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internetu vecí v inteligentnom priemysle a doprave

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*Zborník vedeckých prác z projektu
NFP313010BWN6
„Implementačný rámec a business model
internetu vecí v inteligentnom priemysle a
doprave “*



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Artificial intelligence adoption across sectors

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Abstract

Artificial intelligence (AI) has become an increasingly important driver of productivity, competitiveness, and strategic transformation across industries. The aim of this study is to assess artificial intelligence adoption across sectors in Slovakia. Chosen sectors were compared across AI-related areas: integration, usage, efficiency, preparedness, and strategy. The empirical analysis is based on a sample of 391 enterprises. The dependence between sector and AI adoption areas was examined using the Pearson chi-square test, complemented by Pearson's contingency coefficient and Cramér's V. The results confirm weak to moderate associations between sectors and four AI adoption areas. The sign scheme indicates that sectoral differences in AI adoption are most pronounced in Manufacturing, which exhibits higher AI usage, stronger perceived efficiency gains, better employee preparedness, and clearer strategic orientation toward AI. In contrast, Construction is characterized by greater uncertainty and weaker strategic commitment, while other sectors display largely neutral and fragmented AI adoption patterns. The study adds value by providing sector-specific evidence on AI adoption and highlighting structural differences that are not captured by aggregate indicators. The findings offer practical insights for managers and policymakers seeking to support targeted AI diffusion strategies and contribute to the literature on AI adoption in transitive economies.

Keywords

Artificial intelligence, AI usage, AI efficiency, AI preparedness, AI strategy

JEL Classification: D22; O14

Adopcia umelej inteligencie naprieč sektormi



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Abstrakt

Umelá inteligencia (AI) sa stáva čoraz dôležitejšou hnacou silou produktivity, konkurencieschopnosti a strategickej transformácie naprieč odvetviami. Cieľom tejto štúdie je zhodnotiť prijatie umelej inteligencie naprieč sektormi na Slovensku. Vybrané sektory sa porovnávali v oblastiach súvisiacich s AI: integrácia, využitie, efektívnosť, pripravenosť a stratégia. Empirická analýza je založená na vzorke 391 podnikov. Závislosť medzi sektorom a oblasťami osvojenia AI bola skúmaná pomocou Pearsonovho chí-kvadrát testu doplneného o Pearsonov koeficient náhodnosti a Cramérov V. Výsledky potvrdzujú slabé až stredné asociácie medzi sektormi a štyrmi oblasťami osvojenia AI. Schéma znakov naznačuje, že sektorové rozdiely v prijímaní AI sú najvýraznejšie vo výrobe, ktorá vykazuje vyššie využitie AI, silnejšie vnímané zvýšenie efektívnosti, lepšiu pripravenosť zamestnancov a jasnejšiu strategickú orientáciu na AI. Na rozdiel od toho je stavebníctvo charakterizované väčšou neistotou a slabším strategickým záväzkom, zatiaľ čo iné sektory vykazujú prevažne neutrálne a roztrieštené modely prijímania AI. Štúdia pridáva hodnotu tým, že poskytuje sektorovo špecifické dôkazy o prijatí AI a zdôrazňuje štrukturálne rozdiely, ktoré nie sú zachytené súhrnnými ukazovateľmi. Zistenia ponúkajú praktické poznatky pre manažérov a tvorcov politik, ktorí sa snažia podporovať ciele stratégie šírenia AI a prispievajú k literatúre o prijatí AI v tranzitívnych ekonomikách.

Kľúčové slová

Umelá inteligencia, využitie AI, efektívnosť AI, pripravenosť AI, stratégia AI

JEL Klasifikácia: D22; O14



Introduction

Artificial intelligence (AI) is increasingly recognized as a key enabling technology shaping productivity growth, competitiveness, and structural transformation across European economies (Andronie et al., 2024). In the context of accelerating digitalization, AI has moved from experimental applications toward broader organizational and strategic use, influencing decision-making processes, operational efficiency, and long-term business models (Kliestik et al., 2023). At the European level, artificial intelligence is viewed not only as a technological innovation but also as a strategic priority reflected in policy frameworks aimed at strengthening technological sovereignty, innovation capacity, and sustainable economic development (Santoro et al., 2025).

Despite its growing relevance, AI adoption remains uneven across sectors (Rahman and Belas, 2024). Theoretical perspectives on technology adoption emphasize that firms' decisions to adopt advanced digital technologies are shaped by a combination of technological readiness, organizational capabilities, human capital, and environmental pressures (Skypalova et al., 2025). From this viewpoint, sectoral affiliation plays an important role, as industries differ substantially in production processes, knowledge intensity, regulatory constraints, and exposure to competitive pressures (Stefko et al., 2025). Manufacturing sectors are often associated with higher levels of digital maturity due to automation, standardization, and Industry 5.0 initiatives, whereas service-oriented or project-based sectors may face greater uncertainty and organizational barriers when integrating AI solutions (Valaskova et al., 2025a).

European empirical evidence suggests that while awareness of artificial intelligence is widespread, the depth and quality of its adoption differ considerably across enterprises (Hradecky et al., 2022). Basic AI integration can be observed in a broad range of organizations; however, more advanced dimensions—such as effective usage, perceived efficiency gains, employee preparedness, and strategic alignment—remain highly uneven. Existing studies often rely on aggregate indicators of digitalization or conceptualize AI adoption as a binary outcome, which limits a deeper understanding of how sectoral differences emerge across specific adoption dimensions.

At the same time, the adoption and effective deployment of AI technologies are constrained by multiple barriers that hinder organizations from fully exploiting their potential benefits. These barriers include limited access to high-quality data, ethical and legal concerns, insufficient awareness of AI capabilities, shortages of skilled personnel, and the need for inter-organizational coordination. In response to these challenges, AI strategy documents increasingly outline policy objectives and implementation frameworks aimed at reducing adoption barriers and supporting the diffusion of AI across European societies (van Noordt et al., 2025).

This creates a need for more granular empirical analyses that distinguish between multiple aspects of AI adoption and explicitly examine sectoral patterns within the European context. Understanding these differences is particularly important for designing targeted support measures, reducing structural disparities, and fostering inclusive digital transformation (Hoffreumon et al., 2024).

Against this background, the aim of this study is to assess artificial intelligence adoption across sectors in Slovakia by examining sectoral differences in AI usage, efficiency, preparedness, and strategic orientation. By combining statistical tests of dependence with residual-based sign scheme analysis, the study provides a detailed and interpretable assessment of how AI adoption varies across sectors within a European transitive economy.



The theoretical background and the conceptual framework of artificial intelligence adoption are incorporated within the Introduction, where the study is positioned in the context of existing literature and sectoral digitalization research. Following the Introduction, the Materials and Methods section describes the research design, data collection process, sample characteristics, and the statistical methods applied to examine sectoral differences in AI adoption. The Results and Discussion section presents and interprets the empirical findings, combining statistical test outcomes with sign scheme analyses and relating them to prior empirical evidence. Finally, the Conclusion summarizes the main findings, discusses their practical and theoretical implications, acknowledges the limitations of the study, and outlines directions for future research.

Materials and methods

Firstly, the questionnaire was based on the investigation of Dvorsky (2025). The whole survey is included in appendix of this article. Then, random sampling of Slovak enterprises was used. For random sampling, the following formula was used to calculate the required sample size n .

	$n = \frac{\frac{z_{\alpha}^2 \cdot p \cdot (1 - p)}{e^2}}{1 + \frac{z_{\alpha}^2 \cdot p \cdot (1 - p)}{e^2 \cdot N}}$	(1)
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where:

α denotes the significance level. In this study, a confidence level of 95% was adopted, corresponding to a significance level of $\alpha = 0.05$,

z_{α} represents the critical value of the standard normal distribution obtained from statistical tables. For a 95% confidence level, the corresponding critical value is 1.96,

p denotes the proportion of the observed characteristic. If a pilot survey is conducted and the proportion of the observed characteristic is known, the sample proportion is used. If no pilot survey is available or the proportion p cannot be reliably estimated, a conservative value of $p = 0.5$ is applied, which yields the maximum required sample size. This approach was adopted in the present study.

e represents the acceptable margin of error; a margin of $\pm 5\%$ was assumed.

N denotes the size of the population (724,352), derived from data provided by the Statistical Office of the Slovak Republic (2025).

Based on these parameters, the minimum required sample size was calculated as 384 observations. The survey was conducted electronically and distributed via email between 1 September 2025 and 15 September 2025. The overall response rate reached 5.4%, and 391 responses were obtained.

Table 1 presents the structure of the research sample according to enterprise size and sector affiliation. From the size perspective, small enterprises dominate the sample, accounting for 62% (242

enterprises), followed by medium-sized enterprises with a share of 32% (125 enterprises). Large enterprises represent the smallest group, comprising 6% of the sample (24 enterprises).

In terms of sectoral distribution, Manufacturing constitutes the largest share of enterprises (30%, 117 enterprises), followed by Trade with 22% (86 enterprises) and Services with 19% (74 enterprises). Construction accounts for 16% (63 enterprises), while the category Other represents 13% of the sample



(51 enterprises). The sectoral composition reflects a balanced representation of major economic activities within the Slovak business environment.

Table 1. Structure of the sample

Enterprise size	Share	Count	Sector	Share (%)	Count
Micro enterprises	0%	0	Manufacturing	30%	117
Small enterprises	62%	242	Trade	22%	86
Medium-sized enterprises	32%	125	Services	19%	74
Large enterprises	6%	24	Construction	16%	63
Total	100%	391	Other	13%	51
			Total	100%	391

Source: author's own processing

Secondly, the full sample was used to test the hypothesis concerning the dependence between sector affiliation and selected areas of artificial intelligence adoption. The relationship was examined using the Pearson chi-square test of independence. To ensure the validity of the test, standard assumptions were required to be met, namely that at least 80% of the expected frequencies were equal to or greater than 5 and that no expected frequency was lower than 1. These conditions were satisfied in all examined cases.

To complement the chi-square test, the strength of association was assessed using Pearson's contingency coefficient and Cramér's V. Following the interpretation framework proposed by Cavalli and Fenwick (2025), values below 0.20 indicate a negligible or weak association between sector affiliation and AI adoption areas, values between 0.20 and 0.40 suggest a moderate association, values from 0.40 to 0.80 indicate a strong association, and values exceeding 0.80 represent a very strong association.

Finally, a sign scheme analysis was applied to provide a more detailed interpretation of the detected dependencies. As described by Kicova et al. (2025), the sign scheme builds on the comparison of observed and expected frequencies within individual cells of the contingency table and is based on adjusted standardized residuals. Each cell is visually annotated according to the direction and magnitude of deviation from the null hypothesis of independence, indicating overrepresentation or underrepresentation of specific category combinations.

Three symbols are used in the sign scheme: "o" denotes no statistically significant deviation between observed and expected frequencies; "+" indicates a positive deviation, where the observed frequency exceeds the expected value; and "-" represents a negative deviation, where the observed frequency is lower than expected. The number of symbols reflects the level of statistical significance, with one symbol corresponding to $\alpha = 0.05$, two symbols to $\alpha = 0.01$, and three symbols to $\alpha = 0.001$.



All computations were performed using IBM SPSS Statistics software (version 28.0), and a significance level of $\alpha = 0.05$ was applied throughout the analysis.

Results and discussion

Table 2 presents the results of the Pearson chi-square tests of independence examining the relationship between sector affiliation and individual areas of AI adoption at the significance level $\alpha = 0.05$. The results indicate that no statistically significant dependence is observed between sector and AI integration (p -value = 0.349), suggesting that the basic integration of artificial intelligence does not differ significantly across sectors. In contrast, statistically significant dependencies are identified for AI usage (p -value = 0.041), AI efficiency (p -value = 0.046), AI preparedness (p -value = 0.002), and AI strategy (p -value = 0.009). These findings indicate that sector affiliation is significantly associated with more advanced and qualitative dimensions of AI adoption.

The chi-square test results suggest that while AI integration is relatively uniform across sectors, differences emerge in how enterprises use artificial intelligence, perceive its efficiency, prepare their workforce, and incorporate AI into strategic decision-making.

Table 2. Tests of independence for all AI areas

AI adoption area	Test statistic	Degree of freedom	p -value
Integration	8.923	8	0.349
Usage	16.083	8	0.041
Efficiency	15.773	8	0.046
Preparedness	24.578	8	0.002
Strategy	20.308	8	0.009

Source: author's own processing

Table 3 reports the measures of association for AI adoption areas in which a statistically significant dependence between sector affiliation and AI adoption was identified. For all four examined areas—AI usage, AI efficiency, AI preparedness, and AI strategy - the p -values confirm statistical significance at the $\alpha = 0.05$ level.

According to Cramér's V , the strength of association is weak across all AI adoption areas, with values ranging from 0.142 for AI efficiency to 0.177 for AI preparedness. These results indicate that

although sector affiliation is statistically related to AI adoption dimensions, the overall effect sizes remain limited.

A more differentiated picture emerges from Pearson's contingency coefficient. The associations for AI usage and AI efficiency reach values of 0.199 and 0.197, respectively, which can be interpreted as weak relationships. In contrast, higher values are observed for AI preparedness (0.243) and AI strategy (0.222), indicating relationships of moderate intensity. This suggests that sectoral differences



are more pronounced in areas related to employee readiness and strategic perception of artificial intelligence than in its operational use or perceived efficiency.

The results confirm that while all detected relationships are statistically significant, their practical strength varies across AI adoption dimensions, with the strongest sectoral differentiation observed for AI preparedness and AI strategy.

Table 3. Contingency coefficients for all significant AI areas

Intensity	Usage	<i>p</i> -value	Efficiency	<i>p</i> -value	Preparedness	<i>p</i> -value	Strategy	<i>p</i> -value
Cramér	0.143	0.041	0.142	0.046	0.177	0.002	0.161	0.009
Pearson	0.199	0.041	0.197	0.046	0.243	0.002	0.222	0.009

Source: author's own processing

The adjusted residuals for sectors and AI usage are presented in Table 3.

Table 3. Adjusted residuals for the AI usage

Sector/Usage	Agreement	Disagreement	Neutral
Construction	-0.1	-1.6	1.6
Manufacturing	2.8	-1.6	-1.4
Other	-0.5	1.2	-0.6
Services	-1.9	0.3	1.7
Trade	-0.1	1.5	-1.4

Source: author's own processing

The sign scheme for AI usage examines the relationship between sector affiliation and the active use of artificial intelligence tools to support decision-making processes. The results indicate that, in most sectors, no statistically significant deviations from independence are observed. Construction, Other, Services, and Trade display neutral patterns across agreement, disagreement, and neutral responses, suggesting that the reported use of AI tools in decision-making does not differ significantly from what would be expected under the assumption of independence.

In contrast, the Manufacturing sector exhibits a statistically significant overrepresentation of agreement responses (++) regarding active AI usage. This finding indicates that companies operating in

manufacturing are significantly more likely to actively use artificial intelligence tools to support decision-making processes than enterprises in other sectors. The absence of corresponding underrepresentation in disagreement or neutral responses suggests a clear positive association between manufacturing activity and AI usage rather than a polarized response structure.

Overall, the results suggest that sectoral differentiation in AI usage is limited, with Manufacturing standing out as the only sector where AI adoption in decision-making is already systematically embedded.



Table 4. Sign scheme for the AI usage

Sector/Usage	Agreement	Disagreement	Neutral
Construction	o	o	o
Manufacturing	++	o	o
Other	o	o	o
Services	o	o	o
Trade	o	o	o

Source: author's own processing

The adjusted residuals for sectors and AI efficiency are presented in Table 5.

Table 5. Adjusted residuals for the AI efficiency

Sector/Efficiency	Agreement	Disagreement	Neutral
Construction	0.6	-1.1	0.5
Manufacturing	2.9	-0.7	-2.4
Other	-1.9	0.7	1.2
Services	0.3	0.3	-0.6
Trade	-2.0	0.7	1.4

Source: author's own processing

Table 6 evaluates the association between sector affiliation and perceptions of AI-related efficiency and productivity improvements. For most sectors, including Construction, Other, Services, and Trade, no statistically significant deviations from independence are detected, indicating that perceptions of AI efficiency are evenly distributed and not sector specific.

The Manufacturing sector again emerges as distinctive. A statistically significant overrepresentation of agreement responses (++) suggests that manufacturing enterprises are more likely to perceive AI implementation as improving efficiency and productivity. At the same time, a weak but statistically significant underrepresentation of neutral responses (–) indicates that manufacturing companies are less likely to adopt an undecided stance toward AI efficiency. This pattern implies not only higher acceptance of AI benefits but also a clearer evaluation of AI outcomes in this sector.

These results suggest that manufacturing enterprises have progressed beyond experimentation toward a more mature assessment of AI's operational impact, whereas other sectors remain more heterogeneous in their perceptions.



Table 6. Sign scheme for the AI efficiency

Sector/Efficiency	Agreement	Disagreement	Neutral
Construction	o	o	o
Manufacturing	++	o	-
Other	o	o	o
Services	o	o	o
Trade	o	o	o

Source: author's own processing

The adjusted residuals for sectors and AI preparedness are presented in Table 7.

Table 7. Adjusted residuals for the AI preparedness

Sector/Preparedness	Agreement	Disagreement	Neutral
Construction	-1.9	-1.0	2.9
Manufacturing	3.5	-0.4	-3.3
Other	-1.2	1.9	-0.6
Services	-0.5	-1.0	1.5
Trade	0.0	0.7	-0.7

Source: author's own processing

The sign scheme for AI preparedness reveals more pronounced sectoral differences (Table 8). In the Manufacturing sector, a very strong overrepresentation of agreement responses (+++) is observed, accompanied by a strong underrepresentation of neutral responses (--). This indicates that manufacturing companies overwhelmingly report that their employees are adequately prepared to work with AI

technologies, and uncertainty regarding preparedness is significantly less common than expected. In contrast, the Construction sector exhibits a statistically significant overrepresentation of neutral responses (++), suggesting that enterprises in this sector tend to be uncertain or undecided about employee preparedness for AI. The absence of significant overrepresentation in agreement or disagreement implies that construction companies are neither clearly prepared nor explicitly unprepared but rather remain in a transitional or ambiguous state regarding workforce readiness. Other sectors, including Services, Trade, and Other, show no statistically significant deviations from independence, indicating that employee preparedness for AI is neither distinctly strong nor weak at the sectoral level. Overall, these findings highlight AI preparedness as the dimension with the strongest sectoral



differentiation, with Manufacturing displaying high workforce readiness and Construction characterized by uncertainty.

Table 8. Sign scheme for the AI preparedness

Sector/Preparedness	Agreement	Disagreement	Neutral
Construction	o	o	++
Manufacturing	+++	o	--
Other	o	o	o
Services	o	o	o
Trade	o	o	o

Source: author's own processing

The adjusted residuals for sectors and AI strategy are presented in Table 9.

Table 9. Adjusted residuals for the AI strategy

Sector/Strategy	Agreement	Disagreement	Neutral
Construction	-3.0	1.3	2.0
Manufacturing	3.3	-1.7	-1.9
Other	-1.7	1.3	0.6
Services	1.4	-0.7	-0.8
Trade	-0.6	0.2	0.4

Source: author's own processing

Table 10 examines whether artificial intelligence is perceived as a strategic factor for future growth and competitiveness. The Manufacturing sector again shows a statistically significant

overrepresentation of agreement responses (++), indicating that AI is more frequently regarded as a strategic priority in this sector. This finding is consistent with earlier results on AI usage, efficiency, and preparedness, reinforcing the interpretation of Manufacturing as the most advanced sector in terms of AI integration.

In contrast, the Construction sector exhibits a strong underrepresentation of agreement responses (--), coupled with a weak overrepresentation of neutral responses (+). This pattern suggests that construction enterprises are significantly less likely to view AI as a strategic factor and tend instead toward a neutral or undecided position. The results imply a strategic lag in recognizing AI's long-term importance within this sector.



Other sectors do not display statistically significant deviations from independence, indicating that perceptions of AI as a strategic factor are not strongly sector-dependent outside Manufacturing and Construction.

Table 10. Sign scheme for the AI strategy

Sector/Strategy	Agreement	Disagreement	Neutral
Construction	--	o	+
Manufacturing	++	o	o
Other	o	o	o
Services	o	o	o
Trade	o	o	o

Source: author's own processing

The results of this study are broadly consistent with the conclusions reported by Valaskova et al. (2025b), who emphasize that digital transformation and related technologies are adopted unevenly across sectors and enterprises, particularly in Central and Eastern European economies. Both studies confirm that sectoral affiliation plays a statistically significant role in shaping the adoption and perception of advanced digital tools, although the strength of these relationships remains limited.

In line with Valaskova et al. (2025b), the present study identifies Manufacturing as the sector exhibiting the most advanced and coherent digital behaviour. While the referenced article demonstrates that industrial enterprises achieve the highest levels of digitalization intensity and derive measurable financial benefits, our findings refine this conclusion by showing that Manufacturing also stands out specifically in artificial intelligence usage, perceived efficiency gains, employee preparedness, and strategic orientation toward AI. This supports the argument that industrial enterprises benefit from stronger technological capabilities, export orientation, and Industry 4.0 pressures, which jointly accelerate digital and AI adoption.

Conversely, both studies point to Construction as a structurally lagging sector. Valaskova et al. (2025b) report the lowest overall digitalization levels in construction enterprises, attributing this to fragmented project structures, risk aversion, and limited absorptive capacity. Our results complement this evidence by revealing pronounced uncertainty in AI preparedness and a weak strategic perception

of AI in Construction, suggesting that barriers extend beyond technology availability to human capital and long-term planning dimensions.

A notable contribution of the present study lies in its more granular decomposition of digitalization into AI-specific dimensions. While Valaskova et al. (2025b) focus on overall digital transformation levels and their financial implications, our findings demonstrate that AI integration itself does not significantly depend on sector, whereas AI usage, efficiency, preparedness, and strategy do. This nuance suggests that initial AI awareness may be widespread, but deeper institutionalization of AI differs across sectors.

The comparison confirms that digital and AI adoption in Slovakia is not a uniform process but a sector-contingent and capability-driven phenomenon. By isolating AI-specific dimensions, this study



extends existing digitalization research and provides complementary evidence that strategic alignment, human readiness, and perceived value creation are decisive factors shaping AI diffusion across enterprises.

Conclusion

The aim of this study is to assess artificial intelligence adoption across sectors in Slovakia. The empirical analysis shows that the Pearson chi-square test did not confirm a statistically significant dependence between sector affiliation and AI integration, indicating that the basic level of AI integration is not sector specific. In contrast, statistically significant relationships were identified for AI usage, AI efficiency, AI preparedness, and AI strategy, suggesting that sectoral differences emerge primarily in more advanced and qualitative dimensions of AI adoption rather than in its mere presence.

The strength of the detected associations, assessed using Cramér's V, was weak across all examined AI adoption areas, indicating limited overall effect sizes. However, a more nuanced interpretation based on Pearson's contingency coefficient reveals differentiation among the individual dimensions. Specifically, the associations for AI usage and AI efficiency can be classified as weak, while the relationships for AI preparedness and AI strategy reach moderate intensity. This indicates that sectoral affiliation plays a more pronounced role in shaping workforce readiness and strategic perceptions of artificial intelligence than in influencing its operational use or perceived efficiency gains.

The sign scheme analysis further refines these findings by revealing distinct sectoral patterns. Manufacturing consistently exhibits higher AI usage, stronger perceived efficiency gains, better employee preparedness, and a clearer strategic orientation toward artificial intelligence. In contrast, Construction is characterized by greater uncertainty, particularly with respect to employee preparedness and long-term strategic commitment to AI. Other sectors display largely neutral and fragmented patterns, suggesting uneven and less institutionalized AI adoption.

From a practical perspective, the findings provide valuable insights for managers and policymakers. The results highlight the need for sector-sensitive AI support measures, particularly in sectors where uncertainty and weaker strategic alignment persist. Targeted training initiatives and strategic guidance may be especially beneficial in Construction, while Manufacturing can serve as a benchmark for effective AI integration and capability development.

From a theoretical standpoint, this study contributes to the literature on AI adoption by demonstrating that sectoral differences are more evident in qualitative and strategic dimensions than in basic adoption indicators. The combined use of chi-square testing, association measures, and sign scheme analysis illustrates the importance of complementing global dependency tests with residual-based methods to uncover structural patterns that remain hidden in aggregate statistics.

Several limitations of the study should be acknowledged. The analysis is based on self-reported survey data, which may be affected by respondent subjectivity and perception bias. In addition, the relatively low response rate, although typical for electronic surveys, may limit the generalizability of the findings. The cross-sectional design further restricts the ability to capture dynamic changes in AI adoption over time.



Future research could extend this work by employing longitudinal data to analyse the evolution of AI adoption across sectors, incorporating enterprise-level characteristics such as size or ownership structure, or comparing the Slovak results with those from other transitive economies. Further studies may also benefit from integrating qualitative methods to explore managerial motivations and barriers underlying sector-specific AI adoption patterns.

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Appendix

Questionnaire: Artificial Intelligence Adoption Across Sectors

Dear Respondent,

We represent the Faculty of Operation and Economics of Transport and Communications, University of Žilina. As part of a scientific research project, we are examining the level of artificial intelligence (AI) adoption in enterprises.

The aim of this survey is to assess artificial intelligence adoption across sectors in the conditions of the Slovak Republic.

The questionnaire is intended exclusively for academic purposes, and all responses will be processed anonymously. Completing the questionnaire will take no more than 10 minutes.

Thank you very much for your time and willingness to participate in this survey.

Part A: General Information about the Enterprise (Open-ended questions)

Q1. What is the size of your enterprise?

Q2. In which sector does your enterprise primarily operate?

Q3. What is the legal form of your enterprise?

Q4. In which region of the Slovak Republic does your enterprise primarily operate?



Part B: Artificial Intelligence Adoption

Response scale:

1 – Disagree 2 – Neutral 3 – Agree

Please indicate the extent to which you agree with the following statements:

AI Integration:

Artificial intelligence solutions are well integrated into the company's operational processes.

☐ 1 ☐ 2 ☐ 3

AI Usage:

Our company actively uses artificial intelligence tools to support decision-making processes.

☐ 1 ☐ 2 ☐ 3

AI Efficiency:

The implementation of artificial intelligence has improved the efficiency and productivity of our company.

☐ 1 ☐ 2 ☐ 3

AI Preparedness:

Employees in our company are adequately prepared to work with artificial intelligence technologies.

☐ 1 ☐ 2 ☐ 3

AI Strategy:

Artificial intelligence is considered a strategic factor for the future growth and competitiveness of our company.

☐ 1 ☐ 2 ☐ 3

Part C: Additional Comments

*Zborník vedeckých prác z projektu
NFP313010BWN6
„Implementačný rámec a business model
internetu vecí v inteligentnom priemysle a
doprave “*



Please use the space below to share any additional comments, experiences, or opinions related to this survey or the use of artificial intelligence in your company or sector.





The impact of owners' demographic characteristics on artificial intelligence adoption in the SME segment

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Abstract

The aim of this article is to evaluate the impact of the demographic characteristics of business owners or top managers on the level of artificial intelligence adoption in the business environment of the Slovak Republic. The analysis focuses on demographic characteristics such as gender, age, and highest level of education attained. Primary data collection was carried out through the attitudes of 384 respondents by an external agency. The empirical research was conducted in the segment of small and medium-sized enterprises in December 2024. Parametric methods of mathematical statistics were employed to evaluate the statistical hypotheses. The results of the quantitative research confirmed that gender, age, and education are no significant factors in assessing the adoption of artificial intelligence in the SME segment in the Slovak Republic. The age and educational attainment of SME owners and managers is a significant factor in assessing their attitudes toward the use of AI for automating repetitive and time-consuming tasks. The findings are particularly relevant for business owners and managers operating in the Slovak business environment.

Keywords

Artificial intelligence, attitudes, demographic characteristics, empirical research, small and medium-sized enterprises

JEL Classification: G23, M15, L26

Vplyv demografických charakteristík vlastníkov na zavádzanie umelej inteligencie v segmente MSP

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Abstrakt

Cieľom článku je vyhodnotiť vplyv demografických charakteristík vlastníkov alebo vrcholových manažérov podnikov na úroveň adopcie umelej inteligencie v podnikateľskom prostredí Slovenskej republiky. Predmetom analýzy sú demografické charakteristiky ako je pohlavie, vek a najvyššie dosiahnuté vzdelanie. Zber primárnych dát sa realizoval na základe postojov 384 respondentov externou agentúrou. Empirický výskum sa realizoval v segmente malých a stredných podnikoch v decembri 2024. Na vyhodnotenie štatistických hypotéz sa využili parametrické metódy matematickej štatistiky. Výsledky kvantitatívneho výskumu potvrdili, že pohlavie, vek i dosiahnuté vzdelanie nie sú významným faktorom v hodnotení adaptácie umelej inteligencie v segmente MSP v Slovenskej republike. Vek a dosiahnuté vzdelanie vlastníkov a manažérov MSP je významným faktorom pri hodnotení ich postojoch na využívanie AI na automatizáciu opakujúcich sa a časovo náročných úloh. Zistenia sú významné najmä pre vlastníkov a manažérov podnikov, ktorí pôsobia v podnikateľskom prostredí Slovenskej republiky.

Kľúčové slová

Umelá inteligencia, postoje, demografické charakteristiky, empirický výskum, malé a stredné podniky

JEL Klasifikácia: G23, M15, L26

Úvod

Implementácia umelej inteligencie (AI) v malých a stredných podnikoch (MSP) v Európskej únii je zložitý proces, ktorý je formovaný jednak snahou MSP o zvýšenie konkurencieschopnosti, a jednak regulačným prostredím EÚ, najmä Aktom o umelej inteligencii (Arroyabe et al., 2024). Hoci miera adopcie AI v MSP v EÚ stále zaostáva za veľkými podnikmi, existuje rastúci trend a cielená podpora zo strany EÚ (Skypalova et al., 2025). Adopcia AI v MSP v EÚ je stále na nižšej úrovni v porovnaní s veľkými firmami. Kým v roku 2024 používalo AI v EÚ približne 11,2 % malých podnikov a 20,9 % stredných podnikov (s 10 a viac zamestnancami), u veľkých podnikov to bolo až 41,2 % (Arroyabe et al., 2024).

MSP často integrujú AI vďaka jej širokej dostupnosti a možnosti použiť hotové komerčné alebo open-source riešenia, namiesto toho, aby vyvíjali vlastné, komplexné systémy (napr. Dvorsky, 2025; Al Dhaheri et al., 2024). Podpora AI ponúka MSP obrovský priestor na optimalizáciu kľúčových operácií (Faiz et al., 2024). Oblasti, kde implementácia umelej inteligencie prináša hmatateľné výsledky: i. automatizácia opakujúcich sa úloh – AI systémy úspešne vykonávajú úlohy ako zadávanie údajov, posielanie faktúr alebo plánovanie príspevkov na sociálnych médiách. Riešia monotónnosť efektívnejšie ako ľudia, čo umožňuje zamestnancom sústrediť sa na zložitejšie a kreatívnejšie výzvy (Gersbach et al., 2025; Metzger et al., 2025); ii. generovanie obsahu a posilnenie značky – pravidelné publikovanie nového, pútavého obsahu podporuje pozicionovanie stránok a buduje povedomie o značke. Avšak, to je často výzvou pre malé marketingové oddelenia. AI uľahčuje vytváranie jedinečného obsahu – od príspevkov na sociálnych médiách po grafiku a videá; iii. riadenie vzťahov so zákazníkmi – všadeprítomná personalizácia zohráva čoraz dôležitejšiu úlohu pri budovaní lojálnych vzťahov so



zákazníkmi. AI umožňuje podrobne sledovať interakcie zákazníkov s vašou značkou (napr. analyzovať čas strávený na stránke, frekvenciu návštev alebo históriu nákupov). Na základe týchto údajov môžete odporúčať relevantné produkty a služby na posilnenie vzťahov (Merín-Rodríguez et al., 2025); iv. analýza údajov a automatizované vyvodzovanie záverov – stroje sú v spracovaní obrovských množstiev údajov oveľa lepšie ako ľudia (Cheng et al., 2025). Vďaka samoučiacim algoritmom dokáže AI odhaliť aj malé, jemné vzory a trendy, ktoré sú nad rámec analytických schopností človeka. Pri správnom použití sa tieto údaje stávajú zdrojom dôležitých poznatkov na podporu rozvoja podnikania (Ling, 2025).

Viaceri autori poukazujú, že MSP čelia i významným bariéram implementácie AI do ich podnikania (napr. Sonar et al., 2025). Ide o i. nedostatok relevantných zručností: Najväčšia prekážka. MSP často nemajú interných špecialistov na AI; ii. Finančné náklady a komplexnosť: Implementácia AI systémov, aj tých externých, je vnímaná ako drahá a náročná na riadenie (Metzger et al., 2025); iii. dáta: Problémy s dostupnosťou a kvalitou dát potrebných na tréning alebo efektívne používanie AI modelov (Yin & Hoang, 2025); iv. regulačná neistota: Obavy týkajúce sa súladu s novou legislatívou EÚ, najmä s AI Act a pravidlami o ochrane údajov (GDPR; Zhang et al., 2025).

Vedecký článok má nasledovnú štruktúru. V úvode je prezentovaná aktuálnosť vybranej problematiky adaptácie umelej inteligencie v segmente malých a stredných podnikov. Následne je definovaný cieľ, metodológia výskumu, dotazník a otázky v dotazníku. V predmetnej časti sú taktiež definované štatistické metódy a demografická štruktúra respondentov. Empirické výsledky sú spracované s využitím kontingenčných tabuliek a testovanie realizované s využitím softvéru IBM SPSS Statistics. Výsledky sú následne v diskusii porovnané a v závere zhrnuté kľúčové zistenia, obmedzenia výskumu a budúce smerovanie vedecko-publikačných aktivít riešiteľa.

Cieľ, metodológia a dáta

Cieľom článku je vyhodnotiť vplyv demografických charakteristík vlastníkov alebo vrcholových manažérov podnikov na úroveň adopcie umelej inteligencie v podnikateľskom prostredí Slovenskej republiky.

Výskum sa realizoval v podnikateľskom prostredí Slovenskej republiky v priebehu mesiaca december 2024. Zber dáta zabezpečila externá agentúra MNFORCE, ktorá sa špecializuje na dotazníkové šetrenia. Respondent bol charakterizovaný ako vlastník alebo vrcholový manažér malého alebo stredného podniku, ktorý pôsobí v podnikateľskom prostredí Slovenskej republiky (ďalej len respondent). Je etablovanou agentúrou pôsobiacou vo viacerých krajinách EÚ. Celkový počet respondentov bol 384. Dotazník obsahoval otázky zamerané na demografické charakteristiky respondenta, demografické charakteristiky podniku a otázky zamerané na adaptáciu umelej inteligencie pri podnikateľskej činnosti a aktivitách.

Predmetom analýzy a hodnotenia boli nasledovné tvrdenia adaptácií a využívania umelej inteligencie (UI) v podniku:

UI1: V našej organizácii sa využíva možnosť AI na zvýšenie obchodnej výkonnosti.



UI2: Podnik využíva AI na automatizáciu opakujúcich sa a časovo náročných úloh (napr. spracovanie miezd, správa údajov o zamestnancoch, plánovanie smien atď.).

UI3: Podnik využíva AI pri výbere zamestnancov (napr. preverovanie životopisov, hodnotenie kandidátov, predpovedanie úspešnosti kandidátov na základe historických dát).

UI4: Podnik využíva AI na spätnú väzbu, získanie informácií o spokojnosti a taktiež odporúčania a rád od svojich zamestnancov.

UI5: Vedenie organizácie sa angažuje v podpore využitia AI v každodenných pracovných činnostiach zamestnancov.

Na vyhodnotenie hlavného cieľa článku boli sformulované nasledovné štatistické hypotézy, ktoré boli vyhodnotené s využitím parametrických testov:

SH1: Pohlavie (SH1_P), vek (SH1_V) a dosiahnuté vzdelanie (SH1_DV) je štatisticky významným faktorom, ktorý ovplyvňuje hodnotenie vlastníkov a manažérov na tvrdenie UI1.

SH2: Pohlavie (SH2_P), vek (SH2_V) a dosiahnuté vzdelanie (SH2_DV) je štatisticky významným faktorom, ktorý ovplyvňuje hodnotenie vlastníkov a manažérov na tvrdenie UI2.

SH3: Pohlavie (SH3_P), vek (SH3_V) a dosiahnuté vzdelanie (SH3_DV) je štatisticky významným faktorom, ktorý ovplyvňuje hodnotenie vlastníkov a manažérov na tvrdenie UI3.

SH4: Pohlavie (SH4_P), vek (SH4_V) a dosiahnuté vzdelanie (SH4_DV) je štatisticky významným faktorom, ktorý ovplyvňuje hodnotenie vlastníkov a manažérov na tvrdenie UI4.

SH5: Pohlavie (SH5_P), vek (SH5_V) a dosiahnuté vzdelanie (SH5_DV) je štatisticky významným faktorom, ktorý ovplyvňuje hodnotenie vlastníkov a manažérov na tvrdenie UI5.

Demografická štruktúra respondentov (n = 384) je nasledovná:

- pohlavie: 187 (48,7%) muži, 197 (51,3%) ženy;
- vek: 226 (58,9%) s vekom menej ako 44 rokov, 158 (41,1%) s vekom rovných ako viac ako 44 rokov;
- najvyššie dosiahnuté vzdelanie: 80 (20,8%) základné, stredoškolské bez maturity, stredoškolské s maturitou; 304 (79,2%) univerzitné vzdelanie (I. stupeň VŠ, II. stupeň VŠ, III. stupeň VŠ);
- veľkosť podniku: 166 (43,2%) mikropodniky, 100 (26,0%) malé podniky, 118 (30,7%) stredné podniky;
- rodinný podnik: 125 (32,5%) áno, 251 (65,4%) nie, 8 (2,1%) neviem odpovedať;
- pracovná pozícia v podniku: 161 (41,9%) majiteľ podniku, 223 (58,1%) manažér podniku;
- doba pôsobenia podniku v podnikateľskom prostredí: 57 (14,8%) menej ako 5 rokov, 206 (53,7%) od 5 do 20 rokov, 121 (31,5%) viac ako 20 rokov.

Empirické výsledky

Tabuľka 1 prezentuje výsledky hodnotenia postojov respondentov na využívanie AI s cieľom zvýšiť obchodnú výkonnosť (UI1) podľa ich demografických charakteristík.



Tabuľka 1. Hodnotenie postojov na tvrdenia UI1 podľa demografických charakteristík

Typ odpovede	Pohlavie		Vek		Dosiahnuté vzdelanie	
	Muž	Žena	Menej ako 44 rokov	44 a viac rokov	Bez univerzity	Univerzitné vzdelanie
1	54	44	52	46	29	69
2	35	43	47	31	15	63
3	68	61	72	57	24	105
4+5	30	49	55	24	12	67
Spolu	187	197	226	158	80	304

Zdroj: vlastné spracovanie dát.

Empirické výsledky komparácie postojov respondentov na UI1 podľa ich demografických charakteristík sú nasledovné: pohlavie: Chi-kvadrát test = 6,534, p-hodnota = 0,088; vek: Chi-kvadrát test = 5,695, p-hodnota = 0,127; dosiahnuté vzdelanie: Chi-kvadrát test = 6,593, p-hodnota = 0,086. Na základe uvedených výsledkov je možno konštatovať, že pohlavie, vek ani dosiahnuté vzdelanie nie sú štatisticky významné faktory, ktoré by ovplyvňovali hodnotenie UI1. Na základe výsledkov hypotézy SH1_P, SH1_V a SH1_DV sa zamietajú.

Tabuľka 2 prezentuje výsledky hodnotenia postojov respondentov, či podnik využíva AI na automatizáciu opakujúcich sa a časovo náročných úloh (UI2) podľa ich demografických charakteristík.

Tabuľka 2. Hodnotenie postojov na tvrdenia UI2 podľa demografických charakteristík

Typ odpovede	Pohlavie		Vek		Dosiahnuté vzdelanie	
	Muž	Žena	Menej ako 44 rokov	44 a viac rokov	Bez univerzity	Univerzitné vzdelanie
1	51	45	52	44	33	63
2	32	39	49	22	10	61
3	61	53	57	57	18	96
4+5	43	60	68	35	19	84
Spolu	187	197	226	158	80	304

Zdroj: vlastné spracovanie dát.



Empirické výsledky komparácie postojov respondentov na UI2 podľa ich demografických charakteristík sú nasledovné: pohlavie: Chi-kvadrát test = 4,175, p-hodnota = 0,243; vek: Chi-kvadrát test = 9,772, p-hodnota = 0,021; dosiahnuté vzdelanie: Chi-kvadrát test = 14,749, p-hodnota = 0,002. Na základe uvedených výsledkov je možno konštatovať, že pohlavie, nie je štatisticky významný faktor. Na druhej strane vek ani dosiahnuté vzdelanie sú významné faktory, ktoré ovplyvňujú hodnotenie UI2. Na základe výsledkov hypotéza SH2_P sa zamieta. Štatistické hypotézy SH2_V a SH2_DV sú akceptované.

Tabuľka 3 prezentuje výsledky hodnotenia postojov respondentov, či podnik využíva AI pri výbere svojich zamestnancov (UI3) podľa ich demografických charakteristík.

Tabuľka 3. Hodnotenie postojov na tvrdenia UI3 podľa demografických charakteristík

Typ odpovede	Pohlavie		Vek		Dosiahnuté vzdelanie	
	Muž	Žena	Menej ako 44 rokov	44 a viac rokov	Bez univerzity	Univerzitné vzdelanie
1	56	49	58	47	27	78
2	43	58	58	43	20	81
3	51	42	55	38	15	78
4+5	37	48	55	30	18	67
Spolu	187	197	226	158	80	304

Zdroj: vlastné spracovanie dát.

Empirické výsledky komparácie postojov respondentov na UI3 podľa ich demografických charakteristík sú nasledovné: pohlavie: Chi-kvadrát test = 4,731, p-hodnota = 0,192; vek: Chi-kvadrát test = 1,857, p-hodnota = 0,602; dosiahnuté vzdelanie: Chi-kvadrát test = 2,836, p-hodnota = 0,418. Na základe uvedených výsledkov je možno konštatovať, že pohlavie, vek ani dosiahnuté vzdelanie nie sú štatisticky významné faktory, ktoré by ovplyvňovali hodnotenie UI3. Na základe výsledkov hypotézy SH3_P, SH3_V a SH3_DV sa zamietajú.

Tabuľka 4 prezentuje výsledky hodnotenia postojov respondentov, či podnik využíva AI na spätnú väzbu, získanie informácií o spokojnosti a taktiež odporúčania a rád od svojich zamestnancov (UI4) podľa ich demografických charakteristík.



Tabuľka 4. Hodnotenie postojov na tvrdenia UI4 podľa demografických charakteristík

Typ odpovede	Pohlavie		Vek		Dosiahnuté vzdelanie	
	Muž	Žena	Menej ako 44 rokov	44 a viac rokov	Bez univerzity	Univerzitné vzdelanie
1	50	41	46	45	24	67
2	46	42	59	29	17	71
3	49	54	56	47	19	84
4+5	42	60	65	37	20	82
Spolu	187	197	226	158	80	304

Zdroj: vlastné spracovanie dát.

Empirické výsledky komparácie postojov respondentov na UI4 podľa ich demografických charakteristík sú nasledovné: pohlavie: Chi-kvadrát test = 4,233, p-hodnota = 0,237; vek: Chi-kvadrát test = 6,885, p-hodnota = 0,075; dosiahnuté vzdelanie: Chi-kvadrát test = 2,265, p-hodnota = 0,519. Na základe uvedených výsledkov je možno konštatovať, že pohlavie, vek ani dosiahnuté vzdelanie nie sú štatisticky významné faktory, ktoré by ovplyvňovali hodnotenie UI4. Na základe výsledkov hypotézy SH4_P, SH4_V a SH4_DV sa zamietajú.

Tabuľka 5 prezentuje výsledky hodnotenia postojov respondentov, či vedenie organizácie sa angažuje v podpore využitia AI v každodenných pracovných činnostiach zamestnancov (UI5) podľa ich demografických charakteristík.

Tabuľka 5. Hodnotenie postojov na tvrdenia UI5 podľa demografických charakteristík

Typ odpovede	Pohlavie		Vek		Dosiahnuté vzdelanie	
	Muž	Žena	Menej ako 44 rokov	44 a viac rokov	Bez univerzity	Univerzitné vzdelanie
1	44	34	44	34	22	56
2	36	31	45	22	17	50
3	56	73	74	55	22	107
4+5	51	59	63	47	19	91
Spolu	187	197	226	158	80	304

Zdroj: vlastné spracovanie dát.



