avoiding duplication. For instance, as of 2021, all EU Member States with AI strategies included a skills dimension coordinating actions from school curricula to lifelong learning in a unified plan (European Commission, 2021).
- Digital infrastructure for skills development includes not only physical infrastructure but also platforms and content. Governments can create open educational resources for AI, such as free online tutorials, and promote massive open online courses (MOOCs) on AI topics for widespread reach. For example, Finland's government-backed 'Elements of AI' online course

became a globally popular resource for teaching citizens basic AI concepts. By strengthening the enabling environment for skill development, these investments enhance the effectiveness of educational and training policies.

- Regulatory and ethical guidelines, frameworks, and accreditation standards serve as various 'soft' policy tools that indirectly promote the need for skills. For example, if a government issues an AI ethics framework for industry, companies may respond by training their staff in those principles. Similarly, requiring transparency or risk assessments for AI systems in specific sectors might necessitate new expertise, effectively creating demand for training in those areas. This mechanism underscores that policy encompasses not only funding and programs but also shaping the incentive landscape for skill development.
- Public-Private Partnerships (PPPs) as an emerging prominent mechanism for AI skills development. This trend reflects the recognition that neither sector can effectively address the rapidly evolving skills landscape alone (Access Partnership, 2025). PPPs aim to leverage the strengths of each sector: the public sector's reach, mandate for equity, and educational infrastructure, combined with the private sector's cutting-edge technological knowledge, understanding of market needs, agility, and resources. Existing case studies illustrate various PPP approaches, such as the California State University system partnering with major tech companies (Microsoft, OpenAI, Google) to provide AI tools (ChatGPT Edu) and training access to students and staff, the National Applied Artificial Intelligence Consortium involving community colleges and companies like Dell and Intel (California State University, 2025). The potential benefits include leveraging private sector expertise and agility, pooling resources, ensuring market relevance of training, and scaling initiatives more rapidly. However, challenges include ensuring alignment of public and private goals, establishing effective governance structures, managing intellectual property, and ensuring equitable access and outcomes, particularly for underserved populations. Examples like Singapore's multi-stakeholder approach to its national strategy or US initiatives leveraging industry commitments for K-12 education (The White House, 2025) illustrate the diverse ways PPPs are being employed.

In deploying these mechanisms, policymakers must consider the appropriate mix and sequencing. Early in the AI adoption curve, heavy investment in awareness and education might be needed; as the ecosystem matures, incentives for specialized training and continuous learning gain prominence. A theoretical insight is that an optimal policy mix addresses both the supply and demand of skills. By aligning these, governments can more effectively shape the evolution of AI skills in society.

6.5. Policy Levers for AI Development and Adoption Skills

Following the proposed distinction between ***AI development*** and ***AI adoption skills***, governments may employ several key policy instruments aimed explicitly at nurturing either of those. In the case of the high-level talent required for ***AI Development Skills*** these may include:

1. Investment in R&D and higher education, already a cornerstone of most national AI strategies. Governments can provide substantial funding for AI research through grants to universities, dedicated research institutes, and collaborative research programs (Futurium, 2025). Support extends to higher education institutions to establish specialized AI degree programs (Bachelor's, Master's, PhDs), create endowed chairs, and develop advanced curricula. The goal is to build a strong domestic pipeline of highly qualified researchers and engineers.
2. Talent Attraction and Retention (Immigration Policies): Recognizing the global nature of AI talent, many countries use immigration policy as a strategic tool (Center for Security and Emerging Technology, 2025). This includes creating or adapting visa categories for individuals with extraordinary ability Policies may offer pathways to permanent residency for STEM graduates and AI experts. Some strategies propose dedicated entrepreneur visas to attract AI startup founders (Center for Security and Emerging Technology, 2025).
3. Fostering innovation ecosystems to create environments where AI innovation can flourish. This involves policies that support AI startups and scale-ups through funding (e.g., venture capital initiatives, scale-up funds), incubators, and accelerators. Promoting collaboration between universities, research institutions, and industry is key, often facilitated through dedicated hubs or clusters (Civil Service College Singapore, 2025). Other tools include R&D tax incentives for businesses investing in AI, and strategic government procurement of AI solutions to stimulate

the market. Access to high-performance computing infrastructure and relevant datasets is also crucial (Futurium, 2025).

4. Public-Private Partnerships that involve joint R&D centers (like the MIT-IBM Watson AI Lab), government co-funding of industry-led research, support for AI startups emerging from universities, and collaborative efforts to build shared data or computing infrastructure.

Addressing the need for widespread AI literacy and utilization requires a different set of policy tools, often focused on broader education and workforce development. Policy levers for ***AI Adoption Skills*** may include:

1. Integrating AI literacy into education. This includes integrating AI concepts, computational thinking, data literacy, and ethical considerations into curricula across various subjects, not just computer science (IBM, 2025). Initiatives often involve developing new teaching resources, online learning modules, and providing professional development for teachers to equip them to teach AI concepts and use AI tools effectively in the classroom (The White House, 2025). Examples include proposed legislation like the US AI Literacy Act, programs like Day of AI, and national digital literacy strategies that incorporate AI elements. Higher education institutions are also encouraged or mandated to offer AI literacy courses for students across all disciplines.
2. Workforce reskilling and upskilling. This includes promoting lifelong learning opportunities, supporting apprenticeships in AI-related fields, funding bootcamps or certification programs targeting specific AI adoption skills, and offering subsidies or tax credits for employer-provided training. Sector-specific training initiatives may target industries undergoing significant AI transformation. For example, in the US, guidance encourages using Workforce Innovation and Opportunity Act (WIOA) funds for AI skills development (The White House, 2025).
3. Promoting Ethical AI awareness and training to build public and workforce understanding of responsible AI use (Bipartisan Policy Center, 2025). This involves developing and disseminating ethical guidelines for AI, funding public awareness campaigns, and incorporating ethics modules into AI training programs at all levels (UNC Executive Development, 2025). The goal is to foster a culture where bias mitigation, fairness, transparency, and privacy are considered integral to AI deployment.
4. Public-Private Partnerships again for collaboration in developing and delivering training programs, creating K-12 educational resources, launching AI literacy campaigns, establishing industry-recognized certifications, and developing ethical guidelines or standards (World Economic Forum, 2024). Governments may partner with tech companies, educational institutions, non-profits, and industry associations (The White House, 2025).

Governments may employ diverse policy instruments to foster AI development and adoption skills. For AI innovation, measures focus on investing in R&D, specialized higher education programs, talent attraction via immigration policies, and creating innovation ecosystems supported by public-private partnerships. To boost AI adoption, policies emphasize AI literacy in education, workforce reskilling, ethical AI training, and collaborations with industry and educational institutions to deliver training and resources.

6. CONCLUSION

The lack of appropriate digital skills in society is a key obstacle to the successful implementation of AI, which is why countries are placing a strong emphasis on education, ethics, and regulation in their AI strategies. AI is a tool that can bring great benefits, but it requires understanding and the right approach. It is impossible to stop technological progress, so the application and implementation of AI must be approached responsibly. An analysis of AI implementation strategies in countries reveals a wide range of approaches, reflecting the diversity of economies, legal systems, and priorities of individual countries. Despite these differences, there are many common themes, such as an emphasis on ethics, regulation, talent development, and infrastructure, indicating a global understanding of the key factors for AI success. Differences in sectoral priorities and specific initiatives reflect the specificities of individual countries and their response to the unique challenges and opportunities related to AI.

This research is expected to contribute to the theoretical understanding of how governments shape skill formation in the context of a general-purpose technology like AI. By differentiating between AI development and adoption skills, we sharpen the conceptual focus for policy analysis – highlighting that public interventions must simultaneously cultivate *frontier innovators* and *broad digital competence* in the population. We integrate insights from digital transformation studies, skill formation theory, and innovation policy to propose frameworks (human capital, ecosystem, inclusion) that can be used to analyze not only AI skills policy but also other emerging technology skill agendas. These frameworks contribute to the literature by bridging the often-separate discussions of education policy and innovation policy, showing how they intersect in the case of AI. Additionally, our synthetic review of policy tools provides a structured typology of interventions (education, training, incentives, partnerships, etc.), which can serve as a basis for comparative analysis.

Practically, our findings may help policymakers design more effective AI skill strategies. One key implication is the need for policy balance and coordination: efforts must balance investing in high-end AI expertise with broad-based digital upskilling, and they must coordinate across education systems, labor markets, and industry initiatives for maximum effect. Governments should recognize that addressing the AI skills challenge is a long-term endeavor requiring continuous adaptation – as AI technology evolves, so too must curricula and training programs. The rationale and tools discussed imply that governments should act both as *enablers* (providing resources, infrastructure, incentives) and *stewards* (ensuring inclusion and ethical considerations in skills development).

In conclusion, this research has underscored the critical role of government policy in shaping the skills landscape necessary for navigating the era of Artificial Intelligence. AI's transformative potential necessitates a proactive approach to human capital development, addressing both the specialized expertise required for AI *development* and the broader competencies needed for widespread and responsible AI *adoption*. A significant, dual skills gap currently exists, characterized by acute shortages of high-end AI talent and a pervasive lack of AI literacy and critical usage skills across the general workforce. This gap hinders innovation, limits productivity gains, and exacerbates societal risks associated with AI, including inequality and bias.

Based on the synthesis of findings, the following recommendations are proposed for governments seeking to cultivate a comprehensive AI-ready workforce:

- Develop a clear and aligned national AI skills vision that explicitly defines objectives for both AI development and AI adoption skills. This vision should be integrated with broader economic, industrial, and social policy goals, clarifying the desired balance between fostering innovation leadership and ensuring inclusive societal adaptation.
- Implement a balanced and contextualized policy portfolio targeting both skill types. Avoid an exclusive focus on either elite talent or basic literacy. The specific mix and sequencing of investments should be tailored to the nation's unique starting position, resources, and strategic priorities.
- Mandate the integration of AI literacy – including core concepts, practical application, critical evaluation of outputs, and ethical considerations – across all levels of the education system and diverse disciplines. Invest heavily in teacher training and curriculum development to support this integration. Simultaneously, higher education pathways should be ensured to produce sufficient specialized AI talent aligned with projected industry needs.
- Prioritize foundational and human-centric skills alongside technical expertise. Implement a dual focus in education and training. While nurturing cutting-edge technical AI skills is vital, equally important is strengthening broadly applicable foundational skills – digital literacy, critical thinking, creativity, complex problem-solving, collaboration, communication, ethical reasoning, and adaptability – across all educational levels and workforce development programs (Frank Hawkins Kenan Institute of Private Enterprise, 2025b). These human skills are essential complements to AI capabilities.
- Strengthen lifelong learning ecosystems. Invest significantly in building a robust and accessible lifelong learning infrastructure. Support flexible learning pathways, including high-quality online courses, industry-recognized micro-credentials, and modular training programs. Provide financial support and guidance for individuals undertaking reskilling or career transitions, particularly those displaced by automation. Promote skills-based hiring practices in public and

private sectors to validate diverse learning experiences (Frank Hawkins Kenan Institute of Private Enterprise, 2025b).

- Address the digital divide by ensuring widespread, affordable access to high-speed internet and digital devices, a prerequisite for both AI development and participation in digital skills training.
- Promote policies for secure and ethical data access for AI research and development where appropriate, balancing innovation needs with privacy protection.
- Strengthen governance mechanisms and establish clear inter-agency coordination structures to ensure a coherent "whole-of-government" approach to AI skills policy. Commit to transparency regarding government use of AI and policy outcomes (REI Systems, 2025), and adapt evidence-based strategies.
- Actively develop, promote, and enforce clear ethical guidelines and standards for AI development and deployment. Ensure these principles are integrated into all government-supported skills initiatives, procurement policies, and public sector AI applications.
- Foster agile and well-governed public-private collaboration. Encourage and facilitate PPPs to leverage private sector expertise, resources, and market knowledge, particularly for practical skills training and apprenticeships (UNESCO IESALC, 2025). However, establish clear governance frameworks for these partnerships to ensure transparency, accountability, alignment with public interest goals (including equity), and avoidance of undue corporate influence. Develop national skills gap analyses and industry skilling roadmaps through collaborative processes (Access Partnership, 2025).
- Last but not least, invest in policy implementation capacity, build technical expertise related to AI and data science within government agencies responsible for education, labor, and technology policy. Improve official statistical systems and develop better methodologies for monitoring and evaluating the impact of AI skills policies (Korea Development Institute, 2025). Foster stronger inter-agency coordination mechanisms (National Audit Office, 2025). Address the "AI policy literacy" gap among policymakers and civil servants.

Governments worldwide are responding with diverse national AI strategies and a range of policy instruments targeting education, R&D, workforce training, immigration, and public-private partnerships. However, strategies often vary in their emphasis, implicitly or explicitly prioritizing either development or adoption goals. Effective government intervention appears contingent on policy coherence across domains, strategic alignment with national context, robust stakeholder engagement, and adaptive governance mechanisms. Best practices involve sustained investment in R&D and STEM pathways for development skills, universal AI literacy integration in education, and accessible lifelong learning opportunities to adopt skills. Crucially, fostering "human skills" like critical thinking, ethical reasoning, and collaboration is becoming integral to effective AI adoption.

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PROVIDING MOBILITY SERVICES FOR OLDER ADULTS IN URBAN AREAS WITH AN AI SUPPORT-INTELLIGENT MANAGEMENT IN PUBLIC TRANSPORT

Zuzanna Kłos-Adamkiewicz[a], Federica Rossi[b]

[a] *University of Szczecin, Institute of Management, Poland*
[b] *Politecnico di Milano, Department of Architecture and Urban Studies, Italy*

ABSTRACT

Purpose: *This paper analyses the challenges for urban mobility in creating transport services for older adults, including Intelligent Management with the support of Artificial Intelligence (AI) solutions. It emphasizes sustainable mobility goals through the reduction of car dependency and the promotion of public transport, along with increasing mobility among older adults and limiting social exclusion.*

Need for the study: *The paper shows a holistic approach to transport service provision aimed at promoting aging-in-place and creating age-friendly cities with inclusive transportation systems, which might be made with AI help. It analyses the diversity of mobility needs of the growing demographic group of older adults, including specific domains of life, habits, and factors determining daily mobility.*

Methodology: *The study presents a theoretical process model for developing transport services that address the needs of older adults. It includes the most important issues related to the creation of sustainable mobility options with the main aim of reducing social exclusion.*

Findings: *The research shows that providing safe and attractive mobility solutions that reduce car use in favour of public transport and other forms of urban mobility is crucial for supporting multimodal and sustainable travel patterns. It also enhances the quality of life of older adults and their independence, allowing them to age in place.*

Practical Implications: *The proposed model serves as a starting point for policymakers and transport service providers to shape the accurate level of transport services and create liveable and sustainable urban environments for all.*

Keywords: public transport, transport services, AI, Intelligent Management, mobility needs of older adults, transport management, aging in place

JEL codes: J11, J14, O18, R40, R41, R42

2. INTRODUCTION

The aging population in urban areas, especially Europe, has become a growing concern. Older adults face unique challenges related to their daily mobility. As people live longer, the issue of creating age-friendly cities with efficient and inclusive transportation systems became a crucial task

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(Lin & Cui, 2021) Also, the growing older population is highly diverse in regard to multiple features, such as age, income, location, and above all- health (Haustein & Siren, 2015; Webber et al., 2010).

