DOI 10.18.276/978-83-8419-053-1-16

28th European Conference on Artificial Intelligence (ECAI 2025)

A MODEL APPROACH TO THE RELATIONSHIP BETWEEN EMPLOYEE RELATIONS, AGILITY, AND INNOVATION IN A SMARTLY MANAGED ORGANIZATION BASED ON RESEARCH

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ABSTRACT

Purpose: *In an organisation managed based on artificial intelligence, innovation plays a key role in building an effective operating model. On the other hand, developing interpersonal relationships and agile behaviours is desirable in response to the growing demands of a turbulent environment.*

Need for the study: *There are relatively few studies dedicated to understanding how interpersonal relationships and agility affect the generation and diffusion of new solutions. Therefore, these processes are still insufficiently explored.*

Methodology: *Using diagnostic survey methods and structural equation modelling, the authors conducted a study to discover whether there are relationships between relationships, agility, and innovation in the organization. The research sample consisted of two hundred and fifty-four managers representing the economic sector. A model of the interdependence of the above-mentioned features was proposed.*

Findings: *Based on the research, it was found that the type of relationships between organisational members and the organisation's innovation are correlated. The analysis also indicates that innovative behaviours are easier in agile organisations and that agility influences the relationship between interpersonal connections and innovation. The discussed results and their conclusions can be viewed as a contribution to the existing body of knowledge, which should continue to be expanded.*

Practical Implications: *The authors recognise an opportunity to add new constructs to the analysed model, which will become the subject of research in their next phase.*

Keywords: intelligent management, smart organization, relationships, innovation, agility, model approach

Jel codes: C1, M12

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1. INTRODUCTION

Intelligent organisational management aims to automate management decisions and is related to the design of management behaviours. (Lv& Li, 2021). The main substrate for the creation of enterprise intellectualisation mechanisms is artificial elements (complex computer systems, local networks, etc.). However, the natural intelligence of employees also plays an important role. It is supported by their professional development aimed at competence formation through training in knowledge, skills and abilities (Odrekhivskyi et al., 2023). It results both from the serious limitations of contemporary artificial intelligence systems, which, among other things, are unable to generalize (von der Malsburg et al., 2022), and from the fact that interactions with AI systems force solving ethical, social and environmental problems (Kumar, 2023, 18).

Many researchers point out that artificial neural networks support creative and innovative behaviours (e.g. Clegg et al., 2022; Siemion, 2022). Innovation is a key feature of organizations in the era of constantly changing environment and related constant challenges, as well as intensifying competitive struggle. The founder of the concept of innovation, J. Schumpeter, understood it as the creation of new combinations of existing resources,-however, in more modern times this concept is also defined in other ways. Innovation can also be perceived as a process that integrates science, technology, economics, and management, aiming to achieve novelty and extending from the emergence of an idea to its commercialization, or as new knowledge introduced into products, services, and processes (Kogabayev&Maziliauskas, 2017; Mazur-Wierzbicka, 2018, 2019). Some additionally highlight creativity as a particularly important element of innovation. For example, Cropley et al. (2011) note, following other authors, that creativity was previously considered the first stage of innovation, followed by the application of ideas resulting from creativity. However, in more recent theories, the interdependence of these two features is not viewed as sequential, although creativity still always precedes the implementation of innovation. A similar position is represented by Meutia et al. (2018), who write, among other things, that creativity is the initial phase of innovation. Also in works such as Roy & Mohapatra (2023), Ek Styv'en et al. (2022) or Rzepka & Sabat (2022) far-reaching relationships are noted between being creative and innovative.

The turbulent conditions in which organizations currently operate increasingly force them to adopt flexible behaviours. This issue has become particularly apparent in recent years, as the COVID-19 pandemic, followed by the outbreak of the war in Ukraine and the resulting energy crisis, have highlighted the necessity of rapid adaptation to change (Jojczuk et al., 2023). The agility of organizations and the adaptation of leaders to these conditions began to be discussed in the 1980s and 1990s. In the early 1980s, agility began to be defined as the ability to respond quickly to changes in the environment, but a certain group of researchers believe that the term has its roots in the context of production and is related to the need to find a new production system that responds to new factors of production in the manufacturing industry (Desalegn et al., 2024). However, this topic, along with the factors or dimensions of its occurrence, was addressed in a more structured manner only in the first decade of the 21st century. The dominant dimensions of organizational agility include, among others: business, markets, strategy, and process (Silva & Oliveira, 2023). Some authors emphasize the important role of leadership in an organization, noting that building trust in employee teams fosters the creation of flexible leaders. Tyagi et al. (2022) wśród czynników determinujących efektywność i zaangażowanie członków zwinnych zespołów wymieniają między innymi obecność liderów, którzy wykazują służebną postawę wobec współpracowników oraz skłonnych do dzielenia się swoją wiedzą i umiejętnościami, jak również promujących refleksyjność, co dodatkowo zachęca do innowacyjności. Trzeciak & Banasiak (2022) also mention solutions naturally related to the human factor in the organization, such as a transparent and appropriate evaluation system, defining planned employee development, and team atmosphere. It is also worth noting the agile mindset, which is attributed a key role in the process of effectively introducing flexibility (e.g., Eilers et al., 2022; Asseraf&Gnizy, 2022). Organizational agility, like innovation, should also be considered in the broader context of intelligent management. Research results published in works such as Gonçalves et al. (2022), Saputra et al. (2023), and Wang et al. (2022) clearly indicate the positive impact of using AI tools on decision-making processes, including their speed and the accompanying proper judgment of managers.

