

The Impact of Artificial Intelligence on the Changing Work Environment: Differences in Perceptions Across Education Level, Type of Work, and Job Position in Slovakia¹

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Abstract

Background: The rapid development of artificial intelligence is transforming business operations, work processes, and organizational structures. Companies increasingly rely on data-driven decision-making and automation to enhance efficiency and competitiveness. However, the successful integration of artificial intelligence does not depend solely on technological readiness, but also on employees' perceptions, attitudes, and adaptability. Previous studies suggest that educational level, type of work, and hierarchical position may influence how individuals perceive technological change and its consequences.

Purpose: This study examines how employees in Slovak enterprises perceive the future impact of artificial intelligence on business operations. It investigates whether educational background, type of work, and job position influence workplace attitudes toward artificial intelligence.

Study design/methodology/approach: A quantitative survey was conducted among employees of Slovak companies in 2024. Data were collected through an online questionnaire using Likert-scale statements. After data cleaning, 260 responses were analyzed. The hypotheses were tested using non-parametric statistical methods to examine differences between groups.

Findings/conclusions: The results indicate that educational level has only a limited effect on perceptions of artificial intelligence, with significant differences appearing mainly in relation to decision-making and data analysis. In contrast, clear differences were found between employees performing mental and physical work, with mental workers expressing more positive attitudes. Differences were also found across hierarchical positions, with managers reporting more favorable expectations regarding efficiency, innovation, and organizational change. The findings highlight that the integration of artificial intelligence is not only a technological issue but also a managerial and organizational challenge.

Limitations/future research: The study is based on a convenience sample and a cross-sectional research design, and it represents an investigation limited to Slovakia. Therefore, the findings should be interpreted as

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exploratory and may not be fully generalizable. Future research should examine larger and more diverse samples and explore the long-term organizational and psychological effects of artificial intelligence adoption.

Keywords

artificial intelligence, employee perceptions, digital transformation, changing work environment, job positions, mental and physical work, future effects

Introduction

The rapid development and spread of artificial intelligence (AI) is fundamentally changing the world of work around the world. Recent organizational behavior research emphasizes that AI should be understood as a multilevel workplace phenomenon that affects individual employees, work groups, and organizational structures simultaneously (Bankins et al., 2024). Automation, data-driven decision making and machine learning are becoming more widely used not only in the technology sector, but also in traditional industries (Babashahi et al., 2024). For businesses, the use of AI has many benefits; AI-driven decision-making systems can increase organizational efficiency, reduce operational costs and drive innovation. The application of AI also has implications for human resource management (Berber et al., 2018), which is becoming increasingly "technology-intensive" (Rimac Bilusic & Poloski Vokic, 2025) and more efficient (Blahusiakova, 2023). Since AI is constantly evolving and has an infinite number of applications in many different fields (Kostin, 2018), companies may find the right type of AI for every task in the near future. The challenge, however, is recognizing the benefits they can gain by using these tools in time (Raskovich et al., 2024). Automation and AI will have a significant impact on the structure of the workplace, and although many new jobs will be created, the automation of low-skilled tasks may lead to the exclusion of certain groups of workers. The introduction of technology is not always a clear positive: it can create uncertainty and resistance among workers, which can inhibit the adoption of new systems (Frey & Osborne, 2017). AI-related uncertainty may also generate psychological and behavioral risks, as AI awareness can increase counterproductive work behavior through psychological contract disruption and emotional exhaustion (Bai et al., 2024). Employee perceptions are particularly important because the effective adoption of AI principles depends on communication, managerial support, training, and employees' understanding of how AI is governed within organizations (Kelley, 2022). Of particular importance is how workers from different

occupational and educational backgrounds perceive and value these changes, and how this affects the competitiveness and operational efficiency of organizations. Recent evidence further shows that employees' intentions to use AI at work are shaped by perceived usefulness, trust in AI, and affective attitudes toward AI-based technologies (Nguyen et al., 2026). Accordingly, examining employees' perceptions across their educational backgrounds, types of work, and job positions is relevant because AI adoption may be interpreted differently depending on employees' skills, work tasks, organizational roles, and perceived exposure to AI-related change. Our research explored the views of workers with different educational levels and job positions, as well as those with mental and physical jobs, on the likely impact of AI in the near future.