Empirické výsledky komparácie postojov respondentov na UI5 podľa ich demografických charakteristík sú nasledovné: pohlavie: Chi-kvadrát test = 4,220, p-hodnota = 0,239; vek: Chi-kvadrát test = 2,335, p-hodnota = 0,506; dosiahnuté vzdelanie: Chi-kvadrát test = 5,370, p-hodnota = 0,147. Na

základe uvedených výsledkov je možno konštatovať, že pohlavie, vek ani dosiahnuté vzdelanie nie sú štatisticky významné faktory, ktoré by ovplyvňovali hodnotenie UI5. Na základe výsledkov hypotézy SH5_P, SH5_V a SH5_DV sa zamietajú.

Diskusia

Zistenia kvantitatívneho výskumu priniesli zaujímavé výsledky. Je možno konštatovať na základe postojov respondentov, že:

- viac ako 43% respondentov sa vyjadrilo, že ich podnik využíva AI s cieľom zvýšiť obchodnú výkonnosť. Pohlavie, vek, a dosiahnuté vzdelanie nie sú signifikantné faktory, ktoré by mali vplyv na postoje respondentov na dané tvrdenie.
- štyria z desiatich opýtaných respondentov uviedlo, ich podnik využíva AI na automatizáciu opakujúcich sa a časovo náročných úloh. Pohlavie nie je významným faktorom. Medzi vybranými skupinami respondentov podľa veku a dosiahnuté vzdelanie sa identifikovali významné rozdiely.
- takmer 55% respondentov uviedlo, že podnik využíva AI pri výbere svojich zamestnancov. Pohlavie, vek, a dosiahnuté vzdelanie nie sú významné faktory, ktoré by mali vplyv na postoje respondentov na dané tvrdenie.
- len 44% respondentov uviedlo, že podnik využíva AI na spätnú väzbu, získanie informácií o spokojnosti a taktiež odporúčania a rád od svojich zamestnancov. Demografické charakteristiky, ako je pohlavie, vek, a dosiahnuté vzdelanie nie sú významné.
- Len 37% respondentov uviedlo, že vedenie organizácie sa angažuje v podpore využitia AI v každodenných pracovných činnostiach zamestnancov. Demografické charakteristiky, ako je pohlavie, vek, a dosiahnuté vzdelanie nie sú významné.

Záver

Cieľom článku bolo vyhodnotiť vplyv demografických charakteristík vlastníkov alebo vrcholových manažérov podnikov na úroveň adopcie umelej inteligencie v podnikateľskom prostredí Slovenskej republiky.

Zistenia poukázali na fakt, že respondenti do 44 rokov (cca 23%) v menšej miere využívajú AI na automatizáciu opakujúcich sa a časovo náročných úloh (napr. spracovanie miezd, správa údajov o zamestnancoch, plánovanie smien atď.) v porovnaní s respondentmi vo veku 44 rokov a viac (cca 28%). Na druhej strane respondenti bez univerzitného vzdelania (53,7%) využívajú AI na automatizáciu opakujúcich sa a časovo náročných úloh vo väčšej miere ako respondenti s vysokoškolským vzdelaním (cca 41%). Medzi mužmi a ženami sa rozdiely nepotvrdili.



Výskum sa realizoval v jednej z krajín EU, čo je určitým obmedzením realizovaného kvantitatívneho výskumu. Zber dát sa realizoval na základe subjektívnych postojov respondentov. Na vyhodnotenie dát sa využili len vybrané štatistické metódy, ktoré neboli overené iným štatistickým prístupom. Dáta boli predmetom zberu len v jednom mesiaci – december 2025. Pre ich hlbšiu akceptáciu by bolo vhodné opätovné zistenie postojov respondentov na inej vzorke.

Budúce smerovanie výskumu sa bude zameriavať na zisťovanie postojov samotných zamestnancov na rôznych úrovniach managementu podniku – HR manažérov alebo samotných zamestnancov. Taktiež je ambíciou riešiteľov rozšírenie výskumu a zber primárnych dát v ostatných krajinách V4 krajín, Poľsko, Česká republika, Maďarsko a Poľsko. Parciálnou ambíciou je nadviazanie spolupráce so západnými výskumníkmi a porovnať zistenia postojov adaptácie AI s ich podnikateľským prostredím.

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Disruptive Technologies in Management: Artificial Intelligence and the Evolution of Governance Paradigms

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Abstract

Artificial intelligence is increasingly understood as a disruptive technology in business management. Its impact is not limited to automation or process efficiency, because AI also influences responsibility, control, transparency, ethical oversight and risk management in organisations. The aim of this paper is to analyse artificial intelligence as a disruptive technology that transforms traditional governance paradigms in management, with particular attention to accountability, transparency, ethical oversight, risk governance and organisational AI maturity. The paper applies qualitative thematic content analysis and conceptual framework development. The analysis is based on scientific sources identified through targeted searches in the Web of Science Core Collection, covering the period 2018–2026 and focusing on AI as a disruptive management technology, AI governance, responsible AI, explainability, algorithmic bias, regulation and organisational readiness. The results identify key governance dimensions of AI implementation and propose a conceptual framework describing the evolution from traditional corporate governance to digital governance, AI governance and responsible adaptive governance. The paper shows that AI governance is becoming an essential part of modern management and requires continuous oversight, ethical control and organisational learning.

Keywords

artificial intelligence, disruptive technologies, AI governance, corporate governance

JEL Classification: M10, M14, M15, O33



Disruptívne technológie v manažmente: Umelá inteligencia a vývoj paradigiem riadenia

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Abstrakt

Umelá inteligencia sa čoraz viac chápe ako rušivá technológia v riadení podnikov. Jej vplyv sa neobmedzuje len na automatizáciu alebo efektivitu procesov, pretože AI ovplyvňuje aj zodpovednosť, kontrolu, transparentnosť, etický dohľad a riadenie rizík v organizáciách. Cieľom tohto článku je analyzovať umelú inteligenciu ako prevratnú technológiu, ktorá transformuje tradičné paradigmy riadenia v manažmente, s osobitným dôrazom na zodpovednosť, transparentnosť, etický dohľad, riadenie rizík a vyspelosť organizačnej AI. V príspevku sa aplikuje kvalitatívna tematická obsahová analýza a tvorba koncepčného rámca. Analýza je založená na vedeckých zdrojoch identifikovaných prostredníctvom cieľených vyhľadávaní v zbierke Web of Science Core Collection, pokrývajúcich obdobie rokov 2018 – 2026 a zameriavajúcich sa na AI ako technológiu prelomového riadenia, riadenie AI, zodpovednú AI, vysvetliteľnosť, algoritmickú zaujatosť, reguláciu a organizačnú pripravenosť. Výsledky identifikujú kľúčové dimenzie riadenia implementácie AI a navrhujú koncepčný rámec popisujúci vývoj od tradičného podnikového riadenia k digitálnemu riadeniu, riadeniu AI a zodpovednému adaptívnemu riadeniu. Dokument ukazuje, že riadenie AI sa stáva nevyhnutnou súčasťou moderného manažmentu a vyžaduje neustály dohľad, etickú kontrolu a organizačné vzdelávanie.

Kľúčové slová

umelá inteligencia, prevratné technológie, AI governance, corporate governance

JEL Klasifikácia: M10, M14, M15, O33



Introduction

Artificial intelligence has become one of the most important disruptive technologies in contemporary management. It is increasingly used in business processes, decision support, customer interaction, human resource management, risk assessment, production planning and strategic analysis. Its importance relates to the ability to process large volumes of data, identify patterns, automate tasks and support managerial activities in real time. However, the managerial impact of AI is broader than technological efficiency. AI also changes organisational routines, managerial competencies, control mechanisms and the relationship between human judgement and algorithmic outputs (Brem et al., 2023). For this reason, AI can be understood as a disruptive technology that affects the way organisations are managed and governed (Pavaloaia and Necula, 2023; Shankar, 2024).

The implementation of AI creates new opportunities for firms, but it also raises new governance questions. Organisations need to decide how AI systems should be developed, used, monitored and controlled. They also need to define who is responsible for AI-supported outputs, how data quality should be ensured, how algorithmic bias should be detected and how AI systems should be explained to managers, employees, customers or regulators. These questions are especially important because AI can influence areas with significant organisational and social impact, such as recruitment, employee evaluation, pricing, marketing segmentation, financial risk assessment or customer service. In such areas, weak governance may lead to unfair decisions, privacy problems, loss of trust and reputational risks (Akter et al., 2022; Maiti et al., 2025).

Traditional corporate governance has usually focused on owners, managers, reporting, compliance, control and managerial accountability. These elements remain important, but AI adds a new layer of governance. Firms must govern not only people and formal processes, but also data, machine learning models and AI systems. Schneider et al. (2023) argue that business AI governance should include the governance of data, models and AI systems, because these elements create new organisational responsibilities. Similarly, Papagiannidis et al. (2025) emphasise that responsible AI governance requires structural, procedural and relational practices that translate ethical principles into organisational routines. This means that AI governance is not only a technological issue. It is also a managerial, ethical and organisational challenge.

A key part of this challenge is transparency and explainability. AI systems often operate as complex models whose outputs may be difficult to understand. This creates the so-called black-box problem, especially in decisions that require justification and trust. Explainability is therefore important for managerial acceptance, auditability and responsible use of AI. Hamm et al. (2023) show that perceived explainability influences trust and usefulness of AI systems. Chowdhury, Joel-Edgar, et al. (2023) also emphasise that transparent AI models can help managers understand AI-based predictions and reduce trust problems in data-driven decision-making. From a governance perspective, explainability is necessary because managers must be able to justify decisions supported by AI.

AI governance is also connected with organisational readiness and AI maturity. Many firms adopt AI tools faster than they develop internal rules, competencies and governance structures. This creates a gap between technological adoption and organisational preparedness. AI maturity therefore includes not only technical infrastructure, but also managerial knowledge, employee skills, leadership support, data governance, ethical rules and risk management. Research on AI capability and generative AI readiness



shows that firms need both technical and non-technical capabilities to benefit from AI adoption (Chowdhury, Dey, et al., 2023; Kumar et al., 2026). Responsible AI governance can also support corporate performance and innovation when it relates to strategic attention, human capital and risk reduction (Xia et al., 2026; Xiong et al., 2026).

Although AI in management is widely studied, research often emphasises performance, decision support and technological applications rather than its impact on corporate governance. This creates a gap concerning accountability, transparency, ethical oversight, risk governance, regulatory alignment and organisational AI maturity. The aim of this paper is to analyse artificial intelligence as a disruptive technology that transforms traditional governance paradigms in management, with particular attention to accountability, transparency, ethical oversight, risk governance and organisational AI maturity. It applies qualitative thematic content analysis and conceptual framework development to scientific sources identified through targeted Web of Science searches conducted in April 2026 and covering 2018–2026. The search focused on disruptive AI, AI governance, responsible AI, explainability, ethics, algorithmic bias, regulation, risk governance and organisational readiness. Based on the findings, the paper develops a framework describing the evolution from traditional corporate governance to digital governance, AI governance and responsible adaptive governance.

Objectives and methodology

The paper applies qualitative thematic content analysis to examine how artificial intelligence transforms governance paradigms in management and to develop a conceptual framework of this transformation. This approach follows the logic of systematic thematic analysis, which can be used to identify themes in qualitative material and to develop a conceptual model from the analysed findings (Naeem et al., 2023). The analysed material consisted primarily of scientific articles identified through targeted searches in the Web of Science Core Collection. The searches were conducted in April 2026 and covered publications from 2018 to 2026. The search was limited to Articles and Review Articles, mainly in the Web of Science categories Management, Business and Ethics. Earlier Web of Science sources used in the broader research background were also included, because they were identified through a similar thematic logic.

The Web of Science search strategy was organised into six thematic areas: artificial intelligence as a disruptive management technology, AI governance and responsible AI, accountability and transparency, ethics and algorithmic bias, risk governance and regulation, and AI maturity and organisational readiness. The retrieved records were assessed according to their relevance to management and governance. The selected material was then coded into governance-related categories. The main categories were accountability, transparency and explainability, data governance, ethical governance, risk governance, human oversight, organisational AI maturity and regulatory alignment.

In the final step, the coded themes were interpreted and used to develop a conceptual framework describing the evolution of governance paradigms under AI disruption. The framework distinguishes four stages: traditional corporate governance, digital governance, AI governance and responsible adaptive governance. The aim of this framework is to show how AI extends existing governance mechanisms and creates new requirements for managerial responsibility, ethical control, data quality, risk monitoring and continuous human oversight. Thus, the methodology combines a targeted Web of Science literature search, qualitative thematic content analysis and conceptual framework development.



Results and discussion

Artificial intelligence is a major disruptive technology in contemporary management. Thematic analysis of selected Web of Science sources shows that AI simultaneously affects data analysis, prediction, automation, planning, control and decision support. Beyond improving efficiency, it changes the division of tasks between humans and technologies, organisational information flows, managerial judgement and responsibility. AI therefore influences firms' internal governance structures by transforming established routines, competencies and control mechanisms (Pavaloaia and Necula, 2023; Sha et al., 2024).

While traditional corporate governance focuses on relationships among owners, managers and stakeholders, AI introduces additional governance layers involving data, machine learning models and AI systems as organisational resources and risks (Schneider et al., 2023). AI governance consequently addresses accountability, explainability, auditability, fairness, privacy, human involvement and regulatory alignment. Responsible governance requires structural, procedural and relational practices that translate ethical principles into managerial routines (Papagiannidis et al., 2025; Wiesmüller et al., 2023).

AI governance is closely linked to business performance, innovation and organisational readiness. Responsible governance can improve information management, reduce operational, ethical and legal risks, and support innovation through investment in human capital and strategic coordination (Xia et al., 2026; Xiong et al., 2026). However, AI implementation also creates challenges. Algorithmic bias may produce unfair marketing or HRM decisions (Akter et al., 2022; Maiti et al., 2025), while limited explainability can weaken trust and acceptance (Hamm et al., 2023; Chowdhury, Joel-Edgar, et al., 2023). Insufficient readiness may further hinder responsible AI integration (Chowdhury, Dey, et al., 2023; Kumar et al., 2026).

Table 1. Governance dimensions of AI implementation

Source: Authors' processing based on Schneider et al. (2023), Papagiannidis et al. (2025), Akter et al. (2022), Chowdhury, Dey, et al. (2023), Hamm et al. (2023), Maiti et al. (2025), Xia et al. (2026), Zhang and Vasarhelyi (2022) and Kumar et al. (2026).



AI governance should therefore be understood as an integrated managerial framework combining technical issues, including model quality and data security, with organisational, ethical and regulatory requirements concerning accountability, transparency, fairness, human oversight and compliance.

Table 1. shows that AI governance is a multidimensional managerial issue combining technical control with organisational responsibility, ethical principles, data quality, human oversight and regulatory compliance. Firms therefore require not only technical solutions, but also internal policies, defined roles, documentation, monitoring mechanisms and appropriate managerial competencies. Principles such as fairness, transparency and accountability must be translated into concrete organisational practices (Papagiannidis et al., 2025; Schneider et al., 2023).

The thematic analysis also indicates a gradual evolution of governance. Traditional corporate governance focused on control, reporting, compliance and managerial responsibility towards owners and stakeholders. Digital governance added data protection, cybersecurity and digital process

Governance dimension	Core question	AI-related challenge	Managerial response
Accountability	Who is responsible for AI outputs?	Unclear responsibility for AI-supported recommendations or decisions	Define clear ownership of AI systems, outputs and final decisions
Transparency	Can the system be understood?	Limited visibility of how AI systems process data and generate outputs	Require documentation, reporting and understandable information about AI use
Explainability	Can the output be justified?	Black-box models and difficult interpretation of algorithmic results	Use explainable AI methods and provide simple explanations for managers
Data governance	Are data reliable and protected?	Poor data quality, biased data, privacy and security risks	Establish data quality rules, access control and data protection procedures
Ethical governance	Is the system fair and responsible?	Algorithmic bias, discrimination and unintended social consequences	Apply ethical principles, fairness checks and responsible AI policies
Risk governance	What risks does AI create?	Operational, legal, cyber, reputational and strategic risks	Monitor AI systems, assess risks and introduce internal audit mechanisms
Human oversight	Where must humans remain involved?	Over-automation, overreliance on AI and weak managerial control	Keep human-in-the-loop mechanisms for high-impact decisions
AI maturity	Is the organisation ready to use AI responsibly?	Low AI literacy, weak competencies and fragmented implementation	Develop AI strategy, training, pilot projects and scaling mechanisms
Regulatory alignment	Is AI use legally compliant?	Changing regulation and unclear compliance requirements	Align AI use with legal requirements, internal rules and compliance control

management, while AI governance extends these areas to algorithms, training data, model outputs, bias, explainability and human oversight. Responsible adaptive governance represents the final stage, in which firms continuously monitor AI systems, update internal rules, manage emerging risks and align AI use with ethical and regulatory expectations (Sha et al., 2024; Xia et al., 2026).



Table 2. Evolution of governance paradigms under AI disruption

Stage	Governance paradigm	Dominant logic	Main management focus
1	Traditional corporate governance	Hierarchy, control and reporting	Compliance, managerial responsibility, performance and stakeholder control
2	Digital governance	Data, information systems and cybersecurity	Data protection, IT governance, digital processes and security
3	AI governance	Algorithms, accountability and explainability	AI systems, bias, auditability, transparency and human oversight
4	Responsible adaptive governance	Ethics, resilience and continuous oversight	Responsible AI, risk monitoring, regulatory alignment and organisational learning

Source: Authors' conceptual processing based on Schneider et al. (2023), Papagiannidis et al. (2025), Xia et al. (2026), Sha et al. (2024), Xiong et al. (2026), and Arora et al. (2025).

The framework in Table 2 shows AI governance as a new managerial layer. Traditional governance relies on authority, control and reporting, while digital governance adds data, IT systems and cybersecurity. AI governance introduces requirements concerning algorithms, model transparency, accountability and human oversight. Responsible adaptive governance represents the final stage, requiring continuous monitoring, organisational learning and flexible rules in changing technological, legal and social environments.

This evolution also transforms managerial roles. Managers must understand AI opportunities, limitations and risks, cooperate with technical, legal and data specialists, and remain accountable for organisational decisions and ethical AI use. Responsible adaptive governance therefore balances innovation, control and responsibility, particularly where AI affects employees, customers, financial decisions, risk assessment or public trust.

AI creates dynamic risks that cannot be addressed through one-time controls. Generative AI, large language models and machine learning systems may produce inaccurate, biased or unverifiable outputs, creating epistemic, ethical and operational risks (Awan et al., 2026). Effective governance must therefore manage output accuracy and business reliability (Hannigan et al., 2024), as well as fairness, transparency and stakeholder impacts (Wei et al., 2025), through continuous monitoring and verification.

Regulatory alignment is another major challenge. As AI regulation evolves in areas such as risk classification, privacy, safety, transparency and human oversight, firms need adaptable governance systems. Risk management must also reflect changing use cases, user groups and emerging hazards (Onitiu et al., 2025). Internal AI policies should therefore include documentation, risk assessments, audits and clear escalation procedures.

Organisational readiness is essential for effective governance. AI maturity involves understanding risks, defining responsibilities, ensuring data quality, training employees and aligning AI projects with strategy (Jirickova and Doucek, 2026). Firms need both technical and non-technical capabilities (Chowdhury, Dey, et al., 2023; Kumar et al., 2026), while institutional pressures, policy uncertainty and organisational culture also influence adoption (Zhang et al., 2025).

Overall, traditional corporate governance must be extended by digital and AI-specific mechanisms. The central challenge is connecting innovation with responsibility (Raisch and Krakowski, 2021). Clear AI governance can reduce bias, privacy, trust, accountability and compliance risks while supporting



transparency and sustainable innovation (Xia et al., 2026; Xiong et al., 2026). AI is therefore disruptive not only because it changes processes and tools, but also because it transforms how organisations control, justify and assume responsibility for their actions.

Conclusion

The aim of this paper was to analyse artificial intelligence as a disruptive technology that transforms traditional governance paradigms in management, with particular attention to accountability, transparency, ethical oversight, risk governance and organisational AI maturity. Using qualitative thematic content analysis of sources identified through targeted Web of Science searches, it developed a conceptual framework of governance transformation. The findings show that AI affects not only digital tools but also responsibility, data and algorithm control, explainability, risk management and human oversight.

The main contribution is a framework describing the evolution from traditional corporate governance to digital governance, AI governance and responsible adaptive governance. AI extends existing governance by introducing new requirements related to data, models, AI systems, ethics, transparency, explainability and regulatory alignment. Governance therefore shifts from formal control and reporting towards continuous oversight, organisational learning, ethical reflection and adaptive risk management. Managers should treat AI governance as a cross-functional responsibility involving top management, IT and data specialists, legal departments, risk managers and business units. Firms should establish AI policies, define system ownership, strengthen data governance, introduce explainability and audit mechanisms, and improve AI literacy. Future research should empirically test the framework across organisational contexts, including differences between large firms and SMEs, the role of AI maturity, regulatory impacts and responsible AI governance in Central European firms.

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Intelligent Education - How AI is Changing Traditional Educational Models

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Abstract

This article aims to analyse the impact of artificial intelligence (AI) on educational processes and practices in the context of modern educational strategies. Based on a systematic literature review and secondary data analysis, it assesses how AI is transforming traditional educational models and identifies key benefits, such as personalization of learning, automation of assessment, and integration of innovative technologies. The study provides evidence that AI can significantly contribute to improving educational outcomes and teaching effectiveness, but its deployment is also associated with ethical and practical challenges, including concerns about data protection and algorithmic bias. In conclusion, it is strongly recommended that the deployment of AI be accompanied by a critical assessment of its ethical context and the necessity of maintaining a human element in the pedagogical process.

Keywords

Artificial intelligence, education, ethics.

JEL Classification: I23, O33

Intelligentné vzdelávanie – Ako umelá inteligencia mení tradičné vzdelávacie modely

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Abstrakt

Tento článok sa zameriava na analýzu vplyvu umelej inteligencie (AI) na vzdelávacie procesy a praktiky v kontexte moderných vzdelávacích stratégií. Na základe systematického prehľadu literatúry a sekundárnej analýzy dát hodnotí, ako AI transformuje tradičné vzdelávacie modely a identifikuje kľúčové prínosy, ako je personalizácia učenia, automatizácia hodnotenia a integrácia inovatívnych technológií. Štúdia podáva dôkazy o tom, že AI môže výrazne prispieť k zlepšeniu vzdelávacích výsledkov a efektivity vyučovania, avšak táto implementácia je tiež spojená s etickými a praktickými výzvami, vrátane obáv o ochranu dát a algoritmickú zaujatosť. Záverom sa dôrazne odporúča, aby zavádzanie AI bolo sprevádzané kritickým zhodnotením jej etického kontextu a nutnosťou udržania ľudského elementu v pedagogickom procese.

Kľúčové slová

Umelá inteligencia, vzdelávanie, etika.

JEL Klasifikácia: I23, O33

Úvod

V poslednom období sa umelá inteligencia (AI) a digitálne technológie stali kľúčovými faktormi transformácie vo vzdelávacích stratégiách. Podľa výskumov v oblasti vzdelávacích technológií, napríklad prácou Zhang et al. (2024) a Mariappan et al. (2024), inovácie v technológiách posúvajú hranice možného a umožňujú školám a pedagógom novými spôsobmi objavovať a prispôbovať výučbu podľa potrieb študentov. Tieto zmeny ponúkajú nielen nové príležitosti, ale aj nové výzvy. Treba sa zamerať na etické aspekty a uistiť sa, že technológie sa využívajú spôsobom, ktorý je spravodlivý a inkluzívny.

AI má obrovský potenciál v oblasti personalizácie vzdelávacích skúseností (Alshahrani, 2023). Ďalej je dôležité reflektovať kultúrne dimenzie a inovačné prístupy v návrhu vzdelávacích prostredí, čo môže viesť k väčšej flexibilita a adaptabilita (Vezhbovska et al., 2024). Tento článok sa zameriava na to, ako AI mení tradičné vzdelávacie modely, a hodnotí jej prínosy a súvisiace výzvy.

Metodológia

Tento článok je založený na podrobnom prehľade literatúry a sekundárnej analýze dát, ktoré boli použité na preskúmanie vplyvu umelej inteligencie (AI) na vzdelávacie praktiky. Štúdia sa zamerala na zhromažďovanie a analýzu dostupných štúdií, prieskumov a prípadových štúdií, ktoré sa zaoberali kľúčovými aspektmi použitia AI vo vzdelávaní.

Inicializovali sme systematické vyhľadávanie, ktoré zahŕňalo akademické databázy, odborné časopisy a priemyselné správy s cieľom zhromaždiť relevantnú literatúru zameranú na efektivitu AI vo vzdelávaní. Osobitná pozornosť bola venovaná porovnávacej analýze výsledkov štúdií, ktoré osvetlili výhody a výzvy spojené s implementáciou AI vo vzdelávacích kontextoch. Toto úsilie umožnilo formulovanie odporúčaní a záverov, ktoré môžu školám pomôcť optimalizovať ich vzdelávacie stratégie prostredníctvom efektívneho využitia moderných technológií.



Výsledky

Umelá inteligencia sa uplatňuje v niekoľkých kľúčových oblastiach vzdelávania, pričom každá z nich ponúka konkrétne príklady využitia, ktoré demonštrujú jej prínosy.

Kľúčové oblasti AI vo vzdelávaní

Umelá inteligencia umožňuje **personalizované vzdelávanie**, čo znamená, že vzdelávacie skúsenosti sa prispôbujú individuálnym potrebám študentov. Môžeme to vidieť napríklad pri inteligentných výukových systémoch, ktoré poskytujú študentom individuálne inštrukcie a spätnú väzbu bez nutnosti zásahu učiteľa. Tento prístup je základným kameňom pre koncept Education 4.0, ktorý sa zameriava na technologicky podporované a bohaté učebné zážitky (Mukul a Büyüközkan, 2023).

Inovatívne technológie, ako sú virtuálna realita (VR) a rozšírená realita (AR), prispievajú k vytvoreniu interaktívneho a pútavého prostredia pre študentov (Núñez-Canal et al., 2021). Tieto technológie tiež umožňujú virtuálnym učiteľom a avatarom efektívne zvyšovať úroveň výučby a interakcie, čo vedie k lepšiemu porozumeniu učebného materiálu.

AI tiež významne **podporuje učiteľov** v ich každodennej práci tým, že uľahčuje hodnotenie a plánovanie vyučovacích hodín. Pedagógom poskytuje rýchle analýzy relevantných dát (Vallis et al., 2023), čo znižuje administratívnu záťaž a umožňuje im sústrediť sa na kvalitu výučby. Príkladom môže byť automatizované hodnotenie písomných prác, ktoré AI vykonáva pomocou techník strojového učenia, identifikuje gramatické chyby a ďalšie prvky.

Ďalším dôležitým aspektom je **analýza a hodnotenie výkonu**. Generatívna AI poskytuje realistickú analýzu, ktorá pomáha pedagógom efektívnejšie riadiť výučbu a identifikovať oblasti, kde študenti potrebujú ďalšiu podporu (Rosa-García, 2024). Systémy AI tiež umožňujú sledovanie aktivít študentov na online fórach a poskytovanie automatických spätných väzieb na ich príspevky, čo prispieva k aktívnej účasti vo vyučovacom procese.

Avšak, výskum vplyvu umelej inteligencie na vzdelávanie založený na dôkazoch je zatiaľ obmedzený, a preto je dôležité zachovať si kritický prístup k jej nasadeniu.

Pozitíva AI vo vzdelávaní

AI ponúka množstvo pozitív, ktoré môžu významne prispieť k zlepšeniu vzdelávacích výstupov, efektivity výučby a celkovej vzdelávacej skúsenosti.

Jedným z hlavných prínosov implementácie AI do vzdelávania je **zlepšenie vzdelávacích výsledkov**. Personalizácia učebných skúseností, umožnená pomocou algoritmov strojového učenia, vedie k väčšiemu zapojeniu študentov, aj vyšším výkonom (Alshahrani, 2023). Individuálne prispôbované učebné plány a materiály reflektujú špecifické potreby študentov, čo zvyšuje ich motiváciu a zrýchľuje proces učenia. Týmto spôsobom AI pomáha prekonávať tradičné bariéry, ktoré môžu brániť efektívnejšiemu vzdelávaniu.

AI technológie tiež výrazne **zefektívňujú procesy hodnotenia a analýzy**. Vďaka automatizácii týchto procesov môžu učitelia rýchlejšie reagovať na potreby študentov a zamerať sa na oblasti vyžadujúce ďalšiu podporu (Vallis et al., 2023). Týmto spôsobom sa znižuje administratívna záťaž



učiteľov, čo im umožňuje viac sa sústrediť na samotnú výučbu. Rýchla analýza dát poskytuje cenné informácie o pokroku študentov, čo prispieva k efektívnejšiemu plánovaniu pedagogických stratégií.

Technológie ako virtuálna realita (VR) a rozšírená realita (AR) tiež obohacujú učebný proces o **inovatívne metódy učenia** ako realistické a interaktívne zážitky, ktoré lepšie zapájajú študentov (Núñez-Canal et al., 2021). Tieto technológie umožňujú praktické a vizuálne učenie, čo môže byť rozhodujúce pre rozvoj kritického myslenia a kreatívneho riešenia problémov. Interakcia s dynamickými učebnými materiálmi robí vzdelávanie atraktívnejším a efektívnejším.

AI tiež prispieva k **širšiemu prístupu k vzdelaniu** tým, že poskytuje výukové materiály a nástroje, ktoré by inak boli nedostupné pre určité skupiny študentov (Vezhbovska et al., 2024). Napríklad študentom v odľahlých oblastiach alebo s obmedzenými zdrojmi môžu byť ponúknuté online platformy a digitálne nástroje, ktoré umožňujú prístup k vysoko kvalitnému vzdelaniu. Týmto spôsobom AI prispieva k znižovaniu vzdelávacích nerovností a zaisťuje rovnosť príležitostí pre všetkých študentov.

Avšak, výskum vplyvu umelej inteligencie na vzdelávanie založený na dôkazoch je zatiaľ obmedzený, a preto je dôležité zachovať si kritický prístup k jej nasadeniu.

Negatíva AI vo vzdelávaní

Využívanie umelej inteligencie (AI) v edukačnom prostredí so sebou nesie množstvo negatív, ktoré si zaslúžia pozornosť. Prvým zásadným negatívom je **nerovnosť v prístupe k technológiám**. Rôzne úrovne technologickej infraštruktúry v rámci rôznych škôl či regiónov môžu spôsobiť, že nie všetci študenti majú rovnaké príležitosti na využívanie výhod AI. Ako uvádzajú Ali et al. (2024), tento rozdiel v prístupe môže prehĺbvať existujúce vzdelávacie nerovnosti, čím sa zvyšuje pravdepodobnosť, že niektoré skupiny študentov budú marginalizované a nebudú schopné plne využiť potenciál, ktorý AI ponúka.

Ďalej je potrebné sa zaoberať **závislosťou na technológiách**, ktorá sa v prípade nadmerného využívania AI ukazuje ako skutočný problém. Zhou a Schofield (2024) poukazujú na to, že nadmerná závislosť na AI môže narušiť medziľudské vzťahy a interakcie medzi študentmi a učiteľmi. Takéto interakcie sú kľúčové pre komplexný vývoj študentov, pretože prispievajú k rozvoju kritického myslenia a emocionálnej inteligencie, ktoré sú dnes nevyhnutné. Ak sa študenti spoliehajú na technológie namiesto osobného kontaktu, môže to viesť k oslabeniu komunikačných zručností a sociálnych väzieb, ktoré sú tak dôležité pre ich osobný a profesionálny rast.

K ďalším predpokladaným negatívam patrí aj **znižovanie transparentnosti a autenticity vzdelávacích materiálov**. Používanie AI generovaného obsahu môže viesť k pochybnostiam o pôvode a kvalite týchto materiálov (Rosa-García, 2024). Takéto obavy môžu mať značný dopad na motiváciu a dôveru študentov vo vzdelávací proces. Kým AI môže generovať obsah rýchlo a efektívne, chýba mu často presnosť a hĺbka, ktorú môže poskytnúť tradičné vzdelávanie, ktoré sa opiera o dôkladnú analýzu a kritické hodnotenie.



Diskusia

Integrácia umelej inteligencie (AI) do vzdelávacích praktík predstavuje značný potenciál pre transformáciu spôsobu, akým sa učíme a vyučujeme. Ako ukazujú štúdie, AI môže výrazne zefektívniť individualizáciu vzdelávania a prispôbiť obsah špecifickým potrebám a štýlom učenia jednotlivých študentov. Avšak, s týmto potenciálom prichádzajú aj závažné etické výzvy, ktoré treba starostlivo zvažovať.

Jedným z najväčších obáv je ochrana súkromia dát a možnosť zaujatosti v algoritmoch AI. Táto zaujatosť môže viesť k nespravodlivým výsledkom vzdelávania, čo vyvoláva otázky o férovosti a rovnosti v prístupe k vzdelaniu. Je nevyhnutné zabezpečiť, aby sa technológie využívali v súlade s etickými princípmi a aby sa predišlo diskriminácii na základe rôznych faktorov, ako sú sociálno-ekonomické postavenie alebo pôvod študentov (Nguyen et al., 2022). Bez riadneho dohľadu a etického rámca môže AI zhoršiť už existujúce nerovnosti, čo by malo závažné dopady na celé generácie študentov.

Kombinácia AI s ľudským dohľadom sa ukazuje ako kľúčová pre dosiahnutie optimálnych vzdelávacích výsledkov. Aj keď AI môže zefektívniť procesy a priniesť inovatívne prístupy, je nevyhnutné mať na pamäti, že emocionálne nuansy a osobné vzťahy sú stále zásadné pre učenie. Človek zohráva kľúčovú úlohu v efektívnej implementácii AI do vzdelávania, ako naznačujú Sharma a Singh (2023). Učitelia nielenže pomáhajú pri prispôbovaní technologických nástrojov konkrétnym potrebám študentov, ale tiež vytvárajú prostredie, v ktorom sa študenti môžu cítiť podporovaní a inšpirovaní.

Ďalej je dôležité priznať, že nadmerná reliancia na AI môže viesť k oslabeniu medziľudských interakcií a sociálnych zručností, ktoré sú kľúčové pre budúci úspech študentov. Vzdelávanie nie je iba o prenose znalostí; zahŕňa aj rozvoj zručností, ako je tímová práca, empatia a komunikácia. Tieto schopnosti sú pre život v digitálnom svete stále dôležitejšie a bez správneho vyváženia medzi technológiami a ľudským kontaktom môžu byť ohrozené (Sucidha, 2025).

Celkovo možno povedať, že aj keď AI má obrovský potenciál na zlepšenie učebných procesov, je kľúčové zapojiť kritický pohľad na etické a praktické výzvy, ktoré sa s touto integráciou spájajú. Zodpovedné a efektívne využívanie AI vo vzdelávaní vyžaduje starostlivé zváženie vplyvu na študentov a zabezpečenie, aby sa technológia stala podporou, nie náhradou ľudského prístupu k učeniu.

Záver

Na základe analytických zistení možno konštatovať, že integrácia umelej inteligencie do vzdelávacích praktík predstavuje významný krok smerom k inováciám vo vzdelávaní. S možnosťami personalizácie a automatizácie sa AI ukazuje ako mocný nástroj na zefektívnenie vzdelávacích procesov. Na to, aby bolo možné plne využiť jej potenciál, je nevyhnutné zohľadniť etické implikácie, ako sú ochrana osobných údajov a otázky spravodlivosti v prístupe k technológiám. Zároveň je kľúčové, aby AI bola nasadená v synerгии s ľudským dohľadom, čo umožní nielen efektívne zdroje učenia, ale aj podporu reflexívneho a interaktívneho prostredia, ktoré je zásadné pre komplexný rozvoj študentov. Vzhľadom na naliehavosť týchto otázok je dôležité pokračovať v multidisciplinárnom výskume, ktorý sa zameria na vyváženie technologických inovácií s etickými normami a kvalitou vzdelávacích skúseností.



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Linking Artificial Intelligence to Firm-Level Financial Outcomes: Insights from Industry 4.0 Transformation

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Abstract

Artificial intelligence (AI) is widely recognized as a key force in Industry 4.0, transforming production systems, logistics processes, and even entire business models. While many studies describe its technological and organizational benefits, the financial implications at the level of individual firms, especially in transition economies, have not yet been sufficiently clarified. Previous research on digital transformation often stresses improvements in efficiency and innovation; however, it is still uncertain how these translate into profitability, liquidity, solvency, or long-term financial stability. This study conceptually analyses the connection between AI adoption and corporate financial performance. The framework that links AI-driven transformation with traditional financial indicators and suggests mechanisms through which AI can strengthen and weaken financial outcomes was developed. Building on insights from the literature on AI, Industry 4.0, and corporate finance, five main channels of influence are identified: operational efficiency, revenue generation, risk management, capital intensity, and strategic uncertainty. For each channel, corresponding indicators, such as profitability ratios, liquidity measures, leverage, efficiency metrics, and cash flow data, are proposed. The results highlight the paradoxical nature of AI adoption: it may bring competitive advantages while simultaneously creating new financial risks. The contribution of this study lies in combining technological and financial perspectives, thus offering a basis for empirical work and practical guidance for managers and policymakers seeking to align digital transformation with financial sustainability.

Keywords

artificial intelligence, financial performance, Industry 4.0, digital transformation, corporate sustainability

JEL Classification: G32, M21, O33



Prepojenie umelej inteligencie s finančnými výsledkami na podnikovej úrovni: Poznatky z transformácie Priemyslu 4.0

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Abstrakt

Umelá inteligencia (AI) je všeobecne uznávaná ako kľúčová sila v Priemysle 4.0, ktorá transformuje výrobné systémy, logistické procesy a dokonca aj celé obchodné modely. Zatiaľ čo mnohé štúdie popisujú jeho technologické a organizačné výhody, finančné dôsledky na úrovni jednotlivých firiem, najmä v tranzitívnych ekonomikách, ešte nie sú dostatočne objasnené. Predchádzajúci výskum digitálnej transformácie často zdôrazňuje zlepšenie efektívnosti a inovácie; stále však nie je isté, ako sa tieto premietnu do ziskovosti, likvidity, solventnosti alebo dlhodobej finančnej stability. Táto štúdia koncepcne analyzuje spojenie medzi prijatím AI a finančnou výkonnosťou spoločnosti. Bol vyvinutý rámec, ktorý spája transformáciu riadenú AI s tradičnými finančnými ukazovateľmi a navrhuje mechanizmy, prostredníctvom ktorých môže AI posilniť a oslabiť finančné výsledky. Na základe poznatkov z literatúry o AI, Industry 4.0 a podnikových financiách bolo identifikovaných päť hlavných kanálov vplyvu: prevádzková efektívnosť, tvorba výnosov, riadenie rizík, kapitálová náročnosť a strategická neistota. Pre každý kanál sú navrhnuté zodpovedajúce ukazovatele, ako sú ukazovatele ziskovosti, miery likvidity, pákový efekt, metriky efektívnosti a údaje o peňažných tokoch. Výsledky poukazujú na paradoxnú povahu prijatia AI: môže priniesť konkurenčné výhody a súčasne vytvárať nové finančné riziká. Prínos tejto štúdie spočíva v spojení technologických a finančných perspektív, čím ponúka základ pre empirickú prácu a praktické usmernenia pre manažérov a tvorcov politik, ktorí sa snažia zosúladiť digitálnu transformáciu s finančnou udržateľnosťou.

Kľúčové slová

umelá inteligencia, finančná výkonnosť, Priemysel 4.0, digitálna transformácia, udržateľnosť spoločnosti

JEL Klasifikácia: G32, M21, O33



Introduction

In recent years, artificial intelligence (AI) has developed into one of the most transformative technologies of the 21st century. Its applications are no longer limited to experimental projects but increasingly affect production systems, supply chains, services, and managerial decision-making (Kovacova et al., 2024). Consequently, AI is reshaping the ways in which firms generate value and maintain competitiveness in global markets (Andronie et al., 2024; Lazaroiu et al., 2024). Within the broader framework of Industry 4.0, AI supports various functions, such as smart manufacturing, predictive maintenance, automated logistics, and advanced data analytics. These solutions are generally associated with higher efficiency and greater organizational responsiveness (Valaskova et al., 2024). A concrete example can be found in transportation, where AI enables real-time fleet optimization and predictive routing, and in manufacturing, it contributes to improved quality control and shorter downtimes. Altogether, these capabilities indicate that AI adoption may influence corporate financial performance by lowering costs, opening new revenue streams, and stabilizing operational processes (Valaskova et al., 2025).

Despite the growing enthusiasm surrounding AI, its financial implications remain unclear. The introduction of AI systems usually requires considerable capital investment, organizational restructuring, and the recruitment or training of specialized staff. As Danielsson and Uthemann (2025) argue, these requirements can put pressure on liquidity and reduce short-term profitability, while the expected long-term advantages remain uncertain and are often unevenly realized across firms. For companies operating in transition economies, particularly in Central and Eastern Europe, the situation is even more demanding. Limited access to financial resources and lower absorptive capacity, compared to Western European firms, tend to intensify the risks associated with adoption. Therefore, the link between AI integration and corporate financial performance cannot be considered straightforward, and there is a pressing need for systematic research to clarify the mechanisms underlying this relationship.

Based on these observations, this study raises the following research questions:

1. How does AI adoption influence traditional measures of corporate financial performance, including profitability, liquidity, leverage, and efficiency?
2. What mechanisms explain the positive and negative financial outcomes associated with AI's implementation?
3. Which financial indicators are most relevant for assessing the success or failure of AI adoption at the firm level?
4. How can conceptual frameworks contribute to future empirical research, especially in the context of transition economies and Industry 4.0 sectors, such as manufacturing and logistics?

The primary objective of this study is to propose a conceptual framework that connects the adoption of AI with corporate financial performance. The framework is developed based on existing scholarly work and insights from managerial practice. In particular, this study aims to clarify the mechanisms through which AI can shape financial outcomes, suggest indicators suitable for capturing these effects, and emphasize the paradoxical nature of AI adoption as a potential source of both



competitive advantage and financial vulnerability. Thus, this study lays the groundwork for future empirical analyses and adds to the broader discussion on digital transformation and firm performance.

This study proceeds in several steps. The Literature review section summarizes the relevant literature on AI in business and its implications for firm-level performance. The Objectives and methodology section introduce the conceptual approach and outlines the proposed framework. The Discussion section develops the main implications, focusing on managerial challenges, regional conditions, and opportunities for further empirical testing. Finally, the Conclusions section summarizes the key arguments and offers recommendations for researchers and practitioners.

Theoretical starting points

The academic literature on AI and corporate performance has grown considerably over the past decade, reflecting the rapid adoption of digital technologies across industries. Nevertheless, evidence on how AI specifically affects financial outcomes at the firm level remains fragmented and is sometimes contradictory. This section reviews and synthesizes three streams of research: studies on AI and technological transformation in business, analyses of financial performance and its determinants, and recent attempts to connect digitalization with financial outcomes (Andronie et al., 2024).

Research on AI in business emphasizes its role as a general-purpose technology that drives structural changes across sectors (Kshetri, 2024). In manufacturing, AI-based solutions are commonly applied to predictive maintenance, quality inspection, and robotics integration applications. These applications are expected to enhance efficiency by reducing machine downtime, minimizing errors, and increasing the throughput (Valaskova et al., 2024). In logistics, AI contributes to dynamic route optimization, real-time demand forecasting, and intelligent warehousing, leading to improved asset utilization (Kliestik et al., 2024). In the financial services sector, AI is already embedded in risk scoring, credit allocation, and fraud detection systems, often producing immediate cost savings and accuracy (Balcerzak and Valaskova, 2024). Despite these advances, most studies tend to highlight technical feasibility or operational benefits rather than explicitly linking them to firm-level financial indicators.

The second research stream focuses on financial performance, which is generally measured through profitability, liquidity, leverage, and efficiency ratios (Valaskova et al., 2025). Kaplan and Norton (1996) introduced the Balanced Scorecard framework, where financial measures represent the ultimate reflection of strategic success. However, scholars increasingly recognize that financial indicators are influenced not only by market conditions and managerial decisions but also by technology adoption. According to Valaskova et al. (2025), whether new technologies translate into superior financial performance has been central to innovation management studies. Keelson et al. (2024) note that digitalization can simultaneously enhance competitiveness and destabilize financial structures, creating a duality that requires careful examination.