Employee relations are a very important element of every organization (Mazur-Wierzbicka & Cierniak-Emerych, 2024). As an intangible value, they are often included in the broadly understood organizational capital of a given entity, understood as a set of intellectual property assets of the organization, its processes and methods, as well as communication and information infrastructure (Chmielewiec, 2019). Enterprises more heavily based on human capital (Rzepka & Witkowski, 2024) have greater ease in obtaining external financial resources for their activities, as in the assessment of the holders of these resources, they represent greater creditworthiness (Honjo et al., 2022). At the same time, they widely use motivational compensation systems and various non-monetary benefits to retain the most important talents from the perspective of their operations (Hasan & Uddin, 2022). The increasing importance of interpersonal relationships in organizational activities is also evidenced by the presence of the concept of relational capital in the literature. This capital can be defined in various ways: for example, as an expression of the value of relationships that an enterprise maintains with all entities in its environment (Garcia-Merino et al., 2014), as knowledge acquired and obtained from these relationships, or as resources created based on personal relationships, such as trust, norms, commitments, reputation, and identity (Sanchez-Famoso et al., 2020). However, it is worth mentioning that in the context of using tools based on artificial intelligence, at least some of these values may be diminished. As noted by Ojo &Afolaranmi (2024), AI technologies lack the nuanced emotional understanding necessary for true intimacy, and they do not foster the building of authentic trust and achieving significant relational depth.

Based on the above, both agility and the relationships between an organisation’s employees should be considered as very important factors affecting the way it operates. They should be considered in the context of innovation as one of the most important dimensions of an organisation’s functioning.

2. LITERATURE REVIEW

The issue of innovation has been present in the literature for a long time, and authors of various publications, in search of key determinants for introducing innovative solutions, point to different types of investments that should be made to more effectively utilize the potential of innovation. El-Bar (2021) distinguishes two types of such investments, one of which enables the creation and promotion of knowledge, while the other translates knowledge into specific innovative solutions. Some researchers focus primarily on assets that foster innovation, which are based on material values. This can include the broadly understood area of R&D or the development of information and communication technologies (El-Bar, 2021; Czerwińska et al., 2023), as well as certain business activities related to tangible asset transfer. For example, one of the more recent studies highlights innovation based on foreign trade exchange, where the import of high-quality semi-finished products leads to an increased number of patents (Zhong, 2023).

In many works, intangible values are seen as a crucial stimulator of innovative capabilities. Innovation is relatively often associated with the organizational culture of a company. As Salilew (2019) writes, a strong organizational culture allows for the effective use of employees’ capabilities and improvement of their performance. Rodriguez-Gonzalez et al. (2023) and Rzepka (2023) argue that the impact of organizational culture on a company's performance is largely determined by employees' attitudes toward the implemented innovative changes. They write that particular importance is given to the fuller contact of employees with individual supply chains and the improvement of their perception of organizational innovations. Naveed et al. (2022) and Pedraza-Rodriguez et al. (2023) emphasize the role of organizational members' acceptance of changes made in the workplace. In another study, it is noted that shared values, mutual relationships, adopted patterns of thinking and behaviour, as well as methods of cooperation, have a significant impact on organizational effectiveness (Domańska-Szaruga & Knap-Stefaniuk, 2022). A relatively new research topic is the impact of family ties between employees on the functioning of a company, as discussed by Memili et al. (2020) and Chrisman et al. (2021). In the first case, researchers focus on the management problems of companies owned by several families. They propose certain mechanisms to limit the potential negative impact of divergent non-economic goals related, among other things, to family altruism and transgenerational succession. In the second case, the authors conclude, based on examples from companies in the hotel industry and healthcare sector, that small and medium-sized family businesses can achieve transgenerational sustainability and success if they leverage their strong non-financial aspects while simultaneously minimizing the impact of family-focused goals on the company's performance. In small family businesses, owners prefer intuitive, informal decision-making and exercising control over every important aspect of the operation, which includes unwillingness to delegate certain functions to third parties. However, it is uncertain whether this unwillingness is primarily due to the nature of such enterprises or their size (Rieg et al., 2022). Family relationships among employees influence organizational psychological capital, which Fischer-Kreer et al. (2021) view as an essential resource for family businesses during times of stress. However, such relationships are not limited to family businesses. As Obiekwe et al. (2019) argue, fostering close bonds between coworkers, even when they are not related, generates greater engagement, increases attachment to the employer, and contributes to greater empowerment in teamwork. From an economic perspective, such a network of connections allows the participating entities to operate with low transaction costs (Ramirez-Sólis et al., 2022).