1. Theoretical background and hypotheses development

This section reviews the relevant theoretical background related to artificial intelligence in business environments and develops the research hypotheses. Based on previous empirical and conceptual studies, the role of education, type of work, and hierarchical position in shaping employees' perceptions of artificial intelligence is examined.

1.1. Increasing business competitiveness through AI

Companies are constantly looking for ways to innovate and increase their competitiveness (Soltysik et al., 2024). In recent years, Artificial Intelligence (AI) has played an increasingly important role in this process, especially since the Covid-19 pandemic significantly accelerated the automation and digitization of work tasks (Cramarenco et al., 2023). AI is not just a new technology, but an engine of transformation that is reshaping work processes, business models and boundaries between industries. It is becoming increasingly popular and pervasive in cross-border e-markets, transforming the global economy (Mirbabaie et al., 2022), embedded in business strategies and decision-making processes (Shrestha et al., 2019), and has become a key factor in

business value creation (Dwivedi et al., 2019). Its application not only increases efficiency, but also opens up new opportunities for companies in innovation and customer experience. It is pervasive (Wang & Siau, 2019) and applicable across a broad spectrum of industries, from automated customer service systems to predictive analytics and intelligent supply chains (Mirbabaie et al., 2022). According to research by Ransbotham et al. (2017), more than 80% of companies already consider AI to be of strategic importance and almost 85% believe it can provide them with a competitive advantage. AI can contribute to business competitiveness when it is connected to concrete organizational processes, as evidence from AI-supported marketing shows improvements in cost optimization, campaign efficiency, and managerial decision-making (Konečný et al., 2025).

While one of the biggest benefits of AI is cost reduction and efficiency gains (Enholm et al., 2022), its application is multifaceted and still relatively new in the corporate sector, leaving organizations facing a number of challenges (Mirbabaie et al., 2022). Digital transformation, the application of new technologies, is transforming organizational forms, production processes and business models (Nambisan et al., 2019), leading to a number of workplace changes. However, digital transformation should not be reduced to the implementation of new technologies alone, since successful transformation also requires the identification, analysis, documentation, and redesign of business processes (Ivanišević et al., 2025). Many companies have implemented digital transformation to gain a competitive advantage, but success is not guaranteed: the transition involves risks and difficulties, mostly at the organizational and employee level (Cramarenco et al., 2023). Employees are the most important actors in digital transformation, as they operate and apply the technology, and their motivation, openness to change (Don Ton & Berke, 2024) and commitment are key to the success of a company's AI strategy (Ye et al., 2024). Employee mental health is also a key factor: a balanced, mentally healthy workforce can significantly increase an organization's performance and competitiveness (Soulami et al., 2024). Conversely, if employees experience stress and burnout, this has a negative impact on productivity, concentration, and increases absenteeism and turnover rates (Dimoff & Kelloway, 2018).

The successful integration of AI depends not only on technological advances, but also on shaping corporate culture and employee attitudes. Organizations need to design their AI-enabled business strategies with innovation and teamwork at the forefront (Fredstrom et al., 2022; Perifanis & Kitsios, 2023). It is important that leaders create an environment that supports employee skill development while providing them with stability, inclusion and well-being (Jiang et al., 2022). An innovative organizational culture stimulates continuous improvement in operational performance (Strugar Jelaca, 2018), but the active participation of employees, either directly or indirectly, is essential for success (Enholm et al., 2022; Pap et al., 2022). These findings align with evidence that AI adoption improves employee well-being primarily when it enhances task optimization and workplace safety (Valtonen et al., 2025).