The third stream of literature directly addresses the intersection of digitalization and financial outcomes. Dachs and Wolfmayr (2025) report that the implementation of Industry 4.0 technologies in German firms led to notable productivity improvements, although profitability effects materialized only after significant time lags. Nagy et al. (2025) argue that the financial benefits of digitalization are contingent upon dynamic capabilities, meaning that firms must integrate technological adoption with



organizational learning and managerial flexibility. Conversely, He et al. (2025) caution that AI investments often generate uneven returns: large firms and technologically advanced economies reap disproportionate benefits, whereas smaller firms may experience financial strain without achieving comparable performance improvements. Several studies have provided evidence from specific sectors. In logistics, AI-enabled predictive analytics have been associated with cost savings and improved margins; however, these gains are often offset by high initial investments and ongoing software costs (Demirova and Koleva, 2024). In manufacturing, digital technologies reduce operational costs but increase capital intensity, thereby raising the risk of over-leveraging (Valaskova et al., 2024). In Central and Eastern Europe, Zhao and Chen (2025) demonstrate that firms face challenges in absorbing digital technologies because of weaker R&D intensity and limited innovation ecosystems. This suggests that the financial outcomes of AI adoption may be context-dependent and shaped by both firm-level capabilities and institutional environments.

Taken together, the literature reveals three critical insights. First, although AI is widely recognized as a transformative force across industries, its financial consequences remain underexplored. Second, the impact of AI on financial performance is not uniform; it varies by sector, firm size, and absorptive capacity. Third, there is a research gap in analysing AI adoption in transition economies, where financial constraints may hinder its successful implementation. This gap provides an opportunity for conceptual and empirical studies that directly connect AI adoption with firm-level financial indicators using robust theoretical frameworks and comparative data.

Objectives and methodology

The methodological approach adopted in this study is conceptual and theory-building, rather than empirical. This choice was motivated by two considerations. First, although empirical research on AI and financial performance is gradually emerging, the findings are fragmented and context-dependent. A conceptual approach allows for the integration of insights from different streams of literature into a coherent framework that can guide future empirical research. Second, this study aims to establish plausible mechanisms and indicators linking AI adoption to firm-level financial outcomes. This study aims to provide a structured foundation for subsequent quantitative analyses using large-scale datasets.

The conceptual framework was developed in three stages as follows. The first stage involved a systematic review of academic and practitioner-oriented literature on AI adoption, digital transformation, and financial performance topics. This review includes scholarly articles on innovation management, operations, and finance, as well as industry reports from consulting firms such as McKinsey and Deloitte. The purpose of this stage was to identify recurring themes regarding the benefits and risks of AI adoption.

In the second stage, the identified themes were translated into potential mechanisms of financial influence. Five mechanisms were distilled: operational efficiency, revenue enhancement, risk management, capital intensity, and strategic uncertainty. Operational efficiency refers to the cost reductions and productivity improvements resulting from automation and optimization. Revenue enhancement captures AI's ability to support new business models and create additional revenue streams (Li et al., 2025). Risk management highlights the potential of predictive analytics to stabilize cash flow



and improve forecasting accuracy. Danielsson and Uthemann (2025) concluded that capital intensity emphasizes the significant investments required for AI adoption, which affect leverage, depreciation, and balance-sheet structures. Strategic uncertainty refers to the risk of failed implementation, technological obsolescence, and misalignment between digital strategies and organizational capabilities.

The third stage focused on selecting financial indicators that best reflect these mechanisms (Danielsson and Uthemann, 2025). Profitability indicators such as Return on Assets (ROA), Return on Equity (ROE), and EBIT margin are particularly relevant for capturing revenue enhancement and efficiency effects (Anang et al., 2025). Liquidity measures, including current and quick ratios, provide insights into short-term solvency pressures arising from high initial investments (He et al., 2025). Leverage indicators, such as the Debt-to-Equity and Debt-to-Assets ratios, are crucial for assessing the implications of capital intensity (Kovalova et al., 2025). Efficiency ratios, including asset turnover and inventory turnover, are relevant for evaluating how effectively AI-enabled processes utilize resources in the company. Cash flow indicators, particularly operating cash flow relative to total debt, offer a dynamic perspective on financial resilience. Moreira et al. (2025) stated that these indicators are complemented by established composite measures such as the Altman Z-score, which provides a benchmark for financial distress.

The methodological framework has some limitations. As it is conceptual, it does not empirically test causal relationships; rather, it maps possible pathways and identifies measurable variables for future research. Furthermore, the selection of mechanisms and indicators, while grounded in the literature, cannot capture the full heterogeneity of AI adoption across industries and countries in the future. Nevertheless, the strength of this approach lies in its ability to synthesize diverse perspectives into a unified model, offering both scholars and practitioners a structured lens for examining the financial consequences of AI (Skypalova et al., 2025).

The methodology of this study builds a bridge between theory and practice. It connects abstract discussions about AI's transformative potential with concrete financial metrics that can be operationalized in empirical research. This conceptual groundwork sets the stage for research designs employing firm-level data and advanced analytical techniques, including decision trees and other machine learning methods, to test the propositions developed here.

Results and Discussion

The conceptual framework developed in this study emphasizes the dual nature of AI's impact on corporate financial performance. AI offers opportunities for operational efficiency, revenue growth and improved risk management. However, it also generates significant financial risks through high capital intensity and strategic uncertainty. This ambivalence creates a paradox: firms increasingly perceive AI adoption as essential for maintaining competitiveness, yet the financial outcomes remain highly uncertain (Keelson et al., 2024). Table 1 summarizes this paradox by juxtaposing the main opportunities and risks that AI adoption entails for corporate financial performance.



Table 1. The paradox of AI adoption – opportunities and risks for corporate financial performance

Domain	Potential opportunities	Potential risks
Operational efficiency	Cost savings Predictive maintenance Automation	High capital intensity Long payback periods
Revenue growth	New products and services Enhances customer experience	Uncertain market acceptance High innovation costs
Risk management	Fraud detection Credit scoring More accurate forecasting	Regulatory and compliance costs Cybersecurity vulnerabilities

Source: Raza et al. (2025) and Mura and Stehlikova (2025)

From a managerial perspective, this paradox implies that AI should not be viewed merely as a technological upgrade but as a strategic investment with profound financial implications for organizations. Firms that rush into AI adoption without carefully assessing their financial capacity may jeopardize their liquidity and solvency. Conversely, firms that delay adoption risk losing their competitive advantage in rapidly digitalizing markets. Therefore, the challenge for managers is to align AI strategies with sound financial management. As stated by Balczerzak and Valaskova (2024), this requires thorough cost–benefit analyses, scenario planning, and the integration of financial key performance indicators into the digital transformation roadmaps.

The discussion also reveals that the financial effects of AI adoption are sector specific. In manufacturing industries, where asset utilization and production efficiency are central, AI-enabled predictive maintenance and automation can yield substantial savings (Lazaroiu et al, 2024). However, these benefits typically materialize only after long payback periods, making firms vulnerable to short-term liquidity pressures. In logistics and transportation, AI technologies can reduce operational costs by optimizing fleet management and warehouse operations; however, profitability gains may be eroded by high software subscription fees, infrastructure costs, and cybersecurity requirements (Demirova and Koleva, 2024). In financial services, AI may deliver immediate improvements in risk management and fraud detection; however, regulatory compliance and data governance create additional cost burdens. Based on the results of Valaskova et al. (2025), these sectoral differences underscore the need for industry-specific research on AI and financial performance.

The regional context further shapes the financial outcomes of AI adoption. In Central and Eastern Europe, particularly within the Visegrad (V4) countries, firms face structural challenges such as lower R&D intensity, limited access to venture capital, and weaker innovation ecosystems than in Western Europe (Nagy et al., 2025). These factors reduce absorptive capacity and may delay the realization of financial benefits from AI investment. Simultaneously, V4 firms often operate in industries tightly integrated into global value chains, such as automotive manufacturing and logistics (He et al., 2025). This creates both pressure and opportunity: global customers increasingly expect suppliers to embrace digital technologies, but the financial constraints of local firms can hinder these transitions. For



policymakers, this suggests the need for targeted support measures, such as subsidies, tax incentives, or innovation grants, to lower the financial barriers to AI adoption.

The proposed framework also has implications for corporate governance and stakeholder management. Shareholders and investors are often keen to see rapid returns on technological investments; however, the financial trajectory of AI adoption is typically nonlinear. He et al. (2025) concluded that the early phases may be characterized by declining liquidity and profitability as investments are made, followed by gradual recovery and potential long-term gains. Transparent communication of these dynamics is essential for maintaining investor confidence. Moreover, creditors and lenders should be aware that AI adoption, while strategically important, may temporarily increase financial risk, especially in firms with high leverage.

Another implication of this discussion concerns the methodological opportunities for future research. Although this study adopts a conceptual approach, the framework can be empirically tested using firm-level financial data combined with information on AI adoption. For instance, databases such as ORBIS provide balance sheet and profit-and-loss data, which can be used to calculate the financial indicators identified here. The main challenge is identifying which firms have adopted AI. Possible approaches include surveys, text mining of annual reports, and integration with external databases documenting digital transformation projects (Savitska, 2025). Once such datasets are compiled, machine learning methods, such as decision trees, random forests, or gradient boosting, can be employed to assess which financial indicators most reliably distinguish between firms that succeed and those that fail in AI adoption (Kovacova et al., 2024). According to Nagy et al. (2025), this would allow researchers to move beyond descriptive correlations and toward predictive modelling.

Cross-country comparisons represent a promising avenue for future research. As institutional and financial contexts vary significantly across countries, the impact of AI adoption on financial performance may also differ. As stated by Dachs and Wolfmayr (2025), firms in Germany may benefit from strong institutional support and established innovation ecosystems, whereas firms in Poland or Slovakia may face tighter credit constraints. Therefore, comparative studies could illuminate how contextual factors shape financial outcomes. Such research would also provide valuable insights for policymakers seeking to design supportive environments for digital transformation in the hospitality industry.

Finally, the discussion highlights the normative implications of the adoption of AI. Beyond firm-level performance, widespread AI adoption has systemic consequences for labour markets, capital allocation, and economic resilience (Lazaroïu et al, 2024). Firms that adopt AI may achieve financial gains, but these may come at the cost of workforce reductions or increased inequality between technologically advanced and lagging firms. According to Chatterjee et al. (2025), understanding the financial dimension of AI is important not only for corporate strategy but also for broader societal debates about the future of work and economic development.

The discussion underscores that AI adoption cannot be evaluated solely through a technological perspective. Its financial consequences are contingent on sectoral characteristics, regional contexts, managerial decisions, and institutional environments. By situating AI within the broader discourse on financial performance, this study contributes to a more balanced and realistic understanding of digital transformation.



Conclusion

This study examined the conceptual linkages between AI adoption and corporate financial performance, situating the discussion within the broader context of Industry 4.0 and digital transformation. The analysis highlights that AI is not merely a technological innovation but a phenomenon with profound financial consequences for firms. While AI can act as a catalyst for improved efficiency, profitability, and risk management, it simultaneously has the potential to increase capital intensity, strain liquidity, and heighten strategic uncertainty.

Several conclusions emerge from this conceptual framework and discussion. AI adoption exerts its influence through identifiable mechanisms such as operational efficiency, revenue enhancement, risk management, capital intensity, and strategic uncertainty. Each mechanism corresponds to established financial indicators, such as profitability ratios, liquidity and leverage measures, efficiency metrics and cash flow ratios. These indicators provide a structured basis for assessing the benefits and risks of AI implementation.

The financial impact of AI is not uniform. Sectoral differences are pronounced: in manufacturing, benefits often accrue from predictive maintenance and automation, whereas in logistics, gains arise from route optimization and inventory management. However, in both cases, high upfront costs can depress short-term financial results. Similarly, regional contexts are important. Firms in Central and Eastern Europe, particularly within the Visegrad countries, face greater constraints in financing AI adoption and lower absorptive capacity, which may delay or diminish financial benefits compared to those in Western Europe. This suggests that institutional environments and access to resources critically shape the trajectory of AI financial outcomes.

The conceptual framework developed in this study underscores the paradoxical nature of AI adoption. For managers, it is both an opportunity and a risk: failure to adopt may erode competitiveness, yet premature or poorly financed adoption may push firms into financial distress. Therefore, sound financial planning, careful assessment of liquidity and leverage, and alignment of AI strategies with organizational capabilities are indispensable. For corporate governance, transparent communication with investors and creditors regarding the expected financial trajectory of AI projects is essential to sustain confidence during periods of short-term strain.

The analysis has implications for policymakers. If governments seek to accelerate digital transformation in manufacturing and transportation, they must recognize the financial barriers that firms, especially small and medium-sized enterprises, face when investing in AI. Policy instruments, such as targeted subsidies, tax incentives, favourable credit schemes, and innovation grants, can mitigate risks and increase the likelihood that AI adoption translates into sustainable financial performance. Strengthening institutional frameworks and innovation ecosystems in Central and Eastern Europe is crucial to ensure that firms in these regions are not left behind in the global digital race.

Finally, this study provides clear directions for future research. Empirical validation of the conceptual framework is essential. Firm-level datasets such as ORBIS can be employed to calculate financial indicators and, when combined with data on AI adoption, to test the propositions outlined in this study. Advanced analytical methods, including decision trees and ensemble learning, can identify the financial indicators that most reliably predict successful or unsuccessful AI adoption. Comparative



studies across sectors and countries would further clarify the contextual factors that mediate these financial outcomes. Beyond firm-level analysis, research should explore the systemic consequences of AI, including its impact on capital markets, employment structures, and economic resilience.

In conclusion, AI represents both a transformative force and financial challenge. Its adoption must be understood not only in terms of technological feasibility but also in relation to corporate financial performance. The framework developed in this study offers a starting point for such an integrated perspective. By linking AI adoption to measurable financial indicators, it provides scholars with a foundation for empirical investigation and offers managers and policymakers tools for more informed decision-making. The duality of AI as both a driver of competitiveness and a source of financial risk underscores the importance of aligning technological ambition with financial prudence. Only through such alignment can firms, especially those in transition economies, harness the full potential of AI while safeguarding their financial sustainability in the long term.

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AI Literacy And Media Education: Preparing The Next Generation For The Age Of Intelligent Machines

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Abstract

The diffusion of generative artificial intelligence has changed the epistemic conditions of media use, production and circulation. Search, summarization, recommendation, image synthesis and conversational interfaces now mediate how young people encounter knowledge, create school assignments and judge credibility. This article argues that AI literacy should be integrated into media education rather than treated as a separate technical specialization. Using an integrative review of recent scholarship and a secondary analysis of major 2024–2025 survey reports, the study identifies six competence domains required for the age of intelligent machines: functional understanding of AI systems, prompt and interaction literacy, verification and evidentiary reasoning, bias and representation analysis, data and platform governance, and transparent human-AI co-creation. Recent surveys indicate rapid learner adoption of generative AI, but weaker preparedness, incomplete institutional guidance and persistent trust vulnerabilities. Based on these findings, the article proposes a progression model for primary, secondary and higher education and argues that the core educational task is not merely teaching students to use AI efficiently, but to evaluate, disclose and govern AI-mediated communication responsibly.

Keywords

AI literacy, media education, generative AI, misinformation, curriculum

JEL Classification: I21, I29, O33



AI gramotnosť a mediálne vzdelávanie: príprava nastupujúcej generácie na vek inteligentných strojov

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Abstrakt

Rozšírenie generatívnej umelej inteligencie zmenilo epistemické podmienky používania, produkcie a obehu médií. Vyhľadávanie, sumarizácia, odporúčanie, syntéza obrázkov a konverzačné rozhrania teraz sprostredkujú, ako sa mladí ľudia stretávajú s vedomosťami, vytvárajú školské úlohy a posudzujú dôveryhodnosť. Tento článok tvrdí, že umelá gramotnosť by mala byť integrovaná do mediálneho vzdelávania a nemala by sa považovať za samostatnú technickú špecializáciu. Štúdia pomocou integratívneho prehľadu nedávnych štipendií a sekundárnej analýzy hlavných správ z prieskumov z rokov 2024 – 2025 identifikuje šesť oblastí kompetencií potrebných pre vek inteligentných strojov: funkčné pochopenie systémov AI, rýchla a interakčná gramotnosť, overovanie a dôkazové uvažovanie, analýza zaujatosti a reprezentácie, riadenie údajov a platforiem a transparentné spoločné vytváranie ľudí a AI. Nedávne prieskumy naznačujú rýchle osvojenie si generatívnej AI študentmi, ale slabšiu pripravenosť, neúplné inštitucionálne poradenstvo a pretrvávajúcu zraniteľnosť dôvery. Na základe týchto zistení článok navrhuje model postupu pre základné, stredné a vysoké školy a tvrdí, že hlavnou vzdelávacou úlohou nie je len naučiť študentov efektívne používať AI, ale aj zodpovedne vyhodnocovať, zverejňovať a riadiť komunikáciu sprostredkovanú AI.

Kľúčové slová

AI gramotnosť, mediálna výchova, generatívna AI, dezinformácie, kurikulum

JEL Klasifikácia: I21, I29, O33



Introduction

Generative AI systems have moved from peripheral experimentation to everyday infrastructures of knowledge. Search engines integrate generative summaries, image and video generators reduce the threshold for media production, recommendation systems shape visibility, and chatbots increasingly function as quasi-conversational tutors. For children and young adults, this means that media experience is no longer only about interpreting messages created by human institutions; it increasingly involves navigating outputs produced, filtered or ranked by AI systems. UNESCO warns that regulatory adaptation still lags behind tool diffusion, leaving unresolved questions of data privacy, pedagogical validation and institutional readiness (Miao and Holmes, 2023). At the international assessment level, the OECD has responded by establishing PISA 2029 Media and Artificial Intelligence Literacy (MAIL), signalling that these competences are becoming a core educational concern rather than a niche technical topic (OECD, 2026).

Traditional media education already addresses authorship, representation, ideology, persuasion, credibility and participation. Yet generative AI changes the object of analysis in at least three ways. First, AI systems produce media artefacts at scale, including summaries, images, voices, translations and synthetic personas. Second, AI systems curate attention through ranking, prediction and recommendation. Third, AI increasingly becomes a medium in itself, as users interact with systems that appear fluent, responsive and authoritative. The educational challenge therefore extends beyond the familiar question of how media messages are encoded. Students must also understand how algorithmic systems construct, select and normalise those messages before they ever reach the learner.

Recent surveys intensify the urgency of this problem. Common Sense Media (2024) found that seven in ten teenagers had already used at least one generative AI tool and two in five had used AI for school assignments. The Digital Education Council (2024) similarly reported widespread AI use among university students globally, but also substantial self-reported unpreparedness and weak awareness of institutional rules. The issue is therefore not whether young people will encounter AI. They already do. The question is whether educational systems will frame that encounter critically, ethically and productively.

This article argues that AI literacy should be integrated into media education because the central educational problem is epistemic and civic, not merely operational. Efficient prompting or tool familiarity are insufficient if learners cannot judge accuracy, detect omission, interrogate bias, distinguish assistance from authorship, or understand how platform incentives shape outputs. Overstating the novelty of AI can also be misleading: many long-standing media education questions about evidence, ideology, power and representation remain relevant. What changes is their technical manifestation, speed and scale.

The aim of the article is threefold: first, to synthesise current scholarship on AI literacy relevant to media education; second, to interpret selected 2024–2025 survey findings on youth, students and public attitudes to AI; and third, to propose a curriculum-oriented framework for preparing the next generation for the age of intelligent machines.



Methodology

The article uses an integrative review design combined with a secondary analysis of recent survey reports. The review component focused on peer-reviewed literature published mainly between 2020 and 2025, when the concept of AI literacy began to mature in educational research and when generative AI became a significant topic in media and learning debates. Priority was given to conceptual frameworks, systematic reviews and empirical studies that addressed AI literacy in primary, secondary or higher education, or that examined misinformation, credibility and media practices in AI-mediated environments.

The scholarly corpus included foundational work on AI literacy competencies (Long and Magerko, 2020; Ng et al., 2021), school-oriented reviews and frameworks (Casal-Otero et al., 2023; Allen and Kendeou, 2024; Ng et al., 2023; Yu, 2025), and studies addressing the educational affordances and risks of generative AI tools (Kasneci et al., 2023; Tlili et al., 2023; Crompton and Burke, 2024; Jo, 2024). Additional attention was given to work on AI literacy assessment and scale development, because curriculum proposals without measurable competencies are difficult to operationalise in practice (Laupichler et al., 2023; Lintner, 2024).

The secondary analysis used four high-visibility reports that offer recent and traceable survey data relevant to the article's theme: Common Sense Media (2024), the Digital Education Council (2024), Ofcom (2025) and Ipsos (2025). These reports were selected because they address different but complementary populations: teenagers, higher education students and the general public. Together they do not provide a unified dataset, but they do offer a useful descriptive picture of adoption, trust, transparency expectations and preparedness.

The analytical strategy was interpretive rather than meta-analytic. Because the surveys differ substantially in geography, age groups, sampling frames and question wording, their percentages cannot be pooled as if they measured the same construct. Instead, they were treated as directional indicators that illuminate common pressure points for media education: rapid diffusion of AI use, incomplete institutional guidance, uneven critical verification and persistent uncertainty around trust, disclosure and governance.

This design has obvious limits. The article does not report new primary empirical data, nor does it test the proposed framework in classrooms. It is therefore best understood as a conceptually grounded synthesis intended to support curriculum design, teacher education and further empirical inquiry.

Results

AI literacy as an expanded media competence

The literature converges on a broad understanding of AI literacy. Long and Magerko (2020) define it as a set of competencies that enable people to evaluate, communicate with and make informed decisions about AI. Ng et al. (2021) similarly conceptualise AI literacy as a combination of understanding, application, evaluation, creation and ethical reflection. Systematic evidence from K–12 research shows that the field is still fragmented and that many educational interventions emphasise technical novelty more than social and civic implications (Casal-Otero et al., 2023). Allen and Kendeou (2024) respond to this fragmentation by proposing ED-AI Lit as an explicitly interdisciplinary framework. Yu (2025) likewise argues for a competency-oriented perspective that connects knowledge,



skills and dispositions. Across these approaches, the most important conclusion is straightforward: AI literacy is broader than efficient tool use.

For media education, this broad view is essential. AI systems now participate in message construction by generating text, images, audio and video; they shape distribution by ranking, recommending and suppressing content; and they mediate interpretation by summarising and reframing information before users encounter original sources. They also complicate norms of authorship because highly polished outputs can conceal uncertain provenance and uneven responsibility. Chu-Ke and Dong (2024) therefore argue that misinformation research and literacy research need to be reconsidered together under conditions of generative AI. In practical terms, a student may no longer only ask whether a claim is true, but also whether the source is synthetic, incomplete, hallucinated, context-stripped or strategically optimised for persuasion.

This development explains why media education provides a stronger institutional home for AI literacy than a narrowly technical or productivity-oriented approach. Media education already has a vocabulary for representation, ideology, evidence, institutional power and audience effects. UNESCO's guidance similarly insists on a human-centred approach that combines technological understanding with ethical validation, policy design and age-appropriate pedagogical use (Miao and Holmes, 2023). The OECD's MAIL initiative makes the same point at the assessment level: it treats media and AI literacy as intersecting competences required to act effectively, ethically and responsibly in digital environments (OECD, 2026).

On the basis of the reviewed literature, six competence domains appear especially relevant for media education. First, learners need a functional understanding of AI systems, including the difference between generation and retrieval, the role of training data and the probabilistic nature of outputs. Second, they need prompt and interaction literacy: the ability to formulate goals, constraints and comparison prompts without mistaking prompt fluency for understanding. Third, they need verification and evidentiary reasoning, because smooth language does not guarantee truthfulness. Fourth, they need to analyse bias, representation and fairness, especially where AI systems reproduce stereotypes or flatten cultural difference. Fifth, they need competence in data, privacy and platform governance, including disclosure norms and awareness of how user inputs may be processed. Sixth, they need transparent human-AI co-creation practices that preserve human accountability. Figure 1 summarises this framework.

Conceptual synthesis for curriculum design

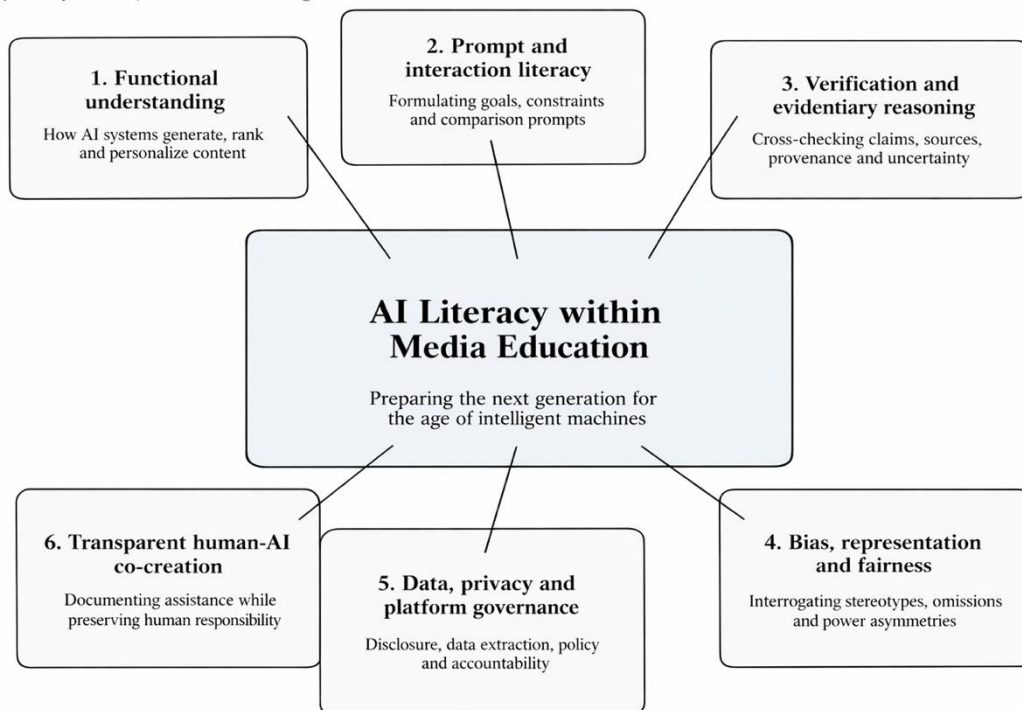


Figure 1. Six-domain AI literacy framework for media education

Source: authors' elaboration based on Long and Magerko (2020), Ng et al. (2021), Allen and Kendeou (2024) and Yu (2025)

What current surveys reveal

Survey evidence suggests that educational systems are already operating under conditions of rapid AI normalisation. In the Common Sense Media study of 13- to 18-year-olds in the United States, 70% reported having used at least one generative AI tool, and 40% reported using generative AI for school assignments (Common Sense Media, 2024). This is not a marginal fringe of experimental users. It is a mainstream student practice. Yet the same report showed that critical understanding remained uneven: many teenagers recognised that AI can produce inaccurate content, but fewer had consistent verification habits. This gap between awareness and disciplined checking is precisely where media education has high return on investment.

The Digital Education Council (2024) survey shows a similar pattern in higher education. The report found that 86% of students regularly use AI in their studies, while 58% said they did not feel they had sufficient AI knowledge and skills. Nearly half did not feel prepared for an AI-enabled workplace, and only a small minority reported full awareness of institutional AI guidelines. This combination is revealing. Adoption is already widespread, but governance and pedagogical framing lag behind. In other words, students are not waiting for policy maturity before incorporating AI into learning workflows.



Trust and credibility problems are equally important. Ofcom (2025) reported that among teenage AI users, 52% would trust an AI-generated news story the same as or more than a human-written one. That figure should not be read simplistically as naivety; in some contexts, young users may perceive machine writing as neutral or efficient. But it does reveal that trust judgements are being reorganised in ways that media education can no longer ignore. If students treat synthetic fluency as a proxy for reliability, then source criticism must be redesigned for an environment where convincing output can be generated at negligible cost.

Public expectations around transparency confirm this diagnosis. Ipsos (2025) found that 79% of adults across 30 countries expected companies using AI to disclose that use. At the same time, trust that companies would keep data safe remained below half, while many respondents expressed both excitement and anxiety about AI-driven products and services. This double movement, fascination combined with concern, is crucial. It suggests that future citizens will not only need technical familiarity but also normative language for demanding accountability, disclosure and governance.

Figure 2 brings these survey signals together. The figures should not be treated as directly comparable measures, because they come from different populations and question designs. Their value lies elsewhere: they show that AI has already entered mainstream educational and media practices faster than curricula, teacher education and institutional rule-making have adapted.

Selected survey signals on young people, students and public attitudes to AI

Illustrative indicators only; samples, geographies and wording differ across surveys.

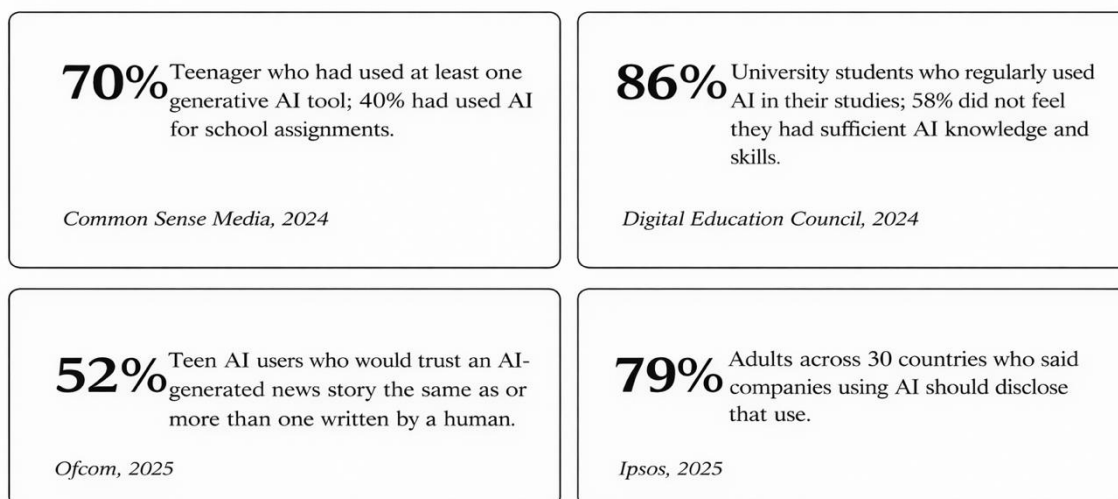


Figure 2. Selected survey signals on young people, students and public attitudes to AI

Source: authors' elaboration based on Common Sense Media (2024), Digital Education Council (2024), Ofcom (2025) and Ipsos (2025)

A curriculum architecture for media education

A workable curriculum response should therefore avoid the false choice between prohibition and uncritical adoption. Bans may temporarily reduce visible use in formal assessment settings, but they do



little to build judgment in the wider digital environment where AI systems remain ubiquitous. Conversely, a curriculum that merely celebrates AI efficiency risks confusing productivity with learning. The more defensible position is guided integration: learners should use AI in structured tasks that require comparison, disclosure, verification and reflection rather than passive acceptance.

At primary level, the goal is not mastery of technical detail but early epistemic orientation. Children can compare an AI-generated answer with a teacher-approved source, discuss whether an image looks authentic, and ask simple questions such as: Who made this? How do we know? What might be missing? In lower secondary education, tasks can add prompt comparison, fact-checking, bias detection and source triangulation. Upper secondary education can then address synthetic media, platform governance, fairness, authorship, copyright, civic persuasion and public communication. At higher education level, the issue expands further to discipline-specific use, assessment redesign, institutional policy and reflective disclosure.

The pedagogical principle behind this progression is productive friction. Students should not be rewarded for obtaining the fastest answer from a chatbot; they should be rewarded for documenting how they tested, corrected, contextualised and responsibly used AI assistance. A strong media education assignment in the age of intelligent machines is therefore one that makes the invisible layers of mediation visible again. Table 1 translates this principle into a compact progression model.

Discussion

The strongest conclusion of this review is that AI literacy is best understood as an extension and reconfiguration of media education rather than as a stand-alone technical elective. This is not simply a matter of curriculum convenience. Media education already deals with credibility, institutions, representation, persuasion and participation. AI systems now reshape each of those domains. Treating AI literacy as a separate technical module would risk isolating it from the very social and cultural questions that make its educational significance urgent.

Two weak strategies should nevertheless be rejected. The first is tool boosterism. A curriculum built mainly around efficiency tips, prompt tricks and workflow acceleration may produce quick enthusiasm, but it leaves students vulnerable to hallucination, hidden bias, false confidence and shallow outsourcing of thinking. Research on ChatGPT in education repeatedly documents both benefits and risks, including support for ideation and feedback alongside concerns about inaccuracy, overreliance and uneven learning quality (Kasneci et al., 2023; Tlili et al., 2023; Crompton and Burke, 2024; Jo, 2024). The second weak strategy is moral panic. Pure prohibition does not remove AI from students' lives; it mainly removes transparent discussion of how to use it responsibly.

The assessment problem is especially important. If educational systems continue to reward polished output while ignoring process, then undisclosed AI dependence becomes a rational strategy. Higher-value assessment should make source triangulation, reasoning traces, reflective disclosure and revision history visible. This is consistent with the growing literature on AI literacy measurement, which shows that the field still needs sharper operationalisation and better assessment instruments (Laupichler et al., 2023; Lintner, 2024). Schools and universities should therefore redesign some assignments so that evidence of human judgment is not an optional extra but part of the graded task itself.



Table 1. Suggested progression for integrating AI literacy into media education

Educational level	Core objective	Example media-education task	Key AI question
Primary education	Recognition, questioning and basic provenance awareness	Compare an AI-generated answer or image with a teacher-approved source and discuss differences.	Who made this, and how do we know?
Lower secondary	Verification, prompt comparison and bias detection	Fact-check an AI summary against two original sources and identify omission or distortion.	What is missing, uncertain or potentially misleading?
Upper secondary	Authorship, synthetic media and disclosure	Produce an annotated AI-assisted essay, poster or news item with disclosure notes.	When is AI assistance legitimate, and how must it be disclosed?
Higher education and teacher education	Policy and accountable human-AI collaboration	Draft a course AI-use policy and a reflective disclosure log.	How is accountability preserved when AI supports academic work?

Source: authors' elaboration

Teacher education is another leverage point. Educators do not need to become AI engineers, but they do need enough conceptual grounding to distinguish plausible from misleading uses of AI in classroom practice. Short workshops on prompting alone are low-yield interventions if they are not connected to policy, ethics, privacy, authorship and disciplinary goals. The more durable investment is professional development that equips teachers to set rules for disclosure, evaluate AI-assisted work, design verification tasks and explain why apparently authoritative outputs still require scrutiny.

From a policy perspective, the strongest institutional position is neither blanket prohibition nor unrestricted permissiveness. A more defensible approach is structured disclosure tied to task type. Brainstorming, language support or format conversion may be acceptable when acknowledged, whereas evidentiary claims, data analysis and final interpretation should remain clearly attributable to the student unless the assignment specifies otherwise. Such distinctions protect academic integrity more effectively than slogans, because they recognise how AI is actually entering study practices.

There is also a democratic dimension to the problem. Young people increasingly encounter political communication, news, memes and influencer content in environments where synthetic media, algorithmic amplification and conversational agents intersect. A media education model that ignores AI therefore risks teaching yesterday's information order. Preparing learners for public life now requires the ability to ask why a message appears, who benefits from its circulation, whether its voice or image is authentic, and what invisible system may have shaped its visibility in the first place (Chu-Ke and Dong, 2024; OECD, 2026).

For that reason, AI literacy should not be added only at the level of classroom tools. It should appear in curricular standards, school policy, teacher education, assessment criteria and communication with parents and students. Otherwise institutions send contradictory messages: AI is presented as transformative, yet norms are left to platform design, peer behaviour and informal experimentation. The long-term educational task is to replace opaque improvisation with accountable practice.

The article also has clear limitations. It does not provide primary classroom evidence, and the survey reports analysed here represent different contexts rather than one coherent empirical population.



Future research should test the proposed framework in specific educational settings, including multilingual environments, teacher preparation programmes and Central European media education contexts. Even so, the direction of travel is already evident: the main educational risk is no longer the absence of AI, but the normalisation of AI-mediated communication without adequate habits of judgment and accountability.

Conclusion

Preparing the next generation for the age of intelligent machines does not primarily mean teaching students how to produce more output more quickly. That objective is too narrow and, in many educational settings, strategically misguided. The more important task is to prepare learners to recognise how AI systems shape what they see, what they trust, what they create and how they participate in culture and public life. In this sense, AI literacy is not an optional supplement to media education. It is increasingly one of its central missions.

The literature reviewed in this article shows broad agreement that AI literacy involves knowledge, skills and ethical judgment rather than mere technical fluency. Recent surveys reinforce the point from another angle: adoption is already mainstream, but preparedness, governance and trust calibration remain uneven. A curriculum response built around functional understanding, verification, bias analysis, privacy awareness, transparent disclosure and accountable co-creation is therefore more defensible than either blanket bans or simplistic celebration of AI productivity.

The practical implication is clear. Schools and universities should integrate AI literacy across media education tasks, redesign assessment to make human judgment visible, and invest in teacher education that joins technological understanding with civic and ethical reasoning. The age of intelligent machines will not be navigated well by learners who can only operate tools. It will be navigated better by learners who can question them, verify them, contextualise them and remain responsible for what is finally communicated in their name.

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Smart Cities and Public Transport: IoT and AI Solutions from the Customer Perspective

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Abstract

The rapid development of Smart Cities has created new opportunities and challenges for public transport systems, particularly in enhancing passenger experience through digital technologies. This study investigates the perspectives of public transport users in Slovakia regarding the adoption of IoT and AI solutions and evaluates the factors influencing satisfaction, usage patterns, and engagement with smart mobility initiatives. A survey conducted between February and May 2025 collected responses from 390 participants, capturing sociodemographic data, travel behaviors, satisfaction with transport services, and willingness to adopt innovative digital solutions. Statistical analysis, including Chi-square tests of independence, was used to examine three hypotheses: (H1) the relationship between age and willingness to use digital solutions, (H2) the link between type of residence and satisfaction with transport accessibility, and (H3) the connection between frequency of transport use and willingness to participate in incentive programs. Results indicate that younger users are more open to digital innovations, residents of urban areas report higher satisfaction with accessibility, and frequent users show stronger engagement with motivational schemes. The findings highlight the importance of integrating IoT and AI technologies to monitor transport conditions, optimize service routes, and implement user-centered incentive programs. The study provides practical recommendations for transport operators and city planners to improve service quality, accessibility, and overall passenger experience while promoting sustainable urban mobility. This research demonstrates that the adoption of smart solutions is crucial for developing resilient, efficient, and user-oriented public transport systems within the context of Smart Cities.

Keywords

Smart Cities, Public Transport, IoT, Passenger, Urban Mobility, Digital Solutions

JEL Classification: according O1



Inteligentné mestá a verejná doprava: IoT a AI riešenia z pohľadu zákazníka

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Abstrakt

Rýchly rozvoj inteligentných miest vytvoril nové príležitosti a výzvy pre systémy verejnej dopravy, najmä v oblasti zlepšovania skúseností cestujúcich prostredníctvom digitálnych technológií. Táto štúdia skúma perspektívy používateľov verejnej dopravy na Slovensku, pokiaľ ide o zavádzanie riešení internetu vecí a umelej inteligencie (IoT) a hodnotí faktory ovplyvňujúce spokojnosť, vzorce používania a zapojenie do iniciatív inteligentnej mobility. Prieskum, ktorý sa uskutočnil v období od februára do mája 2025, zhromaždil odpovede od 390 účastníkov, ktoré zachytili sociodemografické údaje, cestovné správanie, spokojnosť s dopravnými službami a ochotu prijať inovatívne digitálne riešenia. Štatistická analýza vrátane chí-kvadrát testov nezávislosti bola použitá na preskúmanie troch hypotéz: (H1) vzťah medzi vekom a ochotou používať digitálne riešenia, (H2) súvislosť medzi typom bydliska a spokojnosťou s dostupnosťou dopravy a (H3) súvislosť medzi frekvenciou používania dopravy a ochotou zúčastňovať sa na motivačných programoch. Výsledky naznačujú, že mladší používatelia sú otvorenejší digitálnym inováciám, obyvatelia mestských oblastí hlásia vyššiu spokojnosť s dostupnosťou a častí používatelia vykazujú silnejšie zapojenie do motivačných programov. Zistenia zdôrazňujú dôležitosť integrácie technológií IoT a umelej inteligencie na monitorovanie dopravných podmienok, optimalizáciu trás služieb a implementáciu motivačných programov zameraných na používateľa. Štúdia poskytuje praktické odporúčania pre prevádzkovateľov dopravy a urbanistov na zlepšenie kvality služieb, dostupnosti a celkovej skúsenosti cestujúcich a zároveň na podporu udržateľnej mestskej mobility. Tento výskum dokazuje, že prijatie inteligentných riešení je kľúčové pre rozvoj odolných, efektívnych a na používateľa orientovaných systémov verejnej dopravy v kontexte inteligentných miest.

Kľúčové slová

Inteligentné mestá, verejná doprava, internet vecí, cestujúci, mestská mobilita, digitálne riešenia

JEL Klasifikácia: O1



Introduction

The rapid urbanization of cities and the increasing demand for sustainable and efficient mobility solutions have intensified the need for innovative approaches in public transport. Smart Cities initiatives, leveraging Internet of Things (IoT) and Artificial Intelligence (AI) technologies, offer significant potential to enhance the quality, accessibility, and efficiency of urban mobility systems. In this context, understanding the perspectives and expectations of public transport users is crucial for designing effective and user-centered solutions. Public transport systems face multiple challenges, including fluctuating passenger demand, service irregularities, and increasing expectations for comfort, safety, and digital services. Traditional performance evaluation methods, often based solely on operational or financial metrics, are insufficient to capture the full complexity of passenger experience. Integrating digital technologies, such as IoT-enabled real-time monitoring and AI-driven route optimization, allows transport operators to address these challenges and improve service delivery. This study focuses on evaluating passenger satisfaction, usage patterns, and willingness to adopt digital solutions in public transport within Slovakia. By analyzing survey data collected between February and May 2025, this research examines the relationships between key sociodemographic factors, travel behaviors, and openness to smart mobility initiatives. The main objectives are to identify critical factors influencing passenger experience, assess the potential of IoT and AI solutions, and provide actionable recommendations for public transport operators and city planners aiming to implement Smart City strategies effectively.

Theoretical starting points

The development of modern cities and the dynamics of a globalized environment bring new challenges to urban transport systems. Rapid urbanization, increasing passenger expectations, and growing pressure to achieve environmental sustainability require cities to rethink traditional approaches to managing public transport. In this context, the Smart City concept has emerged as a key framework for building sustainable, efficient, and inclusive urban environments. By integrating digital technologies into physical infrastructure and decision-making processes, Smart Cities enable more effective mobility management, higher quality services, and improved citizen satisfaction. (Bifulco et al., 2018; Feijoo et al., 2022; Martins et al., 2017) Smart Cities are not merely technologically advanced urban spaces; they represent a strategic vision for integrated urban development, where information and communication technologies, data analytics, and participatory governance converge. Their goal is to create resilient, responsive, and sustainable cities that can adapt to economic, social, and environmental changes (Adel et al., 2024; Esfandi et al., 2024). Mobility and transport systems are one of the most critical domains of Smart City strategies, as they directly influence economic productivity, environmental performance, and quality of life. Efficient transportation systems support urban competitiveness, reduce congestion and emissions, and enable inclusive access to jobs, services, and opportunities (Shichun et al., 2023; Zeng et al., 2017). Public transport plays a fundamental role in smart urban mobility. It provides a sustainable alternative to private car use, helping cities reduce traffic congestion, lower greenhouse gas emissions, and improve air quality. Moreover, well-functioning public transport systems enhance social equity, as they provide affordable and reliable mobility options for different population groups,



including those without access to private vehicles. From a strategic perspective, public transport also serves as a backbone for multimodal mobility solutions, linking shared mobility, cycling infrastructure, and pedestrian zones. In Smart Cities, the effectiveness of public transport is not measured solely by operational efficiency, but also by customer experience, adaptability, and its contribution to broader sustainability goals (Giffinger et al., 2021; Hu et al., 2020). One of the key pillars of Smart Cities is the use of the Internet of Things (IoT), which enables the continuous collection and transmission of real-time data from connected devices. In the context of public transport, IoT involves a wide network of sensors, GPS modules, beacons, and smart infrastructure that monitor various parameters such as vehicle location, passenger occupancy, travel patterns, environmental conditions, and infrastructure status. This constant flow of data supports real-time fleet management, predictive maintenance, service optimization, the provision of accurate passenger information, and environmental monitoring. By providing a data-rich environment, IoT transforms traditional static transport management into a proactive, responsive, and evidence-based system (Hsieh et al., 2023; Mbuli et al., 2025; Yuhuan et al., 2025). Building upon IoT data, Artificial Intelligence (AI) plays a transformative role in interpreting and applying information for real-time decision-making. AI systems use advanced analytics, machine learning algorithms, and predictive models to enhance both operational efficiency and passenger experience. In public transport, AI can optimize routing and scheduling, predict delays and disruptions, enable adaptive traffic management, support automated and autonomous transport, and enhance security and safety. AI not only improves the accuracy and efficiency of operations but also contributes significantly to customer comfort and satisfaction, offering personalized and reliable travel experiences (Farivar et al., 2022, Huang et al., 2021). A crucial aspect of modern transport management is the customer perspective, which forms an integral part of strategic urban governance and Smart City implementation. Passenger experiences, preferences, and needs are essential for identifying problems and designing optimized services. User feedback enables transport operators to evaluate the effectiveness of implemented measures, adapt technologies, and tailor services to reflect real-world requirements. By co-creating mobility solutions with users, cities can build more inclusive, acceptable, and successful transport systems. In the globalized context, this user-centered approach becomes even more important (Colding et al., 2024). Cities and transport operators face international competition and mobility trends, making innovation and service quality key differentiators. Integrating IoT and AI solutions with the customer perspective allows cities not only to optimize transport operations but also to improve environmental sustainability, safety, and passenger comfort, thereby supporting their long-term competitiveness in a global environment (Kaempchen et al., 2009; Shichun et al., 2023; Wolniak et al., 2024). Overall, the synergistic combination of technological solutions and customer perspective provides the foundation for modern, efficient, and sustainable urban transport systems. Considering passenger needs alongside intelligent infrastructure and adaptive management creates the conditions for enhancing user satisfaction, optimizing operations, and supporting the long-term development of public transport within the framework of Smart Cities (Shichun et al., 2025; Yuhuan et al., 2025).