The scientific literature addresses the mutual relationship between agility and innovation. Many studies emphasize the positive connection between these two aspects of organizational functioning, generally attributing a key role to flexible behaviours in innovation processes. For example, Sjödin et al. (2020) propose a model illustrating an alternative approach to microservice innovation based on rapid, iterative development and adapted to changing innovation requirements, which brings more flexibility to the innovation process. In turn, Alamsjah (2022), examining supply chains, finds, among others, that open innovation practices improve companies' agility capabilities, which is also confirmed by the research results presented in another work (Arsawan et al., 2022) Bellis et al. (2024) examine the correlation between agility and innovation through the lens of leadership. They conclude, among other things, that the development of innovative activities requires leaders to become ambidextrous, agilely adapting to different environments and adjusting their behaviours and styles while maintaining consistency in values and norms. However, Annosi et al. (2022) seem to take a different stance on this matter, concluding, based on the example of a large telecommunications company, that actions aimed at developing agility may have an adverse impact on employees' pro-innovation attitudes. If it is assumed that direct management interventions limit the agile behaviours of organizational members, a similar view to that of Annosi et al. (2022) is in fact represented by Lill & Wald (2021), who, based on their own research, surprisingly state that such top-down interactive controls can positively impact employees and their creative abilities. The issue of agility and innovation can also be considered on a regional scale, as exemplified by the work of Andriyani et al. (2024), which identifies important aspects and common practices between agility and open innovation concepts. According to the authors, the adaptation of innovation in the region should focus on critical aspects such as collaboration, prototyping, adaptability, feedback loops, experimentation, risk management, ecosystem development, and data-driven development.

The relationship between agility, innovation and the use of artificial intelligence technologies is also increasingly being studied. For example, based on a study conducted on a group of companies in Slovenia, it is clearly stated that the implementation of AI tools allows for a faster increase in profitability and innovation by providing accurate data and information, facilitating quick and informed decision-making, which ultimately leads to successful results in which products or services meet customer expectations (Rozman et al., 2023, 32-33). Similar conclusions were also drawn from the analysis described in the work of Noronha et al. (2023). However, not all studies confirm the positive correlation of the use of artificial intelligence and agility. As an example, we can mention the analysis conducted by Romanian researchers, which leads them to the conclusion that the use of this advanced technology can have a significantly negative impact on the agility of the internal processes of the organization and agility in relation to changes in the external environment (Stefan et al., 2024, 414).

In summary of the above literature review, it can be stated that scholars recognize the relationships between the interactions among organizational members, its agility, and innovation. At the same time, there is a lack of research that provides an answer to the question of whether organizational agility should be viewed not only as a direct determinant of innovation but also as a crucial element determining how the type of interactions between employees influences the ability to create and implement new solutions.

3. METHODOLOGY AND MATERIALS

Based on the literature on personal relationships within organizations, its agility, and innovation, a model of the interrelationships between these components was developed (Fig. 1). The model includes the following research hypotheses:

- Hypothesis 1 [H1]: There is dependence between the relationships among employees within the organization and its innovation (A1).
- Hypothesis 2 [H2]: The more agile the organization, the more innovative it is (A2).
- Hypothesis 3 [H3]: Dependence between relationships and innovation is mediated by agility (A3xA2).

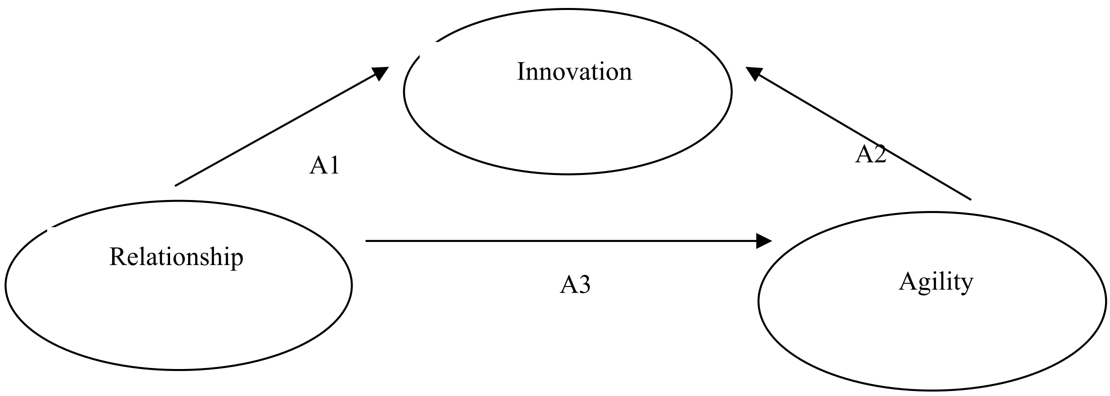

Figure 1. Model of the relationships between internal organizational relationships, agility, and innovation
Source: own elaboration.