1.2. The impact of AI on workers

The continued rise of artificial intelligence (AI) is fundamentally shaping the labor market, affecting almost every profession and influencing the way people work (Frey & Osborne, 2017). The integration of AI into the enterprise not only means new technological solutions, but also impacts on the skills, career paths and well-being of employees. It is predicted that by 2025, 50% of workers will need to learn new skills in order to keep pace with continuous technological advances and innovations (Schwab & Zahidi, 2020). Upskilling and retraining are essential for success: continuous learning and adaptation is what differentiates successful companies from those that lag behind the competition (Randstad, 2020). The spread of AI could also lead to the emergence of new professions and the creation of new jobs (Nubler, 2016; Lane & Saint-Martin, 2021). In parallel, there is a growing demand for highly skilled talent who can effectively apply AI-based technologies (Babashahi et al., 2024).

The digital switchover places heavy demands on workers. The widespread deployment of AI-related technologies requires the need to be prepared for human-machine interaction (Jaiswal et al., 2022) and to retrain employees to adapt to new job requirements (Li, 2022). The development of digital skills is becoming increasingly important: not only technical skills need to be mastered, but also expectations are rising in the areas of information management, communication,

creativity and cybersecurity (Cramarenco et al., 2023; Major & Spalek, 2022; Pelau et al., 2021).

The mismatch between skills and job requirements can be a source of stress, which can reduce employee satisfaction (Ruzele et al., 2025; Gasic et al., 2025) and increase job insecurity (Nemțeanu et al., 2022). Gartner (2018) reports that 83% of companies fail to achieve their digital transformation goals because employees do not actively engage with technology-driven business processes and changes. Similarly, a Microsoft survey cited by Hizam et al. (2023) found that 61% of employees feel anxious about technological developments in the workplace, while 49% fear that digital transformation could lead to negative workplace consequences.

The introduction of new technologies can create uncertainty in the workplace and affect employee engagement and performance (Ye et al., 2024; Hizam et al., 2023). The use of AI technologies has many benefits, but employers need to develop appropriate strategies to adequately address these employee needs (Horobet et al., 2021). AI can also increase competition among employees and create polarization, so management should consciously promote collaboration and teamwork, fostering a positive organizational culture and cohesion among employees (Ye et al., 2024).

A motivated and engaged workforce is one of the most important factors in a company's growth and success. Research by Stamate et al. (2021) has shown that employees' attitudes towards AI play a crucial role in how they feel at work, significantly influencing their job satisfaction and psychological well-being. Although AI creates new opportunities, it can also become a source of stress for some employees, especially those who find it harder to adapt to rapid technological change (Nazareno & Schiff, 2021; Soulami et al., 2024). The impact of AI goes beyond employee well-being: it also affects engagement, productivity and overall satisfaction (Soulami et al., 2024).

Therefore, AI should be implemented in a way that takes into account the specific needs, age and skills of each worker (Wei et al., 2022).

The aim of our research is to investigate how different groups of employees perceive the impact of AI on their corporate life. When developing our hypotheses, we considered the most recent literature, which is discussed in detail in the following chapters. The perception of AI depends on a number of factors, including the educational level of employees, the nature of their work and their position in the organizational hierarchy.

Below we describe the main relationships that form the basis of our research.

1.2.1. The impact of education on the perception of AI

In a knowledge-based economy, the ability to adapt to technological innovation is increasingly important. In addition to general mental ability (GMA), digital skills and educational attainment play a significant role in how individuals relate to new technologies, especially AI, and how this affects job satisfaction and psychological well-being (Stamate et al., 2021). Although education may support digital literacy and analytical confidence, recent workplace AI adoption research suggests that perceived usefulness and trust may be stronger predictors of AI acceptance than demographic characteristics alone (Nguyen et al., 2026). People with higher education, especially those with a technology or engineering background, tend to have more positive attitudes towards AI as an efficiency-enhancing and decision-support tool (Oksanen et al., 2020; Soulami et al., 2024). In contrast, for workers with intermediate or lower education, technological change often poses uncertainty and threat, especially when their jobs may be replaced by automation. Lower-skilled workers who perform routine tasks are more likely to lose their jobs if they are unwilling to adapt to new technologies, while higher-skilled workers can gain a competitive advantage in the labor market through lifelong learning (Dosi et al., 2021). Education-related differences should therefore be interpreted together with training opportunities and organizational communication, because employees' understanding of AI principles depends strongly on how organizations explain and support AI adoption (Kelley, 2022). This suggests that higher-skilled workers are more open to adopting AI, while lower-skilled workers may perceive it as threatening, hence our first hypothesis:

