

READINESS OF POLISH COMPANIES TO IMPLEMENT AI

Katarzyna BRATNICKA-MYŚLIWIEC¹, Ewa RACZYŃSKA*²

¹ Uniwersytet Ekonomiczny w Katowicach, Wydział Ekonomii, Katedra Przedsiębiorczości i Zarządzania Innowacyjnego; katarzyna.bratnicka@uekat.pl, ORCID: 0000-0002-3761-0641

² Uniwersytet Ekonomiczny w Katowicach, Wydział Ekonomii, Katedra Przedsiębiorczości i Zarządzania Innowacyjnego; ewa.raczynska@ue.katowice.pl, ORCID: 0000-0002-7834-1353

* Correspondence author

Purpose: The aim of this study is to identify the extent to which Polish enterprises are ready to implement artificial intelligence (AI) technologies and to examine whether this readiness is related to the firms' ability to unlearn outdated routines, beliefs, and practices. The study also investigates the mediating role of inter-organizational cooperation in the relationship between organizational unlearning and AI readiness.

Design/methodology/approach: Based on empirical data collected from 371 companies operating in Poland, we conducted quantitative analyses of the relationships between organizational unlearning, inter-organizational cooperation, and AI readiness. To determine the strength and direction of the analyzed relationships, we employed correlation analyses, exploratory factor analysis (EFA), multiple regression analysis, variance inflation factor (VIF) diagnostics, and structural equation modeling (SEM).

Findings: Organizational unlearning has a significant positive impact on AI readiness, which is positively correlated with interorganizational collaboration. The ability to unlearn at the organizational level fosters the development of interorganizational cooperation. The research model indicates a synergistic effect.

Research limitations/implications: Rapid technological change may limit the long-term validity of findings. Future longitudinal and mixed-method studies are recommended to capture the evolving dynamics of AI readiness.

Practical implications: The study provides insights for managers seeking to enhance their organization's readiness for AI implementation. It emphasizes the importance of fostering an organizational culture that supports unlearning, collaboration, and experimentation. Encouraging cross-organizational partnerships and promoting reflective practices can accelerate the effective integration of AI solutions into business operations.

Originality/value: This study expands research on AI adoption by linking organizational unlearning and inter-organizational collaboration with AI readiness. It offers empirical evidence from Polish enterprises, highlighting how these capabilities strengthen organizations' ability to implement AI effectively.

Keywords: Artificial intelligence, organizational unlearning, inter-organizational cooperation, AI readiness.

Category of the paper: Research paper.

1. Introduction

In November 2022, ChatGPT was made available for public use, and since then there has been a surge of interest in artificial intelligence. Within three years, many companies have developed their own AI models. With the development of technology, artificial intelligence has been redefined (Masley et al., 2025). The definition of an artificial intelligence system, updated in 2023 by the OECD, emphasizes that it is a machine-based system that infers (for explicit or implicit purposes) how to generate results based on the input data it receives. The results are predictions, content, recommendations or decisions that can affect virtual or physical environments. AI systems differ in their levels of autonomy, input data sources and adaptability after implementation (OECD, 2024). The use of artificial intelligence in an organization's activities is becoming one of the key conditions for organizational development, as well as for building and maintaining competitive advantage. Artificial intelligence can support decision-making processes, increase operational efficiency, and enable the creation of new business models (Dwivedi et al., 2021). AI and universal access to it are transformative in nature – its capabilities allow for increased productivity and efficiency, enable the optimization of resource management, including environmental and social resources, and improve the quality of services in sectors such as healthcare and education (Turyasingura et al., 2024). However, it is worth emphasizing that simply possessing the technology does not guarantee success, and the prerequisite for effectively exploiting the potential of AI is organizational readiness, understood as the ability of an organization to adapt the technology, integrate it with existing processes, and develop the competencies necessary to use the technology effectively (Alsheibani et al., 2018; Kumar et al., 2024; Rasul et al., 2025).

To summarize the above considerations, contemporary organizations are increasingly faced with the need to redefine their structures and processes in the face of the dynamic development of artificial intelligence technology. Although there is a wealth of literature on digital transformation and innovation, relatively little research focuses on the internal management mechanisms that determine organizational readiness to implement AI. In particular, the impact of organizational unlearning and inter-organizational cooperation on the ability of enterprises to adapt artificial intelligence technology remains insufficiently recognized, which constitutes a significant research gap (Fitjar, Rodríguez-Pose, 2013; Lee, Choi, 2003; Zhang, Lyu, Zhu, 2022).

The aim of this article is therefore to examine how organizational unlearning and inter-organizational cooperation influence the readiness of Polish enterprises to implement artificial intelligence (AI) technologies. The study assumes that inter-organizational cooperation acts as a mediator in the relationship between unlearning processes and organizational readiness. Based on empirical data collected in 2024 from companies operating in Poland, an analysis of the relationship between three key constructs was conducted: organizational unlearning, inter-

organizational cooperation and readiness to implement AI. The structure of the article consists of three main parts. The first part presents the latest state of knowledge on artificial intelligence, with particular emphasis on the readiness of Polish companies to implement it, and discusses the theoretical foundations of the three constructs analyzed: organizational unlearning, inter-organizational cooperation and readiness to implement AI. The second part presents the empirical research methodology, including the characteristics of the research sample, the measurement tools used, and the analytical procedures. The third part presents the results of statistical analyses along with their discussion. The article concludes with a discussion of the theoretical and practical implications, the limitations of the study, and suggestions for further research.

2. Organizational unlearning and interorganizational collaboration as determinants of AI readiness

The implementation of artificial intelligence reveals that the barrier to change is not always a lack of knowledge, but rather an excess of outdated knowledge deeply rooted in organizational routines and structures (Pardo del Val, Martinez Fuentes, 2003). The response to this challenge is organizational unlearning, most often understood as the process of consciously rejecting outdated beliefs, practices and cognitive patterns that limit an organization's ability to adapt in a changing environment (Becker, 2019; Hislop et al., 2014; Klammer et al., 2025). Classic definitions of this construct emphasize the aspect of deliberately "getting rid of" knowledge, i.e. Hedberg (1981, p. 18) defines unlearning as "the process by which learners reject knowledge", while Nystrom and Starbuck (1984, p. 53) point out that it consists in "discovering inadequacies and rejecting existing ideas". The common denominator is therefore the treatment of unlearning as a process of consciously rejecting knowledge or cognitive patterns that have lost their usefulness.

This phenomenon is associated with creating space within an organization to generate new knowledge and skills (Klammer et al., 2025). Researchers unanimously emphasize that effective unlearning is intentional and process-oriented (Tsang, Zahra, 2008; Hislop et al., 2014; Klammer et al., 2025). This means that simply discontinuing ineffective procedures is not enough but it is necessary to create conditions for critical reflection on existing ways of operating and replacing them with new solutions. In particular, in situations of profound change, such as the rejection of fundamental organizational assumptions, this process requires questioning the existing logic of action, which is a prerequisite for the assimilation of new practices and knowledge patterns (Klammer, Gueldenberg, 2019).