Older adults face multiple obstacles related to their limited mobility due to factors such as declining health, different disabilities, and lack of or limited access to private vehicles. This may lead to social exclusion and isolation, which may lead to reduced quality of life and/or reduced levels of social participation. Thus, mobility is closely related to health status and quality of life (Groessl et al., 2007; Plouffe & Kalache, 2010).

According to Eurostat projections, the baseline scenario projects that the current pattern of population ageing in the EU is likely to continue until 2100, with both the size and the proportion of older persons in the total population increasing. The proportion of elderly (65 years and over) in the EU total population is projected to increase from 21.1% (94.3 million) at the beginning of 2022 to 32.5 % (136.1 million) in 2100. As such, the share of elderly persons is projected to rise by +11.4 pp, corresponding to an additional 41.8 million persons by 2100. With the overall EU population declining by 2100, this is the only leading demographic age group that is projected to grow, both in relative and absolute terms, indicating a continuation of population ageing (*Population Projections in the EU*, 2023). Those changes will obviously affect almost every aspect of society and the economy, including the transport sector.

This paper aims to explore the subject of a process model of shaping the value of urban transport services that address older adults' mobility needs along with using Intelligent Management in public transport. Based on synthesis of identified segments of older adults and factors that are relevant in terms of older people's mobility patterns, the hypothetical model was proposed, integrating the most relevant determinants of older adults' mobility patterns and their interrelations including AI support.

3. LITERATURE REVIEW

Mobility itself might be presented as a (Scheiner, 2006) chance to meet one's need, the goals of 'unfulfilled activity wishes' and also 'satisfaction with out-of-home leisure activities. It can also be broadly defined as the ability to move using different means, i.e., by walking, by using assistive devices, or by using transportation. Area of mobility covers community environments that expand from one's home to the neighbourhood, and to regions beyond (Webber et al., 2010). WHO presented mobility in a broader way, including both indoor and outdoor movement as well as the use of assistive devices and transportation(International Classification of Functioning, Disability and Health (ICF)).

The mobility of older adults has been the focus of numerous empirical studies. Nevertheless, there are multiple challenges of urban aging, and they require a comprehensive approach to address the mobility needs of this group. Older adults often face numerous problems while accessing public transport services. Those barriers are related to infrastructure accessibility, smart solutions (like journey planners and navigation tools), and access to current information about connections of public transport networks and cancelled courses (Loos et al., 2020; Maresova et al., 2023a).

In addition, the lack of flexible and community-based transport options further limits the mobility of older adults and also, as Kim et al. highlighted (Kim et al., 2019) – when older people do not undertake out-of-home activities it may be caused by lack of transport options or an unfriendly environment, rather than having no need to travel. Mobility is crucial in terms of active aging, as it allows older adults to maintain their independence, participate in physical activeness, engage in social and community life as well as give the possibility to access necessary resources (Maintaining Mobility and Preventing Disability Are Key to Living Independently as We Age | National Institute on Aging).

Moreover, mobility is a key component of aging in place, which refers to the possibility for older adults to choose to continue living in their own homes and neighbourhood despite aging (Mestheneos Elizabeth, 2011). Indeed, this is possible if the provision of services, including transportation, is adequate (Davies & James, 2016; Gilleard et al., 2007; Gonyea & Burnes, 2013).

Outdoor mobility refers to the physical ability to move, and it also refers to all types of trips outside home, either by foot or other types of transportation (Rantanen, 2013). Physical activity, at any age, can reduce the risk of chronic diseases (i.e., cardiovascular diseases, type 2 diabetes, stroke, and certain

types of cancer), but also can help to prevent depression, dementia, and cognitive impairment. As chronic diseases are found to be more prevalent among older adults, and as the global number of this group is still rising, this implies enormous healthcare costs (Mertens et al., 2019).

The aging population is increasingly diverse, and this diversity is no longer considered a homogeneous group, but it is divided into meaningful segments according to number of studies. Various studies segment the older population into homogeneous groups based on a combination of various factors: demographic, health-related, and transport-related(Cui et al., 2017; Lin & Cui, 2021), which all interact with domains of life(Isaacson et al., 2020).

3.1. Factors and Determinants of Older Adults' Mobility Patterns

It is important to base mobility patterns on a theoretical background and on variables that have been found within different, more general studies and are relevant predictors for explaining mobility behaviour(Haustein & Hunecke, 2013). Analysis of mobility behaviour factors can be included in cluster analysis. When considering, for example, a population of older people, it is understandable to include factors such as age, income, accessibility, and the social network, which are important factors in older people's mobility behaviour. Numerous scientific journals describe those approaches, but from the point of view of this paper, it is necessary to include the most common factors that refer to the mobility needs of older adults in terms of model creation.

From the point of view of this paper, based on existing studies the concept of mobility is portrayed through five fundamental categories of determinants: cognitive (Shoval et al., 2011; Ullrich et al., 2019), psychosocial (Isaacson et al., 2020; Wu et al., 2021), physical (Portegijs et al., 2014; Tokey, 2021), environmental (Kramer & Pfaffenbach, 2016; Rantakokko et al., 2016) and financial (Frantál et al., 2020; Sanchez et al., 2017), which will later on be named as domains of life of older adults. And those basic categories are influenced by more general mobility determinants, including age, gender, culture, car access, etc. (Maresova et al., 2023a; Webber et al., 2010) (Table 1).

Table 1. Mobility-related domains of older adults' life

Mobility-related domains of older adults' life				
Cognitive:	**Psychosocial:**	**Physical:**	**Environmental:**	**Financial:**
• Mental status; • Memory; • Speed of processing; • Executive functioning	• Self-efficacy; • Coping behaviours; • Depression; • Fears; • Relations with others that affect one's decisions; • Perceived benefits; • perceived barriers, • social norms; • Social support	• Stamina; • Physical activity; • Physical barriers	• Driving in the night/rain (poor weather conditions); • Weather dependency; • Type of infrastructure; • Outdoor terrain • Home location; • Neighbourhood; • Distance • Residence characteristics; • Social interactions	• Level of income

Source: own elaboration based on (Isaacson et al., 2020; Maresova et al., 2023a; Mertens et al., 2019; Ragland et al., 2019; Webber et al., 2010).

Siren and Hakamies (2016) explained the reasons why traditional approaches in mobility and travel behaviour fail to identify the mobility needs of older adults. Mobility- usually perceived through travel behaviour, demands, preferences, choices, satisfaction, and activity patterns, may not be sufficiently effective to allow specific insight into the needs of different age populations, in this case, older adults (Siren & Hakamies-Blomqvist, 2005). Each age group has its special features and characteristics that impact travel behaviour and also mobility needs.

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When considering older adults, there is a need to highlight the relevant heterogeneity with regard to age, gender, and health conditions (Luiu et al., 2017). The group of demographic factors (Figure 1) have a greater or lesser extent impact on mobility behaviour, such as: (Barišić et al., 2024; Haustein & Hunecke, 2013; Johnson et al., 2020; Luiu et al., 2017; Mercado et al., 2010)

a) Age: which is multidimensional, and there are multiple ways to define 'old age', including: chronological age, functional capacity, or major life events like retirement or widowhood.
b) Gender: which is strongly related to other factors, especially car access, being licensed as a driver, and income, with women being disadvantaged across all factors. Due to longevity compared to men, the majority of the oldest and thus the physically most fragile population is female.
c) Income: Older people with a higher income make more trips, are more likely to drive, and are less likely to use public transport. On the other hand, financial concerns are one reason why older people stop driving a car.
d) Education: a higher level of education is associated with a higher probability of a more positive self-assessment of successful aging, especially in the case of projection of better financial status after retirement.
e) Employment status and retirement: which is also strongly related to other factors, as health has an effect on retirement and retirement may have an impact on health and travel patterns.
f) Household structure and related transitions: it is more likely not living in a single household that reduces mobility but the fact that people who live in single households are older, more often widowed, female, and less healthy.
g) Built environment: car-dependent older adults were more often found in rural districts and multimodal and service-dependent seniors in urban districts. Also, in rural areas, car access is often a precondition to independence, and in urban areas, where there are more mobility options, it is not that common. This factor also includes environmental barriers such as high curbs, lack of sidewalks, and missing environmental facilitators, etc.
h) Car access: is a factor that is found to be associated with better physical and mental health and well-being. Car use and its access are also linked to built environment factors, household structure, and gender.
i) Health: stays in relation to the social and productive activities of older adults. On the other hand, health restrictions reduce older people's activity frequency and increase their unfulfilled activity wishes (stroke, depressive symptoms, obesity, etc.). Older people's health is affected by the built environment and car access and also thereby influences mobility.
j) Social network/ physical capabilities and activities: which play an important role in later life. As for post-retirement persons, social and leisure activities form a larger share of their travel to a larger extent than for working people. On the other hand, for people with restricted mobility, the social network is crucial in order to conduct any out-of-home activities. Without the option to drive, older adults often depend on their social network to get a lift. Social networks are strongly related to older people's activity frequency, diversity, leisure distance, and leisure satisfaction.

The abovementioned factors might be put into more general groups of determinants, just as it has been shown in other studies (Luiu et al., 2017; Maresova et al., 2023a; Webber et al., 2010). However, those groups vary, according to existing research in this field. It is important to underline that health status related to age may require special transportation services, as older adults with disabilities or chronic health conditions may require different types of dedicated services. But those also vary according to income. In some cases, there is only the possibility to use wheelchair-accessible vehicles, door-to-door assistance; on the other hand, when the income is relatively higher, there might be a chance to use private vehicles(Musselwhite et al., 2015), taxis, and other types of ridesharing services. Those services play a meaningful role in maintaining the mobility of older adults and independence, limiting social exclusion. However, the burden of transportation costs still poses a significant challenge.

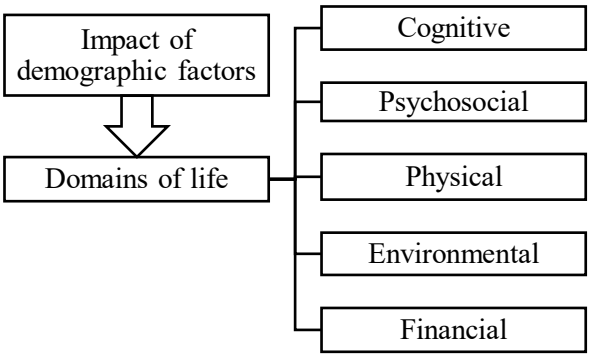


Figure 1. Demographic factors and domains of life as a main determinants of mobility behaviour determinants
Source: own elaboration.

As suggested by Musselwhite (2019), a model of age-friendly transport should cover (in concentric rings around the individual)-walking and cycling, followed by public and/or community transport, and then it all should be surrounded by age-friendly strategy and policy (Musselwhite & Scott, 2019). Improving the mobility of older adults is a process-based approach of multidisciplinary collaboration and coordination with other urban policies and projects, including health, infrastructure, and land use, so it meets the needs of the older adult population (Aguiar & Macário, 2017).

3.2. Mobility types among older adults

The literature directly shows that older adults' mobility needs and preferences are diverse. It all relates to "mobility styles" (Haustein & Hunecke, 2013), which can be regarded as a further development of the lifestyle approach. It is essential to underline that mobility-related attitudes and preferences are highly integrated with the life styles (Haustein & Hunecke, 2013; Lanzendorf, 2002; Ohnmacht et al., 2009). In addition, each generation of older adults has different travel patterns due to longer life expectancy, technology development and more diverse social offer (Cui et al., 2017).

The longest-term decisions made by individuals are the choice of a lifestyle, and the short-term decisions are the daily travel choices. Lifestyle is defined as the pattern of behaviour which conforms to the individual's orientation toward the three primary roles: as a household member, as a worker, and as a consumer of specific leisure types related to available resources (Salomon & Ben-Akiva, 1983). Understanding and identifying an individual's lifestyle is highly important while explaining an individual's behaviour, and travel behaviour as well.

There are various segmentation of mobility types approaches: behaviour base (Ohnmacht et al., 2009; Prillwitz & Barr, 2011), geographic segmentations (Aditjandra et al., 2012; Scheiner, 2006), sociodemographic segmentations (dependent on lifestyles and life stages)(Hildebrand, 2003; Hunecke et al., 2008; Salomon & Ben-Akiva, 1983), mobility styles and mobility types (Anable, 2005; Haustein & Hunecke, 2013; Lanzendorf, 2002; Ohnmacht et al., 2009).

According to Cui et al. (Cui et al., 2017; Lin & Cui, 2021), major characteristics and challenges of the travel patterns of older adults are:

- As older adults age, the number of trips and trip distances decrease, particularly after 75 years old.
- Dependency on private vehicles as the primary mode of transport continues, except for those aged 85 years or more.
- As older adults age, the importance of social relations and shopping trips increases, except for those aged 85 years or more.

In the literature, we can find terms related to 'aging in place' (Alley et al., 2007; Luiu et al., 2017). It is found to be one of the key determinants for the availability and accessibility of public transport, which is also related to the independence of older adults. And so, it can be seen that a lack of transportation options, including public transport, can significantly lower older adults' access to healthcare, social activities, and other services, finally causing social exclusion. 'Aging in place' in

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relation to transportation enables older adults to remain in their homes and communities as they age. Luiu et al. (Luiu et al., 2017) emphasize the importance of accessible transportation options for older adults to maintain their independence and access essential services and social activities.

As proposed by Haustein and Siren (Haustein & Siren, 2015), there are four main segments of older adults:

- affluent mobile drivers (predominant car use, high activity engagement),
- car-dependent seniors (predominant car use, low activity engagement),
- mobile multi-modal seniors (use of all modes, medium to high activity engagement),
- and transport service dependent seniors (walking, public transport, and car use as passenger, low activity engagement).