To achieve the research objective of verifying the hypotheses and thus checking whether the proposed model of interdependencies is correct and corresponds to the collected data, the diagnostic survey method and the structural equation modeling (SEM) method in the form of GSCA (Generalized Structured Component Analysis) were used. GSCA represents a component-based approach to structural equation modeling (SEM), which defines a latent variable as a component or weighted composite of indicators. The GSCA method also allows users to obtain general and local model fit measures, parameter estimates with bootstrapped standard errors and confidence intervals, as well as total and indirect effects of latent variables and indicators.

The measurement data were obtained through a survey conducted in 2023 via one of the national research panels and were part of the international project "Teal Organizations in Economy 4.0" carried out in Poland, England, Hungary, Ukraine, the Czech Republic, Spain, Georgia, and the USA (Rzepka, 2023). A survey was conducted with 254 individuals representing the management staff of enterprises in Poland. The tool used was a proprietary questionnaire, distributed according to the standards of the CAWI technique, and consisting of thematic blocks related to the leader in the organization, innovations and technologies used in the company, prevailing relationships, agility and creativity, social capital, knowledge and information, trust, and organizational structure and culture. The questionnaire consisted of 5 parts, each containing 5-7 closed-ended questions focusing on various topics. The study was conducted in accordance with the recommendations developed by OECD-DAL. For the purposes of inference in this paper, 6 questions from the following thematic blocks were used: innovations and technologies (2 questions), relationships (2 questions), agility and creativity (2 questions). This selection allowed for the examination of the interrelationships between three aspects of an organization's functioning. It provided insight into the dependence of an organization's innovation level on both employee attitudes, particularly openness to mutual collaboration and partnership in pursuit of goals, as well as on agile behaviours within the organization, based on creativity. The full list of questions (formulated as declarative sentences) along with their assignment to the components of the analyzed model is presented in Table 1.

Table 1. Components and questions (indicators) used in the study

Component	Indicator	
	Symbol	**Question**
Relationships	REL1	We all strive to achieve a common goal
	REL2	Competition has been replaced in our company by partnership and cooperation.
Component	**Indicator**	
	Symbol	**Question**
Agility	AGIL1	In our company, employees quickly adapt to the requirements of new equipment.
	AGIL2	In our company, a lot of space is left for creative and innovative activities.
Innovation	INNO1	We strive to ensure that all processes conducted in our company are characterized by innovation.
	INNO2	I have the opportunity to continue my education and development at work.

Source: own elaboration.

The entities represented by the respondents show significant diversity in terms of the type of their business activities, their geographical scope, size, and industries, as presented in Table 2.

Table 2. Characteristics of the structure of enterprises represented by the respondents

Type of activity (%)		geographical scope (%)		Number of employees (%)		Industry (%)	
commercial	16.6	local	9.4	0-9	3.3	aviaton	5.3
manufacturing	28.0	Regional	27.3	10-49	55.1	Fuel industry	4.0
service	55.4	domestic	22.0	50-249	16.6	Automotive industry	3.8
		international	41.3	250-999	16.6	IT	11.4
				1000 and more	8.4	Education	3.8
						Research and Development (R&D)	4.0
						Gastronomy	5.2
						Construction industry	5.3
						Trade	3.4
						Banking sector	10.0

Source: own elaboration.

To verify the correctness of the proposed dependency model, the structural equation modeling (SEM) method in the form of GSCA was used. The use of this method is justified when examining the relationships between different constructs in order to detect mutual dependencies. This type of modeling is also used in the case of analyses including variables such as: innovation, agility and interpersonal relations (e.g.: Homayoun et al., 2024; Arsawan et al., 2022; Dabic et al., 2021). In particular, the following elements were used to validate the data and the model:

- model fit indices such as: FIT, AFIT, FITs, FITm, GFI, SRMR, OPE, OPEs, OPEm,

- estimated component weights and component loadings of indicators on the component, bootstrap standard errors (SE), and bootstrap 95% confidence intervals to determine the statistical significance of the model,
- path coefficient estimates and their bootstrap standard errors (SE), as well as 95% confidence intervals to verify the statistical significance of the mentioned coefficients at the 5% confidence level,
- correlation coefficients between the components of the model,
- quality indicators of the model constructs: PVE, Cronbach's alpha, Rho (Dillon-Goldstein's rho), Dimensionality to determine whether the model correctly reflects the assumed hypothesis connections and to check the reliability level of the model,
- Fornell-Larcker criterion to assess discriminant validity in the model,
- R2 values concerning both indicators in the measurement model (to identify the level of model fit to the measurement data) and components of the structural model (to determine what portion of the variability of a given component is explained by other components in the model,
- variance inflation factor (VIF), whose value helps identify whether the independent variables in the model are highly correlated (multicollinearity),
- The F-squared value for each predictive component to determine their mutual influence on each other,
- Mean values of unscaled components on the same scales as their original indicators to determine the most frequently chosen responses,
- correlation coefficients between all indicators to determine the strength of their mutual relationship, as well as between indicators and components (correlations of each indicator with all components).

4. RESULTS

The first stage of model verification was the analysis of indicators showing the degree of its fit to empirical data. The study used fit indices such as: FIT, AFIT, FITs, FITm, GFI, SRMR, OPE, OPEs, OPEm. Table 3 presents their values for the examined model. The FIT parameter indicates the total variance of all variables (indicators and components) explained by a specific model specification and, in the case of the constructed model, reflects 64.7% of the variables. AFIT (Adjusted FIT) is similar to FIT but takes into account the complexity of the model. Like the adjusted R-square in linear regression, AFIT cannot be interpreted in the same way as FIT (i.e., the percentage of total explained variance). Instead, it can only be used to compare competing models. Among the competing models, the one with the highest AFIT value can be selected. FITs indicates the total variance of all components explained by a specific structural model specification. FITs values range from 0 to 1. The higher this value, the greater the variance in the components accounted for by the specified structural model. For the analyzed model, this parameter is equal to 0.336. FITm indicates the total variance of all indicators explained by a specific measurement model specification. FITm values range from 0 to 1. The higher this value, the greater the variance of indicators accounted for by the specified measurement model. In the analyzed model, it is 0.802. The GFI (goodness-of-fit index) and SRMR (standardized root mean squared residual) measures are proportional to the difference between sample covariances and covariances reproduced by GSCA parameter estimates. A recent study suggested the following cutoff criteria for GFI and SRMR in GSCA (Cho et al., 2020):

- When the sample size = 100, GFI ≥ 0.89 and SRMR ≤ 0.09 indicate acceptable fit. Although both indices can be used to assess model fit, using SRMR with the above cutoff value may be better than using GFI with the suggested cutoff value. Additionally, if SRMR ≤ 0.09, then a GFI cutoff value ≥ 0.85 may still indicate acceptable fit.
- When the sample size > 100, GFI ≥ 0.93 or SRMR ≤ 0.08 indicates acceptable fit. In this case, there is no preference for one index over the other or for using a combination of indices instead of using them separately. The suggested cutoff value for each index can be used independently to assess model fit.

In the case of the constructed model, the GFI index equals 0.996, while the SRMR is 0.038, indicating a good model fit.

Table 3. Model fit indices

FIT	AFIT	FITs	FITm	GFI	SRMR	OPE	OPEs	OPEm
0.647	0.643	0.336	0.802	0.996	0.038	0.357	0.674	0.198

Source: own elaboration.

Table 4 presents the estimated component weights and component loadings of indicators on the component (Estimates). It also shows the bootstrap standard errors (SE) and bootstrap 95% confidence intervals (95% CI) of the weight and loading estimates. The 95% confidence intervals can be used to test the significance of the estimate (i.e., the estimate can be considered statistically significant at the 0.05 level if its confidence interval does not include 0). When a component is specified as a canonical component, the loadings of its indicators will not be shown. In the case of the constructed model, all model parameters are statistically significant at the 0.05 level, and the 95% CI intervals do not contain the value 0, indicating a good model fit.

Table 4. Component Weights and Loadings for the Examined Model

	Estimate	SE	95%CI	
		Weights		
REL1	0.555	0.03	0.504	0.62
REL2	0.557	0.027	0.501	0.608
AGIL1	0.445	0.031	0.387	0.505
AGIL2	0.668	0.039	0.597	0.738
INNO1	0.565	0.028	0.504	0.619
INNO2	0.549	0.028	0.504	0.601
		Loadings		
REL1	0.899	0.017	0.863	0.928
REL2	0.9	0.02	0.859	0.932
AGIL1	0.844	0.037	0.772	0.9
AGIL2	0.934	0.01	0.917	0.952
INNO1	0.901	0.017	0.865	0.929
INNO2	0.895	0.018	0.852	0.927

Source: own elaboration.