It is particularly important to link the process of unlearning with learning. The relationship between these two concepts is dynamic and synergistic, and unlearning is often a prerequisite for effective, transformative learning (Odor, 2018). It enables the abandonment of outdated cognitive and operational models, which in turn strengthens the organization's ability to acquire new knowledge and develop competencies (Fiol, Lyles, 1985). In this sense, unlearning is the foundation of organizational learning in dynamically changing environments where existing patterns of behavior are becoming obsolete (Tsang, Zahra, 2008).

Companies implementing new technologies, including artificial intelligence, are forced to make changes to their structures, processes and management methods. These changes also extend to the areas of communication and interpersonal relations, requiring organizations to eliminate outdated practices in order to effectively implement innovations and adapt to new conditions (Akgün et al., 2003). Empirical research confirms that companies that are able to systematically review and update their procedures implement technological innovations faster (Kim, Chung, 2017) and respond more effectively to environmental uncertainty (Klammer et al., 2025). The ability to abandon outdated decision-making models, communication structures and operational practices therefore promotes readiness to implement artificial intelligence, as it reduces mental and organizational barriers to new technologies (Klammer et al., 2025).

Flexible adaptation of processes and organizational culture enables companies to implement new technologies more quickly (Nonaka, Takeuchi, 1995). Organizational unlearning, on the other hand, potentially facilitates the implementation of product and process innovations, increasing the ability of companies to assimilate modern technological solutions (Zhang et al., 2021). In this sense, unlearning is one of the key elements of dynamic capabilities (Teece, 2007) that enable organizations to adapt effectively to disruptive technologies such as artificial intelligence.

During the unlearning process, organizations should also consider the value of potential knowledge loss by assessing whether the knowledge in question may still be useful in the future (Becker, 2019). However, it should be emphasized that unlearning does not necessarily mean permanent loss – more often it involves consciously abandoning or giving up certain patterns of behavior that have lost their usefulness (Akgün et al., 2006). In this context, it is crucial to involve employees in the decision-making process, as the need to unlearn often meets with resistance due to habitual practices (Collina, 2025).

Effective unlearning creates conditions conducive to organizational openness, which is essential for cooperation with external partners (Klammer, Gueldenberg, 2019). In this context, inter-organizational cooperation can be a natural extension of learning and unlearning processes, enabling the exchange of knowledge, resources and experience needed to implement artificial intelligence technologies. Inter-organizational cooperation refers to relationships and interactions between different organizations aimed at achieving mutual benefits, such as the exchange of knowledge and resources or the pursuit of common and convergent goals (Fitjar,

Rodriguez-Pose, 2013). Inter-organizational cooperation can take many forms and be classified according to the perspective adopted, e.g. strategy, structure, number of partners or nature of links (Pietruszka-Ortyl, 2017). Partnerships can be formal, such as OpenAI and Microsoft, outsourcing, cooperation with universities, but also informal, such as industry forums or open-source.

Organizations that engage in cooperation with technology companies, universities or research institutes have the opportunity to acquire the necessary competences and tools for effective technological development and successful implementation of artificial intelligence (Zhang, Lyu, Zhu, 2022). Companies that collaborate with research units or technology partners implement new technologies more effectively (Cheserbrough, 2003). This enables organizations to acquire key knowledge resources, thereby reducing implementation costs and errors, and increasing operational flexibility in a rapidly changing environment (Bettioli et al., 2023).

Inter-organizational cooperation in AI projects can also contribute to solving problems with technology integration, adapting to new regulations and data management (Cepa, Schildt, 2019). However, organizational culture, lack of trust, or difficulty in dividing responsibilities may prove to be limitations to cooperation (Campion et al., 2022). Organizations undertaking cooperation must have common goals, which increases their willingness to cooperate. In a rapidly changing environment, organizational cooperation can be crucial in AI implementations.

Organizational unlearning creates an environment conducive to openness to collaboration, as it enables organizations to question their own assumptions and practices and to adopt new perspectives from outside. Research confirms that unlearning increases an organization's ability to collaborate effectively with other organizations (Zhang, Lyu, Zhu, 2022; Cepeda-Carrión et al., 2015). Organizations that are willing to revise their strategies and methods of operation integrate better with their partners, which promotes long-term partnerships and mutual learning. In this context, inter-organizational cooperation plays a key role in building organizational readiness to implement AI. It provides access to expert knowledge, reduces the risks and costs of implementation, and promotes the creation of innovative solutions (Lee, Yang, 2014; Taherdoost, Madanchian, 2023). At the same time, it acts as an intermediary mechanism between unlearning processes and organizational readiness, as openness to cooperation allows for more effective use of acquired knowledge and its transformation into practical applications.

3. Artificial intelligence market and organizational readiness for AI implementation

Since ChatGPT entered widespread use, the artificial intelligence market has been growing rapidly and attracting considerable interest from individual users and the business sector. An analysis of Google trends for ‘AI’ in Poland shows a clear increase from November 2022 to the present. These clear increases are related to new functionalities of artificial intelligence models, e.g. in April 2023, GPT-3.5 released new versions of the model equipped with the ability to browse the Internet. Looking at global searches, the situation is more stable, characterized by steady growth without any clear peaks (www1). Market growth forecasts are also promising for artificial intelligence. It is estimated that the AI market in the transmission sector will reach \$34.18 billion in 2025 and as much as \$155.05 billion in 2030, giving a CAGR of 35.3% (MarketsandMarkets, 2025). Currently, the most popular AI models include Google Gemini, OpenAI – ChatGPT, Anthropic – Claude, Meta – Llama, Cohere, Mistral, Mistral AI, Huawei, and Baidu. In 2024, as much as 90% of significant artificial intelligence models came from the industrial sector, which is a significant difference compared to 60% in 2023. Most models are created in the United States, ahead of China and Europe. China, in turn, is the leader in scientific publications on artificial intelligence (HAI, 2025).

Recent data from the Digital Economy and Society Index (DESI 2025) indicate substantial cross-country differences in the adoption of artificial intelligence by small and medium-sized enterprises across Europe. While countries such as Denmark, Sweden, and Belgium report AI adoption rates exceeding 20%, the level of AI use among Polish SMEs remains significantly lower, at below 5%. This positioning places Poland among the lowest-ranked EU countries in terms of AI diffusion, highlighting the presence of structural, organizational, and cognitive barriers to AI implementation.

