DOI 10.18276/978-83-8419-028-9-27



28th European Conference on Artificial Intelligence (ECAI 2025)

# SMART LEARNING WITH AI: DECISION FACTORS IN GENERATION Z'S ADOPTION OF CHATGPT USING THE UTAUT2 FRAMEWORK

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## 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

## 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.

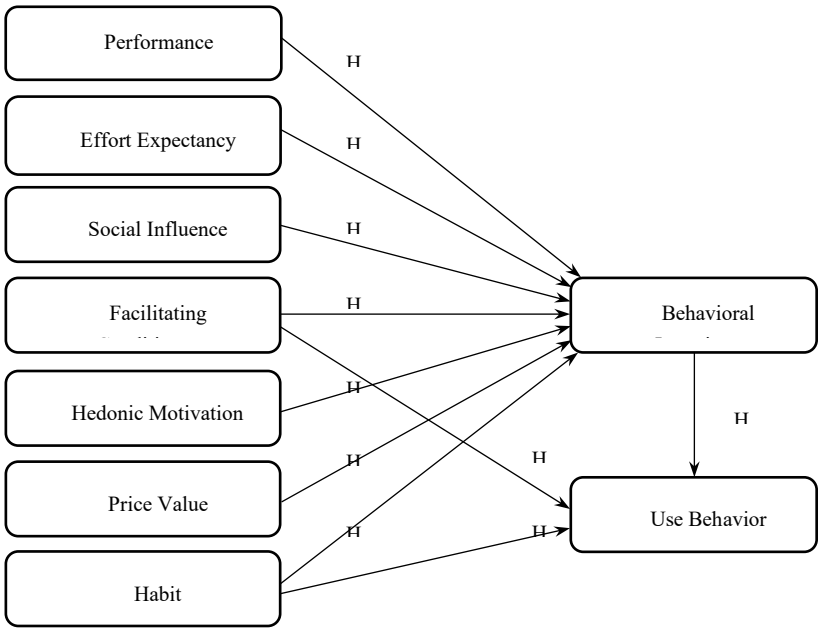


**Figure 1.** Theoretical framework for ChatGPT adoption and usage among Generation Z students
*Source*: own elaboration.

### *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).

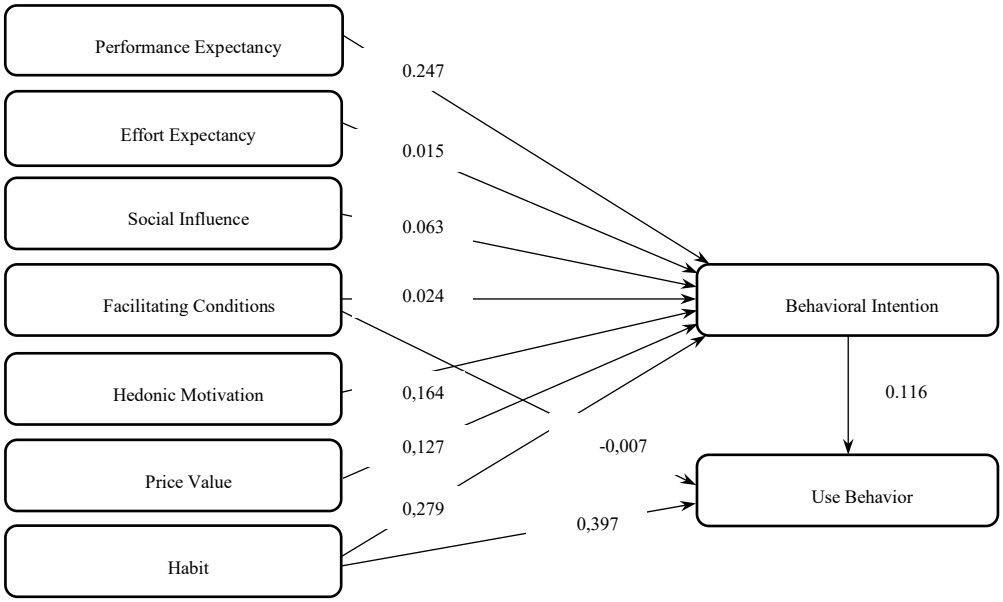


**Figure 2.** Final Structural Model: Path Coefficients and Hypothesis Testing
*Source*: own elaboration.

## 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.

**Funding:** Co-financed by the Minister of Science under the "Regional Excellence Initiative".


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