H1: People with different educational backgrounds have different perceptions of the future impact of AI on business.

1.2.2. Type of work and opinion on AI

AI significantly transforms workplace roles and expectations, so that some job roles may disappear altogether, while others may be reborn in new forms (Hagel et al., 2018). In many cases, the introduction of AI also transforms responsibilities, thus affecting the role of employees in companies,

who need to understand the purpose of AI and how it changes their own roles and responsibilities within the organization (Sanchez-Garcia et al., 2025). The nature of the work is a determining factor in the attitude towards AI, with office workers interpreting AI as a strategic support, while physical workers may face the possibility of uncertainty and job loss (Makarius et al., 2020; Zheng et al., 2017). The type of work may shape AI perceptions, as its usage may increase work engagement when it supports core tasks, but reduces it when employees perceive that AI replaces essential task characteristics (Liu & Li, 2025). Employees performing physical work often perceive AI and automation as a threat, as these technologies typically target repetitive manual work processes and potentially endanger their livelihoods (Haenlein & Kaplan, 2019). Such workers, particularly in small manufacturing companies, face unique challenges with AI, often stemming from lower educational attainment and a lack of necessary skills and resources (Xiao et al., 2025). In contrast, for mental workers, AI can be a supportive tool that facilitates more effective decision-making and innovation, helping them focus on strategic and reflective tasks rather than monotonous and repetitive activities (Stamate et al., 2021). AI usage may also stimulate employee innovative behavior by strengthening self-efficacy, particularly in complex jobs and among employees with greater openness to new technologies (Zhang et al., 2025). Additionally, it can improve employees' workplace experience by automating repetitive and stressful tasks, while increasing flexibility, autonomy, and efficiency (Soulami et al., 2024; Shaikh et al., 2023). Despite this, many people still have reservations about AI, especially those whose jobs are directly affected by automation (Brougham & Haar, 2018) and who fear losing their jobs (Hagel et al., 2018). Organizational AI adoption may trigger both approach-oriented and avoidance-oriented job crafting, depending on whether employees experience AI as a source of autonomy or anxiety (Liu et al., 2026). Based on the above, we hypothesize that the nature of work experience will affect perceptions of AI, which is our second hypothesis:

H2: People doing mental work value the effects of AI more positively than those doing physical work.

1.2.3. The expected impact of AI in the context of job position

Organizational hierarchy can also influence opinions on AI. Executives and managers often view AI as a competitive advantage and an efficiency-enhancing tool, while subordinate employees may be more concerned about the uncertainties associated with automation and the transformation of work processes (Acemoglu & Restrepo, 2018). AI-based technologies may also reshape leadership communication, as they can improve information flows, feedback processes, and employee performance when integrated into organizational communication systems (Florea & Croitoru, 2025). Research suggests that corporate culture also plays a key role in the adoption of AI, as openness to organizational innovation and the willingness of employees to use new technology in the long term (Enholm et al., 2022) determine the success of the adoption of technological innovations (Mikalef & Gupta, 2021). Senior managers play a crucial role in shaping this culture. In innovative organizations, employees are more willing to engage with AI, especially if management supports the integration of technology and provides the necessary resources. The role of top management is also key because successful AI implementation requires significant organizational changes, such as increased collaboration between departments and reengineering of data management processes (Mikalef & Gupta, 2021). Positive attitudes and support from managers are essential for successful implementation (Enholm et al., 2022). However, the use of AI in leadership roles is still a divisive issue. While the majority of employees support AI in helping them schedule and monitor their work processes (Raveendhran & Fast, 2021), many reject the idea of AI fully replacing human leaders. AI in managerial roles is considered less reliable and acceptable; in fact, employees strongly disapprove of AI-based managers when it directly impacts their careers. Conversely, the use of AI in non-managerial roles is viewed as far more acceptable (Dong et al., 2024). The implementation of AI requires significant changes in the structure of the organization, the level of collaboration between departments, and the management of data within the organization (Mikalef & Gupta, 2021). It is therefore important to determine the benefits of strategic use of AI for employees in different positions and how this aligns with organizational goals (Enholm et al., 2022).