The data presented may indicate doubts about the future of artificial intelligence and controversies related to the rapid and unregulated development of artificial intelligence. The AI Now Institute think tank has published a report highlighting lobbying efforts to limit legal regulations that could be argued to restrict innovation. It points to the negative social consequences of the rapid development of artificial intelligence, such as the exclusion of smaller companies in favour of Big Tech, which has the computing power and capital to dominate the market, potential overinvestment, the development of efficiency at the expense of society, and support for a bipolar world policy (2025). Rapid development also necessitates the creation of a legal framework for data processing and inference, as well as responsible and ethical inference based on knowledge available to artificial intelligence models (MC, 2023). However, this does not change the fact that companies currently leading the way in implementing artificial intelligence in their operations will outperform their competitors by 15%. Thanks to the rapid development of AI, the difference in revenue generation between

leaders and companies skeptical about artificial intelligence in 2026 may be more than double (WEF, 2025). The MIT report counters the data presented, pointing out that 95% of AI pilot projects in companies have failed (ROI equal to or less than 0), indicating a learning gap (MIT, 2025).

However, contemporary research on digital transformation emphasizes that the mere presence of technology is not a sufficient condition for effectively exploiting its potential (Dąbrowska et al., 2022; Hanelt et al., 2021; Holmström, 2022). A key factor enabling organizations to effectively implement AI-based solutions is organizational readiness to implement AI, understood as the complex ability of a company to adapt, integrate and operationally utilize technology within existing structures and processes (Rasul et al., 2025; Kumar et al., 2024). As noted by Alsheibani et al. (2018), this readiness also means the ability of an organization to implement and benefit from broadly understood AI solutions. This readiness encompasses both technical aspects, such as IT infrastructure, data quality and system security, as well as organizational factors, including the digital skills of employees, the flexibility of structures, openness to change and the strategic alignment of technology with the organization's goals and processes (Hradecky et al., 2022; Lai et al., 2025).

The implementation of AI involves many changes in internal and external structures and processes in terms of technology and organization (Liu et al., 2020). The level of an organization's readiness to implement AI is determined by its internal potential, such as resources, competencies and openness to innovation (Jöhnk et al., 2021), but the attitude of external audiences – customer expectations and readiness – is no less important. A PwC report (as of October 2024) shows that over 75% of the companies surveyed have started investing in AI at an early stage, and 55% of customers said they were ready to take advantage of AI support. 83% of individual respondents expect procedures in the public sector to be improved through the use of artificial intelligence, which is a higher value than the support seen by consumers in business. Entrepreneurs point to the greatest added value in process automation and improved prediction quality (PwC, 2024). The TOE (Technology-Organization-Environment) framework emphasizes that human, technological and organizational resources play a key role in the process of adapting artificial intelligence, and that their proper preparation significantly increases the success of implementation (Alsheibani et al., 2018). The use of artificial intelligence for advanced processes requires a range of new skills among employees, as well as unlearning old patterns of behavior (Morandini et al., 2023). The basic competences of the future are considered to be skills from the group of cognitive (cognitive) competences, technical (including digital) competences, competences in the use of information and knowledge, as well as social competences (Santana, Díaz-Fernández, 2023). In connection with the development of the European Green Deal, so-called green competences are also recognized (PPP, 2022). As indicated in the PFR and Google report, universal competences related to the use of artificial intelligence include legal and ethical competences and AI security, critical thinking and the ability to interpret AI results, basic knowledge of artificial intelligence, and change management and leadership (2025).

The development of AI is also changing the structure of employment in companies. Globally, there is a shortage of 4.7 million qualified cybersecurity specialists, who are essential in view of the rapid development of technology (CP, 2025). The situation is similar on the Polish market – readiness for technological change is unsatisfactory, with more than half of the employees surveyed having not undergone any training in cybersecurity in the last 5 years (ESET, 2025). Due to staff shortages and rapid technological change in the field of cybersecurity and artificial intelligence, acquiring knowledge seems to be an elite pursuit. Companies not only report staff shortages, but also skills gaps, noting that these are a bigger problem than the lack of employees (ISC2, 2023). The noticeable shortage of workers and skills may be a barrier to the sector's continued growth (OECD, 2023). Google Gemini is currently testing a business model based on providing technology and skilled personnel to customers by introducing a training cycle for interested parties, where upon completion it not only issues a certificate but also connects employers with its graduates (www2). Faced with a growing shortage of specialists in the field of artificial intelligence, companies are increasingly looking for ways to develop internal skills and build partnerships that support the adaptation of technology. Examples of such activities include initiatives by technology companies, such as Google's training programmers, which not only promote AI-related skills, but also create a network of cooperation between companies and experts. This indicates that successful AI implementations require not only technological infrastructure, but also investment in knowledge, skills and inter-organizational relationships (Butler et al., 2021).

The rapid pace of technological development indicates that access to AI solutions alone is not sufficient for successful implementation. The effectiveness of adaptation is determined not only by technological resources, but above all by an organization's ability to learn and respond flexibly to change. However, despite the growing interest in artificial intelligence, relatively little research focuses on the internal organizational mechanisms that determine the effective implementation of this technology (Wamba-Taguimdje et al., 2020; Dwivedi et al., 2021). Previous work has focused primarily on technological aspects such as IT infrastructure, data quality and employees' digital skills, largely ignoring the importance of organizational factors such as learning, unlearning and collaboration processes (Holmström, 2022). However, it is precisely these factors that may be key determinants of organizational readiness to implement AI, influencing the way in which companies adapt and integrate new technologies into their structures. Among the internal factors conducive to organizational readiness to implement artificial intelligence, particular importance is attached to cognitive and relational processes – the organization's ability to unlearn and inter-organizational cooperation. These determine the extent to which companies are able to reject outdated patterns of behavior and, at the same time, build relationships that enable them to acquire new knowledge.

Despite the rapidly growing body of research on AI implementation, existing studies mostly focus on technological and resource-based determinants of organizational readiness, such as IT infrastructure, data quality, and employees' digital skills. Considerably less attention has

been paid to internal cognitive and relational mechanisms that enable organizations to adapt effectively to new and/or disruptive technologies. In particular, organizational unlearning remains underexplored in the context of AI adoption. Although unlearning is increasingly recognized as a core element of dynamic capabilities, empirical evidence explaining its role in shaping organizational readiness for artificial intelligence implementation is still limited.

At the same time, inter-organizational collaboration is typically examined as an independent driver of innovation, with insufficient consideration of its links to internal learning and unlearning processes. Consequently, little is known about how organizational unlearning fosters openness to inter-organizational collaboration and whether such collaboration acts as a mediating mechanism between unlearning and organizational readiness for AI implementation. Addressing this gap, the study integrates organizational unlearning and inter-organizational collaboration within a theoretical framework, examining their direct and indirect effects on a firm's readiness to implement AI-based solutions.