Siren et al. grouped the transport needs of older adults into two main categories: 'serious needs', including medical appointments and emergencies, and 'discretionary needs', including spontaneous trips, visiting friends and relatives, and in general, achieving pleasure(Siren & Haustein, 2016). Some life events (e.g., related to the accidental lower health condition, changing the place of residence, losing a spouse who was a driver for the couple) have an impact on changing one's mobility profile suddenly and substantially (Webber et al., 2010). It is worth noting that not all older adults will have to cope with all of the mobility factors presented in this paper.

4. INTELLIGENT MANAGEMENT IN PUBLIC TRANSPORT- AI SUPPORT FOR MOBILITY SERVICES FOR OLDER ADULTS

Urgent and creative solutions are needed to enhance the independence and well-being of older adults, given the growing worldwide aging population. Artificial intelligence (AI) and robotics have emerged as viable technologies to address these issues.

Given the increasing interest in this topic, the term 'Gerontechnology' was coined to indicate an interdisciplinary field linking existing and developing technologies to the aspirations and needs of aging and older adults (Bronswijk et al., 2009; Chen, 2020).

We can identify three main fields in which AI-powered systems can assist older adults in their everyday lives: health, home-related issues, and mobility. Wearable technology powered by AI can track vital signs and activity levels, encouraging a more autonomous and healthy way of living.

AI-enabled smart home technologies can assist people in achieving their independence and lessen their dependency on both official and informal caretakers, such as family members. For example, AI algorithms in cutting-edge home applications can identify departures from typical behaviour patterns and promptly notify users of emergencies. Domestic robots can also assist with tasks such as carrying objects, answering queries, or finding misplaced objects (Czaja & Ceruso, 2022). Furthermore, AI can be implemented in smart cities to assist and encourage the mobility of senior citizens through the use of handheld devices, smartphones, tablets, and laptops that display information and have touchscreens or keyboards for entering instructions or data(Arnold et al., 2024; Bokolo Jnr, 2024; Musselwhite, 2023).

Specifically, AI applications can help older adults with navigation (e.g., getting detailed step-by-step directions), planning (e.g., booking the journey), and exploration (e.g., asking for and receiving information about the surrounding environment and required Points of Interest for better environmental awareness).

Bokolo Jr. (2024) argued that older adults require help managing their daily mobility. Thus, AI can encourage safe, autonomous, and accessible mobility, particularly for those with physical disabilities, those in wheelchairs, those with legal blindness or vision impairment, those with sensory impairments, and those with learning difficulties. If an older person is hurt while walking across or within a city, AI can connect them to emergency help services and/or to families and caregivers. Text-to-speech, automatic voice recognition, and a graphical touch-based user interface are some multimodal interfaces used(de Arriba-Pérez et al., 2023).

Specifically looking at the public transportation systems, Bokolo Jr. (2024) highlighted their poor inclusiveness and accessibility to older adults. AI can assist this population segment in leaving bus or train stops or stations in this context. By quickly inquiring if the user needs assistance remembering a trip and verifying the itinerary or schedule, AI can assist older adults with memory loss and cognitive impairment. Moreover, AI might serve as a travel assistant by offering a range of accessible and

available modes of transportation and providing guidance in various zones. When departing from a new bus stop or station, it may provide detailed directions to destinations(Bokolo Jr., 2024).

Finally, looking at walkability, AI can improve it by offering solutions like haptic and audio vibrotactile/feedback indicator-based augmented systems for senior citizens(Sobnath et al., 2020).

However, Maresova et al. (2023b)highlighted the following obstacles in the usage of AI technologies by older adults:

1. Many seniors who may not even have a basic level of digital fluency and comfort may find it difficult to use mobility technologies because they demand a smartphone, internet connection, and the capacity to make online payments.
2. Many older adults need wheelchairs or walking aids, which can be challenging to get into and out of public transport or cars, such as autonomous vehicles.
3. Many older adults require door-to-door or hand-to-hand service because of difficulties like recognizing the autonomous vehicle when it arrives, stowing and retrieving bags or mobility aids, locating the right door at complicated locations like hospitals or shopping centers, and physically navigating busy streets and sidewalks.

Finally, integrating AI and robotics in geriatrics presents serious ethical problems. Strong security measures and transparent consent processes are necessary to allay privacy concerns about collecting and using personal data. It is essential to create policies and rules that guarantee the ethical and responsible use of these technologies(Padhan et al., 2023).

To conclude, with the abovementioned cautions, AI technologies can contribute to aging in place or living in a familiar and comfortable environment for as long as possible.

5. MATERIALS AND METHODS

The existing literature emphasizes the crucial role of public transport in addressing the mobility needs of older adults, instead of car usage. This issue is also crucial while meeting the goals of sustainable urban transport development. This research has focused on mobility beyond one's home, including different types of movement, but mainly using private vehicles and public transport, as in this case vehicles and other forms of transportation require more in-depth analysis, and creation of transport services for older adults in order to maintain access to essential services, activities, and people, also including support from AI.

Although there is no single solution to transport modelling, the basic principles, including strengths and limitations, are used with the presented theoretical model. A relatively good model includes various interventions, policies, and projects that can be tested for their performance against given objectives (Ortuzar S. & Willumsen, 2024). It is also important to include the most relevant indicators, which were analysed in this paper.

The paper presents the classic transport process model, which includes analysed mobility factors, demand and supply side, modal split, external and additional factors, and support from the side of AI. The classic model concentrates attention only on a limited number of travellers, in this case older adults, and travel decisions are not made in a particular order. The consumer-process approach to transport services quality management (Kryvoruchko et al., 2018) is also included in this model.

6. MODEL OF SHAPING THE VALUE OF TRANSPORT SERVICES

On the basis of factors that were identified in existing literature related to the travel behaviour of older adults, the theoretical model on how different determinants work together was prepared.

The model integrates the most relevant determinants of older adults' mobility needs, which were presented in Figure 2, in particular:

- Demographic factors.
- Domains of older adults' lives.

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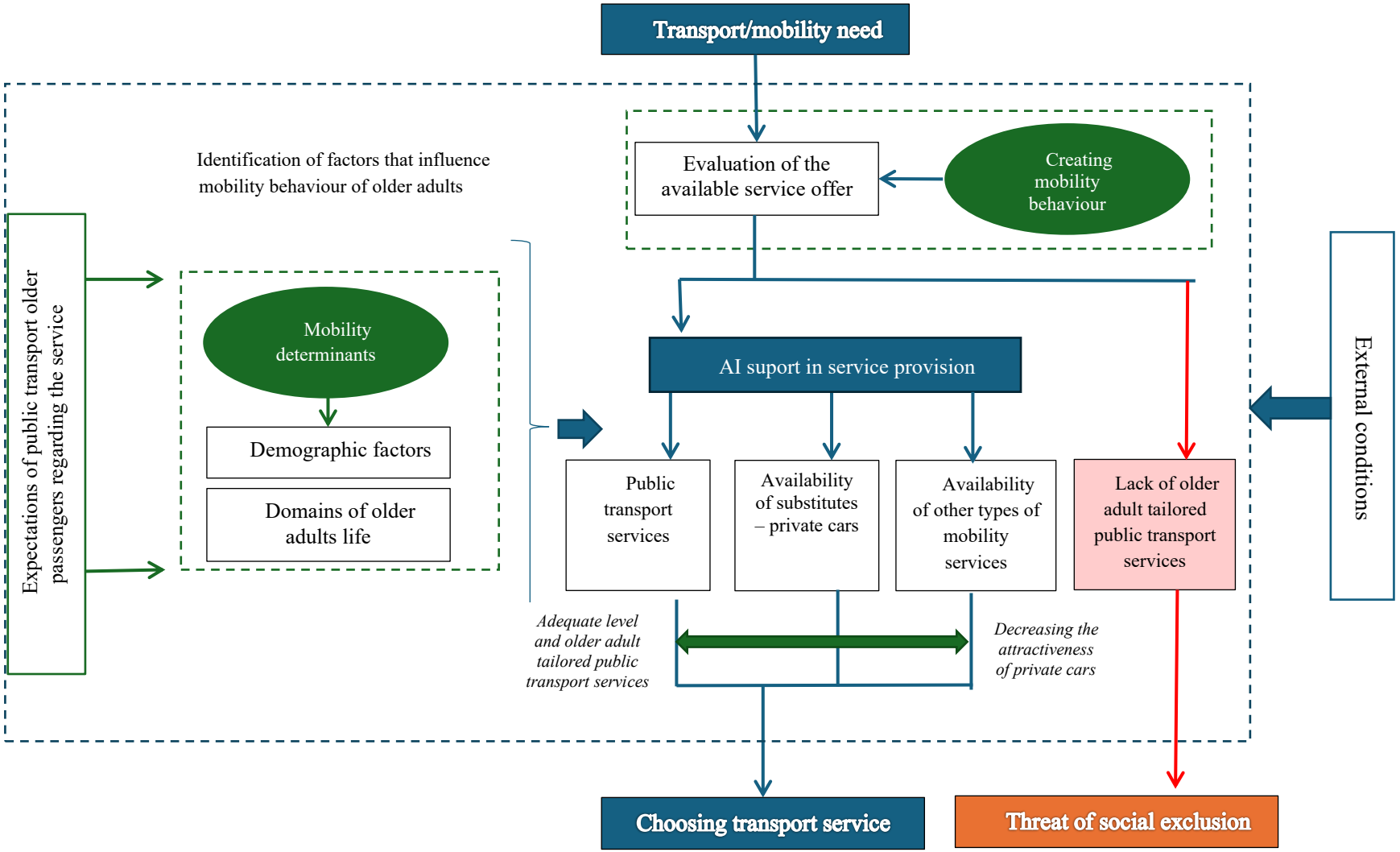


Figure 2. A model for shaping public transport and mobility services in relation to individual motorization, taking into consideration older adults' mobility needs

Source: own elaboration.

While the analysed needs and preferences of older adults are highly diverse, a general framework can be developed to understand the key factors that influence mobility behaviour and patterns within this group of adults. This framework might be helpful when creating public transport services that are demand-responsive and aligned to specific needs.

The proposed model serves as a starting point for policymakers and transport service providers to shape the accurate level of transport services and create liveable and sustainable urban environments for all.

7. DISCUSSION

In this study, it was shown that creating transport services for the group of older adults includes multiple and diverse factors. Reducing car-dependency by providing safe and attractive infrastructure for the safe use of active modes and better public transport services can be regarded as a key task to support multi-modal transport patterns. More and more often, in everyday life, we can see the use of modern technologies, one example of which is the implementation of Intelligent Management, which we can see through AI usage, also in the case of mobility services tailored to the needs of an aging society.

Designing age-friendly cities with inclusive transportation systems is crucial for enhancing older adults' quality of life and independence, allowing them to age in place. The process model presented in this paper, which prioritizes the unique values, needs, and preferences of older adults, might be a starting point for policymakers and also public transport services and mobility providers in the cities to shape the value of the transport services along with creating liveable and sustainable urban environments for all.

Staying active and independent in old age is also in line with the WHO's emphasis on Active Aging (Global Age-Friendly Cities: A Guide, n.d.). But also, as pointed out by Hakamies-Blomqvist, losing one’s mobility is not only a personal tragedy, but also a public health issue which might be seen through a chain of interrelated mechanisms (Hakamies-Blomqvist & Wahlström, 1998). Loss of mobility may occur when an older adult can no longer safely drive a car and/or when physical disabilities interfere with walking (Webber et al., 2010).

Knowing that the mobility model may be used to predict impairment and guide the design and interpretation of research studies, with additional value and information to city authorities and transport services operators is important. Development in the field of technology, including AI, also gives options that allow older adults to compensate for various mobility-related deficits (i.e., robotic walkers, driving assistants, and vehicle control devices, etc.) (Maresova et al., 2023a).

Addressing mobility challenges for older adults involves a multistakeholder approach, including healthcare providers, policymakers, urban planners, and families. Additionally, it is essential to regularly identify opportunities and monitor the development and usefulness of new solutions in mobility, in this case, possible ways of AI usage (Lui et al., 2009; Maresova et al., 2023a).

Based on travel patterns of older adults, and analysed factors that influence these patterns (Cui et al., 2017), the number of limitations of existing alternative transport options that are a threat to the mobility of older adults is as follows:

- Being a car passenger is an inconvenient and unattractive mobility option for older adults.
- Unreliable, poor-quality public transport services limit the number of trips as an alternative transport option.
- Accessibility restrictions for older adults with limited digital literacy.
- An unsupportive pedestrian infrastructure between home, transit nodes, and destinations also limits the use of public transport among older adults.
- Unfriendly pedestrian environments and poor urban design result in high-speed vehicular traffic and low ‘walkability’, which makes walking an unattractive option for older adults.
- The lack of safe cycling infrastructure and other support for safe cycling made this type of transport unattractive for older adults.

This theoretical model is presented to give different groups of stakeholders (especially city authorities and urban transport service operators) a chance to consider broadly the determinants of older

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adult mobility and all of the interactions among them, also about AI support, in order to provide sufficient and accurate services, with the main hope to avoid social exclusion. This model may also give the possibility to establish new research for further development and analysis in the field of mobility factors in different mobility contexts.

Key discussion points include:

Multimodality: Promoting sustainable transport patterns is crucial. This also requires the provision of safe and attractive infrastructure, including active modes of transport, such as walking and cycling, alongside improved public transport services. Integrating these options allows older adults to choose the most suitable transport mode for their individual needs and abilities and avoid social exclusion.

Reducing Car Dependency: Car ownership offers convenience and flexibility, but it is not a sustainable option for all older adults. Declining health, disabilities, and financial constraints can limit access to private vehicles. Therefore, providing viable alternatives is crucial.

Age-Friendly Urban Design: Creating age-friendly cities requires a holistic approach that considers the needs of older adults in all aspects of urban planning, including transportation. This involves designing inclusive transport systems that are accessible, affordable, available, and safe.

The Value of Transport Services: The proposed process model emphasizes the importance of shaping the value of transport services to align with older adults' specific needs and preferences. This includes considering different and diverse factors.

Modern technology support: AI-powered transport services offer tailored solutions for older adults, creating a safer environment that contributes to their enhanced ability to live independently with autonomy as long as possible. AI-powered assistants used in daily mobility can help in the field of planning, designing, and tracking the physical activities of older adults with chronic diseases, ensuring they stay active and manage their conditions effectively. On the other hand, while using modern technology support (including AI), it is important to take into consideration the ethical issues surrounding data privacy.

Active Aging: Supporting active aging is also a key objective. Providing accessible transport options enables older adults to maintain their independence, participate in social activities, and access essential services, contributing to their overall health and well-being. This objective also includes considering various groups of older adults, including those with limited digital literacy.