In the next table (Table 5), estimates of path coefficients (Estimate) and their bootstrap standard errors (SE) as well as 95% confidence intervals (95% CI) are included. None of the confidence intervals contain 0, so the values of the path coefficients are statistically significant at the 5% confidence level.

Table 5. Path Coefficients

	Estimate	SE	95%CI	
Relationship→Agility	0.676	0.037	0.6	0.742
Relationship→Innovation	0.33	0.063	0.225	0.467
Agility→Innovation	0.477	0.07	0.322	0.594

Source: own elaboration.

The correlation coefficients between the individual components of the model indicate a strong relationship (Table 6). Values in the range of 0.5 – 0.7 indicate a strong correlation, while values in the range of 0.7 – 1 indicate a very strong correlation. The strongest correlation is between Agility and

Innovation, while there is a strong relationship between Relationships and Agility, as well as Relationships and Innovation.

Table 6. Correlation Coefficients of Components

	Relationship	**Agility**	**Innovation**
Relationship	1.0	0.676	0.653
Agility	0.676	1.0	0.701
Innovation	0.653	0.701	1.0

Source: own elaboration.

Table 7 provides information on the quality of the model's construction. It includes four indicators:

- PVE (Proportion of Variance Explained): The average amount of variance explained by the indicators through their corresponding components. A value above 70% may indicate unidimensionality.
- Alpha (Cronbach's alpha): A measure of internal reliability for the sum of indicators, assuming equal covariances.
- Rho (Dillon-Goldstein's rho): Composite reliability, more appropriate than alpha in the context of GSCA.
- Dimensionality: The number of eigenvalues greater than 1 for the set of indicators.

The value of Cronbach's alpha, which is a measure of internal reliability, should be at least 0.7 to indicate an acceptable level of reliability. Higher values, such as above 0.8, suggest good reliability, and values above 0.9 indicate very high reliability. However, it is worth noting that a value too high (close to 1) may indicate redundancy of indicators, meaning they measure very similar aspects of the same construct. The value of Dillon-Goldstein's rho (also known as composite reliability) should be at least 0.7 to indicate an acceptable level of model reliability. Values above 0.8 are considered good, and values above 0.9 are very high. Compared to Cronbach's alpha, Rho is more appropriate for assessing reliability in the context of GSCA, as it does not assume equal covariances between indicators. The Dimensionality parameter refers to the number of eigenvalues greater than 1 for the set of indicators assigned to a given component. If Dimensionality is 1, it suggests that the indicators are unidimensional, meaning they measure one common factor. When this value exceeds 1, it suggests the possibility of more than one factor, which may require considering a more complex model, such as with a greater number of components for the given set of indicators. From the analysis of the data values in the table, we can conclude that the model's indicators are unidimensional (PVE > 70% and Dimensionality = 1), thus the model correctly reflects the assumed hypothesis connections. Additionally, Dillon-Goldstein's rho greater than 0.8 indicates that the model's reliability level is good.

Table 7. Model Construction Quality Indicators

	Relationship	**Agility**	**Innovation**
PVE	0.809	0.792	0.806
Alpha	0.764	0.747	0.759
Rho	0.895	0.884	0.892
Dimensionality	1.0	1.0	1.0

Source: own elaboration.

The values of the Fornell-Larcker criterion are used to assess discriminant reliability in structural models. According to the Fornell-Larcker criterion, the average variance extracted (AVE) for each construct should be greater than its highest squared correlation with any other construct in the model. This means that constructs should explain the variance of their indicators better than they share variance with other constructs, ensuring that constructs are discriminant, i.e., different from each other. Discriminant reliability in structural models refers to the model's ability to distinguish between different constructs (latent variables). This means that each construct in the model should explain the variance of its indicators better than the variance of indicators of other constructs. If the model has good discriminant reliability, it means that the constructs are clearly different from each other and do not overlap in terms of what they measure. From the analysis of the values in Table 8, we conclude that each construct in the model explains the variance of its indicators better, indicating proper discriminant reliability.

Table 8. Fornell-Larcker Criterion Values

	Relationship	Agility	Innovation
Relationship	0.9		
Agility	0.676	0.89	
Innovation	0.653	0.701	0.898

Source: own elaboration.

To identify the level of fit of the model to the measurement data, R-squared (R^2) coefficients were used for the indicators in the measurement model. Table 9 presents the amount of variance of each indicator explained by its assigned component in the measurement model. R^2 values indicate how well the component explains the given indicator. A higher R^2 value (close to 1) means that a larger portion of the indicator's variance is explained by the component, suggesting a stronger relationship between the indicator and the component. These values help assess the quality of fit of the measurement model to the data. When a canonical component is chosen for a set of indicators, R^2 values for the indicators are not provided. R^2 values should be higher than 0.7. Analyzing the values from the table, we can say that the model is well-fitted to the measurement data.