Based on the literature review and theoretical considerations presented above, the following research hypotheses were formulated:

- H1: There is a positive relationship between organizational unlearning and a company's readiness to implement artificial intelligence-based solutions.
- H2: There is a positive relationship between organizational unlearning and the level of inter-organizational cooperation.
- H3: There is a positive relationship between inter-organizational cooperation and a company's readiness to implement AI solutions.
- H4: Inter-organizational cooperation mediates the relationship between organizational unlearning and a company's readiness to implement AI solutions.

4. Methods

4.1. Sample selection

In order to empirically verify the hypotheses, a quantitative study was conducted using the online survey technique. The data collection process was carried out in the second half of 2024 and was organized by the Research and Development Centre of the University of Economics in Katowice. The research sample was drawn from a database of over 10,000 records containing contact details of domestic and foreign enterprises operating in Polish. 6201 invitations to participate in the survey were sent to randomly selected entities, sending them to representatives of enterprises by electronic and telephone means. After obtaining consent to participate in the study, respondents received an individual link to an online questionnaire. In the end, 371 completely completed surveys were collected, which corresponds to a return rate of about 6%. The respondents were managers of the surveyed companies or persons appointed by them with knowledge of the functioning of the organization.

The survey included companies with a diverse profile of activity and market coverage. The largest group were companies operating on the domestic market (178 units) and entities of a manufacturing nature (162). The structure of the sample also varied in terms of employment size – from micro-enterprises with 3 employees to large organizations employing more than 5000 people. The age of the analyzed companies ranged from 3 to 90 years, which allowed the study to include both young and mature organizations. The average number of employees in the surveyed enterprises was 194, while the average age of the companies was 22.8 years. Detailed characteristics of the sample are presented in Table 1.

Table 1.
Characteristics of the surveyed enterprises

| Scope of activity | | Business profile | |
|--|-----|--|-------------------------------------|
| Local | 49 | Trade | 38 |
| Regional | 55 | Service | 82 |
| National | 178 | Production | 162 |
| International | 82 | Mixed | 89 |
| Global | 7 | No response | 0 |
| Together | 371 | Together | 371 |
| Characteristics by size and age of the company | | Size of the surveyed companies (number of employees) | Age of the subjects studied (years) |
| Average | | 194 | 22.8 |
| Standard deviation | | 548 | 13.3 |
| Median | | 50 | 22 |
| Minimum | | 3 | 3 |
| Maximum | | 5034 | 90 |

Source: own elaboration.

4.2. Characteristics of the studied variables

The questionnaire used in the survey was constructed on the basis of measurement tools recognized in the literature and covered three main areas of analysis: organizational unlearning, readiness to implement artificial intelligence (AI) and the level of interorganizational cooperation. These variables are directly related to the research model and allow for empirical verification of the accepted hypotheses.

With regard to organizational unlearning, a six-item scale developed by Lyu, Yang, Zhang, Teo, and Guo (2020) was used. This scale refers to an organization's ability to abandon outdated practices, beliefs, and procedures that hinder adaptation to technological and organizational changes. The obtained Cronbach alpha reliability coefficient ($\alpha = 0.890$) confirms the high internal consistency of the scale. The results of exploratory factor analysis ($KMO = 0.889$; $\chi^2 = 1138.8$; $df = 15$; $p < 0.001$) indicate an unambiguous one-factor structure, explaining 64.9% of the variance.

The measurement of AI readiness was based on the eight-item scale proposed by Holmström (2022). This tool takes into account both the technological aspect (the current use of AI solutions) and the strategic aspect (the existence of an AI policy or plan in the enterprise). Cronbach's high alpha coefficient ($\alpha = 0.981$) and KMO test results = 0.948 ($\chi^2 = 4696.7$;

df = 28; $p < 0.001$) confirm the internal consistency and validity of the construct, which explains 88.2% of the total variance.

To assess the level of inter-organizational cooperation, a five-item scale developed by Lee and Yang (2014) was used. This scale refers to a company's relationship with its key stakeholders – customers, suppliers, competitors and research institutions – and includes areas of interaction in marketing, technology and innovation. The obtained Cronbach alpha coefficient ($\alpha = 0.857$) and KMO values = 0.803 ($\chi^2 = 914.5$; df = 10; $p < 0.001$) confirm the homogeneity of the construct and a high level of reliability.

All the scales used were evaluated in terms of reliability and statistical accuracy. The values of Cronbach's alpha coefficients exceed the recommended threshold of 0.7, which indicates their high internal consistency. Univariate solutions in exploratory analyses (EFAs) prove that each of the variables under study refers to a homogeneous theoretical concept, which justifies the creation of synthetic indicators in further analyses. The high values of the Kaiser-Meyer-Olkin measure and the important results of the Bartlett sphericity test confirm the correctness of the adopted measurement model and the accuracy of factor analyses. Taking into account the possibility of collinearity between the analysed variables, the variance inflation coefficient (VIF) was verified. For this purpose, a regression model was built, in which the dependent variable was the readiness to implement AI, and the explanatory variables were organizational unlearning and interorganizational cooperation. Metavariables created by averaging the values assigned to each of the statements included in each of the measurement scales were used for the analysis. This allowed to obtain synthetic indicators for each theoretical construct. The results of the regression and the collinearity analysis are summarized in Table 2.

Table 2.
Results of regression analysis and collinearity test

| Model fit measures | | | | | General Model Test | | | |
|---|-----------------------------------|----------------|---------------------------|------------------------------|--------------------|-------------------------|-------|-------|
| Model | R | R ² | Corrected R ² | Standard error of estimation | F | df1 | df2 | p |
| 1 | 0.634 | 0.402 | 0.396 | 0.893 | 61.6 | 4 | 366 | <,001 |
| a. Predictors: (constant), Organizational unlearning, Interorganizational cooperation, LOGAGE, LOGSIZE. | | | | | | | | |
| Model | Non-standardized coefficients | | Standardized coefficients | t | Sig. | Collinearity statistics | | |
| | B | Std. Error | Beta | | | Tolerance | VIF | |
| 1 | Constant | -1.7483 | 0.4793 | | -3.647 | <,001 | | |
| | Organizational unlearning | 0.5204 | 0.0824 | 0.30132 | 6.317 | <,001 | 0.718 | 1.39 |
| | Interorganizational cooperation | 0.3557 | 0.0512 | 0.34615 | 6.953 | <,001 | 0.659 | 1.52 |
| | Lifetime Log 10 | -0.0391 | 0.2987 | -0.00636 | -0.131 | 0.896 | 0.694 | 1.39 |
| | Log 10 of the number of employees | 0.4618 | 0.1163 | 0.18861 | 3.969 | <,001 | 0.723 | 1.44 |
| Dependent variable: AI readiness | | | | | | | | |

Source: own elaboration.