The process model presented in the paper suggests that a more holistic approach is needed to fulfil the needs in the field of mobility assessment and treatment, and also broader consideration for the development of related policies and programs.

8. CONCLUSION

Reduced mobility among older adults is a complex problem that, in most cases, comes down to social exclusion. This paper shows a theoretical process model for creating services for older adults, taking into consideration the growing number of this group of city dwellers. The key determinants of mobility have been described to show, in detail, what must be considered while creating the services.

Based on the findings included in this paper, future research can focus on:

- In-depth analysis of how different factors concerning mobility interact and what added value and mobility outcomes can be created on the basis of this type of research.
- How to use AI efficiently in the field of daily mobility of older adults to avoid social exclusion.
- Further analysis of environmental factors, and how they can be managed to meet the goals of sustainable mobility in the cities.
- Suggestions in the field of public interventions that can improve selected determinants of mobility and assess their impact on health and well-being.

The model presented in the paper shows that all forms of movement are important and that many interrelated determinants influence mobility. Further research concerning the complex interactions between mobility determinants in different mobility contexts is needed. It should explore the practical implementation of the proposed process model in diverse urban environments and analyse its long-term impact. Additionally, in-depth studies should examine the role of technology, especially AI, in

enhancing transport accessibility and explore innovative solutions to address the evolving mobility needs of an aging population.

Considering that in most European countries the number of adults is increasing, the consumer potential for tailored services is also growing. This should and might be a strong motivation for transport service providers to develop innovative and supportive services for this group of inhabitants.

This study shows the complexity of transport services that need to meet the needs of older adults, but also in other countries that face rising demographic issues. One of the key issues is the reduction of car dependency by providing safe and accessible alternatives, such as public transport, walking, and cycling.

The proposed model, which prioritizes the unique values, needs, and preferences of older adults, offers a valuable framework for policymakers and public transport service providers. By adopting this model, cities can shape the value of transport services in ways that directly address the challenges faced by older adults.

Let's face the fact that creating age-friendly cities with inclusive transportation systems is not just a matter of convenience; it is crucial for enhancing the quality of life and independence of older adults.

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DIGITAL MATURITY OF EUROPEAN UNION ENTERPRISES IN THE CONTEXT OF AI IMPLEMENTATION – AN EMPIRICAL APPROACH USING CLUSTER ANALYSIS

Aneta Becker[a], Jarosław Becker[b], Tomasz Zdziebko[c]

[a] *West Pomeranian University of Technology, Faculty of Economics, Szczecin, Poland*
[b] *The Jacob of Paradies University,* Faculty of Technology, *Gorzów Wielkopolski, Poland*
[c] *University of Szczecin, Faculty of Economics and Management, Szczecin, Poland*

ABSTRACT

Purpose: *The aim of this study was to analyze the extent of AI technology implementation in the economic activities of EU countries and to classify them based on their level of digital advancement.*

Need for the study: *AI plays a central role in the digital transformation of enterprises and the emergence of intelligent management practices. Despite its growing importance, significant disparities remain in AI implementation across the EU, warranting a structured, data-driven assessment of digital advancement levels.*

Methodology: *The study employs cluster analysis techniques – specifically the k-means algorithm and Kohonen self-organizing maps (SOM). The empirical data were sourced from Eurostat (2023) and cover 27 EU member states across ten quantitative indicators, including AI adoption, ICT human resources, GDP per capita, cloud infrastructure, and advanced data analytics.*

Findings: *Three distinct country clusters were identified: high, medium, and low levels of AI adoption. Countries such as Finland, Denmark, and Belgium were classified as highly advanced, while Poland, Bulgaria, and Romania fell into the least advanced group. The results reflect substantial differences in digital infrastructure and economic development levels among EU countries.*

Practical Implications: *The classification can inform the development of targeted digital and innovation policies. Policymakers may use the findings to address regional gaps, allocate resources more effectively, and promote responsible AI deployment within the EU.*

Keywords: artificial intelligence, digital maturity, cluster analysis, intelligent management, ICT infrastructure, EU enterprises

Jel codes: O33; C38; L86; O52

1. INTRODUCTION

The contemporary economy increasingly relies on advanced technologies that are transforming business models and influencing enterprise competitiveness. Among these innovative solutions, artificial intelligence (AI) plays a particularly significant role, serving as one of the pillars of the

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Fourth Industrial Revolution. Its dynamic development in recent years has set new directions for the activities of economic entities and has laid the foundation for entirely new business models.

Artificial intelligence, defined as the ability of machines to perform tasks typical of human intelligence – such as reasoning, learning, and decision-making – is finding increasingly widespread applications across various sectors of the economy (Russell & Norvig, 2009). Initially the subject of purely scientific inquiry, AI has, thanks to the development of digital infrastructure, access to large datasets, and enhanced computational power, become a commercial reality for many enterprises. In particular, the countries of the European Union (EU) recognize the strategic importance of implementing AI within the economy, perceiving its potential to increase productivity, improve service quality, and intensify innovation (*Coordinated Plan on Artificial Intelligence 2021 Review | Shaping Europe's Digital Future*). Consequently, there has been a noticeable growth in research efforts aimed at classifying member states according to their level of AI adoption, with particular emphasis on enterprises as the primary implementers of these technologies. At the same time, AI presents numerous challenges – not only technological but also legal, ethical, and social. Therefore, it is essential not only to study the possibilities for its application but also to examine the regulatory frameworks that should ensure the responsible and safe use of these technologies (*EU AI Act - Updates, Compliance, Training*). In response, the EU has undertaken numerous initiatives aimed at creating a unified set of principles for the development and deployment of AI, while maintaining alignment with the fundamental values of the community (Caroli, 2025).

The aim of this study is to analyze the extent of AI technology adoption by enterprises in EU member states and to classify countries based on their level of digital advancement. The study was based on cluster analysis methods, including the k-means algorithm and Kohonen self-organizing maps (SOM), with empirical material consisting of 2023 Eurostat data concerning ten quantitative indicators describing AI usage, ICT human resources, GDP per capita, cloud infrastructure, and advanced data analytics. The calculations were performed using the 'Statistica' statistical package.

2. LITERATURE REVIEW

The scientific literature and international reports increasingly emphasize the importance of artificial intelligence (AI) and its impact on economic development, innovation, and the competitiveness of enterprises and regions. The aim of this review is to present current research findings regarding the factors influencing AI implementation in enterprises, as well as the variation of this process at the national, regional, and institutional levels. A noteworthy study in this area was presented by S.S. Kazakova et al. (2020), who, based on a survey conducted among 9,640 enterprises from 30 countries, found that despite a high level of AI awareness among firms (78%), its implementation is constrained by a shortage of qualified personnel, high costs, difficulties in adapting operational processes, regulatory uncertainty, and a lack of data standardization. According to D. Antoniuk and O. Kolyada (2024), important factors facilitating the adoption of AI solutions by enterprises include a well-developed digital infrastructure and a high level of human capital, as evidenced by the strong correlations between the values of the DESI (Digital Economy and Society Index) and HDI (Human Development Index) and the level of AI technology adoption in European countries. C. Mocanu et al. (2024) argue that although the majority of small and medium-sized enterprises recognize the benefits of digitalization, only a small proportion actually utilize advanced technologies such as AI or data analytics, which can be attributed, among other factors, to limited technological awareness and restricted access to appropriate resources.

Interesting studies focus on the regional determinants of AI technology adoption, highlighting significant disparities between individual countries and areas of Europe. According to L. Angelo et al. (2024), an analysis of the implementation of online sales tools in Italian enterprises revealed the existence of pronounced regional inequalities, emphasizing the relationship between the level of digital advancement, the development of technological infrastructure, and the employment structure. The work of M. Zlatev and N. Tsonkov (2025) presents an analysis based on a spatial approach, confirming the significant impact of AI implementation in European regions on economic dynamics, with the level of digital infrastructure, the advancement of the ICT sector, and the capacity for knowledge generation determining the spatial differentiation of AI technology usage. In a study conducted by B. Brey and E.

Van der Marel (2023), it was found that the territorial concentration of human capital associated with AI-based digital tools in Europe significantly affects the pace of technology adoption by enterprises, and that persistent disparities in access to qualified personnel may constrain the long-term development potential of the entire continent. In addition to regional differences, the digital and institutional environment of enterprises also plays a crucial role in the process of AI adoption, as exemplified by analyses of Eastern European countries. In a study employing a mixed-method approach combining logistic regression and k-means cluster analysis, A. Ghazaryan et al. (2025) observed that Armenian IT enterprises exhibit a low level of Business Intelligence tool implementation compared to companies from Estonia and Denmark. This was attributed to infrastructural barriers, deficits in analytical competencies, and unfavorable regulations, underscoring the importance of the digital and institutional environment in the technology adoption process.

Growing scholarly interest is also directed toward cultural and social factors that influence the perception of AI and the readiness to adopt it across different countries. C. Cannavale et al. (2025) presented research based on a mixed-method approach – combining regression models with expert interviews conducted in China, Italy, Russia, and the United States – demonstrating that cultural values related to uncertainty avoidance, power distance, future orientation, and collectivism influence AI implementation strategies, and that the variation of these values across countries shapes the dynamics and specific characteristics of AI adoption. In a study by H. T. Vu and J. Lim (2022), based on multilevel structural equation modeling (SEM) using data from 28 European countries, it was confirmed that the acceptance of AI and robotization primarily depends on individual-level factors, including the perceived threat of job loss and the sense of digital self-efficacy. According to the authors, macroeconomic factors exert an indirect influence by shaping these perceptions.

The 2025 OECD report (*A Portrait of AI Adopters across Countries*, 2023), based on harmonized surveys of enterprises from 11 European countries, indicated that AI usage is concentrated in the ICT and professional services sectors, and that the higher productivity of firms adopting AI is associated with access to modern digital infrastructure, technological competencies, and the utilization of other digital tools. Meanwhile, A. Georgieff and R. Hyee (2022) presented research covering 23 OECD countries, in which – using the AI occupational impact index developed by Felten, Raj, and Seamans – they demonstrated that the relationship between AI exposure and employment is heterogeneous and depends, among other factors, on the level of computer usage within a given occupation and on workers' digital competencies. Additionally, J. Menzies et al. (2024), based on a review of 37 publications, found that AI is applied across various areas of enterprises' international activities, such as innovation, foreign market selection, human resource management, logistics, and operation in intercultural environments, and that its implementation involves organizational challenges and necessitates the adaptation of both employees and management.

An important research stream also involves analyses of national strategies and government initiatives aimed at supporting AI integration. S. Fatima et al. (2020), based on a review of 34 national AI strategies developed by highly developed countries, including European nations and leading technological economies, indicated that AI is perceived as a tool for modernizing the public sector, enhancing industrial competitiveness, and developing competencies in data management, algorithms, and regulatory systems. Meanwhile, C. Schaer (2025) argues that although the European Union (EU), aiming to reduce the gap with the United States and China, has declared investments of €20 billion per year in AI development by 2030, the pace of implementation and the level of private sector investment remain lower than in technologically leading countries. Furthermore, the development of AI technology itself and its components (big data and patents) is the focus of technological and analytical research. In their study, M. Pejić Bach et al. (2020) presented findings based on the k-means method, demonstrating that the variation in the use of big data technologies among European enterprises is highly significant, and that internal analytical competencies promote the broader use of diverse data sources, which may serve as a decisive factor in strengthening an organization's competitive advantage. Additionally, C.-Y. Tseng and P.-H. Ting (2013) conducted a patent review based on data from the United States Patent and Trademark Office, through which they assessed the level of AI technology development in selected countries and their positioning in four main AI areas: reasoning and problem-solving, machine learning, network structures, and knowledge processing systems.

3. EMPIRICAL MATERIAL AND RESEARCH METHODS

The empirical material consisted of data from 2023 concerning enterprises employing at least 10 persons and operating in the countries of the European Union (EU). These data were used to assess the extent of artificial intelligence (AI) technology adoption and to identify differences in the level of its implementation among member states. The analysis was based on data from the Eurostat database, the official statistical source of the EU. The selection of variables was guided by substantive considerations, taking into account the classifications adopted in Eurostat's systematics. The year 2023 was chosen as the reference point due to the availability of a complete set of data for all analyzed indicators. The study included a set of indicators describing the application of AI technologies in various areas of enterprise activities (marketing, production, logistics, research and development), as well as contextual data concerning, among others, the employment of ICT specialists, GDP per capita, the use of cloud services, and data analytics. The applied methodology enabled a comprehensive assessment of the level of technological and digital readiness of enterprises in EU member states and the identification of factors facilitating AI implementation. The list of applied indicators is presented in Table 1.

Table 1. Indicators Characterizing the Use of AI Technologies in Enterprises

Variable	Variable Name	Unit of Measurement	Characteristics
x1	Enterprises using at least one AI technology	%	Share of enterprises using at least one AI technology: text analysis, speech and image recognition, machine learning, process automation, or autonomous technologies.
x2	Enterprises using AI for at least one specific purpose	%	Share of enterprises (excluding the financial and primary sectors) using AI for at least one purpose: marketing, production, administration, logistics, ICT security, finance, or innovation activities.
x3	ICT specialists in total employment	%	Share of ICT specialists in total enterprise employment.
x4	Gross domestic product per capita (PPS)	PPS	GDP per capita in purchasing power standards (PPS), enabling international comparisons.
x5	Manufacturing enterprises using AI	%	Share of manufacturing enterprises using AI technologies in their activities.
x6	Manufacturing enterprises using AI for a specific purpose	%	Share of manufacturing enterprises using AI for specific purposes: marketing, production, administration, logistics, ICT security, finance, or research and development.
x7	Professional, scientific, and technical enterprises using AI	%	Share of enterprises from the professional, scientific, and technical sectors using AI in their activities.
x8	Professional, scientific, and technical enterprises using AI for a specific purpose	%	Share of enterprises from the professional, scientific, and technical sectors using AI for specific purposes: marketing, production, administration, logistics, ICT security, finance, or research and development.
x9	Enterprises using data analytics	%	Share of enterprises using data analytics (e.g., Big Data Analytics, Predictive Analytics, Data Mining) in their economic activities.
x10	Enterprises purchasing advanced cloud services	%	Share of enterprises acquiring advanced cloud computing services, e.g., security services, database hosting, software hosting.

Source: own elaboration based on Eurostat (*Glossary*; *Use of Artificial Intelligence in Enterprises*).