Table 9. R-squared Values

INNO1	INNO2	REL1	REL2	AGIL1	AGIL2
0.811	0.8	0.809	0.81	0,712	0.872

Source: own elaboration.

Additionally, R^2 values were determined for individual components in the structural model. The R^2 coefficient in this case indicates what portion of the variability of a given component is explained by other components in the model. $R^2 > 0.90$ for constructs measuring perceptions, attitudes, or intentions indicates potential misfit. In the considered model, the R^2 value for the Agility component is 0.457, while for Innovation it is 0.55. This means that both constructs are explained by approximately 46% and 55%, respectively, which is correct. At the same time, the canonical component (no R^2 value) is the Relationships component.

The Variance Inflation Factor (VIF) helps identify whether independent variables in the model are highly correlated (multicollinearity), which can lead to less reliable estimates of path coefficients. VIF values below 3 suggest that multicollinearity is not a serious problem. Higher values may indicate the need for further analysis or model modification, while low values indicate good model quality, where independent variables are not excessively correlated. Interpreting the values from Table 10, it can be concluded that multicollinearity does not occur, and there is no need for changes in the model.

Table 10. Variance Inflation Factor (VIF)

	Relationship	Agility	Innovation
Relationship	0	0	1.841
Agility	0	0	1.841
Innovation	0	0	0

Source: own elaboration.

Table 11 presents the values of the f^2 indicator, which is a measure of effect size for each predictor in the structural model. It indicates how much impact a given predictor has on the dependent variable. According to general guidelines, f^2 values of 0.02, 0.15, and 0.35 can be considered small, medium, and large effect sizes, respectively (Cohen, 1988). From the analysis of the table, it can be concluded that the predictor Agility has a very large impact on Relationships, while the predictor Innovation has a medium impact on Relationships and Agility.

Table 11. f^2 Indicator Values for the Model

	Relationship	Agility	Innovation
Relationship		0.841	0.123
Agility			0.295
Innovation			

Source: own elaboration.

The average values of unscaled components and their variances were also analyzed (Table 12). Considering that the responses to all questions forming the basis for the verified model were presented on a five-point Likert scale and rounding the values listed in the summary, it should be stated that the most frequently given response for each of the three components was 4 – rather agree.

Table 12. Average Values of Unscaled Components and Their Variances

	Relationship	Agility	Innovation
Average values	4.015	3.851	3.699
Variations	0.598	0.656	0.785

Source: own elaboration.

Table 13 contains the correlation values between individual indicators of the model (lower diagonal) and the differences between sample correlations and model correlations (upper diagonal). The correlation values indicate that all indicators are either strongly (value range 0.5 – 1.0) or moderately related (value range 0.3 – 0.5). The data show that the strongest relationship is between AGIL2 and INNO1 and INNO2, which are indicators reflecting agility and innovation, respectively. Additionally, significant mutual relationships are shown between indicators of agility and employee relations (AGIL2 and REL1 and REL2). All indicators are strongly correlated with all components (Table 14).

Table 13. Correlations Between Indicators and Residual Correlations

	INNO1	INNO2	REL1	REL2	AGIL1	AGIL2
INNO1	0.0	-0.194	-0.007	0.007	0.012	-0.008
INNO2	0.611	0.0	0.007	-0.007	-0.013	0.008
REL1	0.558	0.54	0.0	-0.191	0.028	-0.019
REL2	0.528	0.482	0.618	0.0	-0.028	0.019
AGIL1	0.454	0.431	0.497	0.469	0.0	-0.192
AGIL2	0.637	0.655	0.554	0.622	0.596	0.0

Source: own elaboration.

Table 14. Correlations Between Indicators and Components

	Relationship	Agility	Innovation
INNO1	0.604	0.628	0.901
INNO2	0.568	0.63	0.895
REL1	0.899	0.591	0.612
REL2	0.9	0.625	0.563
AGIL1	0.537	0.844	0.493
AGIL2	0.654	0.934	0.719

Source: own elaboration.

5. DISCUSSION AND CONCLUSION

Based on the research results discussed above, it can be concluded that the proposed model of interdependencies between employee relationships, agility, and innovation within the organization has been positively verified. Consequently, all three previously formulated research hypotheses have been confirmed as true.