The multiple regression analysis showed that the adopted model satisfactorily explains the variability of enterprises to implement AI-based solutions ($R^2 = 0.402$; adjusted $R^2 = 0.396$). This means that about 40% of the variance of this variable can be attributed to the influence of factors included in the model. Organizational unlearning, interorganisational cooperation and enterprise size were statistically significant predictors, while the age of the organisation did not show a significant impact. The obtained values of coefficients of colinearity (VIF in the range of 1.39-1.52) and tolerance (0.65-0.72) confirm that there is no risk of interdependence between variables (Thompson et al., 2017). These results are the basis for further analysis of the relationships between theoretical constructions and verification of the research hypotheses. Based on the results obtained, it was decided to move to the stage of modeling structural equations (SEM), in order to analyze the relationships between the studied constructs in depth.

5. Results

Before modeling the structural equations, a correlation analysis was carried out, the aim of which was to initially assess the direction and strength of the relationship between the variables studied. In preparation for this analysis, arithmetic means and standard deviations for metavariables were calculated, constituting the averaged values of the positions included in individual constructs. The obtained indicators were then used to determine Pearson correlation coefficients, enabling the identification of potential relationships relevant from the point of view of further modeling.

Table 3.

Descriptive statistics and correlations between the studied variables

| Correlation matrix | | | | | | |
|---|---------------------------|----------|----------|----------|----------|-------|
| | | 1 | 2 | 3 | 4 | 5 |
| 1. Organizational unlearning | r (Pearson's correlation) | — | | | | |
| | p | — | | | | |
| 2. AI Readiness | r (Pearson's correlation) | 0.512*** | — | | | |
| | p | <,001 | — | | | |
| 3. Interorganizational cooperation | r (Pearson's correlation) | 0.530*** | 0.550*** | — | | |
| | p | <,001 | <,001 | — | | |
| 4. Log 10 of organizational age | r (Pearson's correlation) | 0.145** | 0.243*** | 0.314*** | — | |
| | p | 0.005 | <,001 | <,001 | — | |
| 5. Log 10 number of employees | r (Pearson's correlation) | 0.147** | 0.315*** | 0.245*** | 0.518*** | — |
| | p | 0.004 | <,001 | <,001 | <,001 | — |
| Mean | 5.59 | 4.44 | 7.20 | 1.28 | 1.65 | 5.59 |
| Standard deviation | 0.998 | 1.72 | 1.68 | 0.280 | 0.704 | 0.998 |
| Note: * p < .05, **p < .01, ***p < .001. | | | | | | |

Source: own elaboration.

The correlation analysis presented in Table 3 indicates that most of the variables studied are moderately or strongly related to each other, with all relationships being statistically significant. The strongest correlations were recorded between organizational unlearning and interorganizational cooperation ($r = 0.530$; $p < 0.001$) and between readiness to implement AI and interorganizational cooperation ($r = 0.550$; $p < 0.001$). There is also a strong positive correlation between readiness to implement AI and organizational unlearning ($r = 0.512$; $p < 0.001$), which confirms that learning and collaboration processes significantly support the preparation of organizations for the implementation of AI technologies. The control variables in the model were the size of the organization and the period of its existence. Both showed positive, albeit weaker, correlations with AI readiness ($r = 0.315$ and $r = 0.243$; $p < 0.001$), suggesting that older and larger enterprises are slightly better equipped to adopt AI technology. As expected, there is also a significant and relatively strong relationship between the number of employees and the lifetime of the company ($r = 0.518$; $p < 0.001$), which confirms the typical relationship between size and age.

In the next step, an analysis was carried out using structural equation modeling (SEM) in the Jamovi program with the SEMLj extension. In the first step, a measurement model was estimated, consistent with the assumptions of the adopted theoretical model. For each latent variable, convergent relevance indicators such as composite reliability (CR) and average variance extracted (AVE) were calculated. The calculations were made using a prepared spreadsheet in Excel, according to the formulas proposed by Hair et al. (2019). The values of the AVE and CR coefficients for all tested constructs exceeded the recommended thresholds (0.50 for AVE and 0.70 for CR, respectively), which confirms the convergent accuracy and reliability of the measurement. These results form the basis for further analysis of the structural model, aimed at verifying the relationships between variables.

Table 4.
AVE and CR coefficients for the analyzed constructs

| Variable | Coefficient | Value |
|---------------------------------|-------------|------------|
| Unlearning | AVE | 0,57939567 |
| | CR | 0,89193902 |
| AI Readiness | AVE | 0,86802688 |
| | CR | 0,98134754 |
| Interorganizational cooperation | AVE | 0,5386444 |
| | CR | 0,84932881 |

Source: own elaboration.

Due to the moderate sample size ($N = 371$), the estimation process uses the bootstrap procedure, which allows multiple randomization of subsamples from the original data set. The analysis used 5000 replications, which increased the stability and reliability of the obtained estimates. The three main variables - organizational unlearning, interorganizational collaboration, and AI readiness - were treated as latent constructs to better reflect their complex nature and the interconnectedness between them. The control variables, i.e. the age and size of

the company, were transformed logarithmically ($\log_1 0$), which improved their distribution and statistical properties, as well as enabled a more precise interpretation of the effects in the structural model. In order to synthetically represent the relationships, tabular analysis (Table 5) was used – for each hypothesis and the relationship described in it, a model parameter (parameter and value of the p statistic) was indicated.

Table 5.

Hypothesis testing results

| Relation (hypothesis) | Estymata (b) | The p-value | Hypothesis verification |
|--|--------------|-------------|-------------------------|
| Organizational unlearning → AI readiness (H1) | 0,552 | $p < 0,001$ | Confirmed |
| Interorganizational collaboration → AI readiness (H2) | 0,434 | $p < 0,001$ | Confirmed |
| Organizational unlearning → Interorganizational cooperation (H3) | 0,586 | $p < 0,001$ | Confirmed |
| Organizational unlearning → Interorganizational collaboration → AI readiness (Mediation) (H4) | 0,457 | $p < 0,001$ | Partially confirmed |

Source: own elaboration.

Based on the results presented in Table 5, the following conclusions can be drawn. Hypothesis H1, assuming a positive relationship between organizational unlearning and readiness to implement artificial intelligence technologies, was confirmed ($b = 0.552$; $p < 0.001$). Hypothesis H2, advancing a positive effect of interorganizational cooperation on readiness to implement AI, was confirmed ($b = 0.434$; $p < 0.001$). Hypothesis H3, assuming a positive relationship between organizational unlearning and interorganizational cooperation, was confirmed ($b = 0.586$; $p < 0.001$). The conducted analysis also confirmed the significance of the indirect effect of interorganizational cooperation in the relationship between organizational unlearning and readiness to implement artificial intelligence technologies. According to the approach proposed by Baron and Kenny (1986) and further developed by Hayes (2017), the significance of both the indirect and direct effects indicates the presence of partial mediation. In this model, the estimated value for the indirect path ($b = 0.457$; $p < 0.001$) confirms that inter-organizational cooperation acts as a mediating factor that strengthens the influence of unlearning processes on organizational readiness. At the same time, the direct effect remains statistically significant ($b = 0.552$; $p < 0.001$), indicating that organizational unlearning affects the readiness to implement AI both directly and indirectly - through increased interorganizational cooperation. Following the typology proposed by Zhao, Lynch, and Chen (2010), this configuration corresponds to complementary mediation, as both the direct and indirect effects are significant and point in the same positive direction. Importantly, the authors emphasize that no minimum difference between coefficients is required for mediation to be established; what matters is the statistical significance and consistency of the effects.