In order to better identify the economic factors facilitating AI adoption in EU countries, the relationship between the level of AI technology utilization and selected macroeconomic indicators was analyzed. Figure 1 graphically presents the relationship between the degree of AI technology implementation in enterprises and the level of gross domestic product per capita, expressed in purchasing power standards (PPS), in EU countries.

The analysis of the chart revealed a general relationship indicating that a higher level of economic development is accompanied by greater intensity in the use of AI technologies within the enterprise sector. In countries with high GDP per capita – Denmark, Finland, Belgium, and the Netherlands – the share of enterprises employing at least one AI technology was relatively high. Luxembourg, in particular, stood out, achieving some of the highest values for both analyzed indicators, reflecting the advanced technological and digital maturity of its economy. Conversely, in countries with lower per capita income levels, namely Romania, Bulgaria, and Poland, the prevalence of AI-based solutions in enterprise activities was significantly lower. A notable outlier was Ireland, where despite a very high GDP per capita, the level of AI adoption remained moderate. This may reflect a diversified economic structure, the concentration of capital in specific sectors, or the dominance of large multinational enterprises with different business profiles. It is also worth noting several countries (e.g., Germany, Slovenia, Austria, and Sweden) that exhibit a relatively high level of AI implementation despite having only an average level of GDP per capita, which may result from active digitalization policies and strong support for technological transformation.

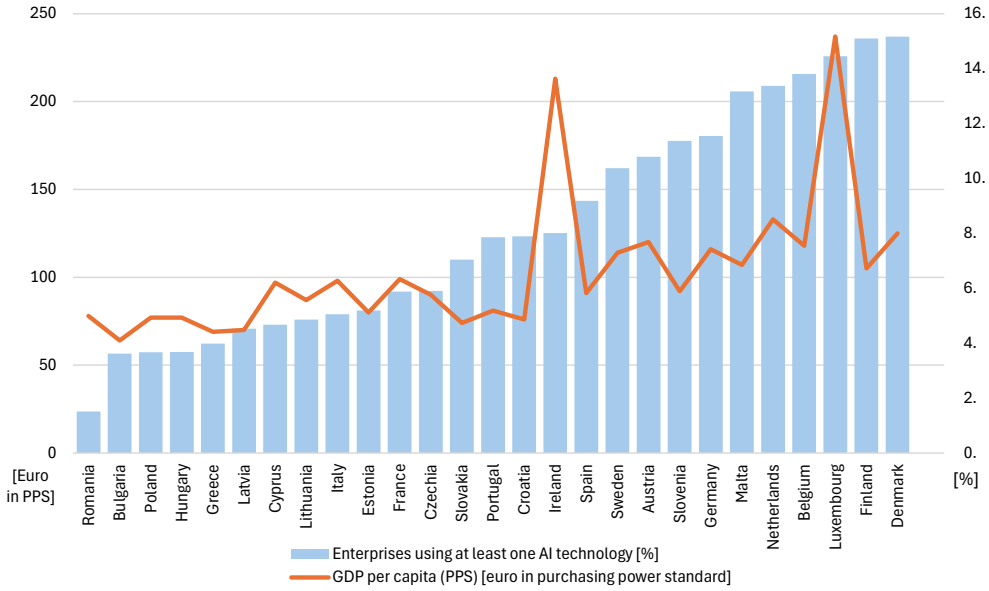


Figure 1. AI Utilization and GDP Level, EU Countries in 2023
Source: own elaboration based on Eurostat (*Glossary*; *Use of Artificial Intelligence in Enterprises*).

To better illustrate the differences in AI adoption depending on the nature of business activity, an analysis was conducted by sector. Figure 2 presents a comparison of the degree of AI technology implementation across three groups of enterprises: overall, in the manufacturing sector, and in the professional, scientific, and technical sector in EU countries.

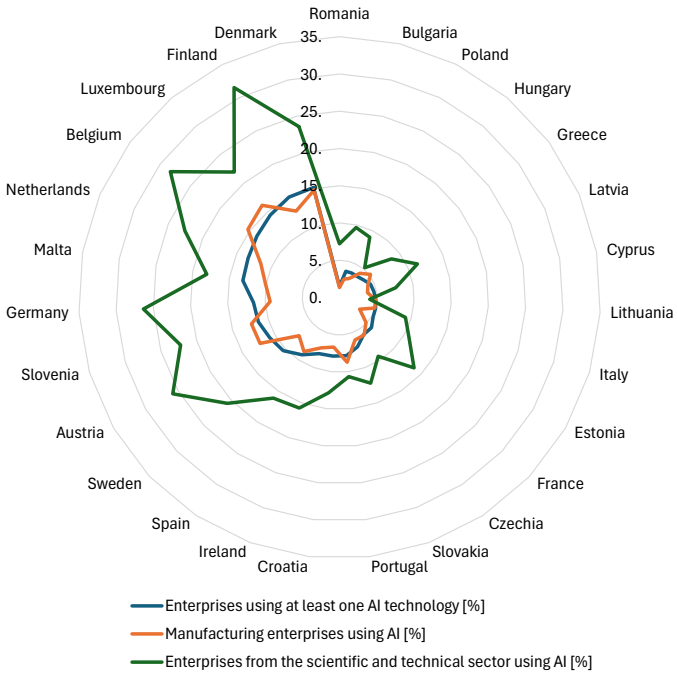


Figure 2. AI in Different Sectors, EU Countries in 2023
Source: own elaboration based on Eurostat (*Glossary*; *Use of Artificial Intelligence in Enterprises*).

The analysis of the data presented in Figure 2 reveals significant variation both among member states and across different sectors of the economy. The highest share of enterprises using AI was recorded in the professional, scientific, and technical sector, particularly in Western and Nordic European countries (Finland, Denmark, Belgium, and the Netherlands). In these countries, nearly 30% of enterprises in this sector utilized AI, suggesting a high level of research advancement, innovation, and the development of knowledge-based services. Manufacturing enterprises exhibited a moderate level of AI implementation, with relatively higher rates observed in Germany, Austria, and the Netherlands, which can be associated with the advanced degree of automation and digitalization in industry (Industry 4.0). In Central and Eastern European countries (e.g., Romania, Bulgaria, Poland), all three groups of enterprises recorded lower values, which may be attributed to financial constraints, a lack of digital competencies, and limited access to modern technological infrastructure.

3.1. The k-Means Method

The k-means method is one of the most widely used unsupervised classification techniques in cluster analysis (Hartigan, 1975), (MacQueen, 1967). It belongs to the group of optimization-iterative methods, where the primary objective is to divide a set of observations into k disjoint and as homogeneous as possible classes. A characteristic feature of the algorithm is the iterative assignment of objects to groups based on the minimization of within-cluster variance, most commonly measured using Euclidean distance (Jain, 2010). The k-means algorithm operates through several stages. First, the expected number of clusters (k) and the maximum number of iterations are determined. Initial cluster centroids are then selected, representing the mean values of the features of the units assigned to each group. Each object is assigned to the cluster whose centroid is closest. After assigning all observations, the cluster centers are updated, and the process is repeated until the assignment stabilizes or the maximum number of iterations is reached (Tan et al., 2018). The k-means algorithm minimizes the sum of squared distances between units and their corresponding cluster centers, thereby gradually improving the quality of the data partition (MacQueen, 1967). With each successive iteration, the within-cluster variability decreases, and the resulting clusters become more homogeneous. The k-means method is widely used wherever there is a need for efficient grouping of large sets of quantitative data. Although the results can be sensitive to the choice of initial cluster centers and the number of clusters, the algorithm is valued for its ease of implementation, clarity of results, and high computational efficiency (Jain, 2010).

3.2. The Kohonen Method (Self-Organizing Map – SOM)

The Kohonen method, also known as the Kohonen neural network or as the Self-Organizing Map (SOM), is an unsupervised data classification technique used for clustering, dimensionality reduction, and the visualization of complex data structures (Kohonen, 2001). Its operation is based on mapping a multidimensional feature space onto a two-dimensional grid of neurons while preserving the topological relationships among objects, thereby maintaining the structure of similarities present in the original data. The SOM algorithm process begins with the creation of a regular grid of neurons, each represented by a weight vector corresponding to the number of variables. During training, the Best Matching Unit (BMU) – the neuron whose weight vector is closest to the input vector, most often calculated using Euclidean distance – is identified (Ultsch & Siemon, 1990). The weights of both the winning neuron and its topological neighbors are then updated, with the neighborhood radius and learning rate decreasing as the number of iterations increases. A key operation in SOM is the iterative adjustment of neuron weights, leading to the gradual organization of the map and the representation of the input data structure within a two-dimensional space. To ensure the proper functioning of the algorithm, all variables should be normalized beforehand, for example, using the min–max method. The output of the SOM is an organized neural map in which spatially close units represent objects with similar feature profiles, enabling the efficient grouping and visualization of hidden relationships within the dataset (Vesanto & Alhoniemi, 2000). Due to these properties, the Kohonen method is widely used in exploratory data analysis and as a tool supporting classification and dimensionality reduction processes.

4. VARIATION IN THE USE OF AI TECHNOLOGIES IN EU COUNTRIES

Based on empirical data from 2023, an analysis was conducted on the level of AI technology implementation and the factors facilitating digital transformation in enterprises across EU member states. Ten indicators were considered, with the aim of illustrating the variation among the member countries. Table 2 presents the basic parameters of descriptive statistics, enabling the assessment of variability and the intensity of differences in AI utilization, as well as the analysis of the asymmetry of the empirical distributions of the studied variables.

Table 2. Descriptive Statistics of AI Indicators in EU Countries

Variable	Mean	Median	Min	Max	Standard Deviation	Coefficient of Variation	Skewness
x1	8,21	7,86	1,51	15,17	4,14	50,37	0,33
x2	6,28	5,88	1,51	12,35	2,97	47,35	0,56
x3	5,08	4,70	2,40	8,70	1,49	29,32	0,75
x4	103,26	92,00	64,00	237,00	39,88	38,62	2,29
x5	7,69	6,70	1,34	16,17	4,22	54,93	0,55
x6	5,82	5,06	1,34	11,71	3,17	54,45	0,78
x7	15,37	12,88	4,07	31,54	7,67	49,91	0,51
x8	12,21	10,02	4,07	26,53	6,30	51,60	0,99
x9	28,34	28,70	15,49	47,55	8,34	29,42	0,21
x10	35,86	32,87	12,95	63,62	14,02	39,11	0,32

Source: own elaboration.

The analysis of empirical data indicated a clear variation in the level of AI adoption by enterprises across the EU. The average level of AI technology utilization among enterprises (x1) was 8.21%, yet the distribution of values was highly uneven. A high coefficient of variation (50.37%) and positive skewness (0.33) indicated the predominance of countries positioned below the average implementation level. Among the leaders were Denmark (15.17%), Finland (15.10%), and Luxembourg (14.45%), while Bulgaria (3.62%) and Romania (1.51%) ranked at the bottom of the list. For the indicator characterizing

AI implementation in specific business areas (x2), significant differences among EU countries were also observed. Although the EU average stood at 6.28%, only a few countries – led by Finland (12.35%) – demonstrated advanced, strategic applications of these tools. A large proportion of countries still limited the use of AI to incidental solutions or applications confined to selected sectors, as confirmed by the high variability (47.35%) and positive skewness (0.56). In contrast, the availability of human resources in ICT (x3) showed smaller disparities, with an average of 5.08% and moderate variability (29.32%). The countries leading in this indicator included Sweden (8.7%), Luxembourg (8.00%), and Finland (7.60%), which may reflect a well-developed educational infrastructure and a strategic approach to digital competencies as a foundation for technological development. It should be noted that the lowest results in this regard were recorded in Romania (2.60%) and Greece (2.40%). The greatest disparities were observed for the GDP per capita indicator expressed in purchasing power standards (PPS) – x4. The average for the analyzed group of countries was 103.26, with a very wide range of values (from 64 to 237) and a pronounced right-skewed distribution (2.29). Very high values for Luxembourg (237.00), Ireland (213.00), and Denmark (133.00) indicate a strong economic base conducive to the development of digital infrastructure and AI technology implementation. At the opposite end were Bulgaria (64.00) and Greece (69.00), confirming the persistent differences in economic potential within the EU.

The sectoral indicators (x5–x8) revealed significant differences in the intensity of AI implementation across types of business activities. For manufacturing enterprises (x5), the average level of AI adoption was 7.69%. Luxembourg (16.17%), Belgium (15.31%), and Denmark (14.80%) dominated, reflecting an advanced level of technology deployment within the industrial environment, while Bulgaria (2.55%) and Romania (1.34%) recorded the lowest values. The analysis of AI technology application in manufacturing for specific purposes (x6) produced similar results – the highest values were still concentrated in technologically advanced countries such as Belgium (11.71%) and Slovenia (11.61%), with a high variability of 54.45%. The professional, scientific, and technical sector emerged as the main area of intensive AI utilization. The indicator describing this phenomenon (x7) reached an average of 15.37%, with Finland standing out at 31.54%, representing the highest value in the entire dataset. Conversely, the lowest level was observed in Lithuania (4.07%). Similarly significant disparities were found for the variable related to the targeted use of AI technologies within the professional, scientific, and technical sector (x8). The obtained results highlighted the significant role of research and development activities and knowledge-based services in shaping technological competencies within the economic structures of EU member states. The range of values for this variable – from 4.07% in Lithuania to 26.53% in Finland – confirms the substantial variation in the level of technological advancement within this sector across the EU. The indicator illustrating the use of data analytics in business activities (x9) displayed relative balance. With an average of 28.34% and lower variability (29.42%), there were instances of exceptionally high saturation with analytics – in Croatia (47.55%) and the Netherlands (41.22%) – but generally moderate values prevailed across most EU countries. The distribution was characterized by weak asymmetry (skewness of 0.21), suggesting that modern data analytics has become a standard component of business operations within the EU. The situation was somewhat different for the variable describing the use of advanced cloud services (x10). The average share was 35.86%, but the distribution of values indicated noticeable stratification – between the leaders, namely Finland (63.62%) and Denmark (62.84%), and Eastern European countries, Romania (19.06%) and Bulgaria (12.95%). This indicates that insufficient technological infrastructure still poses a barrier to AI implementation processes in certain member states.

Compared to other EU countries, Poland was characterized by a relatively low level of AI technology adoption. Most of the analyzed indicators – both general (x1 – 3.67%, x2 – 3.56%), sectoral (x5 – 2.86%, x7 – 9.05%), and contextual (x3 – 4.3%, x4 – 77, x9 – 18%) – were below the EU averages, indicating limited digitalization intensity as well as weaker competency and infrastructural foundations. An exception was the indicator concerning the use of cloud services (x10), which reached 41.71% compared to the EU average of 35.86%, suggesting good availability of tools supporting technological processes in Polish enterprises.