Based on the above, leaders and managers are often focused on the competitive advantages and efficiency gains of AI; thus, the authors hypothesize that they have a more positive outlook toward it, while lower-level employees are less confident due to uncertainty about change:

H3: People with different job positions will have different perceptions of the future impact of AI on business.

The aim of this research is to empirically test these hypotheses using statistical methods in order to better understand the impact of AI on corporate life. The results can help companies to develop more effective AI strategies, taking into account employees' opinions and expectations, reducing their resistance to technological change.

2. Methods

This section presents the research design, data collection procedure, sample characteristics, and statistical techniques applied to test the proposed hypotheses. A quantitative approach was used to examine differences in employees' perceptions of artificial intelligence across educational levels, types of work, and hierarchical positions.

2.1. Data collection and sample

The study focuses on assessing Slovak employees' opinions on the impact of artificial intelligence on the daily operations of businesses in the near future.

A questionnaire survey was selected as the quantitative research method.

The questionnaire consisted entirely of closed-ended questions, some of which utilized Likert scales. This simplified the analysis from a statistical and mathematical perspective. The questionnaire was built on the LimeSurvey platform. A single cross-sectional research design

was used, as data was collected from multiple individuals at a single point in time. From the non-probability sampling methods, convenience sampling was selected; the authors used their own list of more than 5000 companies and individuals, as no official list exists. The aim was to collect a single response per company. The questionnaire was distributed via email to both companies and individuals between March and June 2024, resulting in a total of 331 responses. This research is based on a sample of 260 participants (representing employees from various companies), as several responses were omitted due to data cleaning and others were irrelevant to the topic of this research. IBM SPSS software was used for data processing. Table 1 presents the demographic characteristics of the sample.

Table 1 About the sample (n = 260)

Size of the company	n	%
Micro	94	36.2%
Small	55	21.1%
Medium	37	14.3%
Large	59	22.6%
Non-Competitive Market	15	5.7%
Education level	n	%
High School	192	73.8%
University	68	26.2%
Type of work	n	%
Physical	128	49.2%
Mental	132	50.8%
Position	n	%
Owner	79	30.4%
Manager	57	21.9%
Employee	124	47.7%

Source: the authors

2.2. Statistics

Three hypotheses were formulated, where factor such as different educational backgrounds, work type and job positions were taken into account. The research model is shown in Figure 1.