6. Discussion and directions for further research

In light of the results obtained, the implementation of artificial intelligence appears to be a multidimensional process, involving not only the development of technological infrastructure, but also cognitive, social and organizational adaptation. The confirmation of a positive relationship between organizational unlearning and readiness to implement AI indicates that the ability to reflectively abandon established patterns of behavior is a key condition for strategic technological adaptation. This result is consistent with the findings of Zhao and Yan (2023), Maccioni and Ghiringhelli (2022), and Yin and Hoang (2025), who emphasize that unlearning processes foster innovation by reducing cognitive organizational baggage and increasing knowledge absorptiveness. In the context of AI implementations, unlearning enables not only the acquisition of new tools, but also the redefinition of how technology is thought about – from the perspective of a threat to a strategic resource. However, it should be noted that excessive cognitive and structural change can lead to organizational overload and increased anxiety among employees, which, as Besio et al. (2024) point out, can limit the effectiveness of digital transformation.

The relationship between unlearning and inter-organizational cooperation confirms that a willingness to question existing internal practices increases an organization's openness to exchanging knowledge and experience with external partners. This result is consistent with the findings of Zhang, Lyu and Zhu (2022), who showed that unlearning processes are a prerequisite for effective inter-organizational learning, enabling the transfer and integration of knowledge within cooperation networks. Interpreting this in the light of Chesbrough's (2003) concept of open innovation, it can be concluded that unlearning promotes the crossing of organizational boundaries and the creation of space for experimentation and co-creation of solutions (Antonacopoulou, 2009). This means that companies that systematically review their procedures and cognitive models are more likely to engage in technology partnerships, research consortia or innovation networks (Rossoni et al., 2024). This type of cooperation is not only a channel for knowledge transfer, but also a mechanism for building trust and adaptive capacities that increase an organization's resilience to environmental turbulence (Kupers, Mullie, 2014).

The role of inter-organizational cooperation as a mediator in the relationship between unlearning and readiness to implement artificial intelligence emphasizes the importance of social relations in the process of technological adaptation. The results suggest that the ability to abandon outdated cognitive patterns is not sufficient on its own – only when combined with the active exchange of knowledge and resources between organizations does it lead to a real increase in technological readiness. This result builds on the findings of Lee and Yang (2014), indicating that cooperation networks are not only a source of knowledge, but also a mechanism supporting the absorption and implementation of AI solutions. In this sense, collaboration acts

as a catalyst for unlearning processes, enabling the testing of new concepts in a low-risk environment, strengthening the ability to experiment, and accelerating learning through observation of partners' practices (Kim, Park, 2022). From a strategic management perspective, this means that building inter-organizational networks of trust and learning can be a key condition for the effective digital transformation of enterprises.

From a management theory perspective, the results confirm that readiness to implement artificial intelligence can be interpreted as a manifestation of dynamic organizational capabilities – the ability to learn, unlearn and reconfigure resources in conditions of uncertainty (Holmström, 2022; Teece, 2070). Organizations that actively engage in unlearning and collaboration develop greater cognitive and structural flexibility, enabling them to respond more quickly to technological change and transform knowledge into operational advantage more effectively. In this view, readiness to implement AI is not only a result of technological resources, but also the effect of consciously shaping mechanisms of learning, reflection and adaptation. This means that an organization's ability to derive lasting benefits from AI depends not only on investment in technology, but above all on the ability to combine the cognitive (unlearning) and relational (collaboration) dimensions into a coherent development strategy (Uren, Edwards, 2023).

From a managerial perspective, the findings suggest that strengthening AI readiness requires not only technological investment but also organizational transformation. Managers should focus on fostering a culture of unlearning, for example encouraging employees to question outdated practices, reflect critically, and embrace experimentation. At the same time, establishing interorganizational partnerships with technology firms, research institutions, and industry associations can accelerate knowledge transfer and reduce the risks associated with AI implementation. In the Polish business context, building soft competencies such as openness, adaptability, and collaborative leadership appears crucial for aligning technological and organizational readiness. These actions jointly enhance firms' ability to absorb AI-driven innovations and translate them into sustained competitive advantage.

Summary

Artificial intelligence remains an evolving technology whose long-term societal and economic impact will only become fully evident over time. The findings of this study highlight that the diffusion of AI requires not only technological advancement but also social learning processes within and between organizations. Building readiness for AI adoption involves developing new competencies while intentionally unlearning outdated routines and mental models. These changes have a broader social dimension, as they foster more inclusive and

knowledge-based ecosystems of collaboration. Strengthening interorganizational cooperation contributes to reducing skill gaps and promoting responsible, human-centered AI adoption

At the same time, it is worth to notice that the conducted research has certain limitations, such as: the cross-sectional research design and the reliance on quantitative data, which restrict the ability to capture the dynamic and processual nature of organizational unlearning and collaboration. In addition, the findings reflect the specific institutional and cultural context of organizations operating in Poland, which should be considered when assessing their applicability in other settings. Despite these limitations, this study contributes new knowledge by demonstrating that organizational unlearning and interorganizational cooperation jointly shape readiness for AI implementation, thereby extending existing research that has predominantly emphasized technological and infrastructural factors.

The insights generated by this study can be used by managers and policymakers to design AI implementation strategies that explicitly combine internal unlearning mechanisms with external collaboration initiatives, as well as by researchers to develop more integrative models of organizational readiness for emerging technologies, including AI.

The results of this study open several promising avenues for further exploration. First, the relationship between organizational unlearning and AI readiness may unfold over time, suggesting the need for longitudinal studies capturing the dynamic nature of learning and adaptation processes. Second, future research could incorporate qualitative approaches to better understand the cognitive, cultural, and structural barriers that shape organizations' readiness for AI. Another valuable direction would involve examining moderating factors such as leadership style and organizational culture, which may strengthen or weaken the links between unlearning, collaboration, and technological readiness. Finally, inspired by recent findings on the reciprocal influence between AI adoption and unlearning (Yin, Hoang, 2025), it would be worthwhile to investigate whether the implementation of AI itself stimulates new cycles of organizational unlearning and knowledge renewal.