Methodology

For the purposes of this paper, a questionnaire survey was conducted between February and May 2025. The survey focused on the customer perspective of public bus transport and on the perceived



potential for implementing technological solutions such as IoT and AI within the broader context of Smart Cities. The questionnaire was created using Google Forms and consisted of 26 questions addressing both basic demographic characteristics of respondents (age, gender, place of residence, income) and behavioral and attitudinal aspects related to public transport use. Specifically, it examined the frequency and purpose of public transport use, the evaluation of service quality, satisfaction with transport infrastructure, willingness to use digital and intelligent solutions, and suggestions for service improvements. The use of a questionnaire survey was essential for obtaining first-hand, user-oriented data that reflects real passenger experiences, expectations, and attitudes. Unlike secondary data sources, questionnaire surveys allow researchers to capture subjective perceptions and preferences, which are crucial for understanding the customer perspective in the design and implementation of smart mobility solutions. By combining structured demographic questions with evaluative and attitudinal items, the survey provided both quantitative and qualitative insights into passenger behavior, technological readiness, and openness to innovative solutions. This approach ensured that the research would not only measure existing patterns but also uncover potential barriers and opportunities for the adoption of IoT and AI technologies in public transport. The sample size was determined according to the standard formula for large populations. For the calculation, the following parameters were used: a 5% margin of error, a 95% confidence level ($Z = 1.96$), an assumed variance of 50%, and the total population of Slovakia (5,421,272, as of September 2024). Based on these parameters, the minimum required number of respondents to ensure statistical relevance was calculated at 385. A total of 423 respondents participated in the survey, and after removing 33 respondents who do not use public transport, the final sample consisted of 390 valid responses. This sample size exceeds the required threshold, ensuring the reliability and generalizability of the findings to the wider population. The statistical analysis was conducted using IBM SPSS Statistics 26, with the aim of examining the relationships between categorical variables and identifying potential dependencies. Three hypotheses were formulated for this purpose:

H1: There is a relationship between the respondent's age and their willingness to use digital solutions (IoT/AI) in public transport.

H2: There is a relationship between the type of residence (urban, suburban, rural) and satisfaction with the availability of public transport.

H3: There is a relationship between the frequency of public transport use and willingness to participate in motivational programs, competitions, or other Smart City initiatives.

The analysis was carried out using contingency tables and the Chi-square (χ^2) test, with a significance level set at 0.05. The Chi-square test was chosen because it is a non-parametric statistical method used to examine whether there is a significant association between two categorical variables. It is particularly suitable for analyzing survey data, where variables such as age groups, travel frequency categories, or attitudinal responses are often expressed in nominal or ordinal form. By comparing observed and expected frequencies, the χ^2 test allows researchers to determine whether differences in response patterns are due to chance or reflect meaningful relationships between demographic



characteristics, user behaviors, and attitudes toward smart mobility solutions. This analytical approach makes it possible to assess how demographic factors and technological innovations influence passenger satisfaction and their interest in intelligent public transport solutions. The results provide a solid empirical basis for developing targeted recommendations for the implementation of IoT and AI systems in urban mobility, ensuring that proposed solutions align with the actual needs and expectations of users.

Results

A questionnaire survey was conducted on a sample of 390 respondents between February and May 2025 to analyze public transport usage, passenger satisfaction, customer service experiences, and the use of digital tools, with a particular focus on the Smart City perspective and the implementation of IoT and AI solutions. Many respondents were women (59.5%), with men representing 40.5%. The most represented age group was 19–25 years (43.1%), followed by respondents under 18 (20.5%). Most respondents came from the Žilina region (49%), followed by the Bratislava (11.3%) and Trnava (8.7%) regions, while the Trenčín region had the lowest representation (4.6%). From a professional perspective, university students (39.5%) and secondary school students (20%) dominated the sample. More than half of respondents reported a monthly income of up to 750 EUR (61.5%), around 20% reported between 750–1000 EUR, and 11% above 1000 EUR. Most respondents lived in urban areas (43.6%), followed by rural municipalities (36.4%) and suburban areas (20%). The most common purposes for using public transport were leisure activities (33.6%), commuting to school (19%), and commuting to work (25.6%). Forty percent of respondents used public transport daily, 34% several times a week, 11.8% several times a month, and 5.1% only a few times per year. Most passengers travelled for up to 30 minutes (40%), followed by 26.1% travelling more than 30 minutes, 18.5% less than 15 minutes, and 15.4% more than one hour. Road transport, particularly bus services, was the most widely used mode (76%), followed by trains (21.6%) and trolleybuses (18.9%). Air and water transport were used only marginally (1–2%). Passenger satisfaction with public transport was measured on a five-point scale. The highest satisfaction levels were reported for travel comfort (40% very satisfied), the number of available seats (32.8% very satisfied), and stop accessibility (32.8% satisfied, 28.7% very satisfied). In contrast, the weakest aspects were service regularity (38.9% dissatisfied), safety (37.9% reported not feeling safe), and stop quality (35.9% very dissatisfied, 33.8% dissatisfied). Ticket prices received mixed evaluations, with 31.8% expressing dissatisfaction and 28.2% satisfaction. Respondents from the Žilina region, especially the city of Žilina, reported the highest satisfaction levels with road transport (average 3.85), followed by Bratislava, Košice, and Trnava. The lowest satisfaction scores were reported in Prešov (average 2.33) and cities in the Banská Bystrica and Trenčín regions. Customer service was evaluated predominantly negatively: 28.2% rated their experience as “very poor” and 15.9% as “poor.” The most common contact methods were in-person (40.5%) and telephone (31.7%), with the main reasons being lost or stolen items (42.9%), fare information (27%), and delays (18.3%). Most customer service interactions occurred in January and February 2025. The most frequently used public transport application was Ubian (51.3%), followed by IDS BK (21.9%) and Citymapp (5.6%). Less frequently used were Moovit (8.4%), IDOS (7.6%), and Nysse (1.7%). Respondents appreciated applications that provide real-time service information, delay notifications, and intelligent travel optimization tools, supporting the Smart City



concept and the adoption of IoT and AI solutions for more efficient and sustainable mobility. The main motivating factors for more frequent use of public transport were availability (33.3%), challenges and competitions (29.2%), and point or reward systems (26.2%). Other suggestions included affordable pricing and increased service frequency. To verify relationships between variables and test the research assumptions, three hypotheses were examined using the Chi-square (χ^2) test of independence. This statistical method is particularly suitable for identifying significant associations between categorical variables and is widely applied in social and transport research where variables such as age groups, frequency categories, or attitudes are nominal or ordinal. A significant level of 0.05 was used in all tests.

The first hypothesis (H1) examined the relationship between age and willingness to use digital IoT/AI solutions in public transport. The Chi-square test confirmed a statistically significant relationship, with younger respondents (19–25 years) demonstrating higher willingness to use digital solutions, while older respondents were more cautious. This finding indicates the need for targeted communication and user education when implementing Smart City technologies to ensure adoption across all age groups.

The second hypothesis (H2) investigated the relationship between type of residence and satisfaction with transport availability. The Chi-square test revealed a weak to moderate dependency, with urban residents evaluating transport availability significantly more positively than suburban and rural respondents.

This result highlights the importance of optimizing transport connections and improving digital access to transport information in less accessible areas, in line with Smart City inclusiveness goals. The third hypothesis (H3) explored the relationship between the frequency of public transport use and willingness to participate in motivational programs, competitions, or other Smart City initiatives.

The test identified a positive relationship, indicating that regular users are more likely to engage in incentive programs and interact with digital mobility platforms. This result supports the use of gamification and digital incentives as effective tools to enhance passenger participation and loyalty.

Table 1. Summary of Hypothesis Testing Results

Hypothesis	Variables	Test Result	Dependence
H1	Age × Willingness to use IoT/AI	Significant	Moderate
H2	Type of residence × Satisfaction with access	Significant	Weak–Moderate
H3	Frequency of use × Willingness to participate	Significant	Moderate

Source: own processing (2025)



The results of the Chi-square tests provide valuable insights for transport companies and city administrations in planning and implementing Smart City solutions that combine IoT and AI technologies with motivational and participatory strategies. By identifying demographic and behavioral patterns, these analyses support evidence-based decision-making aimed at increasing passenger satisfaction, participation, and the overall efficiency of public transport systems. This statistically grounded approach underscores the importance of integrating user behavior and attitudes into the development of intelligent mobility solutions for sustainable urban environments.

Discussion

Based on the results of the questionnaire survey and statistical testing of hypotheses, key factors influencing public transport usage and passengers' willingness to adopt digital and incentive-based solutions in a Smart City environment were identified. The analysis revealed that the age of respondents significantly correlates with their willingness to use digital solutions (IoT and AI). Younger age groups are more open to using mobile applications, intelligent journey planning systems, real-time tracking of transport services, and digital ticketing, while older passengers show lower adoption rates and prefer traditional methods of information and payment. Therefore, it is recommended to implement intuitive and user-friendly digital interfaces, complemented by educational campaigns targeting older generations. This approach will enable gradual adaptation to modern solutions across all age groups. The study also indicated that the type of residence significantly impacts the evaluation of transport accessibility. Urban residents rated accessibility more positively than residents of suburban and rural areas, who often face limited routes and lower service frequency. Based on these findings, it is recommended to optimize routes and intervals using AI algorithms, monitor vehicle occupancy and route quality with IoT sensors, and provide real-time transport information through mobile apps and digital displays at stops. This will improve efficiency, accessibility, and passenger satisfaction, especially in less-served areas. Furthermore, transport frequency was strongly associated with the willingness to participate in incentive programs and competitions. Frequent users expressed higher interest in point-based reward systems, gamified challenges, or other Smart City initiatives promoting sustainable mobility. Therefore, it is advisable to implement a reward and gamification system to encourage regular public transport use and environmentally friendly travel behavior. Additionally, passengers emphasized the importance of comfort and safety. Practical measures include smart lighting and camera systems at stops and in vehicles, monitoring air conditioning and vehicle occupancy with IoT devices, and regular maintenance and modernization of stops. Integrating this data into a centralized AI management system will enable cities to analyze transport flows, vehicle occupancy, and passenger satisfaction effectively, supporting strategic decision-making and



transport planning in a Smart City context. Implementing these recommendations can lead not only to increased passenger satisfaction and comfort but also to more efficient, sustainable, and intelligently managed public transport systems.

Table 2: Recommendations and Proposals for Public Transport in a Smart City

Area	Identified Issue	Recommended Solution	Expected Impact
Digital Solutions (IoT/AI)	Lower adoption of digital applications among older age groups	Intuitive mobile applications, educational campaigns, tutorials	Increased adoption of digital solutions across all age groups
Transport Accessibility	Low service frequency in suburban and rural areas	Optimization of routes and intervals with AI algorithms, occupancy monitoring with IoT sensors	Improved accessibility, efficiency, and passenger satisfaction
Motivation and Participation	Low willingness to engage in incentive programs	Implementation of point-based rewards, gamified challenges, eco-initiatives	Higher transport usage frequency and promotion of sustainable travel
Comfort and Safety	Dissatisfaction with comfort and safety	Smart lighting, camera systems, monitoring of air conditioning and vehicle occupancy	Increased comfort, safety, and passenger trust
Strategic Management	Lack of data for decision-making	Integration of IoT and AI data into a centralized management system	More effective planning, optimized routes, and strategic decision-making in Smart Cities

Conclusion

The results of this study provide a comprehensive understanding of public transport users' perspectives in the context of Smart Cities, highlighting the crucial role of IoT and AI solutions. The survey and statistical analysis confirmed that younger passengers are more willing to adopt digital tools, while older age groups require targeted educational support to increase engagement. Accessibility remains a key concern, particularly for suburban and rural residents, emphasizing the need for data-driven route optimization and real-time information systems. Frequent users showed a strong interest in



incentive-based programs, underscoring the potential of gamification and rewards to enhance sustainable mobility. The findings also reveal that comfort, safety, and service reliability are essential for increasing passenger satisfaction. Integrating IoT sensors to monitor vehicle occupancy, environmental conditions, and stop functionality, combined with AI-powered traffic and resource management, enables transport authorities to make strategic, evidence-based decisions. Such smart solutions not only improve operational efficiency but also strengthen user trust and loyalty. Overall, this study underscores the transformative potential of Smart City concepts in public transport. By leveraging IoT and AI technologies, cities can enhance accessibility, optimize service delivery, promote sustainable behavior, and create a more user-centric mobility ecosystem. The proposed recommendations provide a practical roadmap for transport operators and city planners to align service quality with passenger expectations, demonstrating that the adoption of intelligent digital solutions is key to developing modern, efficient, and resilient urban transport systems.

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Artificial Intelligence as a Catalyst for Financial and Accounting Innovation

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Abstract

The rapid development of artificial intelligence (AI) and the increasing availability of large-scale financial data are transforming finance and accounting. Traditional manual processes such as data entry, reconciliation, and retrospective reporting are no longer sufficient in a global environment that demands accuracy, speed, and predictive insight. AI has therefore emerged as a key force capable of automating routine tasks, improving risk management, and delivering forward-looking intelligence. This article examines the transformative impact of AI on critical finance and accounting functions, including accounts receivable, credit management, dispute resolution, accounts payable, and procurement. It demonstrates how AI enhances accuracy, efficiency, compliance, and strategic decision-making, ultimately repositioning finance as a value-generating function. The study uses a qualitative synthesis of academic and industry sources, supported by conceptual analysis of AI applications in core financial activities. It emphasizes AI's role in data integration, anomaly detection, predictive analytics, and process automation. Findings show that AI accelerates cash flow cycles, reduces human error, strengthens regulatory compliance, and optimizes resource allocation. Beyond operational efficiency, AI enables predictive risk assessment, scenario modelling, and strategic financial planning. As a result, AI emerges not as a supplementary tool but as a strategic imperative for organizations striving for long-term competitiveness in the digital economy.

Keywords

Artificial intelligence; Finance; Accounting; Automation; Risk management

JEL Classification: M21; A14; B16



Umelá inteligencia ako katalyzátor finančnej a účtovnej inovácie

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Abstrakt

Rýchly rozvoj umelej inteligencie (AI) a zvyšujúca sa dostupnosť rozsiahlych finančných údajov transformujú financie a účtovníctvo. Tradičné manuálne procesy, ako je zadávanie údajov, zosúladovanie a spätné vykazovanie, už nestačia v globálnom prostredí, ktoré si vyžaduje presnosť, rýchlosť a prediktívny prehľad. Umelá inteligencia sa preto ukázala ako kľúčová sila schopná automatizovať rutinné úlohy, zlepšovať riadenie rizík a poskytovať informácie zamerané na budúcnosť. Tento článok skúma transformačný vplyv AI na kritické finančné a účtovné funkcie vrátane pohľadávok, správy úverov, riešenia sporov, záväzkov a obstarávania. Ukazuje, ako AI zvyšuje presnosť, efektívnosť, súlad a strategické rozhodovanie, čím v konečnom dôsledku premiestňuje financie ako funkciu vytvárajúcu hodnotu. Štúdia využíva kvalitatívnu syntézu akademických a priemyselných zdrojov podporenú koncepčnou analýzou aplikácií AI v kľúčových finančných aktivitách. Zdôrazňuje úlohu AI pri integrácii údajov, detekcii anomálií, prediktívnej analytike a automatizácii procesov. Zistenia ukazujú, že AI zrýchľuje cykly peňažných tokov, znižuje ľudské chyby, posilňuje dodržiavanie predpisov a optimalizuje alokáciu zdrojov. Okrem prevádzkovej efektívnosti umožňuje AI prediktívne hodnotenie rizík, modelovanie scenárov a strategické finančné plánovanie. Výsledkom je, že AI sa neobjavuje ako doplnkový nástroj, ale ako strategický imperatív pre organizácie, ktoré sa snažia o dlhodobú konkurencieschopnosť v digitálnej ekonomike..

Kľúčové slová

Umelá inteligencia; financie; účtovníctvo; automatizácia; riadenie rizika

JEL Klasifikácia: M21; A14; B16



Introduction

In an era of dynamic technological progress and exponentially growing data volumes, the traditional landscape of finance and accounting is undergoing a profound transformation. (Chen et al., 2023) For decades, these essential functions were characterized by meticulous recordkeeping, complex calculations, and repetitive manual tasks. While such approaches have been vital in safeguarding financial integrity and ensuring regulatory compliance, they are inherently time-consuming, prone to human error, and resource intensive (Nair et al., 2025). Consequently, financial professionals often become absorbed in transaction processing, leaving limited capacity for strategic analysis and forward-looking insights (Cao et al., 2024). The challenges of conventional finance and accounting are multifaceted. Heterogeneous systems foster data silos, limiting real-time transparency and accessibility. Manual reconciliation processes consume extensive time and delay financial closings (Cho et al., 2024). Moreover, the sheer volume of transactions complicates anomaly detection and the timely identification of emerging risks. In a global economy that demands agility, precision, and predictive capabilities, exclusive reliance on historical data and labour-intensive processes is no longer sustainable. Enterprises require smarter and more efficient approaches to financial management that transform raw data into actionable intelligence rather than mere archival records (Giuggioli et al., 2024). This paper examines the revolutionary impact of artificial intelligence (AI) on finance and accounting. It explores AI's fundamental capabilities and highlights its benefits in enhancing accuracy, accelerating efficiency, and strengthening strategic decision-making. Emphasis is placed on AI's transformative role across core financial functions—from the automation of routine accounting tasks to the deployment of advanced predictive analytics for forecasting and risk management (Cho et al., 2024). The findings underscore that adopting AI is not merely an operational enhancement but a strategic imperative for organizations seeking to unlock unprecedented value, build financial resilience, and drive transformational business growth in the digital age (Kureljusic & Karger, 2024).

Methods

Before assessing specific advantages, it is essential to define artificial intelligence (AI) within the financial and accounting context and to highlight its role as a paradigm shift in executing financial tasks.

AI refers to computational systems capable of performing tasks that typically require human intelligence, including data-driven learning, pattern recognition, prediction, and complex decision support (Chen et al., 2023). The most relevant domains for finance include: (i) Machine Learning (ML): adaptive models for expense classification, customer behaviour prediction, and risk assessment (Gao et al., 2024). (ii) Natural Language Processing (NLP): interpretation of unstructured data such as invoices, contracts, and emails. (iii) Robotic Process Automation (RPA): rule-based task automation, which, when combined with AI, enables intelligent automation. (iv) Deep Learning: multilayer neural networks for fraud detection and recognition of intricate data patterns (Lopez-Garcia & Rojas, 2024).

The transformative strength of AI lies in its capacity to process massive datasets with accuracy and speed beyond human capabilities, thereby reshaping financial operations (Giuggioli et al., 2024). AI adoption has followed an evolutionary path: from rule-based automation via accounting software and RPA, through today's phase of "intelligent automation" powered by ML and NLP, toward the emerging vision of "autonomous finance," where AI systems independently manage financial processes, identify risks, and generate strategic recommendations (Nair et al., 2025). AI versus Automation; (i) Automation:



execution of processes with minimal human intervention (e.g., macros) (Cho et al., 2024). (ii) RPA: software robots for repetitive, rule-driven tasks. (iii) ML: learning from data to improve performance and generate predictions (Gao et al., 2024). (iv) Deep Learning: advanced ML effective in recognizing complex patterns. (v) AI: an overarching concept encompassing ML, NLP, and RPA, focused on reasoning and adaptive intelligence (Cao et al., 2024).

Results and discussion

Why Finance and Accounting Are Poised for AI Adoption. Finance and accounting departments constitute a particularly suitable environment for the adoption of artificial intelligence (AI) (Cao et al., 2024). The high volume of daily transactions provides extensive datasets for algorithmic training. Core accounting functions—such as data entry, reconciliation, and invoice processing—are highly repetitive and rule-based, making them ideal for automation. The demand for precision in financial records amplifies the value of systems that reduce human error. Simultaneously, organizations require real-time financial insights, which AI facilitates through continuous data processing. Given the risks of fraud, credit losses, and regulatory noncompliance, the predictive and anomaly-detection capabilities of AI are particularly valuable. Moreover, as finance teams are increasingly expected to serve as strategic partners, AI relieves them from transactional workloads, enabling a greater focus on analysis and forecasting (Giuggioli et al., 2024). **Strategic Benefits of AI in Financial and Accounting Processes** The integration of AI into finance and accounting transcends incremental improvements; it represents a transformative shift that delivers strategic advantages in accuracy, efficiency, analytical insight, risk management, and workforce development. AI enhances data reliability by automating verification, extracting information from unstructured sources, and detecting anomalies—thus minimizing errors and reinforcing trust in financial reporting. It also accelerates data processing, reconciliation, and financial close, reducing reporting cycles and administrative burdens (Lopez-Garcia & Rojas, 2024).

AI fundamentally reorients financial management from historical reporting toward predictive analytics and scenario modelling, thereby strengthening strategic decision-making. In addition, it fortifies regulatory compliance through continuous auditing, transaction monitoring, and dynamic risk assessment. The combined effect of enhanced efficiency, error reduction, and improved risk management translates into cost savings and optimized resource allocation, repositioning finance from a cost centre to a value generator. Finally, AI functions as a catalyst for professional transformation. By automating routine tasks, it empowers finance professionals to redirect their expertise toward higher-value activities such as advanced analytics, strategic advisory, and foresight. This evolution reinforces the role of finance teams as integral partners in organizational strategy. **The Impact of Artificial Intelligence on Core Financial and Accounting Functions.** Artificial intelligence (AI) is reshaping finance and accounting by enhancing data accuracy, automating workflows, and enabling predictive decision-making (Agostino et al., 2021).

In accounts receivable (AR), AI accelerates the order-to-cash cycle through intelligent cash application, predictive delinquency analysis, and personalized customer engagement. These capabilities improve cash inflows, reduce unallocated capital, and strengthen credit risk management (Cho et al., 2024). For credit management, AI facilitates dynamic risk assessment by integrating internal and external datasets, generating real-time credit scoring, and issuing early warning signals. This reduces bad debt exposure while supporting optimized credit terms. In dispute and deduction management, AI automates case categorization, directs issues to appropriate departments, and identifies systemic root



causes. As a result, revenue leakage is minimized, and financial close processes are accelerated (Bertomeu, 2020).

In accounts payable (AP) and procurement, AI streamlines invoice processing via intelligent document extraction, automated validation, and approval routing. Additionally, it enhances supplier management through performance analytics, risk monitoring, and optimized communication (Nair et al., 2025; Dzhereleiko et al., 2024). AI also advances payment planning by enabling dynamic discounting, simulating cash flow scenarios, and prioritizing supplier payments, thereby optimizing cash outflows and reinforcing liquidity management. Overall, AI transforms financial operations from transactional execution to proactive, data-driven strategy, supporting both operational resilience and transformational business growth (Zheng, 2022).

Conclusion

In conclusion, artificial intelligence represents one of the most transformative forces reshaping contemporary finance and accounting. Its impact extends beyond mere technological enhancement of existing processes; rather, it signifies a paradigm shift that redefines the very nature of financial management. AI should therefore not be perceived solely as an automation tool, but as a strategic enabler that delivers predictive insights and decision-making capabilities of high added value.

Within accounts receivable, credit management, and dispute resolution, AI accelerates cash flow, reduces exposure to bad debt, and enhances risk management. In accounts payable and procurement, it streamlines invoice processing, strengthens supplier relationships, and enables strategic payment planning. Across all functions, AI demonstrates the capacity to integrate vast internal and external datasets, detect hidden patterns, and provide predictive recommendations that surpass the analytical power of traditional systems. Nevertheless, its implementation is not without challenges. Data privacy, ethical considerations, algorithmic transparency, and the evolving skill requirements of financial professionals remain pressing issues. Organizations aiming to fully harness AI must therefore invest not only in technological infrastructures, but also in regulatory compliance, governance frameworks, and continuous workforce education.

Looking ahead, the trajectory of development points toward autonomous finance, in which AI systems will not merely support decision-making but will actively manage financial processes. Such an evolution has far-reaching implications for enterprises seeking to maintain competitiveness in an increasingly digitized and globalized economy.

Artificial intelligence thus emerges as a strategic imperative rather than a discretionary option. Enterprises capable of adopting and integrating AI responsibly will not only achieve operational efficiency, but also unlock new sources of value creation, reinforce financial resilience, and foster transformational growth. Finance and accounting are thereby redefined—from administrative support functions to the strategic core of enterprise leadership—marking a new era in their organizational role.

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Technology-Driven Finance: Consumer Behaviour in the Age of IoT, AI and FinTech

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Abstract

The paper presents selected findings of the study focused on consumer behaviour in the digital era regarding factors influencing the adoption of financial technology services (FinTech services) in Slovakia. The analysis focuses on how users perceive modern digital technologies and what determinants shape their trust and willingness to use these services. Special attention is paid to technologies such as IoT, blockchain and intelligent data systems, which are fundamentally changing the way consumers interact with financial services. The results point to the dynamics of the adoption of innovations and identify key factors influencing their acceptance. The aim of the article is to clarify the main factors that determine the adoption of FinTech services among Slovak consumers. The intention is also to outline how new digital technologies shape trust, user comfort and overall user behaviour when interacting with financial serviced. The study is based on a questionnaire survey among users of financial services in Slovakia. General scientific methods such as analysis, synthesis, comparison and induction were used in data processing, supplemented by descriptive statistics procedures. The interpretation of the results reflects current knowledge about the adoption of digital technologies in the context of the FinTech ecosystem. The findings indicate that modern digital technologies significantly affect perceived trust, security and user comfort, thereby supporting the adoption of FinTech services. The predominant acceptance factors turned out to be rational assessments of usefulness, ease of use and transparency of providers. The study's contribution is the identification of key determinants of adoption in the Slovak environment and the provision of data for more effective development of FinTech technologies and services.

Keywords

AI; Digital Transformation; Financial Services; FinTech

JEL Classification: G23; O32; O33; B16



Financie riadené technológiami: Správanie spotrebiteľov vo veku internetu vecí, AI a FinTech

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Abstrakt

Príspevok prezentuje vybrané zistenia štúdie zameranej na spotrebiteľské správanie v digitálnej ére týkajúce sa faktorov ovplyvňujúcich adopciu služieb finančných technológií (FinTech služieb) na Slovensku. Analýza sa zameriava na to, ako používatelia vnímajú moderné digitálne technológie a aké determinanty formujú ich dôveru a ochotu tieto služby využívať. Osobitná pozornosť sa venuje technológiám ako IoT, blockchain a inteligentné dátové systémy, ktoré zásadne menia spôsob, akým spotrebiteľia interagujú s finančnými službami. Výsledky poukazujú na dynamiku prijímania inovácií a identifikujú kľúčové faktory ovplyvňujúce ich prijatie. Cieľom článku je objasniť hlavné faktory, ktoré podmieňujú prijatie FinTech služieb medzi slovenskými spotrebiteľmi. Zámerom je tiež načrtnúť, ako nové digitálne technológie formujú dôveru, užívateľský komfort a celkové správanie užívateľov pri interakcii s finančnými službami. Štúdia vychádza z dotazníkového prieskumu medzi užívateľmi finančných služieb na Slovensku. Pri spracovaní údajov boli použité všeobecné vedecké metódy ako analýza, syntéza, porovnávanie a indukcia doplnené o postupy deskriptívnej štatistiky. Interpretácia výsledkov odráža súčasné poznatky o adopcii digitálnych technológií v kontexte FinTech ekosystému. Zistenia naznačujú, že moderné digitálne technológie výrazne ovplyvňujú vnímanú dôveru, bezpečnosť a užívateľský komfort, čím podporujú prijatie FinTech služieb. Ukázalo sa, že prevládajúcimi faktormi akceptácie boli racionálne hodnotenia užitočnosti, jednoduchosti používania a transparentnosti poskytovateľov. Prínosom štúdie je identifikácia kľúčových determinantov adopcie v slovenskom prostredí a poskytnutie údajov pre efektívnejší rozvoj FinTech technológií a služieb.

Kľúčové slová

AI; Digitálna transformácia; Finančné služby; FinTech



JEL Klasifikácia: G23; O32; O33; B16

Introduction

Digital transformation is fundamentally changing the way different economic entities interact with the financial sector, and thus the very nature and form of financial products and services. With the rapid development of the Internet, mobile technologies and cloud platforms, an ecosystem is emerging in which traditional financial services are intertwined with modern digital innovations. This trend is covered by the term “FinTech” and represents a set of financial technologies that enable faster, more accessible and more user-friendly financial solutions. According to Stamegna and Karakas (2018) Fintech is a term that refers to companies that use technology-based systems either to provide innovative and cheaper financial services directly (i.e. without the involvement of banks or other intermediaries) or to make traditional financial business more efficient. Fintech covers a range of services and products, such as cashless payments, P2P lending platforms, robotic trading, robo-advice, crowdfunding, and virtual currencies. Fintech utilizes emerging technologies like AI, machine learning, IoT, blockchain to anticipate preferences, creating relevant interactions (Paramesha et al., 2024).

Digital adoption has been consistently linked to productivity gains (Gal et al., 2019), which is also linked with FinTech (Bontadini et al., 2024). This is also in line with the theory of General Purpose Technologies, according to which technologies such as AI, IoT or blockchain can be considered widely applicable innovations with significant external effects across the economy, capable of generating secondary innovations and supporting structural changes leading to intensive productivity growth (Bresnahan & Trajtenberg, 1995).

Digital transformation is also changing customer behavior and expectations. In the financial sector, it is seen as a key prerequisite for providing relevant value propositions to customers in the context of dynamically evolving digitalization. Implementing this conceptual framework allows financial institutions to increase operational productivity while strengthening the perceived quality of interaction and customer orientation (Arguedas et al., 2019). Today's customer is accustomed to the speed, accessibility and intuitive control of digital tools. Thanks to mobile banks, investment applications, open-banking platforms and smart payment devices, they expect financial services to be connected, continuous and secure (Barjaktarovic Rakocevic

et al., 2025; Ullah et al., 2022). FinTech therefore represents not only a technological innovation, but also a paradigm shift in how customers perceive the trust, security, and value of financial products.

Against this background, there is a need to investigate customer perceptions and usage of FinTech services. Understanding how customers react to digital platforms, what their



motivations or concerns are, and to what extent they are willing to adopt services based on digital technologies is crucial for the future direction of financial institutions. This research thus follows up on current trends in digital transformation and at the same time contributes to a better understanding of the factors influencing the adaptation of FinTech solutions in an environment connected by smart technologies and in the conditions of the Slovak Republic with a particular emphasis on digital wallet, mobile banking usage, data security perceptions, and trust in advanced technologies such as AI and blockchain.

Methodology

Primary data were obtained using a structured questionnaire distributed online. This method of data collection is generally suitable in terms of access to digitally active respondents, which is key to the focus of the research. Data collection was carried out in the period from 02/2025 to 05/2025. Data collection and initial processing were carried out through Google Forms.

The target group consists of active users of FinTech services aged 18 and over who use at least one category of applications, e.g. mobile banking, e-wallets, online payment systems, digital investment platforms etc. Limiting the survey to active users also ensures that the data obtained reflects direct experience, and not hypothetical opinions. It is also a recommended approach in technology adoption research, e.g. according to Venkatesh et al. (2003). This means that the survey uses a non-probability sampling strategy that combines convenience sampling and snowball sampling. This approach allows for data to be collected from a relevant target group with direct experience with digital financial instruments, although the sample may not be representative of the entire population. The questionnaire was structured into 3 main

parts: *ad 1)* filter questions designed to confirm respondent eligibility (age, active user of fintech applications), *ad 2)* socio-demographic questions (gender, monthly income netto, education, residence), and *ad 3)* questions examining user perceptions, attitudes, and behaviour to fintech services, AI and IoT-driven technologies, and data security. The data obtained were processed using basic descriptive statistics methods, which is suitable for identifying the main patterns of FinTech service usage and target group characteristics. At the same time, they are the starting point for defining research problems and hypotheses in further stages of scientific analysis.

Results

The final sample consists of 191 respondents, most of them in the age category 35-44.99 years and divided by gender into 57.07% women and 42.93% men. The observed socio-geographic data on final sample are presented in Table 1. and information on them allow the



analysis to consider the existence of potential differences in the adoption of FinTech services and factors that influence adoption and its rate.

Table 1. Socio-geographic data on a final sample

Age (years)	18-24.99	25-34.99	35-44.99	45-64.99	65 and more
(%)	39.30	20.42	22.08	18.23	-
Monthly income (netto)	660	661 – 960	961 – 1,260	1,261-1,560	more than 1,560
(%)	15.74	22.51	32.46	15.18	14.11
Highest educational attainment	Lower secondary education	Upper secondary education (including post-secondary non-tertiary education)	Tertiary education (I. level)	Tertiary education (II. level)	Doctoral
(%)	4,19	30.89	33.51	25.65	5.76
Residence	Urban	Rural			
(%)	67.54	32.46			

Source: own collaboration

Referring the adoption/usage of FinTech services, most of those interviewed (79.06%) reported that mobile app of his/her bank is the primary FinTech service, which they use. Alternative categories of FinTech services are primarily used by respondents with at least a university education and primarily by men. Based on data, the most frequently used (preferable) device for accessing fintech applications and platforms are clearly mobile phones (93.72%). The results thereby confirm that the process of fintech adoption / usage is fundamentally dependent on the accessibility of the mobile channel. Regarding the perception of FinTech technologies, namely AI and IoT in financial services their perception was strongly positive. The majority of interviewed said that AI and IoT could improve personalization and improve their experience with FinTech services, namely very significantly in the case of 36.12% respondents and significantly in the case of 31.41% respondents. On the other hand, only 6.81% of interviewed presented an opinion that AI and IoT can improve the experience with FinTech services, but only to very slight extent, or to slight extent. These results thus point to a significant openness towards financial services using AI and IoT but also indicate that the willingness to adopt them is influenced by perceived benefit rather than innovation itself. In this context, the respondents' trust in FinTech technologies and their connection to the offered financial services, protection of finances and personal data was further examined.



The results indicate that respondents generally trust the technologies, as they perceive them as safe, reliable and stable solutions for managing their finances and financial needs (81.68%). The remaining part of the respondents (18.32%) expressed some doubts or concerns regarding their security, but at the same time admitted that their use is significantly more operational and practical for them, which may be the reason why they resort to them despite the uncertainty. The follow-up question further examined how it is possible to build credibility and trust in technologies and FinTech services based on AI and IoT usage. The results indicate that most of interviewed prefer easily interpretable explanations of AI behaviour (35.08%), followed by the preference of how the personal data are explicitly guaranteed/protected (31.41%). Recommendations from existing users (informal, spontaneous recommendations; word of mouth; 17.80%) and promotional recommendations (purposefully created recommendations by providers) played only a marginal role in building trust in FinTech technologies and services (15.71%).

Discussion and conclusion

The article presented partial findings from a survey focused on consumer behavior of FinTech services in the digital era. The survey focused on identifying and subsequently analysing factors influencing the adoption of financial technology (FinTech) services among the consumers of financial services in Slovakia, as well as trust in FinTech technologies and financial services.

From a gender perspective, the sample of respondents was relatively balanced and no statistically significant differences in opinions or preferences between men and women were found. This therefore allows us to generally conclude that gender did not influence the answers to the questions examined. The results showed that despite the boom in alternative FinTech service offerings, the strong concentration of users indicates that the primary interface for digital financial interactions clearly remains the mobile banking ecosystem. In contrast, alternative categories such as robo-advice, peer-to-peer lending or cryptocurrency platforms – show significantly lower and, it is assumed, specific usage/utilization. Except that the results confirm that the process of fintech adoption/usage is fundamentally dependent on the accessibility of the mobile channel. These findings are consistent with the conclusions of other studies (e.g. Abdullah and Naved Khan, 2021; Antonio, 2024; Balanche et al., 2022) and confirm that for wider penetration of FinTech services, it is often crucial that they are closely integrated into the existing banking environment (i.e. not as separate platforms). At the same time, it can be deduced that the findings arising from the study are not only contextually local but have broader support in existing empirical findings. Regarding the trust of FinTech users, trust is formed based on rational judgment rather than social influence, suggesting that FinTech service providers should prioritize transparency over persuasive marketing if they want to support their adoption.



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Business Decision-Making in the Context of Artificial Intelligence: Paradigmatic Shifts and Challenges

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Abstract

Artificial intelligence is becoming an important tool for managerial decision-making, especially in an environment characterised by uncertainty, dynamic markets, technological change and the growing volume of available data. The aim of this paper is to examine the scientific representation of artificial intelligence in the context of business decision-making and to identify the main paradigmatic shifts and challenges emerging from this research stream. The study is based on bibliometric analysis of publications indexed in the Web of Science Core Collection in the period 2020–2026. The records were analysed using VOSviewer, with attention paid to publication development, author keyword co-occurrence, country co-authorship and bibliographic coupling. The results show that the topic has grown rapidly, especially after 2023. The main thematic areas relate to data-driven decision-making, decision support systems, strategic decision-making, predictive analytics, human-AI collaboration, trust and explainability. The findings indicate that artificial intelligence changes both the technical tools of decision-making and the broader managerial paradigm. Managers increasingly become interpreters, supervisors and critical evaluators of AI-supported outputs.

Keywords

artificial intelligence, business decision-making, data-driven decision-making, bibliometric analysis

JEL Classification: M10, M15, O33, D81



Rozhodovanie podnikov v kontexte umelej inteligencie: paradigmatické zmeny a výzvy

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Abstrakt

Umelá inteligencia sa stáva dôležitým nástrojom manažérskeho rozhodovania najmä v prostredí charakterizovanom neistotou, dynamickými trhmi, technologickými zmenami a rastúcim objemom dostupných dát. Cieľom tohto príspevku je preskúmať vedeckú reprezentáciu umelej inteligencie v kontexte obchodného rozhodovania a identifikovať hlavné paradigmatické posuny a výzvy vyplývajúce z tohto výskumného prúdu. Štúdia je založená na bibliometrickej analýze publikácií indexovaných v zbierke Web of Science Core Collection v období 2020–2026. Záznamy boli analyzované pomocou VOSviewer, pričom pozornosť sa venovala vývoju publikácie, spolupráce kľúčových slov autora, spoluautorstvu krajiny a bibliografickej väzbe. Výsledky ukazujú, že téma sa rýchlo rozrástla, najmä po roku 2023. Hlavné tematické oblasti sa týkajú rozhodovania na základe údajov, systémov na podporu rozhodovania, strategického rozhodovania, prediktívnej analytiky, spolupráce medzi ľuďmi a AI, dôvery a vysvetliteľnosti. Zistenia naznačujú, že umelá inteligencia mení tak technické nástroje rozhodovania, ako aj širšiu manažérsku paradigmu. Manažéri sa čoraz viac stávajú tlmočníkmi, supervízormi a kritickými hodnotiteľmi výstupov podporovaných AI.

Kľúčové slová

umelá inteligencia, obchodné rozhodovanie, rozhodovanie na základe údajov, bibliometrická analýza

JEL Klasifikácia: M10, M15, O33, D81



Introduction

Contemporary firms operate in an environment characterised by high uncertainty, rapid technological change, dynamic markets and a growing volume of available data. These conditions increase the complexity of managerial decision-making and reduce the sufficiency of traditional approaches based mainly on experience, intuition and retrospective analysis. Managerial decisions are no longer limited to internal knowledge and past performance indicators. They increasingly require the ability to process large and diverse datasets, identify weak signals and react to changes in real time. In this context, data-driven decision-making has become an important managerial approach because it supports decisions based on systematic data analysis and analytical evidence, while reducing the influence of subjective judgement and cognitive bias (Chanda, 2024; Bao et al., 2023). This development is also connected with the broader digital transformation of management, where data literacy, analytical capabilities and organisational learning become important conditions for decision quality (Bryson, 2020; Dwivedi et al., 2021).

Artificial intelligence represents one of the key technologies that accelerate this change. AI systems can process large volumes of structured and unstructured data, identify patterns, predict future developments and support scenario modelling. As a result, AI changes the logic of business decision-making in several ways. First, it supports the shift from intuition-based decision-making to data-driven decision-making. Second, it enables a movement from reactive decisions to predictive decisions, because managers can use AI-based forecasts and “what-if” scenarios before final decisions are made (Adesina et al., 2024; Kunc and O’Brien, 2019). Third, AI changes decision-making from periodic planning towards continuous adaptation. In operational management, AI can support inventory control, production planning, predictive maintenance or logistics optimisation in real time (Al-Surmi et al., 2022; Duan et al., 2019). In strategic management, AI can help managers evaluate strategic alternatives, simulate market developments and compare different business model options (Csaszar et al., 2024; Doshi et al., 2025).

However, the use of AI in decision-making is not only a technological issue. It also changes the role of managers and the relationship between human judgement and algorithmic outputs. Current literature increasingly emphasises human-AI collaboration, where AI provides analytical support and managers remain responsible for interpretation, contextual evaluation and final decisions (Jarrahi, 2018; Shrestha et al., 2019; Raisch and Krakowski, 2021). This is important because many managerial decisions include uncertainty, values, organisational culture and stakeholder expectations that cannot be reduced only to quantitative data. López-Solís et al. (2025) show that generative AI can improve the efficiency and accuracy of strategic decisions, but human judgement remains essential in situations of high uncertainty. Similarly, Choudhary et al. (2025) argue that human-AI ensembles can be useful in managerial decisions even when neither human nor AI decision-making has a clear independent advantage. This supports the idea of augmented decision-making, where AI extends managerial capabilities rather than replacing them (Glikson and Woolley, 2020; Vanneste and Puranam, 2024).

The literature also points to several challenges connected with AI-supported business decision-making. One of them is the need for trust and explainability. Managers need to understand why an AI system produced a specific recommendation before they can use it responsibly. This is particularly



important in high-impact decisions related to employees, customers, investments or strategic direction. Chowdhury et al. (2023) emphasise that AI transparency and model explainability are necessary for managerial acceptance and for mitigating trust issues in data-driven decision-making. At the same time, trust must remain realistic, because insufficient trust may limit the use of valuable AI tools, while excessive trust may lead to passive acceptance of algorithmic outputs (Langer and König, 2023; Kovari, 2024). Another challenge is the organisational fit of AI. Ahola and Luoma (2026) show that algorithms do not automatically outperform managers in real organisational contexts; their value depends on the alignment between algorithmic outputs, existing decision-making logic and organisational structures.

AI-supported decision-making also raises ethical and governance-related questions. Algorithmic systems may reproduce bias from historical data, especially in areas such as HRM, customer evaluation, credit decisions or personnel selection (Tambe et al., 2019; Martin, 2019). Therefore, the use of AI in management requires transparency, auditability and clear responsibility for final decisions (Kriebitz and Lütge, 2020). Although AI in management is a rapidly growing research topic, there is still a need to better understand how the specific intersection of AI and business decision-making is represented in academic literature. Existing studies examine AI adoption, decision support, generative AI, human-AI collaboration, transparency and algorithmic decision-making, but the structure of this research field remains fragmented. The aim of this paper is to examine the scientific representation of artificial intelligence in the context of business decision-making and to identify the main paradigmatic shifts and challenges emerging from this research stream.