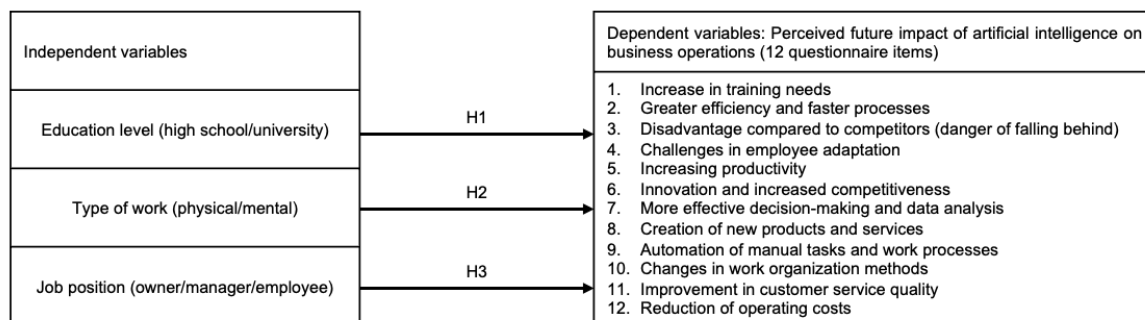


Figure 1 Research model
Source: the authors

Before testing the hypotheses, the reliability and preliminary construct validity of the twelve AI perception items were examined. The internal consistency of the scale was assessed using Cronbach's alpha, which indicated good reliability ($\alpha = 0.890$). To provide preliminary evidence of construct validity, an exploratory factor analysis was also conducted. The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.920, and Bartlett's test of sphericity was statistically significant, $\chi^2(66) = 1574.486$, $p < .001$, indicating that the correlation matrix was suitable for factor analysis. The exploratory factor analysis indicated a one-factor solution with an eigenvalue of 5.657, explaining 47.14% of the total variance. All twelve items loaded positively on the factor, with factor loadings ranging from 0.508 to 0.817. These results support the internal consistency and preliminary construct validity of the AI perception scale.

Since the AI perception items were measured using ordinal Likert-scale responses and the grouping variables were categorical, non-parametric statistical tests were applied. Education level and type of work were treated as two-category nominal grouping variables; therefore, the Mann–Whitney U test was used for H1 and H2. For H3, where job position consisted of three independent groups, the Kruskal–Wallis test was applied.

In addition, normality tests, including the Kolmogorov–Smirnov and Shapiro–Wilk tests, were conducted to examine the distribution of the AI perception items:

$$K = |c p o_i - c p e_i|_{\max} \quad (2)$$

where:

$c p o_i$ and $c p e_i$ = the i^{th} observed and normal cumulative proportions.

$$W = \frac{(\sum_{i=1}^n a_i X_i)}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (3)$$

where:

X_i = ordered sample values

a_i = coefficient based on the sample size.

Based on the measurement level of the variables and the distribution of the data, the Mann–Whitney U test was used for H1 and H2:

$$Z = \frac{U - \mu_U}{\sigma_U} \quad (4)$$

where:

U = minimum value of sum of the ranks (= U_1 or U_2)

μ_U = expected value of U

σ_U = standard error of U .

In case of H3, the Kruskal–Wallis test (H statistic) was calculated:

$$H = \left(\frac{n-1}{n} \sum_{i=1}^k \frac{n_i * (\bar{R} - E_R)^2}{\sigma^2} \right) \quad (5)$$

where:

n = sample size

n_i = the number of observations in each group

E_R = expected value of the rankings

$\bar{R}$ = mean rank sum in group i

σ^2 = rank variance.

Because multiple tests were conducted across the twelve AI-related statements, the Benjamini–Hochberg false discovery rate correction was applied to control for inflated Type I error. In addition, effect sizes were reported to assess the practical magnitude of the observed differences. For the Mann–Whitney U tests, effect size was calculated as $r = |Z| / \sqrt{N}$. For the Kruskal–Wallis tests, epsilon squared was calculated as $\epsilon^2 = (H - k + 1) / (N - k)$, where H is the Kruskal–Wallis statistic, k is the number of groups, and N is the total sample size.

3. Results

Based on the first hypothesis of the research:

"H1: People with different educational backgrounds have different perceptions of the future impact of AI on business." The study examined whether respondents with different educational backgrounds differed in their perceptions of the future impact of AI on business. Education level was treated as a two-category nominal grouping variable, distinguishing respondents with secondary education from those with university education. Since the dependent variables were measured using ordinal Likert-scale items, the Mann–Whitney U test was applied. In addition, the Benjamini–Hochberg false discovery rate correction was used to adjust for multiple testing across the twelve AI-related statements. Effect size was reported using rank-biserial correlation (Table 2):

Table 2 Mann–Whitney U test – education level and opinion about the future impact of AI (n = 260)