References

1. Akgün, A.E., Lynn, G.S., Byrne, J.C. (2003). Organizational learning: A socio-cognitive framework *Human Relations*, 56(7), pp. 839-868.
2. Akgün, A.E., Lynn, G.S., Byrne, J.C. (2006). Antecedents and consequences of unlearning in new product development teams *Journal of Product Innovation Management*, 23(1), pp. 73-88.
3. Alsheibani, S., Cheung, Y., Messom, C. (2018). Artificial intelligence adoption: AI-readiness at firm-level. In: *Pacific Asia conference on information systems 2018* (p. 37). Association for Information Systems.

4. Antonacopoulou, E.P. (2009). Impact and scholarship: Unlearning and practicing to co-create actionable knowledge. *Management Learning*, 40(4), pp. 421-430.
5. Becker, K. (2019). Organizational unlearning: the challenges of a developing phenomenon. *The Learning Organization*, 26(5), pp. 534-541.
6. Besio, C., Jöstingmeier, M., Posner, C. (2024). Digital transformation and organizational restlessness. *Frontiers in Sociology*, 9, 1430384.
7. Bettiol, M., Capestro, M., Di Maria, E., Grandinetti, R. (2023). Leveraging on intra-and inter-organizational collaboration in Industry 4.0 adoption for knowledge creation and innovation. *European Journal of Innovation Management*, 26(7), pp. 328-352.
8. Brennan, K., Kak, A., West, S. (2025). *Artificial Power: 2025 Landscape Report*. AI Now Institute.
9. Butler, T., Espinoza-Limon, A., Seppala, S. (2021). Towards a Capability Assessment Model for the Comprehension and Adoption of AI in Organisations. *Journal of AI, Robotics & Workplace Automation*, 1(1), pp. 18-33.
10. Champion, A., Gasco-Hernandez, M., Jankin Mikhaylov, S., Esteve, M. (2022). Overcoming the Challenges of Collaboratively Adopting Artificial Intelligence in the Public Sector. *Social Science Computer Review*, 40(2), pp. 462-477.
11. Cepa, K., Schildt, H. (2019). Technological embeddedness of inter-organizational collaboration processes. In: *Managing inter-organizational collaborations: Process views*, vol. 64, pp. 91-115.
12. Cepeda-Carrión, I., Leal-Millán, A.G., Ortega-Gutierrez, J., Leal-Rodriguez, A.L. (2015). Linking unlearning with service quality through learning processes in the Spanish banking industry. *Journal of Business Research*, 68(7), pp. 1450-1457.
13. Challapally, A., Pease, Ch., Raskar, R., Charo, P. (2025). *The GenAI Divide State of AI in business 2025*. MIT NANDA.
14. Check Point (2025). *The State of Cyber Security 2025*. 13th Annual Edition.
15. Chesbrough, H.W. (2003). *Open innovation: The new imperative for creating and profiting from technology*. Harvard Business Press.
16. Collina, L. (2025). The Case for AI Literacy in Consulting and Change Management. *Management Consulting Journal*, 8(2), pp. 86-94.
17. Dąbrowska, J., Almpantopoulou, A., Brem, A., Chesbrough, H., Cucino, V., Di Minin, A., Ritala, P. (2022). Digital transformation, for better or worse: a critical multi-level research agenda. *R&D Management*, 52(5), pp. 930-954.
18. Dwivedi, Y.K., Hughes, L., Kumar, V. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management*, 57, pp. 102-128.
19. ESET (2025). *Cyberportret polskiego biznesu 2025. RAPORT: Cyberbezpieczeństwo firm w obliczu nowych wyzwań*.

20. European Commission (2025). *Digital Economy and Society Index (DESI) 2025*. Publications Office of the European Union.
21. Fiol, C.M., Lyles, M.A. (1985). Organizational learning. *Academy of Management Review*, 10(4), 803-813.
22. Fitjar, R.D., Rodríguez-Pose, A. (2013). Firm collaboration and modes of innovation in Norway. *Research Policy*, 42(1), 128-138.
23. Grupa Robocza ds. Sztucznej Inteligencji Podgrupa ds. etyki i prawa (2023). *Raport Analiza związku Aktu w sprawie sztucznej inteligencji z wybranymi obowiązującymi i projektowanymi regulacjami prawnymi*. Warszawa.
24. HAI (2025). *Artificial Intelligence Index Report*. Stanford University Human-Centered Artificial Intelligence.
25. Hair, J.F., Black, W.C., Babin, B.J., Anderson, R.E. (2019). *Multivariate data analysis* (8th ed.). Cengage Learning.
26. Hanelt, A., Bohnsack, R., Marz, D., Antunes Marante, C. (2021). A systematic review of the literature on digital transformation: Insights and implications for strategy and organizational change. *Journal of Management Studies*, 58(5), pp. 1159-1197.
27. Hedberg, B. (1981). How Organizations Learn and Unlearn. In: P. Nystrom, W. Starbuck (eds.), *Handbook of Organizational Design* (pp. 3-27). Oxford: Oxford University Press.
28. Holmström, J. (2022). From AI to digital transformation: The AI readiness framework. *Business Horizons*, 65(3), pp. 329-339.
29. Hradecky, D., Kennell, J., Cai, W., Davidson, R. (2022). Organizational readiness to adopt artificial intelligence in the exhibition sector in Western Europe. *International Journal of Information Management*, 65, 102497.
30. ISC2 (2023). *How the Economy, Skills Gap and Artificial Intelligence are Challenging the Global Cybersecurity Workforce*.
31. Jöhnk, J., Weißert, M., Wyrski, K. (2021). Ready or not, AI comes—an interview study of organizational AI readiness factors. *Business & Information Systems Engineering*, 63(1), pp. 5-20.
32. Kim, E.J., Park, S. (2022). Unlearning in the workplace: Antecedents and outcomes. *Human Resource Development Quarterly*, 33(3), pp. 273-296.
33. Kim, J.S., Chung, G.H. (2017). Implementing innovations within organizations: A systematic review and research agenda. *Innovation*, vol. 19(3), pp. 372-399.
34. Klammer, A., Grisold, T., Nguyen, N., Hsu, S.W. (2025). Organizational unlearning as a process: What we know, what we don't know, what we should know. *Management Review Quarterly*, 75(3), pp. 2147-2171.
35. Klammer, A., Gueldenberg, S. (2019). Unlearning and forgetting in organizations: a systematic review of literature. *Journal of Knowledge Management*, 23(5), pp. 860-888.
36. Kumar, Y., Marchena, J., Awlla, A.H., Li, J.J., Abdalla, H.B. (2024). The AI-powered evolution of big data. *Applied Sciences*, 14(22), 10176.