5. THE PROCESS AND RESULTS OF CLUSTERING EU COUNTRIES

To classify the European Union member states in terms of the adoption of artificial intelligence technologies in enterprises, two cluster analysis methods were employed: the k-means algorithm and Kohonen neural networks. The following sections present the results of both approaches and compare the obtained classifications.

5.1. Clustering Using the k-Means Method

In the conducted classification analysis, the 27 EU member states were divided into three classes, differentiating countries based on the level of AI technology adoption in enterprises and selected factors supporting digital development. The classification was carried out using the k-means method, one of the most commonly used unsupervised clustering techniques. The study included ten indicators, which were previously standardized to equalize their scales. Classical Euclidean distance was used as the measure of similarity, allowing countries to be assigned to clusters based on a similar profile of features. According to the adopted assumptions, three classes of technological advancement and AI implementation were identified:

- Class 1 – countries with the highest values of the analyzed indicators,
- Class 2 – countries achieving average results,
- Class 3 – countries with the lowest results.

The calculations were performed using the Statistica environment, which enabled the assignment of countries to the appropriate clusters and the graphical presentation of the obtained classes.

The obtained classification results constitute a significant complement to the descriptive statistics analysis and enable a synthetic assessment of the position of individual countries in terms of the level of digital transformation advancement. The classification allowed for the identification of leaders in AI technology adoption within the EU, countries with a moderate level of adaptation, and countries requiring intensified efforts in this area. Table 3 presents the results of the division of EU member states into three classes.

Table 3. Classification of EU Countries by Level of AI Technology Adoption – k-Means Method

Class	Name of the country
1	Austria, Belgium, Denmark, Finland, Germany, Ireland, Luxembourg, Malta, Netherlands, Slovenia, Sweden
2	Croatia, France, Hungary, Latvia, Lithuania, Portugal, Slovakia, Spain
3	Bulgaria, Cyprus, Czechia, Estonia, Greece, Italy, Poland, Romania

Source: own elaboration.

The classification results allowed for the identification of three distinct groups of countries:

1. Class 1 included 11 countries characterized by the highest average values for most of the analyzed indicators. These countries exhibited an advanced level of AI technology adoption among enterprises (on average, 12.47% of enterprises using AI) and well-developed digital infrastructure, as confirmed by a high average value for cloud service usage (45.31%). Additionally, the average GDP per capita in this group significantly exceeded the overall average for all analyzed countries.
2. Class 2 comprised 8 countries whose average indicator values indicated a moderate level of AI technology adoption. These values were lower than those observed in Class 1 but clearly higher than those in Class 3. For example, the average share of enterprises utilizing AI technologies was 6.37%, and the average level of cloud service usage reached 28.17%. Notably, the average value of the data analytics usage indicator in this class was the highest among all groups (33.46%), exceeding both the result for Class 1 and the overall average for the entire set of countries.
3. Class 3 included 8 countries characterized by the lowest average values of the analyzed indicators. The results for this group were consistently lower than the overall averages. The average share of enterprises using AI technologies was 4.20%, and the average GDP per capita reached 81.63. Particularly low values were recorded for AI implementation in the

manufacturing sector (3.73%) and the professional, scientific, and technical sector (8.96%), as well as for data analytics usage (20.70%). Although the indicators related to the targeted use of AI in the professional, scientific, and technical sector (8.54%) and the use of cloud services (30.55%) were higher than those observed in Class 2, they still remained below the overall averages recorded for the entire set of countries.

5.2. Clustering Using the Kohonen Method

To deepen the classification analysis, clustering of EU member states was performed using a Kohonen neural network (SOM – Self-Organizing Map). A network with a 1 × 3 neuron structure was trained based on standardized data encompassing the same ten indicators as described in Section 5.3 (listed in Table 1). The training process included 2,000 epochs, using a decreasing neighborhood function (from 1 to 0) and a learning rate (from 0.2 to 0.01), with random weight initialization following a normal (Gaussian) distribution. As a result of the classification, three groups of EU member states were identified, differing in the degree of AI technology utilization by enterprises and the level of digital advancement. A detailed division is presented in Table 4.

Table 4. Classification of EU Countries by Level of AI Technology Adoption – Kohonen Neural Networks

Class	Name of the country
1	Austria, Belgium, Denmark, Finland, Luxembourg, Netherlands, Slovenia
2	Croatia, Germany (↓), Ireland (↓), Malta (↓), Portugal, Spain, Sweden (↓)
3	Bulgaria, Cyprus, Czechia, Estonia, France (↓), Greece, Hungary (↓), Italy, Latvia (↓), Lithuania (↓), Poland, Romania, Slovakia (↓)

(↓) – countries that, compared to the k-means clustering results from Table 3, were assigned to an adjacent class

Source: own elaboration.

The cluster analysis results allowed for the identification of three distinct groups of countries:

1. Class 1 included 7 countries with the highest average values of the analyzed indicators. These countries were characterized, among other aspects, by a high level of AI technology implementation (13.44%) and well-developed digital infrastructure (45.27%). Additionally, the average GDP per capita in this group was significantly higher than the overall average.
2. Class 2 consisted of 7 countries achieving moderate results across the studied variables. The average share of enterprises using AI technologies was 9.72%, and the level of cloud service utilization was 39.29%. It is worth noting that the variable related to data analytics usage (33.17%) was higher in this class compared to the results of Class 1.
3. Class 3 included 13 countries with the lowest average values of the analyzed indicators. The average share of enterprises adopting AI technologies was 4.58%, while the average GDP per capita was 81.54. Particularly low values were recorded for AI use in the manufacturing sector (4.15%) and in the professional, scientific, and technical sector (9.10%), as well as for the variable related to advanced data analytics (25.03%).

5.3. Comparison and Consolidation of Clustering Results

To summarize the research findings, a comparison was conducted between the classifications of EU member states obtained using the k-means method and the Kohonen network, based on the level of AI technology adoption by enterprises. Figure 3 presents the results of both methods and the final comparison, illustrating the similarities and differences in the assignment of countries to the respective groups. The combined analysis of the results enabled the identification of persistent patterns in the level of digital advancement and the intensity of AI-based solution implementation in the enterprise sector.

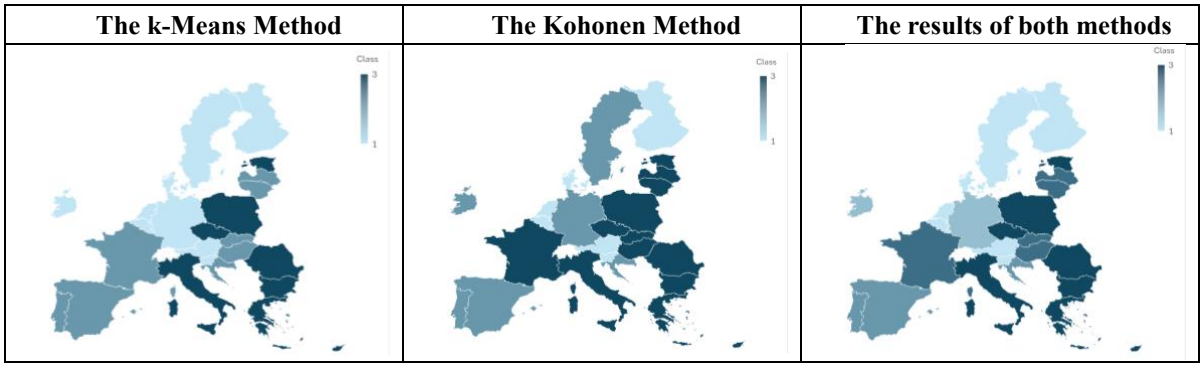


Figure 3. Classification of EU Countries by Level of AI Adoption – Comparison and Consolidation of Results from Both Methods by Identifying Interclass Groups for Different Assignments
Source: own elaboration.

The analysis of the results obtained using both classification methods indicates that, despite employing different algorithms, the structure of the identified groups of countries remains similar. Countries with the highest level of digital advancement were consistently assigned to the first class, while countries with a lower degree of technological development formed a separate cluster requiring intensified modernization efforts. The simultaneous application of the k-means method and the Kohonen network confirmed the stability of the identified patterns and highlighted the persistent nature of the observed disparities in the process of digital transformation among enterprises within the EU.

In the conducted analysis, Austria, Belgium, Denmark, Finland, Luxembourg, the Netherlands, and Slovenia were consistently classified into the first group in both classification approaches. This confirms the high level of advancement of these countries in terms of AI technology adoption by enterprises, intensive use of cloud services, and well-developed digital infrastructure. A stable position in Class 2 was maintained by Croatia, Portugal, and Spain. Conversely, Bulgaria, Cyprus, the Czech Republic, Estonia, Greece, Italy, Poland, and Romania were assigned to the third group in both analyses. This indicates a relatively low level of AI solution implementation, limited human resources in the ICT sector, and underdeveloped competencies in the field of modern digital technologies. The analysis also distinguished countries occupying an intermediate position in the classification. Germany, Ireland, Malta, and Sweden were grouped between Class 1 and Class 2. These countries demonstrated a relatively high level of AI technology adoption by enterprises and a well-developed digital infrastructure, although their results were slightly lower compared to the digitalization leaders. Meanwhile, among the countries positioned between Class 2 and Class 3 were France, Hungary, Latvia, Lithuania, and Slovakia. These countries were characterized by a moderate or low level of technological advancement and a limited extent of AI solution utilization, indicating the need for further investments in the development of digital infrastructure and ICT competencies.

6. CONCLUSION

The study revealed significant disparities in the level of digital maturity of enterprises across EU countries regarding the implementation of AI technologies. The identified groups of countries indicate a clear division between digitalization leaders and countries requiring intensified modernization efforts. The results confirm that success in AI implementation is associated with access to modern digital infrastructure and a well-developed competency base. The findings highlight the necessity for further investments in the development of digital skills, technological infrastructure, and support for innovation, particularly in countries classified in the lowest-performing group. A limitation of the study remains the availability and scope of the data. Future analyses should consider incorporating qualitative factors, such as enterprise digitalization

strategies, the level of technological awareness among management, and the impact of public policy on the AI implementation process across different sectors of the economy.

Additionally, for countries with the lowest digital maturity, policy actions should prioritize targeted support for SMEs, development of sector-specific AI adoption programs, and improvements in ICT education. A better understanding of cultural attitudes toward technology and organizational readiness may also help shape more effective strategies. These directions may serve as the foundation for future policy recommendations and interdisciplinary research.

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28th European Conference on Artificial Intelligence (ECAI 2025)

AN INNOVATIVE APPROACH TO HUMAN RESOURCE MANAGEMENT EDUCATION IN THE GASTRONOMY INDUSTRY ANALYSIS OF THE PROJECT AS A PRACTICAL EXAMPLE

Katarzyna Brzychcy[a]

[a]*University of Szczecin, Institute of Management, Poland*

ABSTRACT

Purpose: *The aim of this article is to present the assumptions and conclusions of the completed project entitled: "Methodology of teaching human resource management to current and future gastronomy industry employees". To reflect on and discuss the observations and conclusions resulting from the implementation of the project aimed at supporting students and graduates of the gastronomy industry in the field of human resource management, as well as to discuss its key stages and results.*

Need for the study: *The presentation of the human resource management topics covered in the project has not only a theoretical dimension, but also a practical one. It highlights areas of deficiency, the need to address which not only develops the competences of managers in the gastronomy industry but also promotes employee stability.*

Methodology: *The method used is project.*

Findings: *The results explored the opinions representatives of the gastronomy, on the possibility of using AI in their workplace. The results indicated areas where AI can benefit and be applied. Concerns about AI and the level of readiness for its implementation were also indicated.*

Practical Implications: *The outcome of the research is the implementation of an educational project within the Erasmus+ programme entitled: "Methodology of teaching human resource management for current and future gastronomy employees", No. 2023-1-PL01-KA220-VET-000167215.*

Keywords: Human Resources Management, Gastronomy, Project

Jel codes: M10, B 40, O3

1. INTRODUCTION

The modern gastronomy market is developing dynamically, posing numerous challenges for the industry in terms of human resource management. Recruiting, training and retaining qualified staff are key factors determining the competitiveness of restaurants and other gastronomy establishments. In this context, increasing attention is being paid to issues related to human resource management, especially with regard to young people, such as students and graduates of gastronomy schools. Experience is certainly the basis for efficient and effective human resource management, but it is not the only factor.

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The diverse relationships that arise in the labour market, generational changes, and new technologies are giving rise to new trends in human resource management, as well as methods and tools to assist in working with employees. Therefore, in addition to experience, it is worth noting the current knowledge in the field of human resource management and equipping students and graduates of gastronomy schools with this knowledge. The above idea was the impetus for the development of a project that was implemented and financed by the Erasmus Plus programme. The implementation of this project has yielded concrete results and conclusions for practical action. This, in turn, has enabled the development of recommendations for working with people in the gastronomy industry, as well as the development of methods and tools for transferring knowledge and developing human resource management skills.

The aim of this article is to present the results of a project carried out to support the development of the competences of young employees in the gastronomy industry. An analysis of the results of this project provides a better understanding of the current conditions and challenges related to human resource management in the gastronomy sector, and also points to the potential of educational and training activities in shaping future specialists. The project presented in this article was innovative in nature, as it addressed a topic that had not been discussed before.

2. LITERATURE REVIEW

Human resource management is a key element in the functioning of any organisation, including the gastronomy sector. It therefore seems that it does not matter in which area of the economy the subject of human resource management is addressed. It always has the same essence. When reviewing the literature, it should be noted that M. Armstrong (Armstrong, 2014) is constantly referred to here, who argues that human resource management includes the processes of planning, recruitment, selection, training, motivation and retention of employees, which are aimed at achieving the strategic goals of the company. In turn, S. Snell and G. Bohlander define human resource management as strategic and operational activities aimed at effective management of people in an organisation, including recruitment, training, employee assessment and motivation (Snell, Bohlander, 2013). Similarly, in the Polish context, R. Kozłowski refers to the strategic objectives of an organisation – human resource management is a process of planning, implementing and controlling activities related to the recruitment, development and retention of employees, aimed at achieving the company's strategic objectives (Kozłowski, 2018). G. Dessler, on the other hand, draws attention to the effective use of human resources – competences, knowledge and experience. For G. Dessler, human resource management is a set of activities aimed at the effective use of employees' potential, their development and motivation to support the implementation of the organisation's strategy (Dessler, 2017). From the point of view of the project and its objectives, the most important thing was to focus efforts on the efficiency of the organisation's resources. Regardless of whether the organisation is large or small, it is important that its resources are used to the fullest extent possible for the organisation's purposes, while maintaining employee satisfaction and contentment.