Statements	U	p	Adjusted p	Rank-biserial correlation
Increasing training needs	5644	0.080	0.243	0.135
Greater efficiency and faster processes	5784	0.139	0.286	0.114
Disadvantage compared to competitors	5509	0.045	0.243	0.156
A challenge for workers to adapt	5956	0.259	0.345	0.088
Increasing productivity	5789	0.143	0.286	0.113
Innovation and competitiveness growth	5886	0.199	0.299	0.098
More efficient decision-making and data analysis	4839	< 0.001*	0.008*	0.259
Creation of new products and services	6343	0.715	0.780	0.028
Automation of manual tasks and workflows	5638	0.081	0.243	0.136
Changing work organization methods	6518	0.985	0.985	0.002
Improving the quality of customer service	6965	0.387	0.464	-0.067
Reducing operating costs	5825	0.167	0.286	0.108

Note: Adjusted p-values were calculated using the Benjamini–Hochberg false discovery rate correction. Effect size is reported as rank-biserial correlation. *p < .05 after correction.

Source: the authors

The results indicate that after the correction for multiple testing, only one statement showed a statistically significant difference between respondents with secondary and university education. Respondents with university education had higher mean ranks for the statement that artificial intelligence will make decision-making and data analysis more effective in the next five years. The effect size was small to moderate, indicating that the difference was statistically significant, but its practical magnitude was limited.

Therefore, H1 is only partially supported. Educational background does not appear to be associated with general differences in AI-related perceptions across all examined statements, but a significant difference was identified in the area of decision-making and data analysis. To illustrate the only statistically significant difference identified after multiple testing correction, a cross-tabulation was prepared for the item “More efficient decision-making and data analysis” (Table 3).

Table 3 Cross-tabulation – education level and opinion on AI-supported decision-making and data analysis (n = 260)

Education	Artificial Intelligence will make decision-making and data analysis more effective in the next 5 years				
	1	2	3	4	Total
High school	11.4%	25.4%	44.0%	19.2%	100.0%
University	4.4%	10.3%	52.9%	32.4%	100.0%

Source: the authors

As shown in Table 3, respondents with university education more frequently selected the highest response category than respondents with secondary education. While 32.4% of respondents with university education fully agreed that AI will make decision-making and data analysis more effective in the next five years, this proportion dropped to 19.2% among respondents with secondary education. This descriptive pattern supports the Mann–Whitney U test result and indicates that the education-related difference is

mainly connected to AI’s perceived role in decision-making and data analysis.

Based on the hypothesis: “H2: People doing mental work value the effects of AI more positively than people doing physical work.” The study examined questions on the type of work (independent, nominal variable) and the future impact of AI (dependent, ordinal variable). To decide which statistical method to use, a normality test was performed (Table 4):

Table 4 Test of Normality – H2 (n = 260)

Statements	Type of work	Kolmogorov - Smirnov			Shapiro - Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Increasing training needs	physical	0.226	128	0.000	0.869	128	0.000
	mental	0.280	132	0.000	0.858	132	0.000
Greater efficiency and faster processes	physical	0.233	128	0.000	0.873	128	0.000
	mental	0.286	132	0.000	0.809	132	0.000
Disadvantage compared to competitors	physical	0.225	128	0.000	0.862	128	0.000
	mental	0.242	132	0.000	0.870	132	0.000
A challenge for workers to adapt	physical	0.211	128	0.000	0.875	128	0.000
	mental	0.284	132	0.000	0.858	132	0.000
Increasing productivity	physical	0.230	128	0.000	0.876	128	0.000
	mental	0.278	132	0.000	0.853	132	0.000
Innovation and competitiveness growth	physical	0.263	128	0.000	0.864	128	0.000