37. Kupers, R., Mullie, R. (2014). *Turbulence: A corporate perspective on collaborating for resilience*. Amsterdam University Press.
38. Lai, M.K., May, A.Y.C., Tay, L.C., Lim, K.G. (2025). Re-examining AI Adoption Antecedents and Its Potential Effect on AI Sustained Use in Small and Medium Enterprises (SMEs). *PaperASIA*, 41(1b), pp. 292-305.
39. Lee, H., Choi, B. (2003). Knowledge management enablers, processes, and organizational performance: An integrative view and empirical examination. *Journal of Management Information Systems*, 20(1), pp. 179-228.
40. Lee, Y.-M., Yang, C. (2014). The relationships among network ties, organizational agility, and organizational performance: A study of the flat glass industry in Taiwan. *Journal of Management & Organization*, 20(2), pp. 206-226.
41. Liu, J., Chang, H., Forrest, J.Y.L., Yang, B. (2020). Influence of artificial intelligence on technological innovation: Evidence from the panel data of China's manufacturing sectors. *Technological Forecasting and Social Change*, 158, 120142.
42. Maccioni, S., Ghiringhelli, C. (2024). Digital transformation through organisational unlearning: insights from practitioners' voice. *Knowledge Management Research & Practice*, 23(4), pp. 413-428.
43. MarketandMarkets (2025). *Artificial Intelligence in manufacturing Market Size, Share & Trends*.
44. Maslej, N., Fattorini, L., Perrault, R., Gil, Y., Parli, V., Kariuki, N., Oak, S. (2025). Artificial intelligence index report 2025. *arXiv preprint arXiv:2504.07139*.
45. Morandini, S., Fraboni, F., De Angelis, M., Puzzo, G., Giusino, D., Pietrantoni, L. (2023). The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. *Informing Science*, 26, pp. 39-68.
46. Nonaka, I., Takeuchi, H. (1995). *The knowledge-creating company: How Japanese companies create the dynamics of innovation*. Oxford University Press.
47. Nystrom, P., Starbuck, W.H. (2015). To avoid organizational crises, unlearn. *Organizational Dynamics*, 12, pp. 53-65.
48. Odor, H.O. (2018). A literature review on organizational learning and learning organizations. *International Journal of Economics & Management Sciences*, 7(1), pp. 1-6.
49. OECD (2023). *OECD Employment Outlook 2023 Artificial Intelligence and the labor Market*.
50. OECD (2024). Explanatory memorandum on the updated OECD definition of an AI system. *OECD Artificial Intelligence Papers, No. 8*.
51. Pardo del Val, M., Martinez Fuentes, C. (2003). Resistance to change: a literature review and empirical study. *Management Decision*, 41(2), 148-155.
52. PFR, Google (2025). *Mapa kompetencji AI w Polsce. Potrzeby i kierunki rozwoju*. Polski Fundusz Rozwoju.

53. Pietruszka-Ortyl, A. (2017). Współpraca międzyorganizacyjna z perspektywy nauk o zarządzaniu. *Zeszyty Naukowe Uniwersytetu Przyrodniczo-Humanistycznego, seria Administracja i Zarządzanie*, 39(112), pp. 11-23.
54. Platforma Przemysłu Przyszłości (2022). *Raport z badań empirycznych w zakresie kompetencji i zawodów przyszłości*. Warszawa.
55. PwC (2024). *Gotowi na sztuczną inteligencję. Oczekiwania polskich konsumentów i firm*. PwC Polska.
56. Rasul, I., Akter, T., Akter, S., Eshra, S.A., Hossain, A. (2025). AI-Driven Business Analytics for Product Development: A Survey of Techniques and Outcomes in the Tech Industry. *Frontline Marketing. Management and Economics Journal*, 5(01), pp. 16-38.
57. Retrieved from: <https://cloud.google.com/blog/topics/training-certifications/google-skills-new-home-AI-learning>, 15-10-2025.
58. Retrieved from: <https://trends.google.com/trends/>, 23-10-2025.
59. Rossoni, A.L., de Vasconcellos, E.P.G., de Castilho Rossoni, R.L. (2024). Barriers and facilitators of university-industry collaboration for research, development and innovation: a systematic review. *Management Review Quarterly*, 74(3), pp. 1841-1877.
60. Santana, M., Díaz-Fernández, M. (2023). Competencies for the artificial intelligence age: visualisation of the state of the art and future perspectives. *Review of Managerial Science*, 17(6), pp. 1971-2004.
61. Taherdoost, H., Madanchian, M. (2023). Artificial intelligence and knowledge management: Impacts, benefits, and implementation. *Computers*, 12(4), 72.
62. Teece, D.J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13), pp. 1319-1350.
63. Thompson, C.G., Kim, R.S., Aloe, A.M., Becker, B.J. (2017). Extracting the variance inflation factor and other multicollinearity diagnostics from typical regression results. *Basic and Applied Social Psychology*, 39(2), pp. 81-90.
64. Turyasingura, B., Ayiga, N., Byamukama, W., Kayusi, F., Tumuhimbise, M., Tumushabe, T. (2024). Application of artificial intelligence (AI) in environment and societal trends: Challenges and opportunities. *Babylonian Journal of Machine Learning*, pp. 177-182.
65. Uren, V., Edwards, J.S. (2023). Technology readiness and the organizational journey towards AI adoption: An empirical study. *International Journal of Information Management*, 68, 102588.
66. Wamba-Taguimdje, S.L., Fosso Wamba, S., Kala Kamdjoug, J.R., Tchatchouang Wanko, C.E. (2020). Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects. *Business Process Management Journal*, 26(7), pp. 1893-1924.

67. Wang, X., Zheng, C., Mutuc, E.B., Su, N., Hu, T., Zhou, H., Wei, S. (2022). How does organizational unlearning influence product innovation performance? Moderating effect of environmental dynamism. *Frontiers in Psychology*, 13, 840775.
68. WEF (2025). *AI in Action: Beyond Experimentation to Transform Industry. Flagship white paper series*. World Economic Forum.
69. Yin, J., Hoang, K. (2025) AI-enabled knowledge renewal: the role of leaders' AI attitudes and unlearning in enhancing employees' creative performance. *Journal of Knowledge Management*. JKM-02-2025-0209.
70. Zhang, F., Lyu, C., Zhu, L. (2022). Organizational unlearning, knowledge generation strategies and radical innovation performance: Evidence from a transitional economy. *European Journal of Marketing*, 56(1), pp. 133-158.
71. Zhao, X., Lynch Jr, J.G., Chen, Q. (2010). Reconsidering Baron and Kenny: Myths and truths about mediation analysis. *Journal of Consumer Research*, 37(2), pp. 197-206.
72. Zhao, Y., Lu, Y., Wang, X. (2013). Organizational unlearning and organizational relearning: a dynamic process of knowledge management. *Journal of Knowledge Management*, 17(6), pp. 902-912.
73. Zhao, Z., Yan, Y. (2023). The role of organizational unlearning in manufacturing firms' sustainable digital innovation: The mechanism of strategic flexibility and organizational slack. *Sustainability*, 15(13), 10371.