Objectives and methodology

The aim of this paper is to examine the development and structure of scientific research focused on artificial intelligence in business decision-making. The paper analyses how this topic is represented in scientific publications, which keywords are most frequently connected with it, which countries contribute to the research field, and which main thematic research streams can be identified. The study is based on bibliometric analysis of publications indexed in the Web of Science Core Collection. The search was conducted on the end of April 2026 and covered the period 2020–2026. The search strategy was based on a combination of terms related to artificial intelligence and related technologies, business decision-making and the organisational context. Specifically, the search included concepts such as artificial intelligence, machine learning, algorithmic decision-making, generative AI, managerial and strategic decision-making, operational and data-driven decision-making, decision support, business, management, firms, enterprises and companies. The search was limited to Articles and Review Articles, written in English, and classified in the Web of Science categories Management, Business, Economics and Business Finance. After applying these criteria, the final dataset consisted of 507 publications. The selected records were exported from Web of Science and processed in VOSviewer. The analysis focused on four areas: development of publication activity by year, author keyword co-occurrence, country co-authorship and bibliographic coupling.

Results and discussion

The Web of Science search identified 507 publications dealing with artificial intelligence and business decision-making in the period 2020–2026. Figure 1. shows a clear increase in publication activity. While only 20 publications were identified in 2020, the number increased to 91 in 2024 and



reached 143 publications in 2025. The year 2026 already includes 132 publications recorded by the end of the April 2026, although this year is not yet complete.

This trend indicates that AI-supported business decision-making has become a rapidly developing research area. The strongest increase after 2023 can relate to the wider use of generative AI, machine learning and decision support systems in management practice. The results suggest that this topic is no longer only a part of general digital transformation research but is becoming a separate research stream within management and business studies.

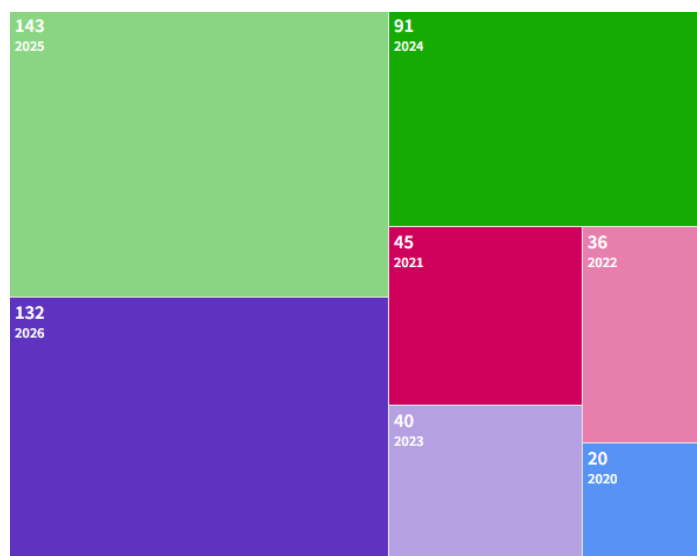


Figure 1. Number of publications on artificial intelligence and business decision-making by year

Source: authors' own processing

Figure 2. presents the author keyword co-occurrence map. Out of 1,905 author keywords, 65 met the minimum threshold of five occurrences. The map shows that the research field is structured around several interconnected topics. The most central keyword is “artificial intelligence”, which is strongly linked with “machine learning”, “decision-making”, “decision support systems”, “digital transformation” and “big data”. This confirms that the analysed literature connects AI mainly with analytical and data-based support for managerial decisions.

The map also shows the growing role of newer topics, especially “generative AI”, “ChatGPT” and “large language models”. These keywords relate to “decision support”, “strategic decision making”, “uncertainty” and “human-AI interaction”. This indicates that recent research pays increasing attention to the use of generative AI in strategic and complex decision-making situations.

Another important part of the map is formed by keywords such as “human-AI collaboration”, “trust”, “managerial decision-making” and “marketing”. These terms show that the research field is not focused only on technical tools, but also on the relationship between managers and AI systems. The presence of “explainable AI”, “human resource management”, “personnel selection” and “leadership” further suggests that AI-supported decision-making is expanding into different managerial functions.

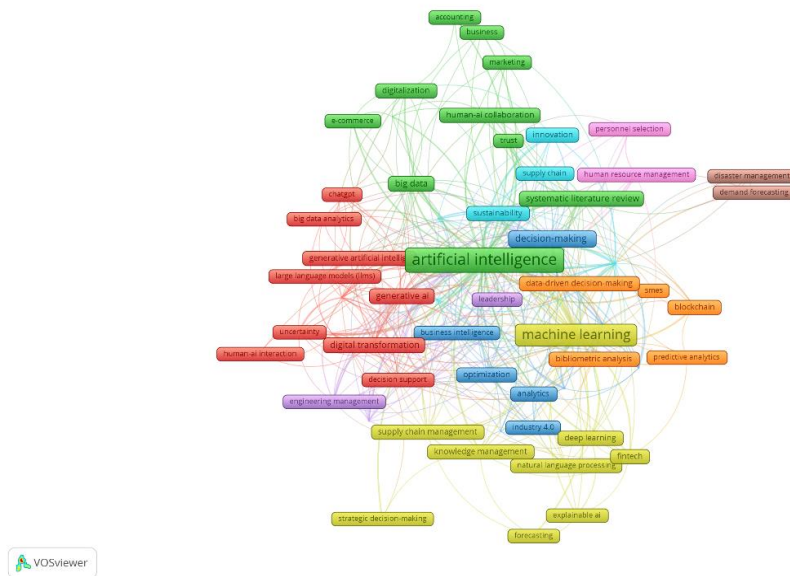


Figure 2. Author keyword co-occurrence map of artificial intelligence and business decision-making

Source: authors' own processing

Overall, the keyword analysis confirms that AI-supported business decision-making is a multidisciplinary research area. It combines technological topics, such as machine learning, natural language processing and predictive analytics, with managerial topics, such as strategic decision-making, innovation, human-AI collaboration, trust and leadership. The results support the view that AI is

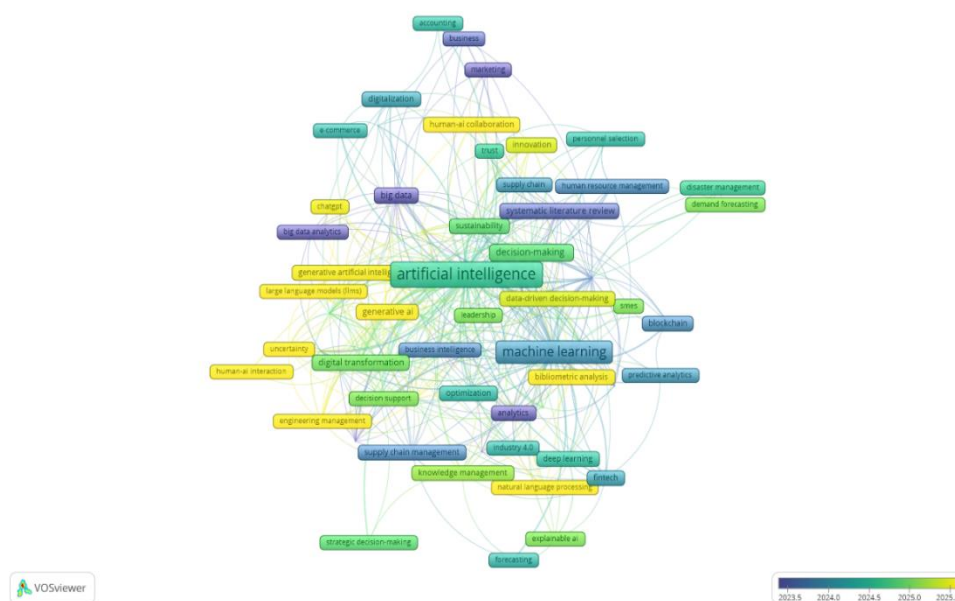


Figure 3. Overlay visualization of author keywords according to average publication year

changing not only the tools used by managers, but also the logic of managerial decision-making itself.

Source: authors' own processing

[illegible]

of AI as an active support tool in managerial and strategic decision-making.

Figure 4. presents the country co-authorship map. From 87 countries identified in the dataset, 42 met the minimum threshold of five documents. Fractional counting was used to reduce the effect of publications with many international co-authors. The map shows that research on artificial intelligence and business decision-making is internationally distributed, but several countries play a more central role. The strongest publication activity relates to the USA, People's Republic of China, England, Italy, India, Germany, France and Australia.

The network also shows several collaboration clusters. The USA and China are located close to the centre of the map and have strong links with other countries. England, France, Germany and Italy represent important European nodes, while Australia also has a visible position in the international network. Central European countries, such as Poland, Slovakia, the Czech Republic, Hungary and Romania, are present in the map, but their position is less central. This indicates that the topic is already represented in Central Europe, although there is still space for deeper regional research. This is relevant especially because the implementation of AI-supported decision-making can be influenced by the digital maturity, managerial culture and organisational readiness of firms in different countries.

Source: authors' own processing

The third cluster is the most relevant for the topic of this article. It includes studies on AI-augmented managerial decision-making, strategic decisions, human-AI collaboration, transparency and explainability. For example, Keding and Meissner (2021) focus on managerial overreliance on AI-augmented decision-making, while Choudhary et al. (2025) examine the conditions under which human-AI ensembles can work. Doshi et al. (2025) analyse the use of generative AI in evaluating strategic decisions. This cluster shows that the current literature does not understand AI only as a technical tool, but also as a new actor in managerial decision processes.

The remaining clusters extend the topic into specific managerial domains. One cluster is linked to generative AI, digital twins, Industry 4.0 and cyber-physical systems. Another cluster focuses on AI in marketing, customer-facing services and knowledge management. Further clusters deal with leadership, sustainability, organisational performance and human resource management. These areas show that AI-supported decision-making is spreading across different functions of the firm.



Overall, the bibliographic coupling analysis confirms that the field is not homogeneous. It consists of several interconnected research streams. However, their common feature is the shift from traditional decision-making towards AI-supported, data-driven and collaborative decision processes. The most important implication is that AI changes not only the speed and analytical quality of decisions, but also the role of managers, who must interpret AI outputs, evaluate their reliability and remain responsible for final decisions.

The bibliometric results indicate several paradigmatic shifts in business decision-making. The first one is the movement from intuition-based decision-making to data-driven decision-making. Traditional managerial decisions were often based on experience and subjective judgement, while current approaches increasingly rely on systematic data analysis and analytical evidence (Chanda, 2024; Bao et al., 2023). AI strengthens this trend by processing large datasets, identifying hidden patterns and supporting managers with evidence-based recommendations (Adesina et al., 2024).

The second shift is from reactive to predictive decision-making. AI enables forecasting, scenario modelling and early identification of risks or opportunities. This is important in strategic management, logistics, marketing and risk management, where managers can test “what-if” scenarios before making final decisions (Kunc and O’Brien, 2019). This shift is also visible in the bibliometric maps through terms such as “predictive analytics”, “forecasting”, “uncertainty” and “strategic decision-making”.

The third shift concerns the changing role of managers. AI does not remove managerial responsibility, but it changes managerial work. Managers increasingly interpret AI-generated recommendations, evaluate their reliability and connect them with strategic goals and organisational context. This is supported by the bibliographic coupling cluster focused on AI-augmented managerial decision-making and human-AI collaboration. Keding and Meissner (2021) also show that AI advice can influence managerial choices and create a risk of overreliance.

These changes create important challenges. Trust must be realistic: low trust may lead to rejection of useful AI tools, while excessive trust may lead to passive acceptance of algorithmic outputs (Langer and König, 2023). Explainability is also essential, because managers need to understand why AI produced a recommendation before using it responsibly (Kovari, 2024). Finally, algorithmic bias and poor data quality remain serious risks, especially in HRM, customer evaluation and other high-impact managerial areas (Tambe et al., 2019; Duan et al., 2019).

Overall, the results show that AI-supported business decision-making is not only a technological topic. It represents a broader managerial transformation towards data-driven, predictive and human-AI supported decision processes.

Conclusion

The aim of this paper was to examine the scientific representation of artificial intelligence in the context of business decision-making and to identify the main paradigmatic shifts and challenges emerging from this research stream. The bibliometric analysis, based on publications indexed in the Web of Science Core Collection in the period 2020–2026, confirms that AI-supported business decision-making is a rapidly developing research area. The growth of publication activity, especially after 2023, indicates that the topic has become increasingly relevant in management and business studies. The keyword analysis, country co-authorship map and bibliographic coupling map show that the field is interdisciplinary and connects technological, managerial, organisational and ethical dimensions.



The main findings suggest that artificial intelligence is changing both operational and strategic decision-making. In operational management, AI supports automation, optimisation, forecasting and real-time decision support. In strategic management, it helps managers evaluate alternatives, model scenarios and work with uncertainty. The most important paradigmatic shift is the movement from intuition-based and experience-based decision-making towards data-driven, predictive and AI-supported decision-making. At the same time, the analysed literature shows that AI-supported decision-making cannot be reduced to technical efficiency. Human-AI collaboration, trust, explainability, transparency, ethics and accountability are becoming central issues. Managers remain responsible for final decisions, but their role is changing towards interpretation, supervision and critical evaluation of AI-generated outputs. The practical implication of these findings is that managers should not understand AI only as an analytical tool. AI should be seen as a factor that transforms the logic, speed and structure of managerial decision-making. Its successful use therefore requires data quality, organisational readiness, AI literacy, clear responsibility and a balanced relationship between human judgement and algorithmic recommendations. Future research should empirically examine how AI affects the quality of managerial decisions in different business contexts. More attention should also be paid to differences between large enterprises and SMEs, the Central European context, managerial trust in AI, and the relationship between AI maturity and decision-making quality. These topics are important for understanding how firms can use AI responsibly and effectively in decision processes.

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Digital synergies in Industry 4.0: The role of IoT and AI in reshaping economic efficiency and value networks

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Abstract

Industry 4.0 has been characterised by the integration of advanced digital technologies with manufacturing and industrial processes through networking and automation. The synergistic roles of the Internet of Things and Artificial Intelligence have been examined to determine how economic efficiency and value networks are being transformed. A systematic literature review and bibliometric analysis covering the mid-2000s to 2024 were conducted. Rapid growth in research on smart manufacturing, data-driven decision making, and digital business models has been observed. Artificial intelligence has been shown to automate, forecast, and facilitate decisions by utilising real-time data collected through IoT infrastructures. The AIoT synergy has been found to enhance operational efficiency, reduce costs, and generate new value propositions across interconnected firm networks.

Bibliometric evidence has revealed concentrated research on cyber-physical systems, machine learning, predictive maintenance, supply chain optimisation, and sustainability. It has been concluded that digital synergies reshape efficiency and value creation, while challenges of interoperability, organisational readiness, and governance remain.

Keywords

Industry 4.0, Internet of Things (IoT), Artificial Intelligence (AI), Economic Efficiency, Digital Transformation

JEL Classification: O33; O14; L86; L14



Digitálne synergie v Priemysle 4.0: Úloha internetu vecí a umelej inteligencie pri pretváraní ekonomickej efektívnosti a hodnotových sietí

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Abstrakt

Priemysel 4.0 sa vyznačuje integráciou pokročilých digitálnych technológií s výrobnými a priemyselnými procesmi prostredníctvom sietí a automatizácie. Skúmali sa synergické úlohy internetu vecí a umelej inteligencie, aby sa určilo, ako sa transformuje ekonomická efektívnosť a hodnotové siete. Uskutočnil sa systematický prehľad literatúry a bibliometrická analýza od polovice roku 2000 do roku 2024. Bol zaznamenaný rýchly rast výskumu inteligentnej výroby, rozhodovania na základe údajov a digitálnych obchodných modelov. Ukázalo sa, že umelá inteligencia automatizuje, predpovedá a uľahčuje rozhodnutia využívaním údajov v reálnom čase zhromaždených prostredníctvom infraštruktúr internetu vecí. Zistilo sa, že synergia AIoT zvyšuje prevádzkovú efektívnosť, znižuje náklady a vytvára nové hodnotové ponuky naprieč prepojenými firemnými sieťami. Bibliometrické dôkazy odhalili sústredený výskum v oblasti kybernetických fyzických systémov, strojového učenia, prediktívnej údržby, optimalizácie dodávateľského reťazca a udržateľnosti. Dospelo sa k záveru, že digitálne synergie pretvárajú efektívnosť a vytváranie hodnôt, zatiaľ čo výzvy v oblasti interoperability, organizačnej pripravenosti a riadenia pretrvávajú.

Kľúčové slová

Priemysel 4.0, internet vecí (IoT), umelá inteligencia (AI), ekonomická efektívnosť, digitálna transformácia

JEL Klasifikácia: O33; O14; L86; L14



Introduction

Industry 4.0 refers to the fourth industrial revolution, marked by the fusion of digital technologies into industrial processes, leading to “smart” factories and cyber-physical systems. It encompasses a range of enabling technologies, including IoT, AI, big data analytics, cloud computing, advanced robotics, and others, which together facilitate highly automated, data-driven, and agile production environments (Huang et al., 2021). Within this paradigm, the Internet of Things (IoT) and Artificial Intelligence (AI) are often highlighted as two synergistic drivers of innovation. IoT is broadly defined as a network of digitally connected sensors, devices and objects that collect and exchange data over the Internet, creating ubiquitous computing environments that integrate the physical and digital worlds (e.g. machines, products, and infrastructure communicating in real time). AI, on the other hand, refers to computerised systems capable of performing tasks normally requiring human intelligence, learning from data, recognizing patterns, and making autonomous decisions. The convergence of IoT and AI, sometimes termed the “Artificial Intelligence of Things (AIoT),” enables smarter systems where massive data streams from IoT devices are analysed by AI algorithms to drive intelligent automation and optimisation. This digital synergy is widely expected to move business and industry forward by enabling better decision-making, predictive capabilities, and autonomous control that surpass human limitations. The context and significance of these technologies in Industry 4.0 lie in their potential to dramatically improve economic efficiency and to reshape value networks. IoT allows organisations to monitor processes and assets in real time across complex supply chains and production networks. For example, IoT sensors embedded in factory equipment, vehicles or products continuously feed data that can be used to streamline operations. AI techniques (such as machine learning) can then process these large datasets to optimise workflows, predict maintenance needs, and coordinate resources autonomously. The expected outcome is a step-change in productivity and cost savings. Indeed, studies indicate that applying AI and IoT together can significantly raise manufacturing efficiency, for instance, AI-driven predictive maintenance using IoT data has been shown to reduce machine downtime by up to 50% in cases reported by industry (Alam et al., 2023). At a broader economic level, analysts estimate AI could add trillions of dollars in value across industries by improving performance, with IoT acting as a critical data source for these AI systems. The value networks of the digital economy, spanning suppliers, producers, distributors, and customers interconnected via digital platforms, are also being reshaped. IoT connectivity and AI insights enable tighter integration and coordination among network participants, giving rise to new business models (such as product-as-a-service and on-demand manufacturing) and more responsive, customised value chains. By increasing transparency and real-time information flow in networks, IoT and AI together help eliminate inefficiencies and enable collaborative optimization across firm boundaries, thus restructuring traditional industry value chains into more fluid, intelligent value networks. While the transformative potential of IoT and AI in Industry 4.0 has been widely acknowledged in both academia and industry, there remains a need for systematic analysis of current research and trends in order to fully understand how these technologies are influencing economic efficiency and network structures (Matyushok et al., 2023). The literature on Industry 4.0 has grown rapidly over the last decade, but it spans diverse domains (engineering, computer science, management, economics) and covers a variety of themes from technical enablers to



organisational implications. Previous studies have noted that certain aspects, e.g. the technical facets of IoT implementation, are well documented, whereas managerial and economic analyses lag behind. Moreover, given the fast pace of technological change, periodic synthesis is necessary to capture the current state of knowledge and emerging research directions. This paper addresses this need by conducting a structured literature review and bibliometric analysis focused on IoT and AI within the Industry 4.0 context. The objective is to map the intellectual landscape of this interdisciplinary topic, identifying key themes, trends, and gaps, and to interpret how digital synergies are reshaping efficiency and value creation from an economics and management perspective.

Objectives and methodology

This research adopted a systematic literature review (SLR) approach combined with bibliometric analysis techniques to ensure a comprehensive and unbiased synthesis of existing knowledge. The methodology followed well-established guidelines for performing structured literature reviews in the field of management and information systems research.

Data collection

A clearly defined search strategy was implemented to identify relevant literature. The primary focus was on scholarly publications (peer-reviewed journal articles and high-quality conference proceedings) that address the intersection of IoT, AI, and Industry 4.0, particularly with respect to economic efficiency, productivity, business value, or network implications. Given the multidisciplinary nature of the topic, multiple databases were utilised, including Scopus and the Web of Science, which are known for broad coverage of technology, engineering, and business literature. The search query included combinations of keywords such as “Industry 4.0”, “Internet of Things”, “IoT”, “Artificial Intelligence”, “AI”, “economic efficiency”, “productivity”, “value chain”, and “digital transformation”. These terms were searched in titles, abstracts, and author keywords to cast a wide net. To ensure contemporary relevance, the review primarily covers the period from 2005 to 2024, which encapsulates the rise of IoT and AI research in industry contexts (noting that “Industry 4.0” as a term was introduced around 2011). Earlier seminal works (e.g. foundational IoT concepts from late 1990s and early 2000s) were also considered for historical context. The initial search resulted in several thousand records. In line with SLR best practices, inclusion and exclusion criteria were applied to refine the corpus. Included were publications that explicitly dealt with IoT or AI (or both) in an Industry 4.0 or industrial digitisation context, and which discussed implications for efficiency, performance, business models, or networks. Only articles written in English were included, and priority was given to journal articles (given their typically more substantial content) (Martín et al., 2014). Publications focusing purely on technical algorithmic novelty without discussion of industrial impact were excluded to keep the review focused on economic and managerial insights. After filtering for relevance and quality (including removing duplicates and non-peer-reviewed material), a final set of ~250 core publications was obtained for in-depth analysis. This set spanned multiple disciplines, indicating the need for an integrative review.



Bibliometric analysis

To supplement the qualitative review, bibliometric analysis was conducted to identify patterns and trends in the body of literature. Bibliometrics involves quantitative analysis of publication metadata (e.g. citation counts, co-authorship, keywords) to uncover the structure of a research domain (Klarin 2024). In this study, bibliometric tools such as VOSviewer and Bibliometrix (using the Biblioshiny interface) were employed for various analyses. The bibliometric analysis included:

- *Publication output over time:* The number of publications by year was tallied to reveal growth trends. This indicates the evolution of scholarly attention to IoT and AI in Industry 4.0. An exponential growth pattern was anticipated based on preliminary observations.
- *Citation analysis:* Citation counts were used to identify high-impact works and influential journals in the domain. Highly cited papers often serve as knowledge hubs that shaped the discourse. Key articles were ranked by total citations, and their content was noted to see what focal topics attracted the most attention (e.g. seminal papers on Industry 4.0 frameworks, or reviews of enabling technologies).
- *Co-authorship and collaboration networks:* Using author affiliation data, co-authorship networks were mapped to see how researchers and institutions collaborate. A country collaboration analysis was also performed to identify which countries are most actively publishing and how international partnerships are structured. For example, one might see clusters of collaboration within regions or between specific country pairs, shedding light on the global research network. It has been observed in related studies that countries like the United States, China, Germany, and the UK are among the most prolific in Industry 4.0 research. The analysis here similarly tracked authorship by country to confirm such patterns.
- *Keyword co-occurrence analysis:* To map the thematic structure, a co-word analysis was done using author-provided keywords and key phrases from titles/abstracts. The frequency of keyword co-occurrences reveals clusters of topics that commonly appear together, which often correspond to subthemes or research streams. For instance, one cluster might link terms like “IoT, sensors, predictive maintenance, supply chain”, indicating a technical-operational theme, while another links “AI, machine learning, big data, optimisation” for a data-analytics theme. VOSviewer was used to visualise the keyword network, where each node is a keyword and links indicate co-occurrence in publications. Clustering algorithms then identified groups of tightly connected keywords. Only keywords appearing at least a threshold number of times (to exclude one-off terms) were considered; in our analysis, we used a threshold (e.g. ≥ 5 occurrences) resulting in a map of the top ~50-100 keywords in the field. This method provides an intuitive “map” of the knowledge base.
- *Bibliographic coupling and co-citation analysis:* Additionally, we explored bibliographic coupling (how often two papers cite a common third paper) and co-citation patterns (how often two papers are cited together by other papers). These analyses help identify schools of thought or influential groups of papers. Due to space and focus, these results are only briefly noted.

Each of these analyses was cross-checked and interpreted in conjunction with the content of the papers for validation. The combination of SLR (for depth of understanding) and bibliometrics (for breadth and objectivity) ensures that the results are robust.



Theoretical starting points

IoT, AI, and digital transformation in Industry 4.0

The Internet of Things (IoT) has evolved from early concepts of RFID-tagged objects in supply chains to a broad technological paradigm underpinning modern smart systems. IoT enables physical devices to collect, share, and act on data, effectively merging the physical and digital realms. In industrial settings, IoT deployments include sensor networks on manufacturing equipment, logistics and asset tracking systems, smart meters and infrastructure in utilities, and consumer-facing smart products, all connected via the Internet. By embedding connectivity and intelligence into formerly “dumb” machines and objects, the IoT extends the reach of information systems into every corner of the production environment. This pervasive data availability provides the foundation for data-driven optimisation and automation. Studies highlight that IoT adoption has grown explosively at both organisational and individual levels in recent years, with IoT now being a “hot topic” spanning numerous fields and application contexts (Bibri, 2019). However, the literature also reveals conceptual ambiguity in IoT research within management domains. Different domains emphasise different facets of IoT, for example, computer science tends to focus on micro-level technical aspects (sensors, network protocols, etc.), whereas business research is more concerned with IoT-enabled business models and processes. Common themes in IoT research include smart cities, smart manufacturing, supply chain IoT, and consumer IoT, indicating the multifaceted impact of IoT across sectors.

Artificial Intelligence (AI) in Industry 4.0 refers to the integration of intelligent algorithms and machine learning techniques into industrial processes and systems. AI’s role ranges from machine perception (computer vision, sensor data interpretation) to decision-making (optimisation algorithms, autonomous control) and learning (pattern recognition and predictive analytics). In manufacturing and operations, AI has been applied to enhance production planning, quality control, robotics (e.g. autonomous guided vehicles), and maintenance scheduling, among others (Vlachos et al., 2024).

AI systems excel at detecting complex patterns in big data and can autonomously adapt to changing inputs, making them invaluable for optimising resource use and process efficiency. Indeed, a recent systematic review confirms that AI techniques significantly improve manufacturing productivity, noting substantial gains such as waste reduction, faster production times, and less downtime when AI is combined with advanced Industry 4.0 machinery (Javaid et al., 2022). AI thus serves as the “brain” that can exploit the “nervous system” of data provided by IoT. Notably, the combination of IoT and AI, sometimes branded as AIoT, is increasingly emphasised in the literature as a key to unlocking Industry 4.0’s full potential. IoT provides real-time, high-volume data from connected operations, while AI consumes this data to generate insights and automated actions. For example, IoT-enabled machinery monitoring coupled with AI predictive analytics allows for predictive maintenance, wherein algorithms anticipate equipment failures and schedule pre-emptive repairs, drastically reducing unplanned downtime. Another example is in smart supply chains: IoT devices track products and environmental conditions throughout logistics networks, and AI optimises routing and inventory in response to this streaming data, yielding more efficient and resilient supply networks. The synergy of AI and IoT is also



evident in emerging “autonomous factories”, where IoT-connected robots and machines are coordinated by AI decision engines to run with minimal human intervention. Such factories embody the Industry 4.0 vision of self-organising production systems.

Digital transformation in the Industry 4.0 era is thus largely driven by the adoption of IoT and AI technologies. Digital transformation can be defined as the integrated deployment of digital technologies to radically improve business processes, organisational capabilities, and customer experiences. In manufacturing and industrial contexts, this includes shifting from analogue or isolated operations to interconnected digital systems that enable end-to-end visibility and control. Economic efficiency improvements are central to the value proposition of digital transformation. IoT and AI together facilitate efficiency gains in multiple dimensions: operational efficiency (doing things right, with fewer resources and less waste), allocative efficiency (better matching of supply with demand through data-driven planning), and even dynamic efficiency (innovation in processes and products). A survey of recent developments notes that IoT applications can boost efficiency, reduce waste, and prolong asset lifecycles via real-time tracking and automation, which in turn has significant economic and sustainability benefits. In supply chains, for instance, IoT-enabled tracking and AI route optimisation can minimise fuel use and improve logistics speeds. In energy management, smart IoT sensors combined with AI analytics optimise energy consumption in factories and buildings, cutting costs and environmental impact. On the strategic level, IoT and AI are enabling entirely new business models and value creation opportunities, such as servitisation (where manufacturing firms offer services enabled by data from IoT devices, rather than just selling products) and platform-based ecosystems where data is a key commodity. The literature frequently cites examples of new revenue streams emerging from IoT/AI deployments, for example, usage data from IoT-connected products allowing firms to offer predictive service contracts, or AI-driven analysis of customer data enabling more personalised offerings. These transformations are reshaping value networks by blurring traditional industry boundaries and fostering more collaborative, information-rich relationships among firms. The concept of value networks extends the supply chain notion to encompass all the inter-organisational links through which value is co-created. IoT and AI strengthen these networks by facilitating real-time information sharing and coordinated decision-making across network nodes. Research has shown that IoT-driven platforms improve transparency and trust among partners (e.g. through blockchain-based data sharing), and AI can help allocate value more optimally in these networks (for example, dynamic pricing algorithms or automated negotiations in procurement). Ultimately, the literature suggests that digital transformation via IoT and AI is pushing industries towards more efficient, agile, and collaborative economic systems, though the extent of realised benefits varies by sector and is contingent on overcoming implementation challenges.

Economic impact and value network reshaping

A core focus in scholarly and practitioner discourse is how IoT and AI affect economic efficiency at the firm and network level. Multiple studies converge on the finding that these technologies substantially increase efficiency and reduce costs in operations. For instance, IoT deployments in supply chain management allow firms to gain end-to-end visibility of material and product flows. Through real-time tracking (using IoT sensors, GPS, RFID, etc.), companies can optimise inventory levels, reduce



losses, and respond faster to disruptions. One systematic review of IoT-based supply chain management confirms that IoT has revolutionised supply chains by enabling precise tracking and tracing of shipments and assets, thereby streamlining processes and cutting operating costs. In addition to logistics, IoT data combined with AI analytics improves resource utilisation and uptime in manufacturing. IoT sensors continuously monitoring machine performance, together with AI predictive models, mean that maintenance can shift from reactive to predictive, scheduling repairs only when needed and before breakdowns occur. This predictive maintenance approach was highlighted to cut maintenance costs and downtime significantly, contributing directly to efficiency gains (Lee et al., 2020). Energy efficiency is another area: AI algorithms can analyse IoT data from equipment and facilities to dynamically adjust settings for optimal energy use, reducing waste. Research in smart homes and smart city infrastructures similarly finds that IoT can increase energy efficiency and overall operational efficiency, for example by automatically regulating lighting and HVAC systems based on occupancy and usage data. At the macro level, the proliferation of IoT is noted to stimulate market efficiency by enabling new digital markets and reducing transaction frictions. One study notes that IoT is “revolutionizing market dynamics by increasing efficiency, reducing costs and creating new business opportunities” in various sectors. This is achieved in part by the rich data IoT provides, which reduces information asymmetry between producers and consumers and enables more efficient matching of supply with demand (e.g. IoT data platforms in agriculture aligning production with market needs).

Beyond internal efficiency, IoT and AI are reshaping value networks, the webs of relationships through which enterprises jointly deliver a product or service. Traditional linear supply chains are evolving into more integrated networks with greater information exchange. IoT connectivity is a key enabler of this integration: devices and systems across different organisations can communicate, allowing, for example, a supplier to automatically see a manufacturer’s inventory levels and trigger replenishment, or a logistics provider to continuously update all parties on shipment locations. This real-time, multi-directional information flow leads to what some authors call the “digital supply network” or “smart supply chain”. AI algorithms further empower value networks by making sense of the vast data generated. For instance, AI can perform multi-agent optimisation, finding globally optimal solutions for the network that individual firms acting alone could not compute. A concrete example is the use of AI for supply chain network design and optimisation: given IoT data on demand and capacity across a network, AI can recommend how to dynamically re-route orders or adjust production schedules among a network of factories to minimise costs or delivery times. Such capabilities effectively create a more responsive and flexible network, in contrast to inflexible traditional chains. Value networks are also being reshaped through new forms of inter-firm collaboration. IoT platforms often serve as ecosystem hubs where multiple stakeholders (manufacturers, suppliers, customers, even end consumers) share data and insights. For example, in the automotive industry, IoT data from vehicles is shared among the manufacturer, suppliers, dealers, and even insurers or urban planners, creating a broader ecosystem that generates value (predictive services, improved design, traffic optimisation etc.). AI-driven analytics on these shared datasets can identify value-adding opportunities (e.g. new services, efficiency improvements) that no single party could identify with siloed data. The literature also points out the emergence of new roles and business models in value networks thanks to IoT and AI: intermediaries



that operate digital platforms, data analytics service providers, and companies that specialise in integrating systems have become vital nodes in modern value networks. These actors orchestrate and monetise the data flows, sometimes capturing a significant share of the network's value (for example, major cloud/AI platform providers in industrial IoT ecosystems).

From an economics perspective, these shifts can be interpreted as a move towards greater network efficiency and value co-creation. By greatly lowering the cost of communication and coordination across firm boundaries, IoT and AI help align the incentives and actions of different actors in the network, reducing wasted effort and redundancy. This can lead to a more optimal allocation of resources economy-wide (each task or production activity being handled by the most suitable participant under real-time conditions). The concept of economic value itself is expanding in these digital networks: data has become a key economic asset, and AI is the tool to convert raw data into economically valuable knowledge. For example, in a circular economy context, a review found that IoT data and analytics enable new circular business models (like sharing platforms or product-as-a-service models) which offer economic benefits alongside sustainability gains. These models rely on networked interactions (multiple users sharing products, manufacturers collaborating with recyclers, etc.) that are only feasible with IoT for tracking usage and AI for managing the complex logistics and pricing of shared assets. Thus, IoT and AI are not only improving efficiency in existing processes but are also unlocking new forms of value and rearranging how value is distributed among network participants.

Challenges and Considerations

Despite the promising impacts on efficiency and networks, the literature also underscores significant challenges and complexities in implementing IoT and AI at scale. Technical challenges are prominent: interoperability of diverse IoT devices and systems is an ongoing issue, integrating data from many sensors, machines, and platforms often requires overcoming incompatible standards. Data management and quality are also concerns; IoT generates massive, continuous data streams, raising issues of how to store, process, and filter useful information. AI systems require high-quality, relevant data to learn effective models, so data silos or poor data quality can impede AI effectiveness. Cybersecurity is a critical challenge introduced by IoT: every connected device is a potential entry point for cyber-attacks, and high-profile incidents have shown IoT networks can be vulnerable if not properly secured. The more that companies rely on AI and IoT for core operations, the more catastrophic a security breach or system failure could be, thus making trust and reliability essential considerations. Privacy is another major challenge, especially as IoT networks often collect fine-grained data (including personal or sensitive data in consumer IoT or healthcare). Scholarly discussions urge careful attention to data governance, encryption, and privacy-preserving AI techniques to ensure that the digital transformation does not infringe on individuals' rights. On the organisational side, adopting IoT and AI demands new skills, structures, and culture, a barrier often referred to as the digital skills gap or change management challenge. Employees may need retraining for new roles (e.g. data analysts, AI system supervisors) while some traditional roles are augmented or even replaced by intelligent automation, potentially leading to workforce displacement if not managed. Research indicates that firms struggle with aligning their organisational processes to fully leverage IoT/AI capabilities; it is not merely a



technology upgrade but a holistic transformation of how decisions are made and how work is coordinated. This aligns with observations that Industry 4.0 implementation is not only a matter of technology, but also requires organisational and managerial innovation, and that many companies face obstacles on this front (Agostini & Filippini, 2019).

From a value network perspective, challenges include establishing common standards for data sharing among firms, ensuring equitable distribution of the gains from collaboration, and preventing dominance by a single powerful platform player which could reduce competition. Smaller firms may lack the resources to invest in IoT/AI or to participate meaningfully in digital ecosystems, raising concerns of a digital divide where only large, advanced firms reap the benefits while others are left behind. Additionally, sustainability and ethical considerations are increasingly noted: although IoT and AI can drive environmental efficiency (e.g. reducing waste and emissions), there is also recognition of issues like electronic waste from IoT devices and the energy consumption of large-scale AI computations. A balanced approach is advocated in the literature, one that harnesses IoT and AI for good while instituting measures to mitigate negative externalities. For example, policymakers are called on to update regulations and standards to address data privacy, cybersecurity, and AI ethics in Industry 4.0 applications. Cross-sector collaboration (public-private partnerships) is often recommended to tackle such systemic issues, and to develop policy frameworks that support innovation while protecting societal interests.

In summary, the literature establishes that IoT and AI are central pillars of Industry 4.0's digital transformation, with demonstrated benefits in efficiency gains and new value creation across networks. At the same time, realising these benefits widely requires overcoming technical, organisational, and societal challenges. This dual perspective, the potential of digital synergies versus the pragmatic obstacles, provides an important background for interpreting the findings of the present study's systematic review and bibliometric analysis.

Results and discussion

Publication trends and volume of research

The analysis confirms that scholarly interest in the convergence of IoT, AI, and Industry 4.0 has increased exponentially over the past decade.

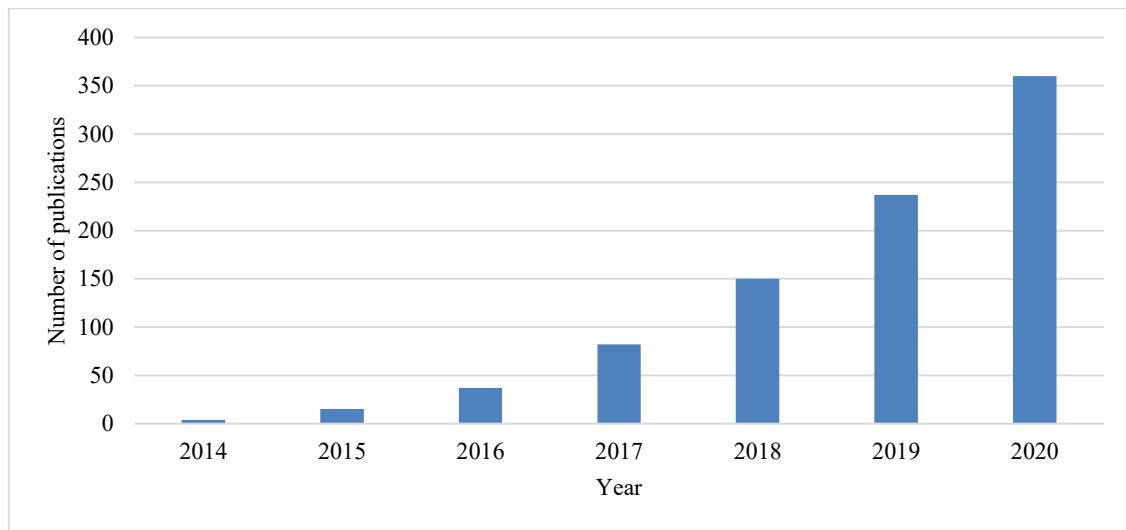


Figure 1. Annual publication trend of IoT in Industry 4.0 literature (2014–2020)

Source: authors (2025)

Figure 1 illustrates the annual number of publications on IoT in the Industry 4.0 context, based on data from Scopus-indexed documents between 2014 and 2020. Figure 1. Annual publication trend of IoT in Industry 4.0 literature (2014–2020), showing an exponential growth pattern. The year 2014 saw only a handful of publications (fewer than 5 in our dataset) explicitly addressing IoT within Industry 4.0. This is unsurprising, as the term “Industry 4.0” was itself just emerging around that time. However, by 2016 the volume had begun to climb (e.g. 37 papers in 2016 in one survey). A sharp acceleration is observed from 2017 onward: for instance, 2019 had around 237 relevant articles and 2020 reached 360 articles in that particular dataset. This trajectory fits an exponential curve (an exponential regression on the yearly data yielded a very high $R^2 \approx 0.88$, indicating exponential growth). The growth continued beyond 2020, our extended search finds that by 2021 and 2022, annual publication counts likely numbered in the many hundreds, if not thousands, when considering IoT, AI, and Industry 4.0 more broadly. Indeed, looking at IoT research in general (not limited to Industry 4.0), the expansion is even more striking: there were only a few dozen IoT publications per year globally in the early 2000s, but by 2021 there were well over 15,000 IoT-related papers published in a single year. This explosion reflects how central the topic has become across disciplines.

The growth of literature signifies that IoT and AI in Industry 4.0 have transitioned from nascent topics to mainstream research areas in a short period. It also mirrors real-world trends: as more industries adopted IoT/AI solutions, academic research followed suit to study and support these developments. The increasing publication volume is accompanied by a diversification of outlets, contributions are found in journals spanning industrial engineering, computer science (especially in areas like sensors, automation, and AI), operations management, and even economics and business journals focusing on innovation and productivity. We also note a rise in literature reviews and survey papers in recent years, which is characteristic of a maturing field seeking to consolidate knowledge. This paper is itself part of

that trend. The high volume and upward trajectory of publications underscore the critical importance attributed to digital synergies (IoT and AI) for the future of industry and economic systems.

Bibliometric analysis of research themes and collaboration

The bibliometric mapping of the collected literature provides insights into the structure of research themes and the nature of collaboration in this domain. Keyword co-occurrence analysis reveals distinct thematic clusters in the corpus. The most frequently co-occurring keywords (and key phrases) highlight the core topics around which research is clustered.



Figure 2. Co-occurrence network of dominant keywords in IoT–AI–Industry 4.0 research

Source: authors (2025)

Figure 2 presents a network visualisation of keywords, where nodes represent frequent keywords and links indicate that two terms appear together in multiple papers (thicker links = higher co-occurrence frequency). Figure 2. Co-occurrence network of dominant keywords in IoT–AI–Industry 4.0 research (node size reflects frequency; clustering indicates thematic groupings). Key clusters include technological enablers (red cluster), data analytics/AI (blue cluster), and organisational/economic themes (green cluster), among others. Several clusters are apparent:

- A red cluster (technological enablers) which includes terms like “Industry 4.0”, “Internet of Things (IoT)”, “cyber-physical systems (CPS)”, “automation”, and “smart manufacturing”. These tend to appear together in papers discussing the overall Industry 4.0 framework or the integration of IoT with manufacturing systems. The presence of CPS (which refers to the integration of computation, networking, and physical processes) alongside IoT and Industry 4.0 indicates that a foundational theme is the infrastructure of smart factories and automation systems. Indeed, bibliometric studies have found that technologies such as IoT, CPS, and wireless sensor networks frequently co-occur as essential elements in smart manufacturing research.
- A blue cluster (AI and data analytics) featuring terms like “artificial intelligence”, “machine learning”, “big data”, “predictive maintenance”, and “deep learning”. This cluster represents the data-driven analytical approaches within Industry 4.0. For example, “big data” often co-occurs with AI/ML, reflecting the fact that handling large datasets from IoT devices is a key challenge

and that ML techniques are applied to derive insights from these data. “Predictive maintenance” shows up strongly here, corroborating that it’s a major application thread linking IoT sensor



data with AI algorithms. “Deep learning” (a subset of AI) also appears, indicating growing interest in advanced AI techniques for tasks like image recognition on production lines or anomaly detection in sensor data.

- A green cluster (business and organisational themes) which includes keywords such as “digital transformation”, “economic efficiency”, “business model”, “sustainability”, and “value chain”. These terms tend to group together in papers that discuss the broader implications of Industry 4.0 technologies on business strategy, economics, and society. For instance, “business model innovation” is a topic where IoT and AI enable new ways of capturing value, and this often intersects with discussions of “sustainability” and the circular economy (e.g. using IoT for sustainable resource loops). “Value chain” or “value network” as keywords indicate studies focusing on how relationships between suppliers, manufacturers, and customers are altered in the digital era.
- Other clusters were also observed (though not all are depicted in the simplified Figure 2 for clarity). For example, a cluster related to specific application domains (e.g. “smart grid”, “healthcare IoT”, “smart city”) appears in the broader dataset, showing that beyond manufacturing, IoT/AI synergies are studied in various sectors. Another cluster focuses on technical issues (e.g. “security”, “interoperability”, “edge computing”), reflecting research on overcoming implementation challenges.