In the context of gastronomy, the specific nature of the industry, characterised by high staff turnover, requires particular attention to aspects related to staff motivation and skills development (Kozłowski, 2018). As part of a project on human resource management in the gastronomy industry, the importance of a comprehensive approach to personnel management was emphasised, covering both recruitment and the development of the skills of the younger generation of employees, which is crucial for improving the quality of services and the competitiveness of the industry. The literature emphasises that effective human resource management in the gastronomy industry has a direct impact on the quality of services provided, customer satisfaction and the competitiveness of enterprises (Nowak, 2019). The challenges facing the industry include seasonal employment, difficulties in recruiting qualified staff, and the need to continuously improve employees' skills in the face of changing culinary and technological trends (Jankowska, 2020).

Scientific literature increasingly emphasises the importance of education and training for the development of gastronomy staff competencies. For example, a study conducted by Kowalski (2021) showed that training programmes aimed at students and graduates of gastronomy schools significantly improve their preparation for work in the industry and increase their motivation and willingness to work. However, it should be noted that introducing the issue of human resource management in terms of knowledge transfer requires an appropriate approach, which is a project. Specialists define a project as

a temporary endeavour aimed at creating a unique product, service or result, carried out according to specific objectives, schedule and budget, using available resources and management methods (PMI, 2017). The above definition focuses on the results of the project. For K. Schwalbe, a project is a temporary activity aimed at creating a unique product or service, with clearly defined objectives and constraints (Schwalbe, 2015).

H. Kerzner proposes a different approach, arguing that a project is an organised set of activities aimed at achieving specific results within defined time, financial and resource constraints (Kerzner, 2013). The available time, financial and resource constraints provide a certain framework that guides the project in a specific way. This allows us to focus on the essence of the project. Adding to this the thesis that a project is a unique undertaking that requires planning, coordination and control in order to achieve the set goals within a specific time and budget (Meredith & Mantel, 2014), it therefore has a certain procedure for action. It can be assumed that this is a process with a specific structure that ensures a certain degree of success based on achieving the desired goal. This is all the more important from the point of view of the gastronomy industry. The specific nature of human resource management in the gastronomy industry is characterised by unique challenges and needs resulting from the nature of the sector. First and foremost, this industry is highly seasonal in terms of employment, which requires flexibility in staff planning and rapid response to changing needs (Kozłowski, 2018). In addition, working in the gastronomy industry often involves a fast pace, the need to provide high-quality customer service and the ability to cope with stressful situations, which requires employees to have appropriate interpersonal skills and mental resilience (Nowak, 2019). Another aspect is the need for continuous staff training to ensure high quality of service and to adapt to changing culinary trends and hygiene and safety standards (Kozłowski, 2018). In addition, the gastronomy industry often faces the problem of staff turnover, which requires employers to implement effective incentive strategies and development programmes to retain qualified staff (Nowak, 2019). It is particularly important to focus on the gastronomy industry, as this sector has been particularly hard hit by the pandemic. Despite financial assistance from the state, restaurants and cafés were unable to withstand the crisis during the COVID-19 pandemic and closed down due to a lack of customers and insufficient financial resources (Szymkowiak, 2021). However, it seems that the Covid-19 pandemic was not the only factor determining changes in the gastronomy market. Cultural and social changes mean that the gastronomy industry is forced to face challenges and customer expectations (Koczy, Maciejewski, 2025). Despite the changes in the gastronomy market, it should be remembered that people who decide to work in gastronomy expect decent conditions, precise and clear rules, but also the development of their own professional career (Alejziak, Kowalczyk, 2023).

The combination of human resource management issues with the gastronomy industry and the recognition of the need to support current and future managers working in gastronomy organisations was the impetus for the project.

Given the focus of this article on a project, the concept of a project must be defined. The literature provides numerous examples of project definitions by both practitioners and theoreticians. The concept of "project" is an ambiguous term, used in management sciences, engineering, and business and administrative practice. The literature on the subject offers a range of definitions that emphasize various aspects of this concept—from its uniqueness and temporality to its purposefulness and complexity. An analysis of these definitions allows us to grasp the essence of "project" as a research and practical category.

The most frequently cited project definitions in the literature come from international project management standards.

The Project Management Institute (PMI) defines a project as "a temporary endeavor undertaken to create a unique product, service, or result" (PMBOK® Guide, 2021). Two key characteristics are emphasized here: temporality (a defined beginning and end) and the uniqueness of the result.

The International Project Management Association (IPMA) notes that a project is "a unique, temporary endeavor undertaken to achieve specific results within time, cost, and resource constraints" (IPMA Competence Baseline, 2015). This definition more clearly emphasizes the constraints that determine implementation.

Puto defines a project as an organized and time-bound sequence of events, with a defined beginning and end, that aims to achieve a predetermined, precisely defined result addressed to an identified group

of stakeholders and that requires significant but limited financial, material, and human resources (Puto, 2022).

Polish literature also offers a variety of approaches. Trocki (2012) is among them. He defines a project as "a complex undertaking with a clearly defined goal, a defined implementation time, and requiring the commitment of financial, human, and material resources". The author emphasizes the complexity and necessity of resource coordination. Pawlak (2006), in turn, defines a project as "a time-bound process of achieving a goal, usually innovative in nature, carried out by a team of people using appropriate management methods". In this approach, innovation and the team aspect are crucial. Ładysz and Jaśkowski (2015), on the other hand, define a project as "a unique undertaking, the implementation of which takes place under conditions of uncertainty, utilizing resources and management methods aimed at achieving a specific goal". They introduce a significant element of risk and uncertainty. Based on a review of selected definitions of the concept of project, common features can be identified. These include:

- Purposefulness – understood as meaning that each project is aimed at achieving a specific goal.
- Temporarity – means that the project has a clear beginning and end. Therefore, it is within a timeframe.
- Uniqueness – refers to the project's outcome and project activities. This uniqueness indicates that the project differs from routine organizational activities.
- Resource intensity – requires the commitment of human, financial, and material resources.
- Constraints – related to time, cost, scope, and quality.
- Risk and uncertainty – result from the complexity and novelty of the project.

Differences, however, concern the emphases: some definitions focus on uniqueness and time (PMI, IPMA), others on complexity and innovation (Trocki, Pawlak), and still others on risk determinants (Ładysz, Jaśkowski).

The concept of 'project' in both scientific and practical terms is multidimensional. The most comprehensive definition should consider both the nature of the goal and outcomes, as well as time, resource, and risk considerations. An analysis of the literature suggests that a project can be understood as a unique, temporary endeavor aimed at achieving a goal, implemented using resources, management methods, and techniques, under conditions of constraints and uncertainty.

All the project attributes indicated in the analysis were identified in the project discussed in this article entitled: "Methodology of teaching human resources management for current and future gastronomy employees"

3. METHODOLOGY

3.1. Participants

The project participants were students and graduates of gastronomy courses and further training courses who were working or willing to work as chefs in Poland, Italy and Germany. In addition, due to the current geopolitical situation, Ukrainian citizens residing in Poland due to the ongoing war also took part in the project. Graduates of gastronomy schools and courses have high qualifications and professional skills, but are not prepared to lead a task force. In addition to students and graduates, the project also involved vocational school teachers, masters and trainers in craft chambers and guilds, and trainers from non-school educational institutions. It turned out that they did not have the appropriate tools to teach human resource management, nor did they have curricula, let alone modern, including digital, tools for conducting classes. Vocational schools teaching gastronomy professions, schools and entrepreneurs teaching the profession of chef in a dual system, chambers of crafts, and training institutions providing extracurricular education indirectly participated in the project. They lack the knowledge, tools and suitably trained personnel to teach human resource management. Taking into account all activities, as well as target groups, experts and multipliers, over 200 people participated in the project.

3.2. Research Protocol and Stimuli

The project was implemented in response to needs identified during other projects involving the organisation of internships and work placements for gastronomy school students. It turned out that

students had deficits in interpersonal skills, including teamwork, communication, problem solving and resolving misunderstandings between themselves. Furthermore, during discussions with head chefs, it became apparent that the selection of staff for teams was random. There were situations in which people were accepted into the team on the basis of a short interview without any analysis of their professional CV or verification of their skills and competences. Chefs mainly lacked knowledge in the areas of motivating employees and resolving conflicts. In addition, surveys were conducted among representatives of the gastronomy industry (students and vocational teachers) in three countries: Poland, Italy and Germany. A total of 172 people took part in the surveys. In addition to the aforementioned surveys, individual interviews were conducted, during which chefs stated that they did not feel confident in communicating with their kitchen team. Based on the above, the main objective of the project was formulated, which was to strengthen the interpersonal skills in the field of human resource management for students and graduates of vocational schools and apprenticeships in the culinary arts, and to improve their digital skills. Specific objectives were also identified:

1. Improving the digital and methodological skills of vocational instructors, teachers and trainers working in vocational and industry schools.
2. Increasing access to modern knowledge in the field of human resource management in the gastronomy industry.
3. Improving students' chances on the labour market by enriching the educational offer.
4. Increasing access to modern knowledge in the field of human resource management in the gastronomy industry.
5. Providing schools and vocational training institutions with teaching methods and programmes on human resource management in the gastronomy industry.

The activities outlined in the project were carried out in an international partnership between Poland, Italy and Germany. The institutions and organisations involved in the project included representatives of vocational education, craft chambers and research organisations.

3.3. Research Apparatus

The primary research method used to achieve the objective was a project implemented as part of the Erasmus+ programme entitled: “Methodology of teaching human resource management for current and future gastronomy employees”, No. 2023-1-PL01-KA220-VET-000167215. Various tools and methods were used in the project's design and implementation. In addition to surveys and interviews to assess the level of knowledge and needs in the field of human resource management, expert knowledge was also used. Study visits were organised to individual project partner institutions, where the possibilities, procedures and legal regulations applicable in their countries in the field of vocational education were discussed. The aim was to ensure that the materials developed were universal in nature and could be used in various formal and informal education systems. The project involved the implementation of work packages in partnership, thanks to which all project partners were involved in the work. The packages formed a logical whole. They can be described as successive steps that form a logical whole. Therefore, both terms will be used interchangeably in the rest of this article.

The activities were planned in five packages/steps. Each package had a designated lead organisation responsible for the implementation and results of each package. The packages included the development of project products, which included, among others, a human resource management curriculum based on five modules: employee selection, team building, task delegation, conflict resolution, and motivation. Each of the developed products was prepared in Polish, English, German, and Italian. Other packages concerned training for multipliers, i.e. people whose task was to pass on knowledge to students and graduates during classes based on the curriculum and lesson plans. The next package involved conducting pilot training courses for students and graduates of vocational schools in the gastronomy industry. The training took place in each partner country. Classes for Ukrainian students were planned in Poland. The next step, after the training, was to verify the knowledge of students participating in classes on human resource management. It is worth noting that the classes with students took the form of workshops during which various teaching methods and tools were used. Multipliers were provided with suggestions for exercises, case studies, topics for discussion, as well as sources of additional theoretical knowledge. In addition, educational films discussing specific issues were developed and recorded.

After testing the products, the next step was to promote them at conferences and on the websites of all project partners. More information about the process of promoting the project products will be provided later in this article.
Taking into account the proper functioning of the project, it was agreed that each organisation/partner would be responsible for managing its own resources, selecting experts, and monitoring planned activities and the schedule. The project leader was responsible for coordinating cooperation and developing a communication strategy and communication. The organisations/partners that invited associated partners to cooperate were responsible for coordinating their support in the project and including these partners in the schedule for the implementation of the entire project.

3.4. Analysis of Measurement Data

In the case under discussion, it is difficult to analyze the measurement data. The project's objectives were achieved, and the main and specific goals were achieved. Therefore, it is worth examining the product dissemination process. The target groups for dissemination activities outside the project partnership were primarily teachers and vocational instructors (individual recipients) as well as public and private institutions operating in the field of vocational education and development (institutional recipients). Each participating institution disseminated the products among the same and similar types of entities, both at the local/regional/national level and within the European Union.

Dissemination was carried out using electronic tools (including the websites of formal and informal partners, social media, newsletters, emails, EPALE, and Erasmus+ Results Platforms). Each project organization/partner had its own network of collaborating institutions with whom it collaborated to disseminate intellectual products. Products were also disseminated within the networks of supporting partners. Institutions within the project partner networks also joined in the dissemination of the product. These included public and private secondary schools offering culinary education, vocational and continuing education centers, private educational institutions, and training companies across Poland, including Chambers of Crafts affiliated with the Polish Craft Associations, industry guilds, and employer associations throughout Poland. In the case of the German partners, dissemination activities took place through DEHOGA – the German association of employers in the gastronomy industry, collaborating partnerships in the vocational education and training sector, vocational schools in Lueneburg and other vocational schools, and the Chambers of Commerce and Industry. In Italy, the project's products were disseminated through the Association of Employers in the Hotel and Gastronomy Industry, a trade union, and vocational schools. Such widespread activities should bring the expected success. However, although all dissemination activities were carefully presented using the language of benefits, the recipients' behavior was reserved. It can be assumed that this stems from behavioral patterns based on uncertainty and a lack of trust. The presented products will eventually be used in work with students and graduates of culinary schools and courses. This assumption can be made based on the interest in the topic during the project preparation and implementation stages, as well as during the dissemination of the developed products.

4. RSULTS

The project's implementation, as well as the analysis of the activities undertaken within it, allow us to formulate the following conclusions:

1. Representatives of the gastronomy industry, both students and graduates of culinary schools, but also chefs and employees, are characterized by a lack of significant deficits in knowledge about human resources management.

The research carried out within the framework of the project has shown that representatives of the gastronomy industry – at different stages of their educational and professional careers – already possess a certain level of knowledge regarding human resources management. This applies not only to basic issues such as communication within a team, conflict resolution or the division of responsibilities, but also to an initial awareness of the importance of HRM in building a competitive advantage. This observation indicates that the project did not have to fill a complete knowledge gap but rather to deepen and structure the already existing competences.

2. The identified gaps and shortcomings concern not only Poland but also other European Union countries – Germany and Italy – meaning the problem has a broader geographic scope.

The international character of the project revealed that the challenges associated with human resources management in gastronomy are not unique to Poland. The results obtained in Germany and Italy show similar needs and limitations, which demonstrates that the identified deficits are systemic and European in scope. This finding underlines the importance of transnational cooperation in addressing these problems and the relevance of the project's outputs beyond the borders of a single country.