The positive verification of hypothesis [H1] means that organizations where types of personal relationships based on cooperation and common goal pursuit prevail also have greater capabilities in introducing innovative solutions. This can be linked to the community of behaviours, values, and norms, as well as acceptance of changes, which some authors discuss in the context of improving operational efficiency and innovation (e.g., Rodriguez-Gonzalez et al., 2023; Naveed et al., 2022; Pedraza-Rodriguez et al., 2023; Domańska-Szaruga& Knap-Stefaniuk, 2022). Proper employee selection can also play an important role here. When companies use creative abilities and innovative traits as hiring and selection criteria, their employees are likely to generate diversity of ideas and engage in more innovative behaviours (Maier et al., 2023, 646). On the other hand, enterprises should develop performance management plans with their employees, taking into account their goals and actual needs (Jia, 2023, 5). Innovation can also come from the relationships of new firm founders with their parent companies. Such a collaborative network can be an important source of information. If venture founders do not have connections with innovative co-inventors, they may do well by focusing more actively on forming alliances or hiring technology personnel from other firms (Boeker et al., 2019).

Regarding agility and the role it can play in the process of creating and transferring new solutions (which hypothesis [H2] addressed), the conclusions from the analysis support the claims of researchers who emphasize that the ability of organization members to respond quickly and flexibly to changes positively impacts the level of innovation (e.g., Sjödin et al., 2020; Alamsjah, 2022). Innovation is characterized by uncertainty. The increasing dynamism of markets and growing customer demands, as well as the demand for personalized products, are challenging organizations to shorter innovation cycles. Agile methods and processes can serve as a way to deal with these uncertainties in the context of the product development process (Schock et al. 2023, 431). A fundamental characteristic of agile workers is the ability to transfer abstract ideas and technologies to a concrete product, and this is something that, together with openness to new technologies, appears to drive innovation (Brand et al., 2019, 181). However, on the other hand, these conclusions somewhat contradict the observations of authors such as Annosi et al. (2022) and Lill & Wald (2021), who see a 'dark side' of agility. The study also confirmed the strong relationship between being creative and the ability to create and implement innovative solutions, which is mentioned in several previously cited publications (Cropley et al., 2011; Meutia et al., 2018; Rzepka & Sabat, 2022; Roy & Mohapatra, 2023; Ek Styvén et al., 2022).

The study also confirmed hypothesis [H3], which posits the mediating effect of agility on the relationship between employee relationships and innovation. The openness of organizational members to interactions with colleagues can facilitate more effective responses in crisis situations or those requiring adaptation, thereby enhancing organizational agility. This agility fosters the development of informal or even familial bonds, whose importance for organizations is increasingly recognized in the literature. At the same time, these relationships can positively impact creativity, which is crucial for innovation. As noted by Rzepka & Sabat (2022), the willingness to implement new, creative solutions determines the effectiveness of utilizing acquired knowledge, which is of primary importance for introducing innovative practices. On the other hand, a turbulent environment can initiate new, previously non-existent types of internal relationships that play a critical role in innovation processes (James et al., 2022). Strong internal relationships may stem from knowledge-based agility and managerial decisions regarding whether to act on new opportunities. As Hutton et al. (2024) point out, organizations can develop their ability to respond to various situations (agility) through personnel rotation, which enhances the skills of selected individuals and contributes to the creation of open innovations.

The positive verification of the hypotheses adopted in the study leads to the conclusion that both interpersonal relationships and agility, by influencing innovation, also impact the possibilities of implementing intelligent management methods in the organization. As mentioned earlier, many researchers point to the close interdependence between the use of AI tools in management processes and the generation and implementation of new solutions. However, it is also true that the processes of adapting modern digital technologies in an innovative environment are still not fully understood, as is the role of the human factor in them (Haefner et al., 2021). As noted by Gama &Magistretti (2023) based on their literature review, the relationships between AI, innovation management, and capabilities are characterized by a high degree of complexity, and as such, they will require further, in-depth analyses in the coming years.

Continuing research on the issues of interest in this study, it is reasonable to include an additional research thread in the form of leadership. Many authors recognize that leadership styles significantly impact the above-discussed areas of organizational functioning. For example, Gren & Ralph (2022) and Reunamäki& Fey (2022) believe that leaders in organizations can negatively affect the agile thinking and behaviours of the teams they lead if they themselves, instead of developing agility, represent more traditional leadership styles based on supervision and control. A leader who wants to develop and empower others to reach their highest potential should possess leadership qualities such as listening, empathy, awareness, persuasion, conceptualization, foresight, commitment to the growth of people, stewardship, and building community (Knoll, 2019). It is worth noting that this empowerment is also of great importance for innovation and creativity.

6. PRACTICAL IMPLICATIONS

The conducted study indicates that to enhance the innovativeness of an organization, management should ensure a proper atmosphere within the internal environment. This particularly involves abandoning behaviour models that promote competition in favor of those that ensure cooperation and focus on jointly chosen and subsequently set goals. At the same time, members of the organization should be encouraged to be more independent by creating a broader scope for taking grassroots initiatives in response to ongoing changes in the organization's environment.

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

Regionalna Inicjatywa Doskonałości

Ministry of Science and Higher Education Republic of Poland

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