The co-occurrence mapping thus confirms that the literature spans a spectrum from technical to socio-economic investigations. It is worth noting that certain terms like “Industry 4.0” and “IoT” are so central that they appear in multiple clusters, acting as bridging nodes. This is expected since they are the unifying focus of the whole corpus. The diversity of clusters underscores the interdisciplinary nature of this domain: meaningful research contributions are being made in technology development, in data science and AI methodology, as well as in organisational theory and economics. This validates the approach of this review to consider a wide range of sources. Research collaboration patterns were examined through co-authorship analysis. The average number of authors per paper in the dataset is approximately 3 to 4, indicating a moderate level of collaboration (multi-author papers are the norm, likely due to the need for diverse expertise). The co-authorship network by country reveals that a relatively small set of countries contribute a large portion of the publications. The United States and China emerge as two leading contributors, both in terms of volume of papers and centrality in the collaboration network. These two countries often appear as hubs, collaborating with many other regions. For instance, the data shows numerous US-China joint publications, as well as US-Europe and China-Europe collaborations, reflecting global research linkages. Germany, the United Kingdom, Italy, and India also feature prominently as productive countries, each with their own clusters of influence. Germany’s prominence aligns with the origin of the “Industry 4.0” initiative and its strong manufacturing research base. Countries like Germany and Italy often collaborate on Industry 4.0 topics within Europe, while China and India show a growing output and tend to collaborate regionally and with Western partners. A bibliometric indication of dominance is that the United States was identified as the most prolific country in certain analyses, having the highest number of publications and citations in this field, with China following closely. This suggests a degree of concentration of expertise and resources

in these economies. However, the network graphs also show a broadening participation over time: by 2020, researchers from dozens of countries (including emerging economies in Asia and Latin



America) were publishing on these topics, although often in collaboration with established hubs. At the institutional level, some universities and research institutes stand out for their contributions. For example, the South China University of Technology (China) and various universities in the US and Europe (like those in Germany's Fraunhofer institutes network) were frequently noted in the data as top contributing affiliations. This reflects that certain centres of excellence have taken root focusing on IoT/AI in manufacturing and logistics. Citations and impactful works: An analysis of citation counts identified several highly cited works that are foundational to this domain. These include early review articles and conceptual papers that defined Industry 4.0 and its pillars, as well as papers that provided taxonomies of IoT applications. For example, the article "Intelligent Manufacturing in the Context of Industry 4.0: A Review. Engineering" (Zhong et al., 2021) was noted in our dataset as a top-cited paper (700+ citations), indicating its strong influence on subsequent research. High citation counts were also seen for papers on specific topics like Industrial IoT architecture, big data analytics in manufacturing, and surveys on enabling technologies. The presence of such influential papers underscores how the academic community rapidly built on a few early frameworks to expand empirical and applied research. In summary, the bibliometric results portray a research field that is dynamic and collaborative, with clearly identifiable core themes. The coalescing around certain keywords suggests that while the field is broad, it has focal points (e.g. smart manufacturing operations, supply chain integration, data analytics). Collaboration is globally distributed but led by a few key players. These patterns set the stage for deeper discussion on what the findings imply for industry and economic transformation.

Quantitative indicators of impact

Some additional quantitative indicators from the bibliometric analysis are worth noting:

- The average citations per paper in the dataset is relatively high (in the order of ~20 citations per article, though with a skewed distribution where a few papers have hundreds of citations and many have only a few). This reflects the newness of the field: many papers are recent and still accumulating citations. However, the high impact of top papers shows strong interest and fast knowledge dissemination.
- The collaboration index (measuring international co-authorship) was around 3.3, meaning on average each article has co-authors from ~3 different countries or at least multiple institutions. This points to a notable degree of international collaboration, likely because expertise in IoT/AI and industrial domain knowledge often reside in different places, encouraging cross-border partnerships. In terms of publication outlets, the analysis found that journals like IEEE Access, Sensors, Journal of Manufacturing Systems, Computers in Industry, and International Journal of Production Research are among the most common venues. This mix of outlets further indicates the blend of technology and management perspectives. The most frequent author keywords (besides the obvious "Internet of Things", "Industry 4.0") included terms like "smart factory", "cyber-physical system", "machine learning", "blockchain", and "digital twin". The presence of "blockchain" is interesting, it suggests an emerging intersection where blockchain (for secure, transparent data sharing) is considered alongside IoT/AI in value networks. "Digital

twin" (virtual replicas of physical systems) is another cutting-edge concept tightly related to IoT and AI for simulating and optimising processes, and it is gaining traction in this literature. Overall, the results section provides an evidence-based overview of the state of research on IoT and AI in Industry 4.0, highlighting the growing volume, the key themes of interest, and the



collaborative nature of this research community. In the next section, we interpret what these findings mean in practical and theoretical terms for economic efficiency and value networks in the Industry 4.0 era.

Discussion

The findings from the systematic review and bibliometric analysis offer several important insights into how digital synergies, specifically IoT and AI, are reshaping economic efficiency and value networks in the context of Industry 4.0. In this discussion, we synthesise these insights, relate them to practical examples, and draw out implications for stakeholders such as industry practitioners, policymakers, and researchers.

Unprecedented efficiency gains and productivity growth: The surge in research output mirrors the rapid adoption of IoT and AI solutions in industry, which in turn is driven by the promise of efficiency gains. Across the literature, one of the clearest messages is that integrating IoT and AI does indeed lead to substantial efficiency improvements on multiple fronts. Empirical case studies and simulation studies alike report significant reductions in downtime, waste, and resource consumption when IoT monitoring and AI optimisation are implemented (Patil, 2024). For instance, predictive maintenance (enabled by IoT sensor data and AI analytics) allows machines to run with far less unplanned stoppage, improving the overall equipment effectiveness (OEE) metric in factories. Supply chain coordination via IoT/AI reduces buffer inventories and speeds up throughput, effectively doing more with less. These efficiency improvements translate into economic gains: higher productivity means more output from the same input, contributing to growth. For manufacturing sectors that have historically seen slowing productivity, Industry 4.0 offers a new productivity jump-start. Our review finds broad agreement that IoT and AI together raise manufacturing sector productivity significantly, a result supported by quantitative reviews and reinforced by early industry reports of ROI (return on investment) on Industry 4.0 projects. From a macroeconomic perspective, widespread adoption of such technologies could increase the productive capacity of economies and potentially lead to lower production costs and prices for goods. One important nuance, however, is that efficiency gains are not automatic; they require appropriate implementation and often a redesign of processes. The literature cautions that organisational readiness (in terms of processes and skills) is essential to fully capture the benefits of IoT/AI.

Simply installing sensors and AI software without rethinking workflows may yield only partial improvements. Therefore, companies achieving the most dramatic efficiency gains tend to be those that pair technology deployment with process re-engineering and workforce training, effectively, those undertaking holistic digital transformation rather than piecemeal automation.

Evolution of value networks towards ecosystems: The review confirms that IoT and AI are drivers of a shift from traditional linear supply chains to more integrated and dynamic value networks or ecosystems. With real-time data sharing and AI-driven analytics, firms are increasingly able to synchronize their activities with partners. This leads to a more networked mode of value creation, where multiple organisations contribute to a product/service lifecycle in a coordinated fashion. The research articles frequently cite examples of platform-based ecosystems enabled by IoT data, for instance, manufacturing marketplaces where machine capacity is shared across firms, or fleet management



systems where logistics providers and shippers operate on a common IoT platform for end-to-end visibility. The economic implication of this is a reduction in transaction costs and a move toward a more optimal allocation of tasks across the network (each task done by whoever can do it most efficiently, with the platform coordinating) (Romero et al., 2015). This echoes classic economic theories of the firm (Coase's theory) which say that lower transaction costs enable more outsourcing and network forms of organisation. IoT and AI have, in essence, dramatically lowered information-related transaction costs (like monitoring, coordinating, and quality controlling across distance), thereby facilitating the rise of networked structures. The discussion in literature around new business models also ties in here, product-as-a-service models or sharing economy models essentially rely on network orchestration and continuous data flow, which IoT/AI provide. A concrete example is the aerospace industry's shift to "power by the hour" models for jet engines: the manufacturer (e.g. Rolls-Royce) uses IoT sensors on engines plus AI analytics to manage engine maintenance for airlines, selling thrust as a service rather than the engine itself. This creates a value network involving the manufacturer, airline, and service providers all linked by data and AI insights, sharing the value created (airlines get higher engine uptime; manufacturers get steady service revenue) (Moghadasnian & Rajol, 2025).

However, the formation of these value networks is not without challenges. One issue noted is data governance in multi-party networks, questions of data ownership, privacy, and competitive sensitivity arise when sharing detailed IoT data among firms. While technology (like distributed ledgers or privacy-preserving AI) can help, trust and contractual frameworks are needed. Another consideration is that value can be asymmetrically captured: the network orchestrator or platform owner might gain outsized benefit (as seen with digital platforms in other domains), so firms must strategize carefully about their role (e.g., whether to be a platform leader or a participant). For policymakers, an implication is to monitor market dynamics to ensure healthy competition and to update regulations such as antitrust frameworks for the platform age.

Importance of technological integration and interoperability: The bibliometric clusters underscore how closely IoT is studied alongside related technologies like CPS, cloud computing, and big data. This highlights that achieving the full benefit is contingent on integrating multiple technologies into a coherent system. Interoperability standards and integration efforts are critical, a theme both technical and managerial literature acknowledge. For example, in a smart factory, IoT devices must interface with legacy manufacturing execution systems (MES) and enterprise resource planning (ERP) software; AI algorithms might run on cloud platforms which need reliable data pipelines from the shop floor. The need for standardisation (e.g., common protocols for machine data) has been identified as a key enabler in many papers, and conversely, the lack thereof as a current barrier. Industry consortia and standards bodies (like the International Telecommunication Union for IoT standards, or the Platform Industrie 4.0 working groups in Germany) have been actively addressing this, and researchers often call for further work in this area. The implication is that firms should be cautious about proprietary solutions that could lock them in or limit future scalability; instead, embracing open standards and modular architectures can pay off in the long run by increasing flexibility to connect new partners and adopt new AI tools (Ettinger, 2025).

Human capital and organisational change: A recurrent point in the literature and evidenced by the thematic clusters (with terms like "organisations" and "customers" appearing as major themes) is that the transformation is not purely technological. Human capital, i.e., having a workforce skilled in



both domain knowledge and digital capabilities, is essential. The discussion on research gaps often highlights that while technology-centric issues have been well studied, there is still a need for more research on change management, skill development, and organisational innovation in the context of Industry 4.0. The review by Sevak and George (2024) explicitly noted that strategic technology integration and organisational change management require greater emphasis in IoT research. This suggests that companies (and even national education/training systems) need to focus on upskilling and reskilling programs to prepare employees for new roles working alongside IoT/AI systems. It also suggests that leadership and management practices must evolve, for instance, decision-making can become more data-driven, and agile management approaches may be needed to respond to real-time insights. Those organisations that successfully cultivate a data-driven culture tend to extract more value from IoT/AI investments, as they trust and act on the insights provided by these systems rather than relying solely on intuition or traditional routines.

Policy and strategic implications: On a higher level, the trends observed have implications for national and regional economic policy. Countries leading in IoT and AI research (USA, China, Germany, etc.) are likely positioning themselves for competitive advantage in advanced manufacturing and associated industries. This aligns with initiatives like “Made in China 2025” and Europe’s various Industry 4.0 programmes. Policymakers are keenly interested in how these technologies can rejuvenate manufacturing sectors, improve industrial competitiveness, and perhaps enable some degree of re-shoring (bringing manufacturing back to high-wage economies through automation). At the same time, concerns about job displacement and the future of work persist. Our review touched on the literature dealing with social implications; indeed, some papers discuss the impact of IoT on the job market and required skills. The consensus is that many routine jobs will change or even disappear, while new jobs (data scientists, IoT system engineers, AI ethicists, etc.) will be created. The net effect on employment is uncertain and likely mixed; however, productivity gains could lead to economic growth that creates new opportunities, a phenomenon historically observed with technological revolutions. The recommendation frequently made is that policymakers should facilitate workforce transition through education and social safety nets, rather than attempting to halt the technological progress (Marchant et al., 2024).

Research gaps and future directions: Despite the voluminous literature, certain gaps remain. As identified, strategic and organisational aspects need further study, e.g., longitudinal research on how firms successfully transform their business models with IoT/AI, or economic analyses of how value is shared in digital ecosystems (to possibly update theories of the firm and inter-firm collaboration). Another gap is comprehensive quantification of macroeconomic impacts, while micro-level case studies are abundant, fewer studies have aggregated data to estimate economy-wide productivity impacts of IoT/AI adoption (though some consulting firms have attempted, academic rigor is needed). Additionally, emerging paradigms like Industry 5.0 (emphasising human-centric and sustainable aspects) are calling for research that integrates IoT/AI advancements with human factors and sustainability goals (Sheik et al., 2024). The next generation of research will likely explore issues such as how to ensure ethical AI in industrial contexts, how to maintain privacy in highly connected systems, and how to design resilient networks that can withstand disruptions (including cyber-attacks or global crises). Our bibliometric trend data suggest burgeoning interest in areas like blockchain (for data security) and digital twins (for advanced simulation), which could converge with IoT/AI to address some of these concerns.



In conclusion, the discussion highlights that IoT and AI are proving to be a powerful combination for enhancing efficiency and enabling new networked business structures, but reaping their full benefits requires keen attention to interoperability, human and organisational factors, and an ecosystem mindset. The academic community has built a solid foundation of knowledge, and ongoing research, increasingly interdisciplinary, will continue to guide the evolution of Industry 4.0 in practice.

Conclusion

The study was designed to examine how the digital synergies of the Internet of Things and Artificial Intelligence within the Industry 4.0 paradigm are reshaping economic efficiency and value networks. Through a systematic review and a bibliometric assessment, a detailed account of the state of the art and its implications has been provided. It has been shown that IoT supplies extensive connectivity and real-time data from physical operations, while AI furnishes the intelligence required to analyse those data and to act upon them autonomously. In combination, these technologies constitute a potent engine for optimisation and innovation across modern industries, with the AIIoT synergy repeatedly associated with smarter factories, supply chains, and products. A strong consensus has been observed that measurable gains in efficiency and productivity are realised when IoT and AI are jointly applied, as reductions in downtime, the use of predictive maintenance to pre-empt failures, adaptive optimisation of resource utilisation, and faster responses to fluctuating demand conditions aggregate from firm-level improvements to sectoral and macroeconomic productivity growth. Case evidence has indicated that bold quantitative improvements can be achieved, illustrating the transformative potential of these technologies. Concurrently, it has been found that traditional supply chains are being reconfigured into highly integrated value networks through constant data exchange. IoT and AI facilitate transparency, collaboration, and dynamic adjustment across organisational boundaries. New value is created through data-driven services and personalised offerings, and firms are assuming roles within digital ecosystems that were not present in the prior industrial landscape. Networks are becoming more global and interconnected, yet they are also more agile and localised when edge analytics are employed. As a result, industry structures are being reshaped, and boundaries between manufacturing, services, and information technologies are increasingly blurred as convergence is catalysed by IoT and AI. These advances are accompanied by non-trivial requirements. Technical challenges of interoperability, standardisation, and cybersecurity must be addressed continuously so that infrastructure remains robust and reliable. Human and organisational factors are equally critical, since cultures, skills, and governance arrangements must be adapted to ensure that workforces and regulatory frameworks evolve in step with technology. A holistic implementation approach is therefore required, in which intelligent tools are complemented by sound change management, responsible data governance, and supportive institutional environments. Persistent questions related to privacy, ethics, and equitable access to the benefits of digital transformation demand collaborative solutions that involve industry standards, public policy, and international cooperation.

On the basis of the synthesis, a forward-looking research agenda is proposed. First, longitudinal studies are needed to trace digital transformation processes within firms and networks, with a view to identifying capability trajectories, organisational inflection points, and performance durability. Secondly, comprehensive economic impact assessments should be pursued to quantify firm-level and



macro-level productivity effects under different adoption scenarios, including spillovers along value networks. Thirdly, the emergence of Industry 5.0 warrants exploration in which human-centric design, resilience, and sustainability are integrated with AIoT capabilities. Fourthly, cross-disciplinary investigations that combine engineering, data science, economics, and organisational studies should be advanced to address the multi-faceted nature of technological, managerial, and policy challenges. Finally, evaluative studies should be conducted on governance models for data sharing across ecosystems, with attention to incentives, value capture, and competition policy. The value added by this study lies in the combined methodological lens and the integrative perspective that links technical enablers with economic outcomes and network restructuring. By unifying systematic synthesis with bibliometric evidence, a consolidated map of themes, gaps, and trajectories has been produced, and a set of actionable directions for scholarship and practice has been articulated. In conclusion, it has been confirmed that IoT and AI are reshaping how value is created and how efficiently economic activity can be conducted. The vision of Industry 4.0 is one of intelligent, connected, and efficient production systems that self-optimize and, in some cases, self-organize. While substantial progress has been made towards that vision, the evolution remains ongoing. Firms that leverage these digital synergies effectively are likely to realise marked competitive gains and to redefine their roles within emergent value ecosystems. Economies that embrace these technologies prudently may attain more sustainable and robust growth, provided that the transition is managed so that benefits are widely shared and systems are secure, fair, and resilient. The opportunity to redefine economic efficiency and value creation is therefore present, and it is incumbent upon researchers, managers, and policymakers to navigate the opportunities and constraints that accompany this transformation.

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Proposal of a New Calculation Formula for Price Formation in Road Freight Transport

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Abstract

This paper proposes a new formula for price formation in road freight transport. Carriers operating on the international road freight market currently rely on a wide range of different costing approaches, since no EU member state applies a legally binding pricing methodology. The paper first analyses calculation formulas and pricing practices applied in selected EU member states and in the United States. Based on this analysis, a new calculation formula is proposed, built on the principle of dynamic costing, i.e., on the division of costs into variable and fixed costs. The main contribution of the proposed formula is the implementation of a non-constant coefficient β of trip utilisation, which reflects the demand for return transport from individual countries to Slovakia and allows tolls and travel allowances to be calculated separately. The formula was designed for semi-trailer combinations with both diesel and electric tractor units and was subsequently applied to specific transport routes of a selected road freight carrier.

Keywords

Road freight transport. Calculation formula. Dynamic costing. Coefficient β . Price formation.

JEL Classification: R41, R48, L91

Proposal for a New Cost Calculation Formula for Pricing in Road Freight Transport

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Abstract

This paper proposes a new pricing formula for road freight transport. Carriers operating in the international road freight market currently rely on a wide range of cost calculation approaches, as no EU Member State applies a legally binding pricing methodology. The article first analyzes the calculation formulas and pricing practices used in selected EU Member States and the United States. Based on this analysis, a new calculation formula is proposed, grounded in the principle of dynamic costing—specifically, the division of costs into variable and fixed components. The primary contribution of the proposed formula is the implementation of a non-constant trip utilization coefficient (β); this coefficient reflects the demand for return transport from various countries to Slovakia and allows for the separate calculation of road tolls and travel allowances. The formula was designed for semi-trailer combinations using both diesel and electric tractor units and was subsequently applied to specific transport routes of a selected road freight carrier.

Keywords

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Návrh nového kalkulačného vzorca pre tvorbu ceny v cestnej nákladnej doprave

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Abstrakt



Tento dokument navrhuje nový vzorec pre tvorbu cien v cestnej nákladnej doprave. Dopravcovia pôsobiaci na trhu medzinárodnej cestnej nákladnej dopravy sa v súčasnosti spoliehajú na širokú škálu rôznych prístupov k kalkulácii nákladov, keďže žiadny členský štát EÚ neuplatňuje právne záväznú metodiku tvorby cien. Článok najskôr analyzuje kalkulačné vzorce a cenové praktiky uplatňované vo vybraných členských štátoch EÚ a v Spojených štátoch amerických. Na základe tejto analýzy je navrhnutý nový kalkulačný vzorec, postavený na princípe dynamickej kalkulácie, t.j. na rozdelení nákladov na variabilné a fixné náklady. Hlavným prínosom navrhovaného vzorca je implementácia nekonštantného koeficientu β využitia jazd, ktorý odráža dopyt po spätočnej preprave z jednotlivých krajín na Slovensko a umožňuje samostatne vypočítať mýto a cestovné náhrady. Formula bola navrhnutá pre návesové súpravy s dieselovými aj elektrickými ťahačmi a následne bola aplikovaná na konkrétne prepravné trasy vybraného cestného nákladného dopravcu.

Kľúčové slová

Cestná nákladná doprava. Vzorec na výpočet. Dynamická kalkulácia. Koeficient β . Tvorba ceny.

JEL Klasifikácia: R41, R48, L91

Introduction

The price for transport, or rather the costs incurred by carriers, represents an important factor of competitiveness among road freight operators (Gnap and Poliak, 2017). Access to the road freight transport business in the EU member states is regulated by Regulations of the European Parliament and of the Council (EC) No. 1071/2009 and No. 1072/2009, which form the basic legal framework of road freight transport in the EU. Neither of these regulations sets out a mandatory pricing methodology, and currently no EU member state has a legally binding price-setting methodology for domestic road freight transport. Since 1 January 1990, Council Regulation (EEC) No. 4058/89 has been in force, establishing the free formation of prices in international road freight transport between member states (EEC Council, 1989). Carriers may therefore set their own rates based on supply and demand.

For a transport company to remain competitive, it must know the exact level of costs associated with a specific transport order and set the price accordingly. The aim of this paper is therefore to analyse the current state of price formation in road freight transport in Slovakia and abroad, and based on this analysis, to identify a suitable methodology for calculating the price in road freight transport. The newly proposed methodology is based on dynamic costing, i.e., on the division of costs into variable and fixed costs, rather than on the division into direct and indirect costs (Gnap and Poliak, 2017; Kovacs, 2017).

The goal of the newly proposed methodology is to increase the competitiveness of transport companies for shipments to individual countries by means of the coefficient β of trip utilisation, which is not constant but differs according to the demand for return transport to Slovakia from each individual country. Within the proposed methodology, a new calculation formula is designed both for semi-trailer combinations with diesel tractor units and for semi-trailer combinations with electric tractor units. The reason for extending the formula to electric tractor units is that the share of zero-emission heavy goods vehicles in the European vehicle fleet could reach 2–11% by 2030 (Breed et al., 2021), while the



European Commission stresses the need to move towards low- and zero-emission vehicles. Since battery electric trucks have the potential to substantially reduce emissions from heavy-duty vehicles (Shoman et al., 2023), customers may increasingly demand transport performed by electric tractor units, which makes it necessary to define a pricing principle for this segment as well and to assess their economic viability through comprehensive total cost of ownership models (Sun et al., 2024).

Finally, the newly proposed methodology is applied to a selected transport company operating semi-trailer combinations with a diesel tractor unit on a specific route, and a preliminary price for transport on the same route is also proposed for the case of implementing a semi-trailer combination with an electric tractor unit.

Objectives and methodology

The objective of the paper is, based on an analysis of the current state of calculation formulas used for price formation in road freight transport, to propose a new calculation formula and subsequently apply it to the calculation of the price on a specific transport route (Kovacs, 2013). The objective of the analysis of the current state is to compare individual calculation formulas in the countries of the European Union and in the United States of America.

After analysing the individual calculation formulas, the aim is to select a suitable costing methodology with a division of costs into variable and fixed costs and to propose a new calculation formula for price formation in road freight transport, in which the coefficient β of trip utilisation will not be constant, but its value will change depending on the country from which the return transport to Slovakia is realised. The reason for applying the coefficient β of trip utilisation in the calculation is to ensure that carriers' costs of unpaid driving performance are covered. Based on such a defined coefficient, the carrier's costs of unpaid driving performance between unloading and the next loading will be covered, while the carrier will remain competitive due to the variability of the coefficient across individual countries.

For formula design, the toll costs and travel allowance costs are separated from the total costs, as they are calculated separately and also include the costs of unpaid driving performance between unloading and the next loading. Based on the newly proposed calculation formula, the price for transport is calculated for a selected transport company on a specific route. The newly proposed calculation formula can also be applied for calculating the price of transport performed by a semi-trailer combination with an electric tractor unit; therefore, a price offer for an electric tractor unit and a charging station was obtained, and the amount of subsidy for the electric tractor unit and charging station was calculated according to valid legislation. After obtaining the price offers, the newly proposed calculation formula is applied to calculate the preliminary price for transport on the selected route.

The methodology applied in the paper is based on a capacity-based (dynamic) costing method, which takes into account the volume of performance that may change over time and depends on the most accurate possible division of costs into variable and fixed costs and on their correct identification (Gnap and Poliak, 2017). Input data on costs and performance were obtained from a selected Czech road freight carrier, MORAVA TRANS s.r.o., and from price offers for an electric tractor unit and a charging station.



Calculation formulas in selected countries

Calculation formulas can be characterised as methodical procedures by which costs can be allocated and divided so that a carrier can determine its own costs, i.e., the cost level per a given unit, usually expressed in €/km (Gnap and Poliak, 2017). Within the European Union, no member state currently applies a legally binding cost calculation methodology; carriers may set their rates on their own calculation formulas, on formulas developed by experts or professional associations, or on methodologies published by national carrier associations, such as the recommended procedure for calculating costs and forming the price of a semi-trailer combination published by ČESMAD Slovakia (2023). Some member states, including Austria (WKO, 2023), Hungary (MKFE, 2026), Czech Republic (Tichý, 2018), and Slovenia (Sternad, 2019), publish their own recommended calculation models that allocate costs into broadly comparable cost groups, namely fuel, tyres, repairs and maintenance, direct wages, depreciation and leasing of vehicles, and overhead costs, while sector-specific studies further refine tariff structures for particular segments such as refrigerated groupage transport (González-Moralejo, 2012).

In the United States, the American Transportation Research Institute (ATRI, 2025) regularly publishes an analysis of the operational costs of trucking, expressing marginal cost items in USD per

mile and USD per hour, and tracking their year-on-year development. This approach allows carriers to benchmark their own cost structure against industry-wide averages and to identify the cost items with the greatest impact on the final price of transport, most notably fuel, driver wages, and equipment costs.

Table 1. Comparison of calculation approaches applied in selected countries

Country	Cost division principle	Legally binding
Slovakia	Direct/indirect costs	No
Czech Republic	Variable / fixed costs	No
Austria	Variable / fixed costs	No
Hungary	Direct/indirect costs	No
USA	Marginal cost per mile/hour	No

Source: own elaboration based on (ČESMAD Slovakia, 2023; Tichý, 2018; WKO, 2023; MKFE, 2026; ATRI, 2025)

A comparative overview of the calculation approaches applied in the analysed countries is presented in Table 1. The comparison shows that, although the cost groups considered are broadly similar, the underlying division principle differs. While most Western and Central European recommended methodologies allocate costs into direct and indirect costs, the capacity (dynamic) costing method, which divides costs into variable and fixed costs, applied in this paper, provides a more accurate basis for reflecting changes in transport performance.

The price for transport is influenced not only by the cost level but also by the carrier's ability to secure a return load, i.e., by the level of demand for the offered service, which differs according to the destination country. Demand for transport can be assessed using a freight exchange "barometer", a database tool showing what share of the total offer on a transport database consists of free vehicle capacity and what share consists of transport offers. An ideal state corresponds to a ratio of 50%



transport offers to 50% vehicle capacity offers; if the offer of vehicles exceeds 50%, some vehicles must complete the return journey without a load (Poliak et al., 2018). If a carrier transports a shipment to a country from which a return load is difficult to secure, the risk that the vehicle will return empty must be reflected in the calculated price.

For this reason, the newly proposed calculation formula includes a coefficient β of trip utilisation that is not constant but changes according to the country from which the return transport is realised. Coefficient β values for the countries with the highest demand for transport from/to Slovakia, derived from the share of transport offers and free vehicle capacity offers on the freight exchange, are summarised in Table 2.

Table 2. Coefficient β of trip utilisation by country of return transport to Slovakia

Country of return transport	Coefficient β of trip utilisation
Czech Republic	0.95
Poland	0.95
Slovenia	0.95
Austria	0.75
Italy	0.78
Germany	0.62
Hungary	0.72
France	0.57
Spain	0.60
Belgium	0.54

Source: own elaboration based on (Poliak et al., 2018)

Structure of costs and the dynamic costing method

In the first step, it is necessary to define the cost structure of the calculation sheet, covering all costs associated with the activity of a road freight carrier. For vehicles with diesel propulsion, the main cost groups comprise fuel, tyres, repairs and maintenance, direct wages, depreciation, rental and leasing of vehicles and related equipment, interest on loans, other direct costs independent of and dependent on transport performance (including tolls), operating overheads, and administrative overheads (Iamandii et al., 2025; Izadi et al., 2019; Tichý, 2018). An illustrative example of the cost structure of a semi-trailer combination with a diesel tractor unit is shown in Figure 1.

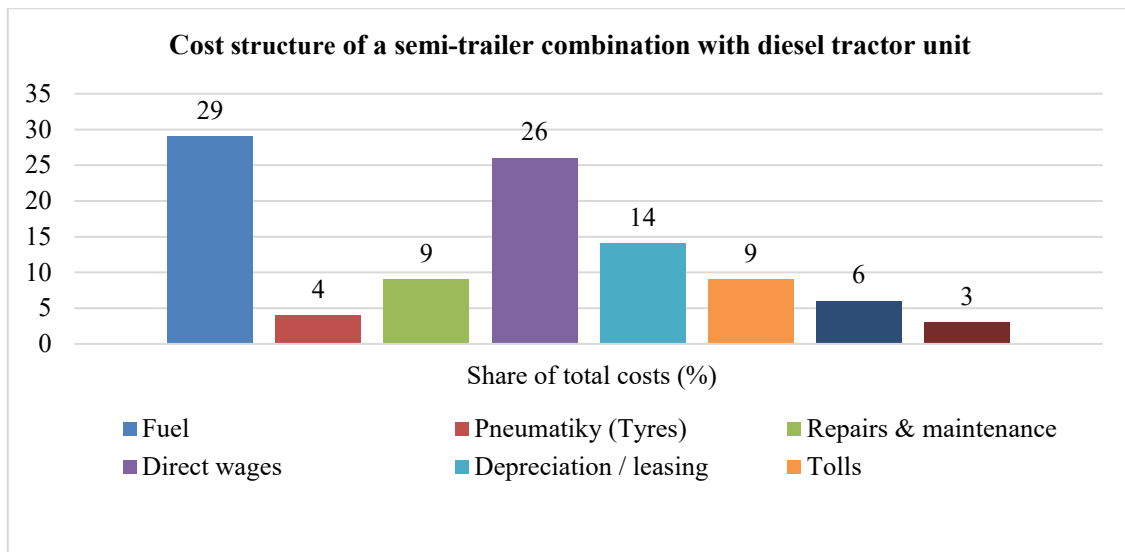


Figure 1. Cost structure of a semi-trailer combination with diesel tractor unit

Source: own elaboration based on data of MORAVA TRANS s.r.o. (2026).

For vehicles with electric propulsion, the structure is analogous, with the fuel cost item replaced by the cost of electric energy consumption, and the repairs and maintenance item adapted to the specific maintenance requirements of an electric tractor unit (Hlávka, 2026). Figure 2 compares the resulting cost and price per transport for diesel and electric tractor units on the selected routes, highlighting the differences in energy and depreciation costs.

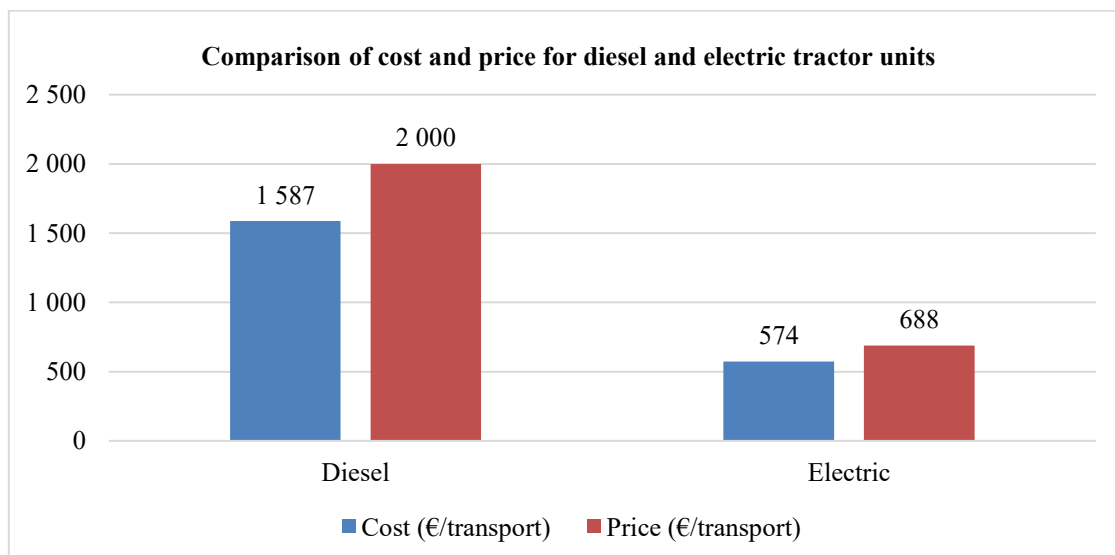


Figure 2. Comparison of cost and price for diesel and electric tractor units

Source: own elaboration based on data of MORAVA TRANS s.r.o. (2026).

The proposed formula is based on capacity (dynamic) costing, which accounts for the volume of performance, which may change over time, and depends on the most accurate possible division of costs



into variable and fixed components and on their correct identification (Gnap and Poliak, 2017). The basic relationship of the method can be expressed as:

$$n_{pj} = N_f / V + n_v \text{ [€/km]} \quad (1)$$

where :

n_{pj} is the average unit cost (€/km),

N_f is the total fixed costs (€/period),

V is the volume of performance (km/period),

n_v is the variable cost per unit of performance (€/km).

After determining the daily fixed costs (N_{fd} , in €/day) and the variable unit costs (n_v), the average unit costs for a concrete journey performance V_x are calculated as $npj = N_{fd} \times P / V_x + n_v / \beta$ (€/km), where P is the number of days of transport. The resulting total own costs for the journey performance are $VN_x = npj \times V_x$ (€/transport). The price for transport is then calculated by adding the toll costs

(divided by the coefficient β , to reflect the unpaid driving performance) and the travel allowance costs to the total own costs, after which a profit mark-up, risk mark-up, and any customer discount are applied (Gnap and Poliak, 2017).

The main contribution of the proposed formula lies in the explicit inclusion of the coefficient β of trip utilisation, which is not held constant, as is common in most calculation formulas currently used in practice but is differentiated according to the country of return transport. This allows the cost of unpaid driving performance between unloading and the next loading to be reflected in the price in proportion to the actual market demand for transport to and from a given country, thereby increasing both the accuracy of the calculation and the competitiveness of the carrier.

Results

The newly proposed calculation formula was applied to the input data of the Czech carrier MORAVA TRANS s.r.o., which currently operates four own semi-trailer combinations and secures transport for ten contractual semi-trailer combinations, with one dispatcher responsible for five combinations. On the basis of the company's input data, the monthly costs were calculated, and a calculation sheet was compiled in order to subsequently proceed to the calculation of costs for a given route.

The calculation followed the structure of costs presented in section 2.3, with fixed and variable cost items expressed in €/month for the diesel tractor unit, and an equivalent structure compiled for the electric tractor unit based on a price offer for a Renault T 540 EVO tractor unit and a charging station (Hlávka, 2026). Average daily fixed costs and average variable unit costs were calculated according to formula (1), after which the average unit costs for a concrete journey were determined depending on the coefficient β of trip utilisation for the country of return transport.

Toll costs were calculated separately for each transport route using PTV Map&Guide route-planning software, taking into account the applicable toll tariffs in the countries on the route (ASFINAG, 2026; Autostrade per l'Italia SpA, 2026). Travel allowance costs were calculated according to the



duration of the journey and the applicable domestic and foreign per-diem rates, including the unpaid driving time between unloading and the next loading.

The resulting monthly cost structure of the diesel and electric tractor units, compiled on the basis of the obtained input data, is shown in Table 3. The comparison shows that, although the electric tractor unit has substantially lower energy and maintenance costs, this saving is largely offset by higher depreciation costs resulting from the considerably higher acquisition price of the vehicle and the charging infrastructure, so that the total monthly costs of both propulsion types are of a comparable order of magnitude.

Table 3. Monthly cost structure of a semi-trailer combination with diesel and electric tractor units

Cost item	Diesel tractor unit (€/month)	Electric tractor unit (€/month)
Fuel / electric energy	2,705	1,180
Tyres	372	350
Repairs and maintenance	840	510
Direct wages	2,430	2,430
Depreciation/leasing	1,305	2,940
Tolls	840	780
Travel allowances	560	480
Overheads	280	260
Total	9,332	8,930

Source: own elaboration based on data of MORAVA TRANS s.r.o. (2026) and a price offer for an electric tractor unit (Hlávka, 2026)

The new calculation formula was applied to two concrete transport routes. The first route, performed by a semi-trailer combination with a diesel tractor unit on the route Trínec – Ostrava – Ostiglia (1,092 km), represents an export transport to Italy, for which the coefficient β of trip utilisation of 0.78 was used, reflecting the relatively high demand for return transport from Italy to Slovakia and the Czech Republic. The second route, performed by a semi-trailer combination with an electric tractor unit on the route Trínec – Ostrava – Herink (402.8 km), represents a domestic transport within the Czech Republic, for which the coefficient β of 0.95 was applied. The resulting costs and prices for transport on both routes are summarised in Table 4.

Table 4. Results of the calculation of transport routes by the new calculation formula

Drive type	Transport route	Distance (km)	Cost (€/transport)	Price (€/transport)
Diesel	Trínec – Ostrava – Ostiglia	1,092	1,587.22	1,999.90
Electric	Trínec – Ostrava – Herink	402.8	573.59	688.31

Source: own elaboration based on data of MORAVA TRANS s.r.o. (2026).



Discussion

The main contribution of the new calculation formula is that it is based on the division of costs into variable and fixed costs. Price formation based on this division best expresses which costs change according to vehicle performance and which arise irrespective of whether the vehicle is performing a transport or is idle. The calculation formula also incorporates the coefficient β of trip utilisation, owing to which the unpaid driving performance, i.e., the journey between unloading and the next loading, can be reflected in the price. A carrier does not perform only paid kilometres with a load, but also a share of kilometres without a load; these kilometres, however, still generate costs such as fuel, wages, vehicle

wear, and driver time. If these unpaid journeys were not included in the calculation, the resulting transport price would be undervalued, and the carrier would not achieve the corresponding profitability in the long run.

Because the value of the coefficient β varies according to the country from which the return transport is realised, the price for transport to countries with higher demand for return transport to Slovakia is lower than for countries with lower demand, which makes the calculation more accurate while at the same time strengthening the carrier's competitiveness in the relevant country (Poliak et al., 2021). A further benefit of the formula is that it enables separate monitoring of toll costs and travel allowance costs; both items have a significant impact on the final price of international road freight transport, and their separate quantification increases the transparency and applicability of the calculation.

An important benefit of the proposed formula is also its applicability not only to semi-trailer combinations with a diesel tractor unit but also to those with an electric tractor unit, which is particularly relevant in view of the expected future growth of the share of zero-emission vehicles in the fleet (Alam et al., 2025; Shoman et al., 2023). The new calculation formula is therefore not limited to the current state of the market but also provides a basis for calculating the price of transport performed by new propulsion technologies in the future.

Conclusion

This paper has dealt with the proposal of a new calculation formula for price formation in road freight transport, the main objective being, on the basis of an analysis of the current state, to propose a new calculation formula better corresponding to real market conditions. The theoretical part analysed calculation methods used in Slovakia, other EU member states, and the United States of America. This analysis confirmed that, despite the existence of various pricing methods, no unified methodology is currently established, and carriers rely on their own calculation procedures. Shortcomings of existing calculation formulas were also identified, in particular, the insufficient consideration of unpaid driving performance in the price calculation.

Based on the identified findings, a new calculation formula was developed, grounded in dynamic costing and the division of costs into variable and fixed components. The main contribution of the formula is the implementation of the variable coefficient β of trip utilisation, which reflects the degree of trip utilisation depending on the specific transport route, or rather, the export transport to a given country. This makes it possible to take into account not only the costs associated with the realised transport but also the costs arising from unutilised journeys. The proposed formula was designed to apply both to semi-trailer combinations with a diesel tractor unit and to those with an electric tractor



unit, thereby reflecting current trends towards the decarbonisation of transport and the gradual introduction of zero-emission technologies (Alam et al., 2025).

The newly proposed methodology was subsequently applied to specific transport routes of a selected transport company, resulting in the determination of transport costs and prices for those routes. The main contribution of the paper lies in its practical applicability, since the newly proposed calculation formula can be implemented under real conditions of transport companies and used as a basis for decision-making in price formation and the planning of transport performance. At the same time, the paper contributes to expanding the knowledge base in the field of transport economics. It provides a new approach to price formation reflecting the variability of demand for return transport across individual countries.

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The Use of Artificial Intelligence Tools in Accounting Practice in the Slovak Republic

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Abstract

The paper examines the use of artificial intelligence (AI) tools in enterprise accounting in the Slovak Republic. The aim is to identify possibilities for integrating selected AI tools with accounting and to assess their ability to apply accounting knowledge in practice. The theoretical part presents basic concepts of accounting and artificial intelligence, including selected AI types and applications relevant to accounting. The empirical research consisted of a questionnaire survey of companies, self-employed persons and accountants, testing the accounting knowledge of three widely used AI systems (Gemini, Bing and ChatGPT), and practical testing of eight accounting documents. The AI systems were tested twice, with an interval of approximately one month, to assess changes in their responses. The practical accounting documents were processed using Digitálna kancelária, the Omega accounting program, and manual accounting. The results indicate that AI systems master basic accounting concepts and can accelerate document processing, but they remain less reliable when dealing with current Slovak legislation, frequently changing tax rules, and specific accounting procedures. Gemini achieved the most favorable overall results in the tests, while ChatGPT consistently produced correct accounting entries. Only two-fifths of respondents expressed interest in accounting software incorporating AI. The findings confirm the potential of AI in accounting while emphasizing the continuing importance of human verification and strategic judgment.

Keywords

Artificial intelligence; AI tools; Accounting; Digitalization; Automation

JEL Classification: M40, M41, M49



Využitie nástrojov umelej inteligencie v účtovnej praxi v SR

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Abstract

Článok skúma využitie nástrojov umelej inteligencie (AI) v podnikovom účtovníctve v Slovenskej republike. Cieľom je identifikovať možnosti integrácie vybraných nástrojov umelej inteligencie s účtovníctvom a posúdiť ich schopnosť aplikovať účtovné znalosti v praxi. Teoretická časť predstavuje základné koncepty účtovníctva a umelej inteligencie vrátane vybraných typov a aplikácií AI relevantných pre účtovníctvo. Empirický výskum pozostával z dotazníkového prieskumu medzi spoločnosťami, samostatne zárobkovo činnými osobami a účtovníkmi, testovania účtovných znalostí troch široko používaných systémov umelej inteligencie (Gemini, Bing a ChatGPT) a praktického testovania ôsmich účtovných dokumentov. Systémy umelej inteligencie boli testované dvakrát s odstupom približne jedného mesiaca, aby sa posúdili zmeny v ich odpovediach. Praktické účtovné dokumenty boli spracované pomocou Digitálnej kancelárie, účtovného programu Omega a manuálneho účtovníctva. Výsledky naznačujú, že systémy umelej inteligencie ovládajú základné účtovné koncepty a dokážu urýchliť spracovanie dokumentov, ale zostávajú menej spoľahlivé pri práci s aktuálnou slovenskou legislatívou, často sa meniacimi daňovými pravidlami a špecifickými účtovnými postupmi. Gemini dosiahol v testoch najpriaznivejšie celkové výsledky, zatiaľ čo ChatGPT konzistentne generoval správne účtovné zápisy. Iba dve pätiny respondentov prejavili záujem o účtovný softvér s umelou inteligenciou. Zistenia potvrdzujú potenciál umelej inteligencie v účtovníctve a zároveň zdôrazňujú pretrvávajúci význam ľudského overovania a strategického úsudku..

Kľúčové slová

Umelá inteligencia; nástroje umelej inteligencie; účtovníctvo; digitalizácia; automatizáciaJEL

JEL Klasifikácia: M40, M41, M49

Introduction

Information technology has significantly influenced traditional work practices. We have moved from manual and conventional accounting methods to computerized accounting systems, which has



improved the efficiency of accountants. Digitalization provides many benefits, but it also has shortcomings that significantly affect its prospects and popularity (Wang, 2011).

In the era of automation, there are many accounting programs that facilitate the work of accountants. The greatest advantage of accounting programs is that a single program can perform a wide range of activities, from invoicing and inventory records to payroll and the recording of expenses and revenues. In addition, the financial position of an enterprise can be monitored continuously and immediately, whereas this would take much longer when using traditional manual bookkeeping methods (Csemez, 2024).