3. Project beneficiaries and stakeholders' express interest in the topic of human resources management and recognize the need to expand their knowledge in this area.

Both direct participants (students, graduates, employees) and indirect stakeholders (school representatives, employers, industry associations) have emphasized the importance of human resources management as an area requiring continuous learning. The growing awareness of the role of HRM in ensuring the efficiency and competitiveness of gastronomy businesses proves that the project met real and articulated needs of the target groups.

4. Recipients also demonstrated reluctance to accept the project's results, which may stem from a lack of trust and a natural uncertainty regarding new solutions.

Despite the recognition of HRM's significance, some participants were initially reluctant to fully embrace the project's products. This hesitation could result from the novelty of the solutions, concerns about their practical implementation, or a general resistance to change in established educational and professional practices. Such reluctance is a common phenomenon in innovation implementation processes and indicates the necessity of long-term support, additional training, and systematic promotion of new approaches.

5. However, there is a lack of consensus regarding the method of conducting the educational process. This concerns procedural difficulties related to introducing a new subject into the formal curriculum. The informal system, on the other hand, requires additional fees for conducting courses.

The project revealed structural limitations within the education system. On the one hand, the introduction of a new subject to the formal curriculum involves complex procedural and legal steps, which makes such changes time-consuming and challenging. On the other hand, informal education, although more flexible, often requires extra financial investment from participants or institutions, which may act as a barrier. This demonstrates the need for systemic solutions and broader support mechanisms for integrating innovative content into existing educational frameworks.

6. The developed materials – products specifically designed for the teaching process – certainly add value. Their broad scope and the variety of lesson proposals make them engaging and encouraging for both teachers and students. A compelling solution is the educational videos that illustrate specific topics covered in the program.

The teaching materials created under the project were highly appreciated for their practicality, modern form, and comprehensiveness. The inclusion of diverse lesson scenarios allows teachers to adapt the content to different educational contexts, while interactive materials and educational videos enhance the attractiveness and effectiveness of the teaching process. The innovative use of multimedia not only diversifies the learning experience but also supports active knowledge acquisition and skill development.

7. The products were widely distributed to individual recipients (teachers, vocational instructors) and institutions (schools, training centers, educational institutions, chambers of crafts, and industry associations). Various electronic tools were used for dissemination: websites, social media, newsletters, emails, EPALE, and the Erasmus+ Results Platform.

The project's international partnership is undoubtedly an interesting solution and added value. This means that, in addition to its intrinsic value, the prepared educational materials also have an international dimension, consisting not only of translations into German, English, and Italian, but also of examples drawn from these countries. This allows for the multicultural nature of the educational materials, thus

providing an opportunity for the exchange of cultural experiences in mixed groups of employees and students.

The project's results have the potential for sustainable use in vocational education in Poland, Germany, and Italy. While initial reactions from recipients were cautious, the scale of dissemination and interest during the implementation phase indicate a high likelihood of future adaptation.

5. DISCUSSION

The project's results clearly demonstrate that all objectives were met, and the planned goals – both the main and specific – were achieved. In the context of international projects that bring together diverse institutions and professional communities, this is particularly significant, as it demonstrates the high quality of the partners' collaboration and the effective management of the implementation process. One of the key elements that determined the value of the results obtained was the broad dissemination of the products. The project partners engaged not only their immediate institutional communities but also extensive national and international collaboration networks. In Poland, a key role was played by secondary schools educating in gastronomy professions, vocational and continuing education centers, private institutions, and numerous industry organizations – from chambers of crafts to employers' associations. In Germany, the main channel was the work of DEHOGA, the association of employers in the gastronomy industry, as well as vocational schools and chambers of commerce and industry. In Italy, trade unions, hotel and gastronomy employers' associations, and vocational schools actively participated in the process. This trilateral nature of cooperation (Poland, Germany, and Italy) allowed the products to penetrate various educational systems and professional environments, increasing the chances of their sustainability and adaptation.

The diversity of communication tools is also noteworthy. Both traditional forms of communication (institutional networks, industry meetings) and modern electronic channels (websites, social media, newsletters, emails, EPALE, Erasmus+ results platforms) were used. This approach demonstrates the partners' high flexibility and ability to adapt their dissemination strategy to different audiences. This can be considered one of the greatest strengths of the entire project.

On the other hand, the analysis of the results also reveals certain weaknesses. The most visible barrier was the recipients' reluctance to accept the proposed solutions. Despite the use of benefits and an attractive form of dissemination, the reactions of institutions and individuals directly involved were not as enthusiastic as expected. This may have stemmed from the inherent uncertainty surrounding innovation and the limited trust that accompanies the introduction of new solutions in vocational education. Difficulties in analyzing the measurement data should also be noted – the lack of precise indicators and the difficulty in clearly defining the level of implementation of the results limit the ability to fully assess their effectiveness.

Looking to the future, however, numerous opportunities for further development and exploitation of the results are evident. The products have the potential to become a permanent part of the educational offerings of schools and gastronomy facilities. The mere interest in the topic during the project's implementation and dissemination indicates that, in the long term, the tools and materials could be integrated into everyday teaching practice. The development of international cooperation is also important, as it could lead to further projects, the exchange of experiences, and the further enhancement of the quality of vocational education in Europe. Furthermore, the growing demand for innovative solutions in education – particularly in the gastronomy and hotel sectors – creates favorable conditions for the implementation of the developed products.

At the same time, potential threats cannot be ignored. The greatest risk is the failure to implement the results in practice due to a persistent lack of recipients. If educational and industry institutions decide not to implement new solutions, there is a danger that they will remain merely theoretical. Furthermore, the volatility of the socio-economic environment, reforms in the education system, and the emergence of competing educational initiatives may weaken the relevance and significance of the results. In summary, the obtained results allow us to assess the project as a successful undertaking, with high educational and social value. Its strengths – such as a broad network of cooperation, international reach, and diverse promotional tools – clearly outweigh its weaknesses. At the same time, the analysis indicates that long-term success will depend on the willingness of institutions and recipients to adopt and use the

developed products. In this context, further actions are recommended to support the process of adapting the results, including through implementation training, presenting best practices, and strengthening trust within the educational and industry communities.

The presented considerations are presented in the form of a SWOT analysis in Table 1.

Table 1. SWOT analysis

Strengths	**Weaknesses**
• Achievement of the objectives and goals – both general and specific. • Development of engaging educational materials – including materials for instructors and students. • Broad dissemination – activities covered Poland, Germany, and Italy. • Diverse promotional channels – traditional partner networks and modern electronic tools (platforms, social media, newsletters). • Involvement of numerous institutions – schools, educational centers, chambers of crafts, and industry associations. • The language of benefits used when presenting results increases the chances of their adoption in the future.	• Audience reticence – despite careful dissemination, there is a lack of immediate, enthusiastic response. • Dependence on the trust and willingness of the community – some institutions and individuals are reluctant to adopt new solutions. • Dispersion of activities – diverse forms and channels can make it difficult to consistently monitor results.
Opportunities	**Threats**
• Long-term product adaptation – the potential for utilizing the results in work with students and graduates of culinary schools. • Development of international cooperation – strengthening the network of educational and industry connections in the EU. • Growing demand for innovation in vocational education – particularly in the gastronomy and hotel sector. • Possibility of further funding and replication of results – for example, in subsequent editions of Erasmus+ or similar programs.	• Lack of sustainability of results – if audience reticence persists, products may not be implemented. • Low level of public trust – fear and uncertainty may inhibit the implementation of new tools. • Competing educational initiatives – other projects may dominate the education market. • Changing socio-economic context – for example, changes in the education system, the labor market, or preferences in the restaurant industry.

Source: own study.

The project was successful in achieving its goals and widely disseminating its results. Its strengths lie in its international reach and extensive network of collaborations, as well as the use of various promotional tools. However, the lack of immediate acceptance by recipients and difficulties in measuring effectiveness indicate challenges in implementation and monitoring outcomes. In the long term, the project has a strong chance of success thanks to the growing demand for innovative solutions in vocational education. However, it is important to note the risks associated with a lack of trust and uncertainty in the educational and industry communities.

6. CONCLUSION

The implementation of a project in the field of human resource management in the gastronomy industry has revealed critical shortcomings of the current vocational and professional education systems. One of the most striking findings is the absence of human resource management -focused classes in the education process for future professionals. This gap significantly limits the ability of employees and managers to fully understand the essence and importance of human resources – competences, experience, and knowledge – within an organisation. Without this awareness, individuals often underestimate how central effective human resource management is to achieving strategic organisational goals.

Another important issue concerns the insufficient development of managerial competences and related social skills among gastronomy professionals. Effective management requires more than technical proficiency in food preparation or service – it relies heavily on leadership, decision-making, delegation, communication, and conflict-resolution skills. A lack of such competences can have serious consequences for organisations. For example:

- Ineffective team management may weaken collaboration, lower morale, and reduce motivation.
- Unclear organisational goals and chaotic decision-making can generate confusion among employees.
- Weak communication often leads to misunderstandings, conflicts, and a lack of trust between staff and management.

In the long term, these deficits negatively affect employee performance, overall productivity, the quality of service, and even customer satisfaction. They also hinder the organisation's ability to adapt to changes, innovate, and compete in a highly dynamic market such as the gastronomy industry.

The mental approach to human resource management. Equally critical is the attitude of gastronomy employees and managers toward human resource management. Although there is a growing awareness of the importance of managing people effectively, the approach is often superficial or dismissive. Many perceive human resource management as an auxiliary activity, the responsibility of HR departments or external consultants, rather than as an integral part of their own managerial role. This mental resistance is particularly problematic in smaller gastronomy businesses, where owners and managers often juggle multiple responsibilities and may deprioritise people management.

This resistance frequently arises from:

- A lack of knowledge about human resource management methods and benefits.
- Fear of change and reluctance to introduce formalised management practices.
- Industry stereotypes that prioritise speed of service and food quality while undervaluing the role of structured management.

The consequences of this mindset are visible: high staff turnover, difficulties in maintaining team motivation, and the absence of a consistent and positive organisational culture. Over time, these problems accumulate, leading to instability and reduced competitiveness.

The case for human resource management in gastronomy.

It is therefore essential for gastronomy professionals to recognise that human resource management is not an optional or secondary task, but rather a core factor of business success. Properly implemented human resource management practices can:

- Strengthen workplace culture and employee loyalty.
- Increase operational efficiency by clarifying responsibilities and processes.
- Foster innovation and adaptability by encouraging open communication and collaboration.
- Improve customer satisfaction by ensuring motivated, well-coordinated teams deliver high-quality service.

Learning about human resource management tools and techniques—such as recruitment strategies, performance appraisals, motivation systems, or training and development programmes—can lead to measurable improvements in both the internal functioning of organisations and their external image. Importantly, investment in human resource management is not merely a cost but a long-term investment in sustainable development.

Directions for future action and research.

The above findings point to several avenues for further exploration:

1. Educational reforms – The integration of human resource management modules into vocational and higher education curricula for gastronomy and hospitality could address existing competence gaps.
2. Practical training – Workshops, simulations, and mentoring programmes could equip current employees and managers with practical human resource management tools.
3. Research initiatives – Further studies are needed to examine the relationship between human resource management practices and specific performance indicators in gastronomy, such as staff retention, customer satisfaction, and financial results.
4. Awareness campaigns – Promoting success stories of businesses that have implemented strong human resource management practices could help overcome stereotypes and resistance.

The project "Methodology of teaching human resources management for current and future gastronomy employees" underscores a crucial point: in the gastronmy industry, success is not determined solely by culinary skills or service efficiency. Sustainable growth requires effective management of people – the organisation's most valuable resource. Building human resource management competences, reshaping mental attitudes, and embedding human resource management into the culture of gastronomy organisations are therefore essential steps toward improving competitiveness and ensuring long-term success.

The "Methodology of teaching human resources management for current and future gastronomy employees" project is an example of an important and innovative undertaking whose significance extends beyond the scope of a single educational initiative. Its implementation demonstrated that properly planned teaching activities based on modern teaching methods can truly support the development of competencies in the gastronomy sector, which is characterized by rapid change and high demands on personnel management. It's worth emphasizing that the project wasn't limited to introducing new teaching content. Its innovative nature also lay in combining theoretical and practical perspectives, which enabled participants to better prepare for the challenges of real-world work. This gave the project an applied dimension, directly addressing the needs of both current and future industry employees.

From a scientific and practical perspective, several key outcomes can be identified:

- improving the quality of the educational process through the implementation of modern teaching methods,
- increasing awareness of the importance of human resources management in the restaurant industry,
- developing soft skills and managerial competencies among participants,
- creating a foundation for standardizing similar initiatives in the future.

Therefore, the project should be considered an innovative educational endeavor that can serve as a model for further activities in the field of vocational and continuing education. Given the results achieved and the broad adaptability, it is recommended that similar solutions be replicated both in the restaurant industry and in other economic sectors where effective human capital management is key to success.

This project "Methodology of teaching human resources management for current and future gastronomy employees" demonstrates that investing in competency development through modern educational programs not only strengthens the competitiveness of enterprises but also supports the development of social capital and an organizational culture based on knowledge and skills. In this sense, it should be considered an initiative whose replication and further development are of strategic importance both for the industry and for vocational education more broadly.

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In an era marked by accelerating technological progress and far-reaching societal transformations, the importance of artificial intelligence (AI) and intelligent management systems is rapidly growing. These two areas – intertwining technological innovation with organizational effectiveness – are shaping the future of public institutions, enterprises, and societies. The dynamic development of AI technologies not only creates new economic and scientific opportunities but also generates a series of challenges related to ethics, law, education, and strategic decision-making. The need to comprehensively analyze these aspects becomes a priority for both academic communities and practitioners seeking to responsibly harness the potential of AI in various spheres of life.

This monograph constitutes a peer-reviewed collection of research articles presented during the international workshop Intelligent Management (InMan), organized within the framework of the 28th European Conference on Artificial Intelligence (ECAI 2025), which took place in Bologna, Italy, on October 25–30, 2025. […]

[…] The international and interdisciplinary character of this publication is reflected in the diversity of its authors, who represent scientific and research institutions from numerous countries, including Bosnia and Herzegovina, the Czech Republic, Hungary, India, Indonesia, Kosovo, Latvia, Lithuania, Poland, Spain, and Sweden. This global composition not only enriches the perspectives presented but also allows for a deeper understanding of how AI and intelligent management solutions are interpreted and implemented in different national, cultural, and institutional contexts. Such diversity provides a valuable comparative insight into the ways organizations and societies adapt to digital transformation and the ethical, social, and strategic dilemmas it brings.

From the Preface

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