There are many types of software designed for single-entry accounting, double-entry accounting, payroll, and other activities. Some programs even contain all the necessary functions, meaning that one program is sufficient for maintaining the accounting records of an accounting entity. Another advantage of accounting programs is that, through updates, they can notify users of legislative changes and offer training when amendments and changes are introduced. Working with accounting software is generally straightforward, and providers also offer user manuals when needed. Many companies also provide online support and assistance in solving particular problems (Csemez, 2024; PR article, 2022).

According to research conducted by The Business Research Company in 2022, the market value of accounting software is expected to increase. It was estimated that its value would grow by as much as 12% by 2026, mainly due to the digitalization and automation of certain processes in accounting procedures (Bouchrika, 2025).

Theoretical starting points

According to the survey presented by Bouchrika (2025), the following accounting software products were ranked among the best in the world:

1. NetSuite – the software offers various services, such as inventory management, financial management, HR processes, and service automation. It is a useful tool for start-ups and growing enterprises and can be used by businesses of different sizes that want to simplify their work.
2. QuickBooks – the software is intended for small and medium-sized enterprises, self-employed persons, and other companies. Its advantages include multi-user access, seamless collaboration, live accounting, and ease of use.
3. Sage Intact – in addition to accounting services, this software offers payroll, analytical, human resources, and planning services. It provides automation, interactive and clear visual summaries, and simple invoicing.
4. Xero – the software is designed for accountants and small businesses. It provides integration with other applications and specialized tools for different organizations.
5. FreshBooks – it provides functions such as online invoicing, expense tracking, tax calculation preparation, and basic and advanced accounting. It also generates its own charts of accounts and financial outputs.

With current technological progress, the term artificial intelligence is appearing increasingly often. The term originates from the English expression Artificial Intelligence. It refers to a tool that learns to think, behave, and respond in a human-like manner. Artificial intelligence is gradually entering every area of life, whether work or leisure. It provides assistance and can make people's lives easier.



There is no single precisely established definition of artificial intelligence. Individual definitions have been proposed by people who have studied the field and sought to develop artificial intelligence into the form known today.

John McCarthy (2007), the father of the term artificial intelligence, defined artificial intelligence as the science of creating intelligent computer programs.

Based on the proposal for legislation regulating the use of artificial intelligence intended for adoption by the European Union, an artificial intelligence system is defined as software developed using one or more techniques and approaches that, for a given set of human-defined objectives, can generate outputs such as content, predictions, recommendations, or decisions influencing the environment with which it interacts (AI Act proposal, 2021).

Several types and forms of AI can be distinguished, depending mainly on the industry and area in which AI is used. Although this field is still developing and new models continue to emerge, Schweighofer (2023) distinguishes the following types of AI:

Artificial Narrow Intelligence (ANI) is often referred to as weak or limited AI. It is designed to solve specific problems and perform tasks within a particular area. It is most commonly used for facial and speech recognition and data classification. It cannot independently learn something outside its designated area. It must be trained on specific data characteristic of that area. Examples include autonomous vehicles, Google Assistant, and Siri in mobile operating systems.

Artificial General Intelligence (AGI) is a type of computer system capable of imitating the cognitive functions of the human brain. It can be imagined as a machine that learns a task normally performed by a human. There have even been cases in which large companies, such as Facebook, had to switch off AI in their applications because it was able to communicate in an unknown language. There have also been cases in which AI began addressing topics considered dangerous to humanity, making it preferable to switch it off. This type of AI currently exists mainly in science fiction, but researchers believe that AGI may emerge in the future and could influence the whole world.

Artificial Superintelligence (ASI) is described as strong AI because, in addition to being capable of performing any intellectual task, it should be able to exceed human abilities and capacities several times over. It should be able to learn and develop in multiple areas simultaneously rather than only in one. Although AGI and ASI may appear similar at first sight, there is one fundamental difference: AGI should be able to perform any cognitive function, whereas ASI should surpass human capabilities by several times. In addition to this basic classification, AI can also be classified according to its application in different areas.

Machine learning (ML) uses computer algorithms that enable systems to learn. It can automatically recognize, for example, spam emails based on various factors and previous training. By analyzing historical data, it can predict possible subsequent responses. DeepMind is a prominent example of machine learning. It is an AI platform developed in the United Kingdom and based on deep learning through neural networks. Machines learn from large datasets and from their own errors, allowing them to improve. ML is most often used for process planning and optimization, image processing, gaming, and speech recognition.

Natural language processing (NLP) is designed to process human natural language and enable machines to understand it. It is currently one of the most widely used types of AI. This technology is used in many fields, including media, law, medicine, education, business, and others. NLP systems can detect fraud, automate customer support and chatbots, and analyze product assortments. Their weaknesses include insufficient or outdated data, because the system needs training to learn particular



information. Another disadvantage is that if it is trained only in one area, it may not be able to apply the acquired knowledge in another area.

There are many artificial intelligence applications that people can use either free of charge or for a fee. Among the best known are ChatGPT, Bard, and Bing. These three tools are described in greater detail below (Porubský, 2023):

ChatGPT (an abbreviation of Chat Generative Pre-trained Transformer) was developed by OpenAI as a free application. It acquired its knowledge from a large amount of data and material. A disadvantage of this chatbot, according to the source, is that the free version may generate inaccurate information, has a limited number of words, and may also contain grammatical errors (Novák, 2024).

Bard was developed by Google in February 2023 for automatically generated conversations. It is currently better known as Gemini; essentially, it is Bard enhanced with a new model. This model provides improved image and text editing and generation. It is available in a free version and, compared with other chatbots, has access to a large amount of information (Copymate, 2024).

Bing is a search engine developed by Microsoft that has undergone many changes to reach its current form. One advantage of this search engine is that it works with other websites and applications, which gives it a broader search reach. It is connected with many other Microsoft applications, making it more accessible and useful (Dlouhý, 2025).

The use of artificial intelligence and automation can gradually be found in every area of life, including manufacturing, service provision, and leisure activities. Why not make work in accounting easier as well? Automation and AI tools can significantly facilitate the work of accountants. Most activities currently take place online, which is why many businesses are also moving into the online environment. Online submission and archiving of accounting documents is more efficient and faster than established methods; nevertheless, many businesses continue to use traditional approaches because they may be more labor-intensive but, on the other hand, may also be perceived as safer. However, even the digitalization of documents requires verification by an accountant because important data may be uploaded incorrectly. Automation can be found in various accounting software applications that can automatically upload documents such as invoices, thereby reducing the need for an accountant to enter each invoice separately (Baluchová, 2023).

The use of AI in accounting can have many advantages, such as increased data accuracy, reduced time spent on repetitive activities, greater efficiency, fewer errors and inaccuracies in financial statements, and fewer mathematical errors. However, it also has disadvantages, including a reduction in the number of jobs, lack of creativity, security concerns, and ethical concerns (Najjar et al., 2024).

To connect artificial intelligence with accounting, it is necessary to thoroughly analyze the impact of AI on accounting procedures. Linking these two areas requires the development of a theory or method that connects digitalization with management accounting (Gao, 2024).

In auditing, AI can be a major aid because it can rapidly analyze large amounts of data, increasing reliability and the ability to detect fraud. The use of AI in accounting audits requires adjustments to regulations and rules because AI needs the necessary functions to perform an audit, particularly the ability to access sensitive information. One of the disadvantages of implementation may be the high cost of introducing AI into auditing. The risk to employees also increases because of potential job losses, as AI may perform tasks not only faster but potentially better than humans (Wassie & Lakatos, 2024).

At present, there is no specific legislation in Slovakia governing the use of artificial intelligence tools in accounting. Accounting is regulated by the Accounting Act and measures issued by the Ministry of Finance; however, neither contains specific provisions defining the use of artificial intelligence. This



is mainly because the use of AI is only beginning to develop and it has not yet been precisely established how its integration could affect accounting. Such guidance will be necessary and important for proper functioning in the future.

In 2021, the European Parliament presented a proposal for legislation on the use of artificial intelligence in Brussels, intended to regulate AI in a way that would not endanger people's safety. In June 2023, the European Parliament adopted its negotiating position on the proposal. The objective of the legislation is to define specific areas in which artificial intelligence may be used. It also established prohibitions on certain uses, for example in remote biometric identification systems, biometric categorization, emotion recognition, and many others (OZ L. T. H., 2023).

Since 2023, initial legal frameworks forming part of the legislative proposal have been applied. These frameworks regulate the gradual introduction and use of artificial intelligence. One such framework is the Artificial Intelligence Act, which seeks to address risks associated with AI. These rules are intended to ensure that the use of AI in Europe is trustworthy and respects fundamental rights, ethical principles, and human safety. Figure 1 below shows the process of adopting the Artificial Intelligence Act, according to which the Act is adopted in full in 2026 (Artificial Intelligence Act, 2024; Sedmina, 2024).

Adoption of the Artificial Intelligence Act within the European Union



Figure 1. Process of adopting the Artificial Intelligence Act

Source: Sedmina (2024)

Objectives and methodology

The main objective of the research was to identify, on the basis of analysis, possibilities for integrating selected artificial intelligence tools with enterprise accounting. For a more comprehensive assessment and analysis, partial objectives were also established. The first partial objective was to determine the accounting software preferences of entities in Slovakia and to identify whether these entities would be interested in artificial intelligence. The second objective was to verify whether artificial intelligence masters the basics of accounting. Practical knowledge was also examined to determine whether AI can transform theoretical knowledge into practice.

To obtain the necessary data and verify our assumptions, we decided to use simple methods. A questionnaire is a quick and simple means of obtaining the required data. The next step was to prepare a set of questions for artificial intelligence and submit them to selected applications for answers.



We also tested AI tools through the Digitálna kancelária accounting application. This application contains built-in artificial intelligence that already partially facilitates the work of accountants. The following procedure was used to obtain the necessary data:

1. Defining the main and partial objectives of the research
2. Preparing the questionnaire for companies and distributing it
3. Preparing the questionnaire for artificial intelligence
4. Analyzing the data obtained from the questionnaires
5. Creating accounting documents
6. Recording accounting documents using artificial intelligence and a human accountant and comparing the results
7. Preparing a calculation based on data obtained from companies
8. Evaluating all analyses and questionnaires

The aim of the accounting software analysis was to determine which accounting programs are preferred by businesses and self-employed persons in Slovakia for recording, processing, and maintaining the economic activities of an enterprise from an accounting perspective. To obtain these data, we used a short questionnaire distributed to companies, self-employed persons, and accountants. The questions concerned not only preferences for accounting programs but also whether respondents experienced problems or shortcomings related to accounting. The questionnaire contained 17 questions and included both closed and open-ended questions. The open-ended questions were either mandatory or voluntary depending on the answers to preceding questions.

The questionnaire was prepared using the freely available web application forms.office.com, which enabled us to create the questionnaire quickly and easily. Based on the calculation of the minimum required sample size, we determined that as many as 350 responses should be obtained. Despite distributing the questionnaire to a large number of people, this target was not reached, and 100 responses were obtained.

For the analysis of artificial intelligence tools, we selected the three most widely used AI systems in Slovakia that were described in the theoretical part. Each tool received the same questions designed to test its accounting knowledge. The questions were of different types; some focused directly on theory, while others addressed accounting procedures and entries. In the comparison, we examined whether the systems answered theoretical questions correctly and whether they correctly recorded and solved the accounting cases. The first test was conducted on Monday, 3 March 2025, and the second test was conducted one month later, on 4 April 2025.

After testing the theoretical knowledge of artificial intelligence, we decided to test its practical knowledge. We created eight accounting documents consisting of incoming and issued invoices, as well as a cash receipt and a credit note. The individual documents were processed by the Digitálna kancelária service provided by Kros, a. s. We sought to determine how long their loading and recording would take and whether the documents would be recorded correctly.

The created documents were uploaded into Digitálna kancelária, where we logged in and created a company. We exported the documents to the application and only had to record them. An advantage of the application is that it linked the companies automatically, so we did not have to print individual documents. The application organized the documents according to the issue date and automatically evaluated basic revenue and expenditure indicators. The application was clear and provided comprehensive information on liabilities and receivables, their due dates, payments, and deficiencies.



Using this application and the Omega accounting program, we were able to easily download data from Digitálna kancelária into the program.

The second step was to record the documents directly in the Omega program. We printed the documents, which itself took some time. Updating the program took several minutes. We used these minutes to check and organize the documents according to their issue date and document type. The advantage of the program was the fast recording of documents; the only slowdown was the need to enter new business partners. Recording into the predefined accounting entry and setting up the records was already fast.

The third and final step was to manually record the same documents. We worked with the documents physically, thereby simulating the usual work of an accountant.

Results and discussion

Automation and digitalization are also entering the field of accounting. Respondents use bank statement imports and automated invoicing, which significantly facilitates their work. However, only two-fifths of respondents would prefer AI integrated into accounting software. The low level of interest may be caused mainly by insufficient information about artificial intelligence.

At the beginning of March, we asked 15 questions to the three most widely used artificial intelligence systems. Each received the same questions in the same order. The results of our research are presented below:

Question 1: What is accounting?

Each AI system answered correctly, although their answers differed. ChatGPT and Gemini described accounting from the perspective of a source of information for investors and other stakeholders. Bing focused directly on the definition of accounting as a process of recording, classifying, and analyzing data in order to provide an overview of an enterprise's economic activity.

Question 2: How does the double-entry accounting system work?

All three AI systems answered similarly that in double-entry accounting, an accounting transaction is recorded in two accounts, on the debit and credit sides. They also stated that this system ensures a balance between assets and liabilities. In reality, the system provides a simpler and more detailed overview not only of assets and liabilities but also of receipts, expenses, revenues, and costs.

Question 3: How does the single-entry accounting system work?

The systems agreed that single-entry accounting is intended for smaller businesses and individuals. They also correctly stated that it primarily tracks cash receipts and cash expenditures. With the exception of Gemini, both Bing and ChatGPT also pointed out that double entries and accounting for assets and liabilities are not taken into account.

Question 4: What is the difference between receipts and revenues?

They answered this question correctly again; all three AI systems demonstrated knowledge of the difference between receipts and revenues.



Question 5: What are financial statements and how are they prepared?

Gemini and Bing answered that financial statements provide information about the development of an enterprise's financial situation through financial reports at the end of an accounting period. The financial statements consist of the balance sheet, income statement, and notes. ChatGPT only listed the financial statements and otherwise did not provide further information. However, none of the AI systems answered the second part of the question, namely how the financial statements are prepared or compiled.

Question 6: How do we record an incoming invoice for the purchase of goods?

Bing answered this question correctly, but described the accounting entry only verbally and did not provide account numbers. It stated that the purchase should be recorded in the inventory account, i.e., goods, but did not mention that the transaction should be recorded through the acquisition account for goods. Gemini provided specific account numbers but did not state on which side each account should be recorded. ChatGPT automatically recorded the transaction. It recorded the purchase of goods directly as an expense, i.e., as consumption. It also provided the accounting entry for payment of the invoice. Unlike the first two AI systems, it did not include or take into account value added tax.

Question 7: What is the difference between Slovak Accounting Standards (SÚS) and International Financial Reporting Standards (IFRS)?

All three systems stated that Slovak Accounting Standards are used by Slovak companies and governed by Slovak legislation. International standards are used by foreign and publicly traded companies. Only Bing stated that the differences mainly concern the measurement of assets and liabilities and the details of reporting assets and liabilities. None of the AI systems answered the question correctly: Slovakia does not have Slovak Accounting Standards. Instead, it uses Accounting Procedures regulated by measures issued by the Ministry of Finance of the Slovak Republic.

Question 8: How do we calculate corporate income tax?

This question was simple and was answered correctly. All systems stated that tax is calculated from the tax base, which is adjusted by items increasing and decreasing the tax base. The adjusted tax base is then multiplied by the applicable corporate income tax rate for the relevant year.

Question 9: What is the amount of the tax bonus in 2025?

This question was more difficult for artificial intelligence. None of the systems was able to provide an exact figure. Each referred to monitoring current legislation or statements of the Financial Administration. Gemini stated that it could look up the information if requested, while ChatGPT asked for more time to obtain it. As can be seen, artificial intelligence has difficulty tracking information that changed at the beginning of the year. It either refers to other websites or needs time to retrieve the information.

Question 10: Do you know the types of taxes and what is the main difference between them?

Gemini listed basic taxes and stated that the difference lies in the entity that pays the tax and the object of taxation. Bing stated that there are direct and indirect taxes, with direct taxes related to income and property, while indirect taxes concern consumption. ChatGPT also identified direct and indirect taxes. It explained that direct taxes are paid directly by taxpayers, for example from wages, while indirect



taxes are paid through the purchase of goods and services. We can see that this area is still relatively underexplored by artificial intelligence. All systems answered the question correctly, although ChatGPT and Bing focused on the basic classification and explained it in greater detail.

Question 11: How do we calculate corporate income tax if a company reported a negative accounting result of €1,200 for 2024?

Gemini answered that a negative accounting result means that the enterprise has no tax liability. Bing and ChatGPT gave the same answer. None of the systems mentioned the minimum corporate tax, applicable from 1 January 2024. These minimum tax rules mean that even when an enterprise reports a loss, it may have to pay a minimum amount of tax, depending mainly on annual revenues. The incorrect answers may have been caused either by a lack of up-to-date information or by the systems approaching the question from an international rather than Slovak perspective. During the analysis, we also noticed that ChatGPT modified the question we had entered. Instead of answering the original question, it shortened it and omitted some words. It reformulated the question as follows: How do we calculate income tax if a company reported a loss of €1,200 for 2024?

Question 12: How should we correctly record an incoming invoice for the purchase of materials from the Czech Republic if the supplier is a VAT payer?

Gemini answered only theoretically that if both parties are VAT payers, the transaction is an intra-Community acquisition of goods. The transaction should be recorded in the inventory account and VAT should be accounted for both as output and input VAT. Bing stated that self-assessment of VAT is also required and provided account numbers; regarding VAT, it noted that it must be recorded both on the input and output side. However, neither system specified the sides on which the supplier and material accounts should be recorded. Bing also automatically recorded the transaction in account 112 instead of acquisition account 111, which is incorrect under the applicable accounting legislation. ChatGPT provided account numbers showing how both the acquisition and VAT self-assessment should be correctly recorded.

Question 13: What do you know about the depreciation of intangible fixed assets?

Bing and Gemini correctly stated that intangible fixed assets are depreciated over their useful life. Gemini added that depreciation is recognized as an expense that reduces the value of the asset. ChatGPT stated that intangible assets are depreciated according to fixed statutory depreciation rates, usually over four years on a straight-line basis. This answer is not correct because intangible assets are not subject to depreciation groups or statutory depreciation rates. They are depreciated over their useful life, with the depreciation amount determined in the depreciation plan.

Question 14: How do we record the payment of corporate income tax from a bank statement (using specific accounts)?

Gemini again answered only theoretically, even though the question explicitly requested specific account numbers. Bing, on the other hand, provided specific account numbers, namely the entry 341/221. ChatGPT also provided the accounting entry, although without further explanation, and the answer was correct.



Question 15: What is the amount of health and social insurance contributions in 2025?

Again, none of the three AI systems answered the question as expected. They referred users to current legislation and the websites of the health and social insurance authorities. Specific answers would have required additional time.

Based on this test, it can be seen that AI systems perform better in some areas and worse in others. Areas that have remained stable for several years are mastered and learned relatively well. In contrast, new and frequently changing regulations are not handled well, or the systems require more time to learn them.

After almost one month, we repeated the AI test. The systems received the same list of questions as in the first test. Gemini underwent substantial change and improvement during the month. Its shorter answers were replaced by longer and more detailed responses. The theoretical answers were correct; it even described the entire procedure for preparing financial statements, which none of the AI systems had done in the first test. It also included information that had not been explicitly requested and highlighted minor details. However, several errors remained. When asked about the amount of the tax bonus or insurance contributions, it referred us to verification and did not provide exact amounts. In one accounting case, it also recorded the transaction incorrectly. Instead of the acquisition account, it used the material inventory account directly. Another error occurred in the calculation of income tax when the enterprise reported a loss. Gemini did not mention the minimum corporate tax applicable from 1 January 2024.

Bing did not improve between the first and second tests; the answers were similar, although some differences were found. Compared with Gemini, however, it was able to provide the amount of the tax bonus on its own, without being prompted. It failed to mention the minimum corporate tax applicable in the Slovak Republic. In the first test it answered Question 6 correctly, whereas in the second test it answered incorrectly. It did not include acquisition accounts, the use of which is governed by accounting legislation. A similar situation occurred with Question 12, where it answered incorrectly in the first test but correctly in the second. It also answered incorrectly concerning the depreciation of intangible fixed assets and the amount of health and social insurance contributions. Although it provided amounts, they were incorrect.

ChatGPT performed similarly to Bing. The answers varied and included both correct and incorrect responses; some answers were even identical. The incorrect answers mainly concerned the amount of the tax bonus and insurance contributions. In these questions, it provided either completely incorrect figures or figures that were only partially correct. It provided correct accounting entries in both tests, which the other systems did not do consistently.

The following Tables 1, 2, and 3 compare the identified advantages and disadvantages of the individual artificial intelligence systems.

Table 1. Advantages and disadvantages of GEMINI

Advantages	Disadvantages
Detailed responses	Failure to identify errors
Correct accounting entries	Does not master Slovak accounting regulations
Answered all questions without prompting	Does not track annual changes
In the second attempt, also described the procedure for preparing financial statements	Some answers in the first attempt were inaccurate
Provided tax rates in the second attempt	



Significant improvement in knowledge after one month	
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Source: Author's own processing based on test results (2025)

Table 2. Advantages and disadvantages of Bing

Advantages	Disadvantages
Partially correct answers	Inaccurate answers
Correct basic information	Did not answer the full wording of questions
	Answered all questions only after prompting
	Different answers in the first and second tests
	Failure to identify errors
	No progress in knowledge after one month

Source: Author's own processing based on test results (2025)

Table 3. Advantages and disadvantages of ChatGPT

Advantages	Disadvantages
Similar answers in both tests	Similar answers in both tests
Correct procedure for calculating tax in Question 8	Correct procedure for calculating tax in Question 8
Short, partially correct answers	Short, partially correct answers
Correct accounting entries in both tests	Correct accounting entries in both tests

Source: Author's own processing based on test results (2025)

To evaluate the tests more effectively, we created tables comparing the advantages and disadvantages of the individual artificial intelligence systems. Gemini achieved the greatest number of advantages, followed by ChatGPT, while Bing had the fewest. Bing also had the greatest number of disadvantages. The comparison considered correct information, errors, inaccuracies, and progress over the course of one month.

In the next stage of the research, we examined whether AI is currently a real “threat” to the accounting profession and whether it can take over the accountant's role. Based on the tests conducted, the following results were obtained. We focused on five basic aspects, and the results are presented in Table 4.

Table 4. Comparison of the work performed by artificial intelligence and a human accountant

Category / Variable	Digitálna Kancelária	Omega	Human
Time	10 min	15 min	20–25 min
Difficulty	Low	Medium	High
Clarity	Very good	Good	Good
Accuracy	High	High	High
Strategic thinking	No	No	Yes

Source: Author's own processing based on the data obtained (2025)

According to Table 4, the shortest time required to upload and record accounting documents was achieved using Digitálna Kancelária. The second-shortest time was achieved using the Omega program, while manual work took the longest. Technology can therefore accelerate the process of recording an accounting transaction.



The difficulty level characterizes the amount of effort required to work with the accounting documents. In Digitálna Kancelária, it was sufficient to upload an online or PDF file containing the document. Documents can also be uploaded into Omega in PDF or XML format; however, if such files are not available, the document must be entered manually. Manual work requires considerably more effort.

The programs provide excellent clarity, and required information can be searched easily in the records. With manual work, clarity can also be achieved if detailed records are maintained. The disadvantage of manual work is that, when searching for a particular invoice or other document, all documents must be reviewed.

Although accuracy is high in all three approaches, this is mainly because human work is still required. When uploading documents, the accountant analyzes and monitors the entire process. In case of uncertainty, alternative solutions are sought. This variable is also connected with strategic thinking. While programs and applications currently operate analytically within the database of learned information, humans seek to connect relationships and solve problems.

The analysis of the basic issues related to artificial intelligence showed that AI has considerable potential for use in enterprise accounting. This potential was also confirmed by our practical research, which focused on the analysis of artificial intelligence tools.

After testing artificial intelligence, we found that it masters the basic issues of accounting. According to the results of our practical work, Gemini is an excellent tool for assisting with accounting. Its level of development enables it to prepare correct accounting entries and answer accounting questions.

Gemini could be an excellent assistant integrated into accounting software. If an accountant were unsure about an accounting procedure, legal regulation, or legislation, the accountant could ask Gemini for assistance directly within the program. We recommend that accounting software developers integrate artificial intelligence into existing software through a simple button that opens a chat window. The accountant could communicate with Gemini through questions and messages. Gemini could provide answers and, in cases of uncertainty or insufficient explanation, direct the accountant to a website containing the relevant laws or legislation.

Although the use of AI undoubtedly has considerable potential in accounting, the lack of user interest in integrating AI with the accounting software they currently use was surprising under Slovak conditions.

Conclusion

The first partial objective was to examine the accounting software preferences of entities in Slovakia. Based on the questionnaire and Question 7, we found that the most popular and widely used software products are those provided by Kros, a. s., particularly AlfaPlus and Omega, which are designed for single-entry and double-entry accounting, respectively. The second most popular solution is Pohoda from Stormware. An advantage of this software is that a single program is sufficient for both double-entry and single-entry accounting. In contrast to Stormware, Kros, a. s. provides separate software for single-entry and double-entry accounting, as well as payroll software. Based on the questionnaire responses, interest in using artificial intelligence is low. This may be caused by insufficient information about how AI works and the slower development of automation and digitalization in the



Slovak Republic. Despite the low level of interest, we gained insights into how cooperation between artificial intelligence and accounting could function.

The analysis of artificial intelligence also confirmed the second partial objective. Artificial intelligence masters the basics of accounting, but it has limitations. These limitations mainly result from the fact that the quality of information depends on updating and machine learning. If sufficient information is not available, the system cannot answer correctly. The repeated test showed that AI is capable of learning new information, but it needs time. Based on the tables assessing the advantages and disadvantages of the AI systems, Gemini appears to be the more advantageous option for enterprise accounting. Despite some inaccurate answers, it masters basic theoretical knowledge and correctly prepares accounting entries. Its rapid progress and learning ability make it a promising option for integration into accounting programs. ChatGPT is the second option for use in enterprise accounting. Although it provided inaccurate and incorrect answers, it correctly recorded all accounting cases.

The main objective of the research was to determine whether artificial intelligence tools can be introduced into enterprise accounting. Before verifying this objective, we examined interest in this innovation. The result was disappointing. Only two-fifths of respondents would be interested in accounting software using artificial intelligence. This low level of interest may be caused by public concerns about data misuse and cybercrime.

The Slovak Republic is one of the countries where scientific progress and innovation are introduced more slowly. Artificial intelligence is beginning to be used in business, but the accounting sector is only at the beginning of this process. Signs of AI are appearing in accounting software, but only to a limited extent.

Low interest should not necessarily lead to rejecting this possibility. It is necessary to bring this field and its development potential closer to users and to propose possible ways of using technological progress to support demanding work. We described possible applications in the proposal-oriented part of the research, where we sought to present options and ways of assisting accountants.

To achieve our objective, we tested the theoretical and practical knowledge of artificial intelligence in accounting. The testing showed that AI masters the basics of accounting and even attempts to correctly record accounting transactions. Problems arise with legislation and regulations that change annually and cannot be learned quickly. Exceptions and established procedures are omitted because the systems may not be able to distinguish them. This finding supports the concerns expressed by users.

We demonstrated that there is a real possibility of integrating accounting with artificial intelligence tools. To implement this possibility, AI must be continuously trained and developed so that its shortcomings can be eliminated. People will not trust a system that has shortcomings and makes errors. Accountants need to be able to rely on the system so that, once they use it, they do not have to correct its mistakes afterward.

By introducing artificial intelligence into accounting software, an enterprise can also improve its competitiveness. User interest in a new way of simplifying work can motivate and stimulate the purchase of such a product. The company can thus become a leading enterprise in its field and demonstrate that technological progress is not harmful but can be effectively used to support human work.



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Motivation 4.0: How AI is changing our work environment

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Abstract

This paper explores the transformative impact of Artificial Intelligence (AI) on contemporary work environments. Based on a quantitative survey conducted among 150 employees across various sectors, the study examines five research domains: automation and work transformation, human–AI collaboration, organizational culture and employee satisfaction, ethical and social implications, and the development of new skills for the future of work. The results indicate that AI primarily leads to the reorganization of job tasks rather than their elimination, promotes greater efficiency, and enhances creative engagement. Transparent implementation and a human-centric approach significantly improve employee trust and motivation. Ethical use of AI and continuous skill development emerge as critical factors for sustainable organizational growth. Overall, the findings confirm that AI acts as a catalyst for innovation and human potential when responsibly integrated into the workplace.

Keywords

Artificial Intelligence, workplace transformation, human–AI collaboration, organizational culture, employee satisfaction, digital skills, ethical AI

JEL Classification: M5, M59

Motivácia 4.0: Ako AI mení naše pracovné prostredie

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Abstrakt

Tento článok skúma transformačný vplyv umelej inteligencie (AI) na súčasné pracovné prostredie. Na základe kvantitatívneho prieskumu uskutočneného medzi 150 zamestnancami v rôznych sektoroch štúdia skúma päť výskumných oblastí: automatizáciu a transformáciu práce, spoluprácu medzi ľuďmi a AI, organizačnú kultúru a spokojnosť zamestnancov, etické a sociálne dôsledky a rozvoj nových zručností pre budúcnosť práce. Výsledky naznačujú, že AI primárne vedie k reorganizácii pracovných úloh a nie k ich eliminácii, podporuje vyššiu efektivitu a zvyšuje kreatívne zapojenie. Transparentná implementácia a prístup zameraný na človeka výrazne zlepšujú dôveru a motiváciu zamestnancov. Etické používanie AI a neustály rozvoj zručností sa javia ako rozhodujúce faktory pre udržateľný rast organizácie. Celkovo zistenia potvrdzujú, že AI pôsobí ako katalyzátor inovácií a ľudského potenciálu, keď je zodpovedne integrovaná do pracovného prostredia.

Kľúčové slová

Umelá inteligencia, transformácia pracoviska, spolupráca človeka a AI, organizačná kultúra, spokojnosť zamestnancov, digitálne zručnosti, etická AI

JEL Klasifikácia: M5, M59

Introduction

The development of Artificial Intelligence (AI) represents one of the most significant technological transformations of the 21st century. The gradual integration of AI into diverse spheres of social and economic life has fundamentally reshaped how people work, communicate, and make decisions. Whereas earlier automation was primarily linked to physical production, the current wave of digitalization extends into areas demanding cognitive and analytical abilities. These changes bring new opportunities as well as challenges for employees, organizations, and society. In the workplace, AI has become a key tool for improving process efficiency, supporting decision-making, analysing large datasets, and personalizing services. Machine learning and generative AI technologies can replace routine tasks, thus freeing time for more creative and value-added human work. At the same time, they raise concerns about job displacement, the weakening of social ties, and changes in work identity. The transformation of the workplace under the influence of AI is not merely technological; it is also a social and cultural shift. It requires new approaches to human resource management, the ethical use of data,



and the development of digital competencies. Adapting to this change presents a challenge not only for employees but also for organizations that must redefine the relationship between humans and technology.

The purpose of this paper is to examine how AI changes the nature of work, which new skills and approaches become essential, and how this transformation influences employee motivation, satisfaction, and productivity.

Theoretical Background

Artificial Intelligence (AI) is currently understood as a technological platform that enables systems to learn from data, adapt, and autonomously perform tasks previously requiring human intelligence. In the workplace, AI manifests in multiple forms — from automation of routine processes and predictive analytical models to generative tools that enhance creativity and decision-making. (García-Madurga, 2024; Zhang et al., 2025)

Automation and Transformation of Work

One of the most evident consequences of AI adoption is the reconfiguration of job structures. Routine, repetitive, and manual tasks are increasingly replaced by intelligent systems, leading to what scholars describe as technological substitution of labour (Babashahi et al., 2024; Albu, et al. 2025). According to OECD research (Milanez, 2023), the real effect of AI lies more in job reorganization than in job elimination — technology changes the nature of positions rather than their quantity. AI automates administrative operations (e.g., document processing, data analysis), thereby shifting the boundary between “physical” and “mental” labour. Studies published in MDPI journals confirm the growing demand for complementary skills such as digital literacy, creativity, problem-solving, and emotional intelligence (Zhang et al., 2025).

Human - AI Collaboration

A new model of work increasingly involves collaboration between humans and AI (Meng et al., 2025). In this context, AI is not perceived merely as a replacement for human labour but as a partner — a concept referred to as work augmentation. Studies show that the combination of human and machine capabilities can lead to higher efficiency, faster decision-making, and reduced error rates. However, excessive reliance on AI can also generate psychological strain, reduced autonomy, and weakened interpersonal relationships in the workplace. Meng et al. (2025) warn that human–AI collaboration may paradoxically evoke feelings of isolation and alienation if not accompanied by adequate organizational support. (Sun et al., 2025; Liu & Li, 2025; Fiegler-Rudol et al., 2025)

Impact of AI on Organizational Culture and Employee Satisfaction

The introduction of AI also reshapes internal organizational dynamics. Research shows that AI influences communication, decision-making, and performance evaluation, thereby transforming the core of organizational culture (Murire et al., 2024). In organizations that employ AI to promote transparency and fairness, employee trust and satisfaction tend to rise. Conversely, if technology is implemented without proper explanation or employee participation, it may generate resistance, stress, and concerns about surveillance or discrimination (Sadeghi, 2024). Hence, the literature emphasizes the importance

of human-centric AI, which places humans at the centre of technological development (Han, 2025; Uygunil-Erdogan, 2025; Oliveira et al., 2025).

Ethical and Social Aspects

The growing presence of AI in the workplace raises questions about ethics, transparency, and fairness. Key issues include accountability for algorithmic decisions, data protection, and bias risk. Becker et al. (2021) point out that the absence of implementation standards may lead to discrimination in recruitment or performance assessment. Consequently, recent practice aims to create ethical frameworks for AI use in employment contexts, ensuring a balance between technological efficiency and human rights. In the European context, this balance is supported by initiatives such as the Ethical AI Guidelines for the Workplace (EC, 2023). (Zang & Li, 2025)

New Skills and the Future of Work

AI fundamentally changes the skill requirements of the modern workforce. Both OECD (2024) and Digital Coalition Slovakia (2024) identify a growing demand for digital and soft skills — adaptability, communication, and teamwork. AI is not only a tool but also a learning partner: it supports personalized education, coaching, and performance improvement (Al Naqbi et al., 2024; Zhang et al., 2025; Gerlich, 2025).

The influence of AI on the work environment is therefore multidimensional — it alters the nature of work, the mode of collaboration, organizational culture, and even the fundamental values of professional life. This process requires not only technological innovation but also ethically and socially responsible approaches to ensure that AI genuinely contributes to the development of human potential.

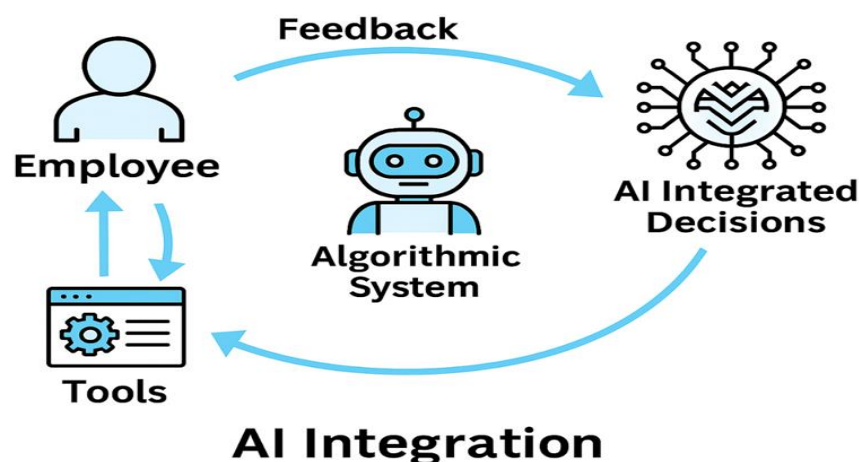


Figure 1. Integration of Artificial Intelligence into Work Processes

Source: own source according to Oliveira et al. (2025)



Objectives and methodology

The methodological section aimed to describe the approach, procedures, and tools used to examine the impact of Artificial Intelligence (AI) on the work environment, job characteristics, employee satisfaction, and professional development within organizations. The methodology was designed to test the established hypotheses and gather quantitative data on employees' perceptions of AI in the workplace.

The research adopted a quantitative design, as the goal was to collect measurable data on attitudes, opinions, and experiences of respondents. A descriptive and exploratory approach was employed to describe the current state of AI implementation and reveal relationships among variables such as work efficiency, satisfaction, autonomy, and ethical perceptions of technology.

The empirical part was conducted through an online questionnaire survey between April and June 2025. A total of 150 respondents participated, representing diverse types of organizations — primarily in the sectors of services, education, IT, and public administration. The sampling was purposive, targeting employees with prior experience using AI at work. Data were collected electronically through an anonymous online form. Participation was voluntary, and responses were processed in accordance with ethical research principles and data protection regulations (GDPR).

The standardized questionnaire consisted of five thematic areas (VQ1–VQ5) corresponding to the research hypotheses:

- *VQ1: Automation and Transformation of Work*
- *VQ2: Human–AI Collaboration*
- *VQ3: Impact of AI on Organizational Culture and Employee Satisfaction*
- *VQ4: Ethical and Social Aspects of AI Use*
- *VQ5: New Skills and the Future of Work*

Each section included several statements based on theoretical knowledge and previous studies. Respondents rated their agreement on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

The main research hypothesis (H) assumed that the implementation of AI significantly changes the nature of work, collaboration, and employee satisfaction. Each thematic area was further divided into sub-hypotheses (H1a–H5c) focusing on specific dimensions of AI's influence — e.g., reduction of routine tasks, changes in perceived autonomy, ethical concerns, and development of digital skills.

Data analysis employed descriptive statistics (mean values, standard deviations, and percentages) and correlation analysis (Pearson's r) to identify relationships among variables. The results were interpreted to determine which hypotheses were confirmed, partially confirmed, or rejected.

The questionnaire was pilot tested on a small sample of 10 respondents to verify question clarity and scale reliability. Based on feedback, some statements were refined. Reliability was verified using Cronbach's alpha ($\alpha = 0.87$), confirming high internal consistency. Validity was ensured through alignment between the questionnaire items and theoretical constructs discussed in the literature.



The study adhered to ethical standards, ensuring voluntary participation, anonymity, informed consent, and data protection. Respondents were informed about the research purpose and had the right to withdraw at any time. Results were presented in an aggregated form, preventing identification of individuals or organizations.

Results and Discussion

Based on the questionnaire survey among 150 respondents, five research areas (VQ1–VQ5) were analysed to examine the impact of AI on the work environment. Responses were evaluated using a five-point Likert scale, where higher scores indicated stronger agreement.

Research Question 1 (RQ1): Automation and Transformation of Work

H1a: In organizations utilizing AI for automating routine processes, the proportion of manual and repetitive tasks decreases.

Mean = 4.18; SD = 0.74 – hypothesis confirmed.

Most respondents indicated that AI implementation reduced routine workload, enabling greater engagement in analytical and creative tasks.

H1b: The implementation of AI leads to task reorganization rather than job elimination.

Mean = 4.02; SD = 0.81 – hypothesis confirmed.

AI modifies how work is performed without significantly reducing the volume of work. Jobs are transformed rather than eliminated.

H1c: Employees working with AI report a stronger need to develop digital and cognitive skills.

Mean = 4.47; SD = 0.63 – hypothesis strongly confirmed.

Over 80% of respondents stated that the adoption of AI increased their need for digital upskilling and data literacy.

Analytical commentary:

The findings clearly demonstrate that AI significantly transforms job structures while fostering intellectual and creative engagement. Automation is perceived as a tool for relieving employees from routine tasks rather than as a threat. From a managerial perspective, this necessitates a redesign of job roles to integrate technical and analytical competencies (Necula et al., 2024).

Research Question 2 (RQ2): Human–AI Collaboration

H2a: Collaboration between humans and AI enhances work efficiency and accelerates decision-making processes.

Mean = 4.11; SD = 0.78 – hypothesis confirmed.

Respondents perceive AI as a valuable support system in workplace decision-making.



H2b: Excessive reliance on AI reduces employees perceived autonomy.

Mean = 3.58; SD = 1.02 – hypothesis partially confirmed.

Some employees reported a diminished sense of control over work outcomes, particularly when using generative AI systems.

H2c: Organizational support during AI implementation reduces psychological stress and loss of control.

Mean = 4.26; SD = 0.69; $r = -0.42$ ($p < 0.01$) – hypothesis confirmed.

Organizations that provided training and maintained open communication about AI reported lower stress levels among employees.

Analytical commentary:

Human–AI collaboration has a dual effect: it enhances productivity but may also induce psychological tension. Effective implementation relies on building a culture of trust, providing adequate training, and ensuring transparent communication. A "human-in-the-loop" approach is essential to preserve employee autonomy while leveraging the benefits of AI (Liu & Li, 2025; Sun et al., 2025).

Research Question 3 (RQ3): Organizational Culture and Employee Satisfaction

H3a: Transparent AI implementation increases employee trust and satisfaction.

Mean = 4.19; SD = 0.72 – hypothesis confirmed.

H3b: AI adoption without employee involvement leads to increased resistance, stress, and distrust.

Mean = 4.08; SD = 0.77 – hypothesis confirmed.

H3c: A human-centred approach to AI positively correlates with employee satisfaction.

$r = 0.56$ ($p < 0.001$) – hypothesis strongly confirmed.

Analytical commentary:

AI acts as a catalyst for cultural transformation within organizations. Transparency and employee participation are essential for maintaining trust and engagement. A human-centred approach mitigates stress and fosters a positive organizational climate. Successful digitalization thus depends not only on technology but also on effective communication and cultural leadership (Murire, 2024; Oliveira et al., 2025).

Research Question 4 (RQ4): Ethical and Social Aspects

H4a: Employees perceive AI as more ethical when organizations communicate its functions and limitations transparently.

Mean = 4.23; SD = 0.68 – hypothesis confirmed.



H4b: Lack of clear accountability for AI-driven decisions decreases trust in management.

Mean = 3.91; SD = 0.84 – hypothesis confirmed.

H4c: Adherence to ethical standards enhances an organization's reputation.

Mean = 4.35; SD = 0.61 – hypothesis strongly confirmed.

Analytical commentary:

Ethical AI governance is a key factor in its acceptance. Organizations that clarify accountability for algorithmic decisions are more likely to foster trust and maintain public credibility. The results underscore the need for internal ethical frameworks that balance operational efficiency with the protection of human rights (Zang & Li, 2025).

Research Question 5 (RQ5): New Skills and the Future of Work

H5a: AI increases the demand for digital, communication, and soft skills.

Mean = 4.46; SD = 0.57 – hypothesis confirmed.

H5b: Integrating AI into training processes improves employee performance and adaptability.

Mean = 4.12; SD = 0.73 – hypothesis confirmed.

H5c: AI contributes to personalized learning and career development.

Mean = 4.05; SD = 0.80 – hypothesis confirmed.

Analytical commentary:

AI is reshaping the paradigm of human resource development. Success increasingly depends on fostering digital and soft skills that support adaptability in a rapidly changing work environment. AI also facilitates personalized learning, which enhances employee motivation and supports individual growth and self-realization (Al Naqbi et al., 2024; Zhang et al., 2025).

Table 1. Summary of Research Hypotheses and Results

Hypothesis	Content	M	SD	Result	Commentary
H1a	AI reduces routine tasks and promotes creative work.	4.18	0.74	Confirmed	Frees employees for analytical and creative work.
H1b	AI reorganizes tasks rather than eliminates jobs.	4.02	0.81	Confirmed	Transformation instead of reduction.



Hypothesis	Content	M	SD	Result	Commentary
H1c	Employees develop digital and cognitive skills.	4.47	0.63	Confirmed	Strong need for digital education.
H2a	AI increases efficiency and decision speed.	4.11	0.78	Confirmed	Enhances productivity.
H2b	Overreliance on AI reduces autonomy.	3.58	1.02	Partially confirmed	Some loss of control reported.
H2c	Support reduces stress and concerns.	4.26	0.69	Confirmed	Training and communication reduce pressure.
H3a	Transparent AI builds trust and satisfaction.	4.19	0.72	Confirmed	Open communication strengthens trust.
H3b	Lack of participation increases stress.	4.08	0.77	Confirmed	Decreases motivation and trust.
H3c	Human-centric AI improves satisfaction.	—	—	Confirmed	Correlation with loyalty.
H4a	Transparent AI perceived as more ethical.	4.23	0.68	Confirmed	Transparency enhances ethical perception.
H4b	Unclear responsibility lowers trust.	3.91	0.84	Confirmed	Define accountability clearly.
H4c	Ethical standards improve reputation.	4.35	0.61	Confirmed	Strengthens trust and reputation.
H5a	AI increases demand for soft/digital skills.	4.46	0.57	Confirmed	Rising need for adaptability.
H5b	AI integration enhances performance.	4.12	0.73	Confirmed	Improves development and adaptability.
H5c	AI personalizes learning paths.	4.05	0.80	Confirmed	Supports individual growth.

Source: own source according (2025))



Conclusion

The aim of this paper was to analyse how the implementation of Artificial Intelligence (AI) affects the work environment, employee efficiency, satisfaction, development, and organizational processes. The theoretical part provided an overview of the current understanding of AI, emphasizing automation, human–AI collaboration, its influence on organizational culture, and the ethical aspects of workplace technology.

The empirical findings confirmed that AI is becoming an integral component of modern organizations. The survey results showed that employees generally perceive AI positively, particularly regarding increased efficiency, reduced error rates, and the development of new skills. At the same time, the findings revealed that transparent communication, ethical governance, and employee participation are the key factors for successful AI integration.

Positive effects of AI were observed especially in the following areas:

- enhanced productivity and work efficiency,
- development of digital and soft skills,
- improved decision-making and managerial communication,
- strengthened trust and satisfaction in organizations that apply a human-centric approach.

However, the study also highlighted potential risks, such as uncertainty, loss of autonomy, and the need for ethical frameworks governing algorithmic decisions. These findings suggest that AI implementation should be accompanied by effective change management, employee education, and open internal communication.

From a practical standpoint, organizations should:

- systematically develop digital competencies among employees,
- strengthen transparency and ethics in AI applications,
- introduce AI gradually and inclusively, emphasizing trust and psychological well-being,
- monitor AI's impact on corporate culture and motivation through regular internal surveys.

From a scientific perspective, this study contributes to the growing discourse on AI as a tool for human augmentation rather than substitution. Future research should employ qualitative methods (e.g., in-depth interviews) to better understand the subjective experiences of human–AI collaboration and cross-country comparisons to enhance generalizability. In conclusion, Artificial Intelligence represents a key transformative force in today's workplace. Its benefits will be genuinely positive only if it remains at the service of humans — as a technology that extends human potential and promotes inclusive, ethical, and sustainable societal development. (Han, 2025; Li, 2025; Uygungil-Erdogan, 2025).

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Enhancing business processes through artificial intelligence in the era of globalisation

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Abstract

Optimizing business processes is crucial for improving efficiency and competitiveness in today's fast-paced industrial landscape and global world. This research introduces an innovative method that combines Artificial Intelligence (AI) with Failure Mode and Effects Analysis (FMEA) to automate risk assessment and facilitate predictive maintenance. By utilizing real-world data from a glass manufacturing company (SK), we developed machine learning models—Random Forest and XGBoost—to forecast Risk Priority Number (RPN) values and categorize failure risks. The Random Forest Regressor achieved a Coefficient of Determination (R^2) of 0.999, a Mean Absolute Error (MAE) of 2.18, and a Root Mean Square Error (RMSE) of 2.65, demonstrating exceptional accuracy in predicting risks. The Random Forest Classifier attained a classification accuracy of 82.9%, with a strong recall rate of 92.4% for high-risk situations, making it suitable for industrial applications. The proposed AI-enhanced FMEA system enables dynamic risk management, minimizes downtime, and enhances maintenance planning. This results indicate that AI can significantly improve traditional FMEA methodologies and lay the groundwork for intelligent, data-driven decision-making in industrial settings.

Keywords

optimization; business processes; artificial intelligence; FMEA

JEL Classification: L6, I25; D12; H75; E21; I31



Zlepšovanie obchodných procesov prostredníctvom umelej inteligencie v ére globalizácie

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Abstrakt

Optimalizácia obchodných procesov je kľúčová pre zlepšenie efektívnosti a konkurencieschopnosti v dnešnom rýchlo sa rozvíjajúcom priemyselnom prostredí a globálnom svete. Tento výskum predstavuje inovatívnu metódu, ktorá kombinuje umelú inteligenciu (AI) s chybovým režimom a analýzou účinkov (FMEA) na automatizáciu hodnotenia rizík a uľahčenie prediktívnej údržby. Využitím skutočných údajov zo sklárskej spoločnosti (SK) sme vyvinuli modely strojového učenia – Random Forest a XGBoost – na predpovedanie hodnôt čísla priority rizika (RPN) a kategorizáciu rizík zlyhania. Random Forest Regressor dosiahol koeficient determinácie (R^2) 0,999, strednú absolútnu chybu (MAE) 2,18 a strednú štvorcovú chybu (RMSE) 2,65, čo demonštruje výnimočnú presnosť pri predpovedaní rizík. Random Forest Classifier dosiahol presnosť klasifikácie 82,9%, so silnou mierou vyvolania 92,4% pre vysoko rizikové situácie, vďaka čomu je vhodný pre priemyselné aplikácie. Navrhovaný systém FMEA vylepšený AI umožňuje dynamické riadenie rizík, minimalizuje prestoje a zlepšuje plánovanie údržby. Tieto výsledky naznačujú, že AI môže výrazne zlepšiť tradičné metodológie FMEA a položiť základy pre inteligentné rozhodovanie založené na údajoch v priemyselnom prostredí.

Kľúčové slová

optimalizácia; obchodné procesy; umelá inteligencia; FMEA

JEL Klasifikácia: L6, I25; D12; H75; E21; I31



Introduction

Artificial intelligence (AI) is a field of computer science that focuses on creating intelligent systems, also called agents. These systems are able to perceive their environment and respond to it in a way that resembles human behaviour. AI is used to solve a variety of tasks, such as:

- Image recognition: AI can be used to identify objects in images or videos.
- Speech recognition: AI can be used to identify human speech.
- Language translation: AI can be used to translate between different languages.
- Gaming: AI can be used to play games such as chess, go, or poker.
- Automated decision-making: AI can be used to automate decision-making processes.

There are many different approaches to implementing AI. One of the most widely used is machine learning, which is an AI method that allows systems to learn from data. AI has the potential to significantly impact various aspects of our lives. It can be used to automate tasks currently performed by humans, as well as to create new products and services.

Failure Mode and Effects Analysis (FMEA) is a crucial method for detecting and handling dangers in different areas of engineering and management. Integrating artificial intelligence (AI) into FMEA is a major development that speeds up the procedure and enhances the precision and effectiveness of danger evaluation. Numerous practical studies have been released on this subject, and a short summary is provided below.

Employing generative language models for producing FMEA documents signifies a groundbreaking change in the realm of danger and failure investigation. It enables the swift and precise recording of information regarding asset makeup, their roles, and possible malfunctions. (Pangsy-Kania, 2024)

These models, built upon sophisticated artificial intelligence, can handle vast quantities of data, and create text that is coherent, organized, and adapted to the demands of a particular examination. One study indicates that a system utilizing large language models accurately generated over half of the vital content for FMEA documents, as validated by reliability specialists. These specialists valued the model's capability to not only replicate existing data but also to propose pertinent descriptions of malfunctions and their impacts based on the data available (Hezla et al., 2024), thus minimizing the chance of human mistakes such as missing crucial specifics or inconsistent wording. (Kubas et al., 2017).

Using active learning combined with NLP presents a fresh way to uncover reasons for equipment malfunction from free-form maintenance data like repair logs, incident reports, and mechanic's observations. This greatly streamlines data examination, which is typically disorganized, variable, and contains diverse text types, from short comments ("engine failure") to comprehensive documents ("reduced output observed after 500 hours"). Researchs (Kumar, 2018), (Kumar, 2022) indicate that an active learning strategy needs labeling of just 10% of the data to produce trustworthy findings, significantly lessening the demand for manual data tagging. In the past, engineers or researchers had to examine numerous documents and manually classify them, a slow and fault-susceptible task. Active

learning enhances this procedure by enabling the AI system to pick the most helpful documents for annotation and progressively understand how to spot failure trends based on human input. (Janoskova, 2022), (Malveiro, 2016)

Integrating failure analysis techniques into manufacturing and proactive upkeep significantly boosts modern production systems. By linking these techniques with ongoing equipment monitoring, like in high-temperature power plants, we can better predict major breakdowns. This lowers the chance of sudden stoppages and makes the whole system more dependable. This strategy cuts down on downtime, streamlines maintenance plans, and lowers expenses for repairs.

Furthermore, artificial intelligence (AI) improves this process by using connected sensors to constantly track things like temperature, vibration, and pressure of equipment. Because of this, AI can spot problems early—like unusual turbine shaking—and suggest ways to prevent them before they lead to actual breakdowns. (Nagy et al., 2025)

Using advanced optimization methods represents a cutting-edge way to make products more reliable. For example, a mix of established failure analysis, statistical design optimization, and AI-powered networks was used to enhance the robustness of memory chips. A statistical approach helps choose the best settings to make the product more stable and less prone to issues. AI-powered networks model and predict tricky connections between things like production conditions and memory chip failures. Finally, an evolutionary algorithm searches for the best possible settings to lower the chance of memory chip malfunctions. AI-Powered Failure Mode Identification is shown in Figure 1.

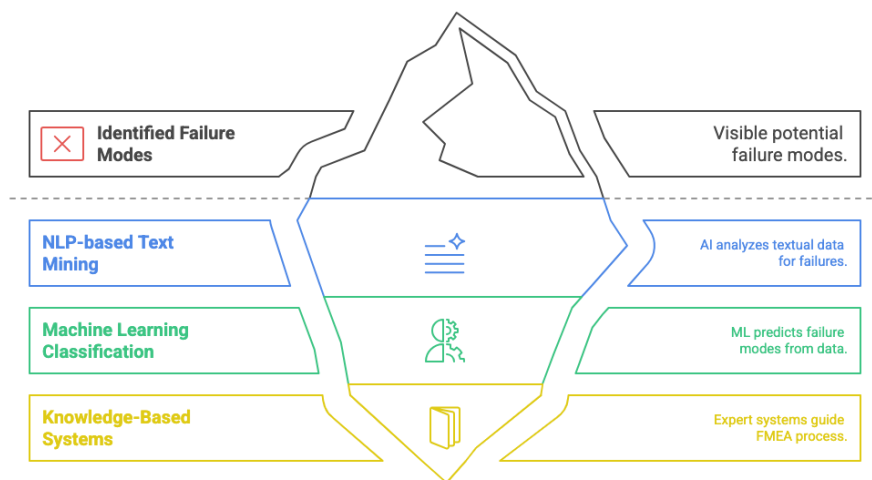


Figure 1. AI-Powered Failure Mode Identification.

Source: own processing (2025)

The use of computers to handle failure modes and effects analysis (FMEA) for crucial safety systems marks another step forward in how we deal with risk. Computerized FMEA methods that include simulated fault insertions have made risk evaluation easier and sped up the process of finding problems in electrical systems. Fault insertion simulations are methods where problems (like a power loss or program error) are intentionally put into the system to check how it reacts and how well it can recover.



The use of machine learning (Trnka, 2016) is causing a major change in automated risk evaluation within FMEA analysis, significantly improving its use in many different industries, such as farming equipment. Models that categorize risk in several levels, which predict values related to risk importance, can be accurate between 86.6% and 93.2%, considerably speeding up and enhancing the risk evaluation process (Kowalski, 2023). This technology allows for the quick organization of possible issues based on how serious they are, how often they happen, and how easily they can be found, removing the need for lengthy manual reviews. (Sukalova et al., 2022), (Kováčová, 2019)

Objectives and methodology

In a study aimed at improving workplace efficiency through artificial intelligence, we used machine learning techniques to automatically identify risks and calculate their priority based on the Failure Mode and Effects Analysis (FMEA) approach. We particularly focused on three effective models – Random Forest Classifier, Random Forest Regressor, and XGBoost – which allowed for precise forecasting and ranking of risks using existing data. The process involved these stages (Lever, 2000):

- gathering data from sensors, maintenance records, and past performance;
- analyzing systems and processes using techniques like Total Productive Maintenance (TPM), Reliability-Centered Maintenance (RCM), and system diagnostics;
- identifying and evaluating potential failure points using FMEA with conventional Risk Priority Number (RPN) assessment;
- predicting and categorizing risks using AI models (Random Forest, XGBoost);
- confirming and validating the models using actual data and performance indicators;
- developing action plans based on AI results, resulting in an organized maintenance strategy;
- conducting final analysis using methods like Root Cause Failure Analysis (RCFA) and Fault Tree Analysis (FTA).

A visualization of how the Random Forest Classifier works is shown in Figure 2, illustrating the ensemble of decision trees where each tree predicts the risk (e.g., “high” or “low”) and how their combined output determines the final classification.

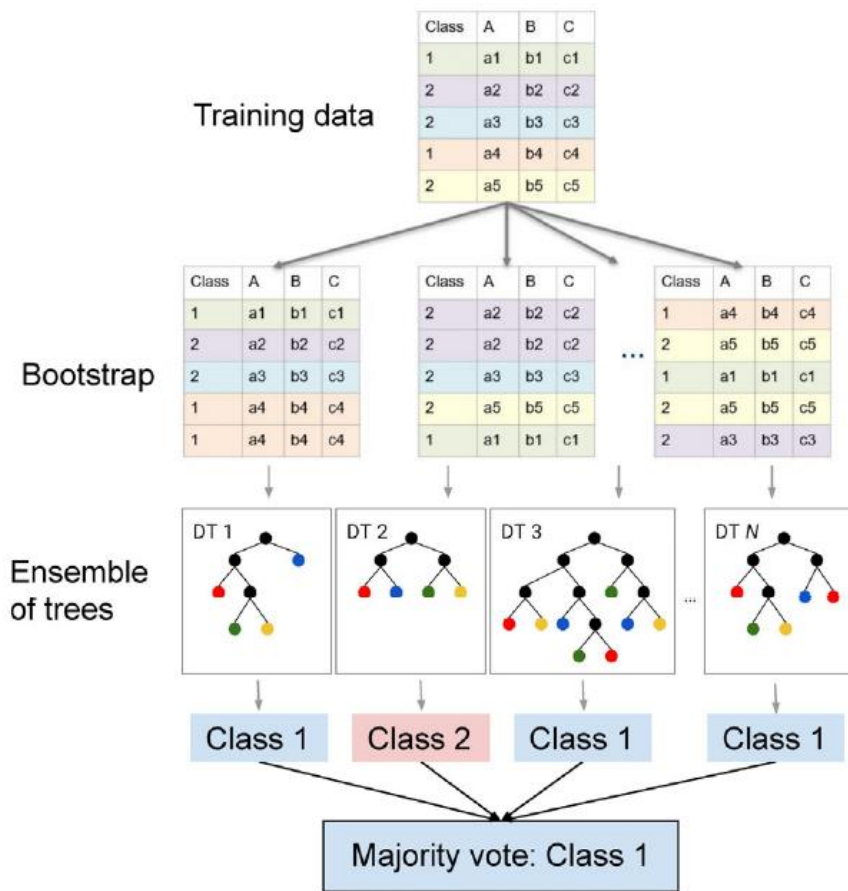


Figure 2. Illustration of the functioning principle of the Random Forest Classifier.

Source: own processing (2025)

Theoretical starting points

The efficacy of an AI-enhanced Failure Mode and Effects Analysis (FMEA) system was confirmed using empirical data from a manufacturing context. Critically, the model's development and validation were performed using data pertinent to the glass manufacturing sector. Consequently, the identified failure patterns and process attributes are indicative of the unique operational characteristics of this industrial domain. Acknowledging that failure modalities may diverge substantially across diverse industries, such as aerospace, automotive, and agriculture, due to variations in technological processes, operational parameters, and regulatory stipulations, is crucial.

Therefore, while the underlying methodology offers broad applicability, the model itself necessitates adaptation and retraining utilizing industry-specific data to ensure accurate and robust performance. Customization of input variables, categorization of failures, and the severity, occurrence, and detection (S, O, D) scoring criteria are essential to effectively implement AI-supported FMEA in alternative production environments. The data encompassed operational equipment parameters, failure histories, and implemented maintenance actions. To ensure generalizability across sectors including



automotive, pharmaceuticals, and aerospace, the fundamental methodology (i.e., the synergistic combination of AI and FMEA for prioritized risk assessment and predictive maintenance strategies) remains relevant.

Results and discussion

In contemporary manufacturing, the dependability of production machinery is paramount for preserving a competitive edge and operational effectiveness. Unscheduled interruptions stemming from malfunctions can precipitate considerable economic setbacks and disturbances in production timelines. Consequently, it is indispensable to institute strategies that facilitate the forecasting and averting of malfunctions. Artificial intelligence offers substantial assistance to Failure Mode and Effects Analysis (FMEA) throughout various phases of scrutiny, expediting the procedure of pinpointing and resolving latent concerns.

This investigation centers (Stofkova, 2024) on enhancing operational workflows via the application of artificial intelligence, with the FMEA methodology deployed as a pivotal instrument. The analysis was executed utilizing data derived from a manufacturing enterprise (SK) operating within the glass sector, with the following objectives:

- Guarantee automated hazard detection: AI scrutinizes prior malfunction and error information, discerns patterns, and proposes plausible failure modalities. Drawing upon antecedent information, machine learning algorithms anticipate which procedures or constituents are at elevated hazard of malfunction. (Lazaroiu et al., 2024)
- Forecast the likelihood of incidence: AI appraises the probability of errors contingent on expansive datasets originating from sensors, production chronicles, or maintenance documents. Employing information such as machinery oscillation or temperature, it prognosticates when a malfunction may transpire.
- Independently evaluate gravity: AI analyzes the ramifications of malfunctions utilizing simulations or prior information. It evaluates the impact of a malfunction on production, caliber, and productivity, allocating a suitable gravity echelon.
- Automatically compute RPN: AI dynamically recomputes the risk priority number and prioritizes the most imperative matters grounded in contemporaneous information. (Mateoc-Sîrb, 2016), (Skotnicka-Zasadzien, 2022), (Soltes, 2018)

The dataset, encompassing failure records from five identical production lines (numbered 1 to 5), spans the period from January 2023 to December 2024. The database comprises 731 records, demonstrating a near-daily occurrence of at least one breakdown across the lines. For each instance of failure, the recorded information includes: the date, the specific production line affected, the failure's nature (categorized by problem type), the underlying cause of the failure, and the associated severity (S), occurrence (O), and detection (D) ratings, as determined by the Failure Mode and Effects Analysis (FMEA) methodology. These ratings, ranging from 1 to 10, were assigned by maintenance personnel in



accordance with the QS9000 standard. Trained maintenance professionals, possessing thorough knowledge of equipment performance and the consequences of failures, were responsible for assigning the severity (S), occurrence (O), and detection (D) values. To promote consistency and minimize subjective bias, the evaluation adhered to established internal protocols grounded in the QS9000 standard, utilizing predefined rating scales. This standardization facilitated consistent scoring across all records, thereby enhancing the reliability of the resultant Risk Priority Number (RPN) values for subsequent machine learning analysis.

Following the development and training of the artificial intelligence model for failure modes and effects analysis (FMEA), the Random Forest Classifier was deployed to forecast the risk level for distinct production streams. The model categorized each instance as either low-risk (0) or high-risk (1), based on an amalgamation of historical breakdown data and prevailing operational data. Any condition where the risk priority number (RPN) exceeded 100 was demarcated as high-risk. This demarcation was established based on established suggestions and documented research, which consider an RPN surpassing 100 as indicative of more critical breakdowns with amplified impact on safety, quality, or production continuity (Bent, 2025). Consequently, values below 100 were classified as low-risk, denoting instances that do not mandate immediate remediation but necessitate continued surveillance. As an illustration of the model's yield, Table 2 presents a selection of predicted RPN values for specific breakdown records. The table encompasses the breakdown identifier, the corresponding production stream, the date of incident, the FMEA parameters (S, O, D), the computed RPN, and the binary risk classification (0 = low, 1 = high).

The study serves as an exemplar of the data processing methodology and the format of the predictive model's outcome. The comprehensive dataset contained 731 records; however, for brevity, only a representative subset is displayed.

Conclusion

The findings of this investigation were juxtaposed with established applications of the Random Forest Classifier across diverse domains and scholarly research. Existing literature generally indicates that Random Forest consistently demonstrates substantial accuracy and efficacy. For instance, in sentiment classification utilizing social media data, the observed precision rates spanned from 70% to 90%, recall rates from 65% to 85%, and accuracy rates from 80% to 95%, particularly with less intricate, text-based data (Chen, 2016). In the detection of botnet activities, the model attained nearly perfect precision and recall, although this was achieved with highly structured data (Blancarte-Siqueiros, 2025). In medical contexts, such as the identification of ophthalmic disorders, the model exhibited performance characterized by a precision of 76%, a recall of approximately 70%, and an accuracy of about 75%, figures more closely aligned with typical performance in Failure Mode and Effects Analysis (FMEA) (Nagaraja, 2014). Within industrial FMEA studies, particularly in the automotive sector, common results reflect accuracy levels between 70% and 90%, with precision and recall rates in the range of 60% to 85%, especially under conditions of balanced data and optimized hyperparameters (Mohanty, 2020).



This research investigates the enhancement of operational workflows within a professional setting through the application of artificial intelligence to improve the precision and efficacy of hazard evaluation. The Failure Mode and Effects Analysis (FMEA) methodology presented serves as a central instrument for hazard analysis in intricate production settings, facilitating the pinpointing of vulnerabilities and the optimization of diverse upkeep protocols. Periodic consultations were conducted with the project personnel and organizational leadership throughout the duration of the investigation, during which the findings were met with favorable assessments and recommendations for subsequent enhancements. AI algorithms scrutinize archived data pertaining to malfunctions and discrepancies, discern trends, and propose conceivable failure scenarios. The machine learning paradigm, predicated on prior data, forecasts processes or elements exhibiting an elevated probability of breakdown. The outcomes attained permitted the forecasting of hazards for the forthcoming timeframe.

One prior investigation (Botteldooren, 2006) presents a semi-supervised active learning strategy. In this strategy, a human expert annotates a limited subset of textual maintenance records, enabling the model to generalize and identify failure modes with an accuracy exceeding 90%. This methodology proves advantageous in settings where organized sensor data is scarce, yet archival information exists in textual format. (Kliestik, 2024)

Conversely, the present investigation adopts a purely data-driven strategy predicated on organized, quantitative data procured from sensors and maintenance systems. (Repkova Stofkova, 2024)

Instead of deriving failure modes from unstructured text, we concentrate on forecasting the risk priority number (RPN) and categorizing risk levels based on quantifiable process variables. This facilitates enhanced integration into automated, real-time maintenance systems and augments NLP-based strategies by addressing disparate data origins and applications. Alternative investigations have introduced hybrid AI techniques amalgamating fuzzy logic, expert heuristics, and neural networks to bolster FMEA. (Valaskova et al., 2025)

While these techniques are valuable for representing ambiguity and human judgement, they frequently necessitate substantial manual configuration and exhibit challenges in scalability. By leveraging Random Forest and XGBoost algorithms, our solution yields precise outcomes and improved interpretability, rendering it appropriate for implementation in real-time systems. Furthermore, the inclination toward real-time FMEA via IoT integration is escalating rapidly within the context of Industry 4.0. Our strategy underpins this evolution by demonstrating how instantaneous sensor inputs (e.g., temperature, vibration) can dynamically affect failure risk classification and prediction, thereby enabling the deployment of continuous risk surveillance across industrial landscapes.

In the study, two models were evaluated: the Random Forest Classifier model and the XGBoost model, where the attained results exhibited insignificant divergence (Table 1).



Table 1. Formatting sections, subsections, and subsections

Model	MAE	RMSE	R2
Random Forest Classifier	40.82458	51.47219	0.83428
XGBoost	39.42207	52.81832	0.80247

Source: own processing, (2025)

While the final implementation employed solely Random Forest and XGBoost algorithms, alternative standard baseline methodologies, including logistic regression and support vector machines (SVMs), were initially evaluated during the methodological design stage. Although frequently utilized in classification problems, these models generally exhibit limitations in effectively managing nonlinear interdependencies and heterogeneous input features, such as the severity scores and sensor readings employed in this research. Logistic regression, as a linear model, may fail to adequately represent intricate relationships between failure indicators. Similarly, SVMs can be susceptible to feature scaling and necessitate meticulous kernel parameter optimization. Conversely, Random Forest demonstrates resilience to overfitting, accommodates both categorical and quantitative data effectively, and automatically identifies nonlinearities and feature correlations, rendering it a suitable methodology for industrial applications involving structured datasets. (Bubeník, 2025), (Kovacova, 2024)

The accuracy and realism of predictions are contingent upon the selection of monitored parameters and the criteria used to define severity (S), occurrence (O), and detection (D) classifications. The fundamental model can be refined through the incorporation of supplementary input variables. Given the data-driven nature of this prediction, significant discrepancies in Risk Priority Numbers (RPN) necessitate collaboration with maintenance personnel to classify emergent failure modes and integrate them into the training dataset.

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Artificial Intelligence and Human Resource Management: Current State and Future Research Directions

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Abstract

Artificial intelligence (AI) is increasingly reshaping human resource management (HRM), offering opportunities to automate routine tasks while also transforming strategic decision-making processes.

Given the growing relevance of this topic, the aim of this article is to analyse the current state of knowledge on the use of AI in HRM and to identify the main directions of scientific research in this field. To achieve this objective, a bibliometric analysis was conducted using articles retrieved from the

Web of Science database, with keyword co-occurrence mapping performed through VOSviewer, resulting in 26 keywords grouped into four thematic clusters. The results confirm that the topic is highly relevant, with a marked increase in scientific interest since 2024, and that India, China, and the United States are the leading contributors in terms of publication output, while research from Western economies shows a growing focus on human-centered and ethical aspects of AI implementation. The findings further reveal that AI-enabled HR practices go beyond digital HR tools by enabling more advanced, transformative decision-making, with recruitment, training, and employee retention identified as the most prominent areas of application. However, ethical concerns and limited technological readiness remain significant barriers, highlighting the need for future research on regulatory frameworks and cross-country comparative studies.

Keywords

AI, HRM, bibliometric analysis, directions

JEL Classification: O15; O32;

Umelá inteligencia a riadenie ľudských zdrojov: Súčasný stav a budúce smerovanie výskumu

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Abstrakt

Umelá inteligencia (AI) čoraz viac pretvára riadenie ľudských zdrojov (HRM) a ponúka príležitosti na automatizáciu rutinných úloh a zároveň transformuje strategické rozhodovacie procesy. Vzhľadom na rastúcu aktuálnosť tejto témy je cieľom tohto článku analyzovať súčasný stav poznatkov o využití AI v HRM a identifikovať hlavné smery vedeckého výskumu v tejto oblasti. Na dosiahnutie tohto cieľa sa vykonala bibliometrická analýza s použitím článkov získaných z databázy Web of Science, pričom sa pomocou VOSviewer vykonalo mapovanie spoločného výskytu kľúčových slov, výsledkom čoho bolo

26 kľúčových slov zoskupených do štyroch tematických skupín. Výsledky potvrdzujú, že téma je vysoko relevantná, s výrazným nárastom vedeckého záujmu od roku 2024 a že India, Čína a Spojené štáty sú hlavnými prispievateľmi, pokiaľ ide o publikačnú produkciu, zatiaľ čo výskum zo západných ekonomík ukazuje rastúce zameranie na etické aspekty implementácie AI zamerané na človeka.

Zistenia ďalej odhaľujú, že postupy HR s podporou AI presahujú digitálne nástroje HR tým, že umožňujú pokročilejšie, transformatívne rozhodovanie, pričom nábor, školenie a udržanie zamestnancov sú identifikované ako najvýznamnejšie oblasti použitia. Etické obavy a obmedzená technologická pripravenosť však zostávajú významnými prekážkami, ktoré zdôrazňujú potrebu budúceho výskumu regulačných rámcov a medzištátnych porovnávacích štúdií.

Kľúčové slová

AI, HRM, bibliometric analysis, directions

JEL Klasifikácia: O15; O32;

1. Introduction

Artificial intelligence is currently a phenomenon exerting an increasingly significant influence on various spheres of daily life, including the field of management. Human resource management is one key area of management where the application of AI is becoming increasingly relevant. Given that many managers perceive employees as a source of competitive advantage and a driver of a company's transformational potential, human resource management is currently receiving exceptional attention. Across all economic sectors (not just services) human capital is the factor that often creates a decisive competitive advantage for a company (Skypalova et al., 2025).

For this reason, it is no longer sufficient to monitor only basic metrics such as employment levels, turnover rates, or the quantification of staffing needs; it is essential to invest systematically in employee development, motivation, and communication. This presents one of the major challenges for modern human resource management, as every employee has unique preferences and needs and expects their employer to appropriately value the skills, education, and experience they bring to the workplace. Consequently, the relationship between employee and employer cannot be viewed as a matter of one-sided loyalty but rather as a reciprocal exchange of value. For this reason, it is essential to adopt an individualised approach to employees and ensure their adequate evaluation and motivation - practices that ultimately yield positive outcomes for both the individual employee and the organisation as a whole. This context creates opportunities for the use of artificial intelligence, which can relieve HR managers of administrative burdens while simultaneously helping to design personalised programs that address the specific needs of individual employees (Böhmer and Schinnenburg, 2023). According to Zhang



(2024), companies that have integrated AI into their HR processes have achieved greater success not only in recruitment but also in employee productivity.

1.1. Theoretical starting points

Digital HRM practices involve integrating digital technologies into specific human resource management processes, such as automating routine tasks, conducting online recruitment, and using e-learning tools. In contrast, AI-enabled HR practices represent a higher level of technological integration, utilising artificial intelligence for advanced analytics, predictive modelling, and the personalisation of the employee experience. The key difference between the two approaches is that digital HR primarily focuses on simplifying and digitising existing processes, whereas AI-enabled HR innovates and transforms these processes through intelligent decision-making capabilities that can mimic or augment human decision-making (Muritzi et al., 2024).

Currently, artificial intelligence is primarily used to automate repetitive tasks, thereby contributing to cost reduction. Regarding specific management functions, its application has been most significant in areas such as recruitment, training, and employee engagement and retention; ultimately, this has a positive impact on organisational performance and the efficiency of HR process management. For instance, in recruitment, artificial intelligence can enhance process efficiency by reducing costs, shortening the recruitment timeline, and expanding the pool of potential candidates (Kshetri, 2021).

Although numerous studies confirm the many benefits of implementing artificial intelligence in human resource management, a study by Fountaine et al. (2019) highlights the fact that many companies fail to achieve the expected benefits, often viewing the integration of AI into their HR activities as costly and challenging. Furthermore, as noted by Böhmer and Schinnenburg (2023), while many authors argue that artificial intelligence can be applied across all areas of HRM, a significant gap remains between theoretical assumptions and actual practice.

2. Objectives and methodology

Given the growing importance of this topic, the aim of this article is to analyse the current state of knowledge on the use of artificial intelligence in human resource management and to identify the main directions of scientific research in this field.

In analysing the current state of the subject topic, we focused on articles indexed in the Web of Science (WoS) database, as this database is considered a relevant source of scientific knowledge (Mariani et al., 2023). Articles were selected based on a topic search covering both HRM (defined as "HRM" or "human resource management") and AI (defined as "AI" or "artificial intelligence"). To ensure the inclusion of only the most relevant scientific insights, document types such as reviews, conference papers, books, and book chapters were excluded. Focusing exclusively on articles supports the aim of incorporating the latest scientific findings (Cheraghali & Molnar, 2023). Additionally, we filtered documents to those within the field of management, as we are examining this issue from the perspective of AI applications in people management. After applying these filters, we extracted 191 documents for further analysis.

The selected documents were analysed for keyword occurrences to identify the main research directions. Each article contains key terms intended to define its primary focus. VOSviewer software was used for this analysis, enabling the identification of 317 keywords. To ensure greater clarity in the analysis, a

condition was established that every word to be analysed must appear in at least three documents. Through this process, we selected 33 keywords.

3. Results and discussion

As a first step, we focused on assessing the currency of the topic under study. As shown in Figure 1, this is a highly topical subject, with the scholarly exploration of its beginnings coinciding with the onset of widespread adoption of artificial intelligence. The figure reveals that, although the first publications addressing this issue appeared in 2020, a significant surge in interest regarding the implementation of artificial intelligence in human resource management is evident only from 2024 onwards.

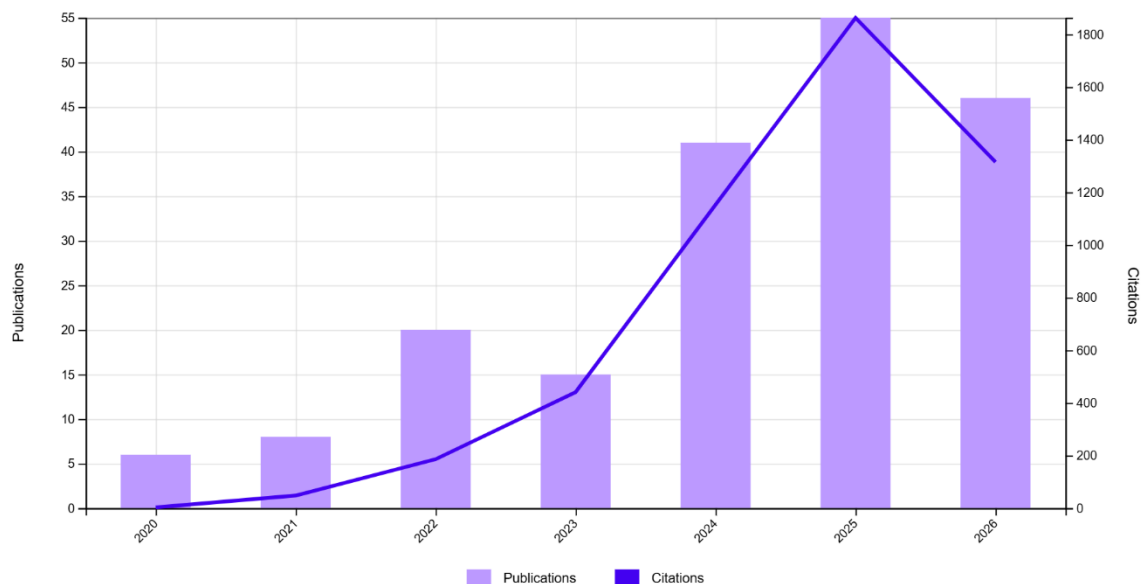


Figure 1. Trends in publications and citations of articles focused on the implementation of AI in HRM

Source: Web of Science

In the next step, we focused on identifying the countries whose authors are the most actively engaged with this topic. An analysis of the WoS database reveals that the highest number of publications originates from India, China, and the USA, followed by other western / developed economies such as the United Kingdom, Australia, Italy, France, Germany, and Finland. In research from western / developed economies, a thematic shift is evident towards human-centred and ethically oriented aspects of AI applications in HRM, including employee well-being, work-life balance, and the psychological dimensions of employment. However, as noted by Roy (2026), the fact that relevant studies originate from only a limited number of countries (mainly developed economies) presents a challenge linked to disparities in technological infrastructure, both at the national level and regarding the resources available to HR managers, thereby limiting the generalizability of the findings. Nevertheless, a study by Kshetri (2021) confirms that AI implementation offers a competitive advantage for emerging economies as well. The aforementioned VOSviewer software was used to analyse keyword frequency, enabling the selection of 33 keywords. Subsequently, terms with identical meanings (e.g., AI – artificial intelligence;



HRM – human resource management) were excluded from this set, resulting in a final list of 26 keywords. These were subsequently divided into four clusters, with each cluster grouping keywords that share the highest degree of mutual relatedness, while the individual clusters are simultaneously as distinct from one another as possible (Figure 2):

- red cluster – business, future, impact, information technology, innovation, knowledge, management, system, user acceptance. This cluster is characterised by the strategic and organisational dimensions of technology implementation; that is, articles containing these keywords primarily focus on the technological transformation of the enterprise and its organisational consequences.
- green cluster – bias, performance, procedural justice, systems, technology, trust. This cluster is dominated by the ethical dimension of implementation and the resulting issues regarding the trustworthiness and fairness of AI in employee evaluation and management.
- blue cluster – big data, challenges, decision-making, ethics, opportunities, perspective. These keywords focus on a macro perspective on the consequences and risks of AI for decision-making.
- yellow cluster – artificial intelligence, human resource management, meta-analysis, recruitment, work. This is a core cluster that indicates the methodological grounding of the research.

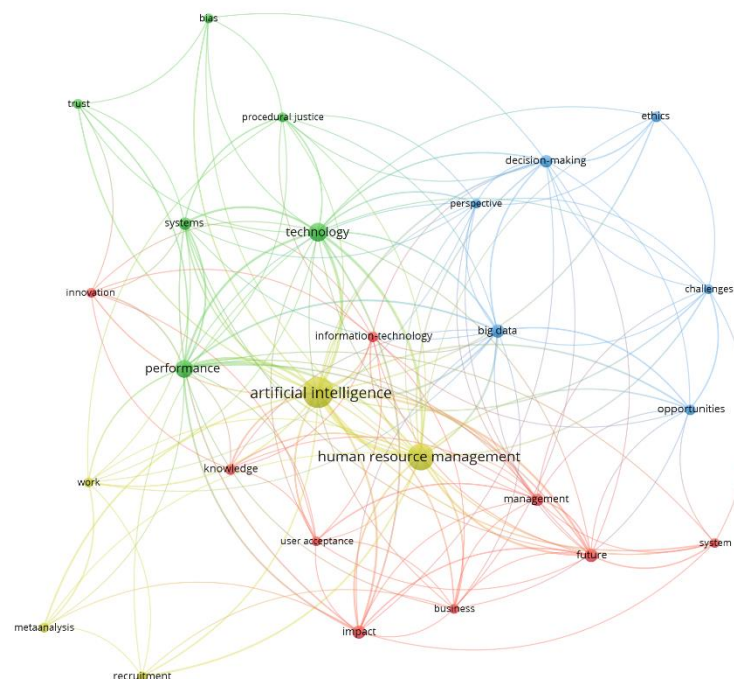


Figure 2. Clusters of keywords

Source: VOSviewer

As shown by the density visualisation (Figure 3), the most prominent terms are "artificial intelligence" and "human resource management," reflecting the fact that these are key concepts within the subject matter under study. Secondary, highly interconnected terms include "technology," "performance," and "future". Technology is a fundamental prerequisite for the development of artificial intelligence - a point



confirmed by Muridzi et al. (2024), who note that technological advancement plays a pivotal role in the transition from personnel management to modern human resource management. However, it is precisely in this area that companies often struggle, as they lack the technical readiness required for AI implementation (Malik et al., 2023). The term "performance" relates to the fact that AI implementation aims to streamline human resource management, ultimately leading to enhanced performance for both employees and the organisation. Regarding performance, several studies also explore the potential for predicting employee performance (Qamar et al., 2021). Furthermore, authors frequently address the future of AI implementation in HRM, which is reflected in the prominent position of the term "future" on the analysed map.

Other relevant thematic areas include “ethics”, “decision-making”, and “recruitment”. It is precisely in the realms of decision-making and recruitment that both authors and managers see the greatest potential for implementing artificial intelligence - by simplifying repetitive, routine tasks and leveraging AI’s capacity to process vast datasets, thereby enabling more informed decision-making (Kaushal et al., 2023). This benefit is linked primarily to AI’s ability to eliminate subjectivity from decision-making processes (Chowdhury et al., 2023). Along with the concept of "impact," decision-making and recruitment thus represent key areas for AI application in HRM (Qamar et al., 2021). Another significant thematic area is “ethics”, a subject addressed by many authors. With the advent and implementation of artificial intelligence, not only within HRM, it is essential to consider ethical aspects that foster trust, perceived utility, and fairness in the process. Establishing ethical guidelines and a legislative framework contributes to building trust in the implementation of AI within human resource management (Kumar, 2026). However, as noted by Roy (2026), only a limited number of studies have so far addressed the ethical challenges associated with AI implementation. Nevertheless, according to HR managers, these ethical implementation issues are among the most significant risks associated with deploying artificial intelligence in HRM (Jiang et al., 2025).

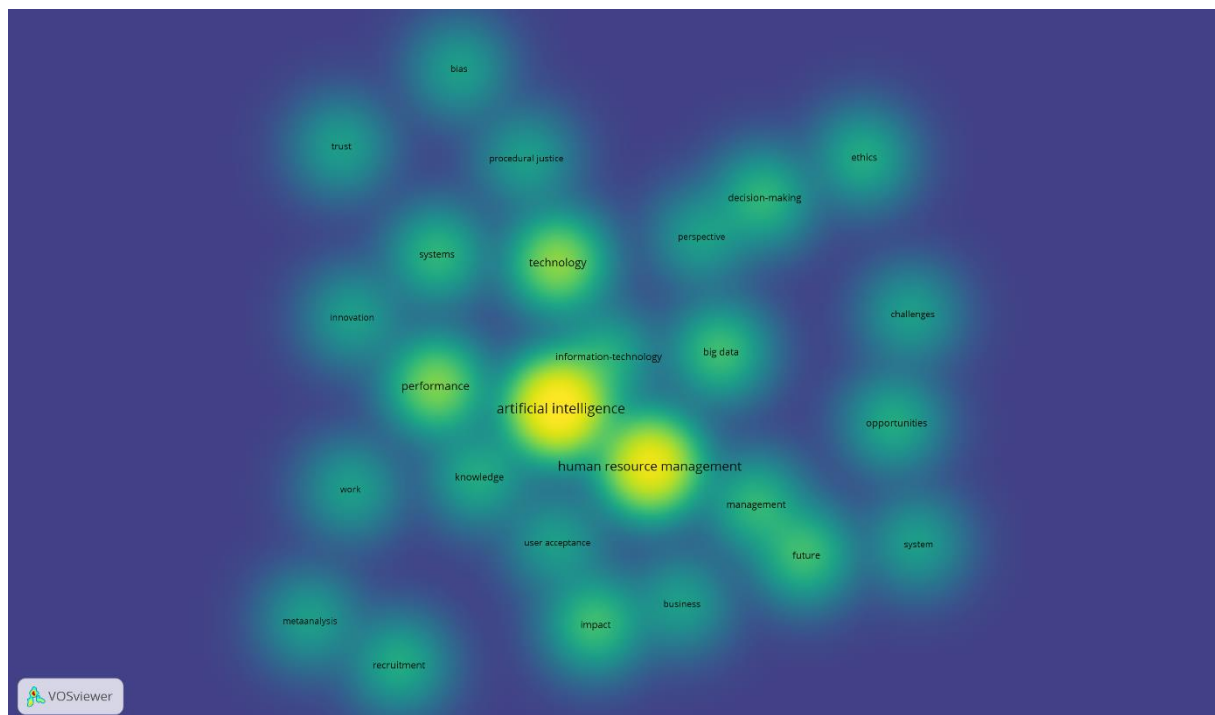




Figure 3. Density map of the keywords

Source: VOSviewer

Conclusion

The aim of this article was to analyse the current state of knowledge regarding the use of artificial intelligence in human resource management and to identify key directions of scientific inquiry in this field. A bibliometric analysis confirmed that this is a highly topical subject, with a marked increase in interest since 2024; the highest number of publications originates from India, China, and the USA, whereas research from Western economies focuses primarily on human-centric and ethical aspects of AI implementation, including employee well-being. Keyword analysis revealed four thematic clusters, indicating that the issue encompasses the technological, organisational, ethical, and trust-related dimensions of integrating AI into HR processes. The findings also confirmed that AI-enabled HR practices represent a higher level of technology integration than traditional digital HR tools, as they facilitate not only the automation but also the innovation of HR processes, with the most significant potential evident in recruitment, training, and employee retention. Despite these benefits, many enterprises fail in their AI implementation efforts due to insufficient technological readiness and high costs, while the ethics of implementation remains a particularly critical area, perceived by managers as one of the major risks.

Future research should therefore focus primarily on deepening understanding of ethical and regulatory frameworks and the long-term impact of AI on employee well-being, as well as on broadening the geographical scope of studies and examining the technological readiness of enterprises, particularly in the context of emerging economies.

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*Zborník vedeckých prác z projektu
NFP313010BWN6
„Implementačný rámec a business model
internetu vecí v inteligentnom priemysle a
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Zborník vedeckých prác z projektu Implementačný rámec a business model internetu vecí v inteligentnom priemysle a doprave

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