	mental	0.286	132	0.000	0.837	132	0.000
More efficient decision-making and data analysis	physical	0.262	128	0.000	0.868	128	0.000
	mental	0.271	132	0.000	0.820	132	0.000
Creation of new products and services	physical	0.229	128	0.000	0.872	128	0.000
	mental	0.267	132	0.000	0.862	132	0.000
Automation of manual tasks and workflows	physical	0.212	128	0.000	0.872	128	0.000
	mental	0.255	132	0.000	0.862	132	0.000
Changing work organization methods	physical	0.241	128	0.000	0.871	128	0.000
	mental	0.255	132	0.000	0.871	132	0.000
Improving the quality of customer service	physical	0.218	128	0.000	0.873	128	0.000
	mental	0.296	132	0.000	0.849	132	0.000
Reducing operating costs	physical	0.211	128	0.000	0.874	128	0.000
	mental	0.271	132	0.000	0.857	132	0.000

Source: the authors

Table 4 shows that none of the items are normally distributed, meaning a Mann-Whitney test was used (Table 5).

Table 5 Mann-Whitney Test - Ranks – H2 (n = 260)

Statements	Type of work	N	Mean Rank	Sum of Ranks
Increasing training needs	physical	128	106.62	13647.0
	mental	132	153.66	20283.0
Greater efficiency and faster processes	physical	128	121.23	15517.0
	mental	132	139.49	18413.0
Disadvantage compared to competitors	physical	128	115.86	14830.0
	mental	132	144.70	19100.0
A challenge for workers to adapt	physical	128	116.01	14849.0
	mental	132	144.55	19081.0
Increasing productivity	physical	128	112.37	14383.0
	mental	132	148.08	19547.0
Innovation and competitiveness growth	physical	128	116.04	14853.0
	mental	132	144.52	19077.0
More efficient decision-making and data analysis	physical	128	109.50	14015.5
	mental	132	150.87	19914.5
Creation of new products and services	physical	128	117.33	15018.0
	mental	132	143.27	18912.0
Automation of manual tasks and workflows	physical	128	117.28	15012.0
	mental	132	143.32	18918.0
Changing work organization methods	physical	128	115.39	14769.5
	mental	132	145.16	19160.5
Improving the quality of customer service	physical	128	121.03	15492.0
	mental	132	139.68	18438.0
Reducing operating costs	physical	128	115.08	14730.5
	mental	132	145.45	19199.5

Source: the authors

Mean rank scores (Table 5) indicate differences in the perceptions of respondents performing physical and mental work. Across the examined statements, respondents performing mental work generally had higher mean ranks, suggesting more positive expectations regarding the future impact of AI.

To test whether these differences were statistically significant, a Mann-Whitney U test was conducted for each of the twelve AI-related statements. The test statistics and effect sizes are presented in Table 6.

Table 6 Mann-Whitney U test results and effect sizes – H2 (n = 260)

Statements	Mann-Whitney U	Wilcoxon W	Z	Asymp. Sig. (2-tailed)	Adjusted p	Effect size r
Increasing training needs	6127.000	14383.000	-4.042	0.000*	0.002	0.251
Greater efficiency and faster processes	5391.000	13647.000	-5.340	0.000*	0.002	0.331
Disadvantage compared to competitors	7261.000	15517.000	-2.049	0.040*	0.040	0.127
A challenge for workers to adapt	6574.000	14830.000	-3.250	0.001*	0.002	0.202
Increasing productivity	6593.000	14849.000	-3.234	0.001*	0.002	0.201
Innovation and competitiveness growth	6597.000	14853.000	-3.249	0.001*	0.002	0.201
More efficient decision-making and data analysis	5759.000	14015.500	-4.730	0.000*	0.002	0.293
Creation of new products and services	6762.000	15018.000	-2.927	0.003*	0.004	0.182
Automation of manual tasks and workflows	6756.000	15012.000	-2.915	0.004*	0.005	0.181
Changing work organization methods	6513.000	14769.500	-3.357	0.001*	0.002	0.208
Improving the quality of customer service	7236.000	15492.000	-2.110	0.035*	0.038	0.131
Reducing operating costs	6474.500	14730.500	-3.414	0.001*	0.002	0.212

Note: Adjusted p-values were calculated using the Benjamini-Hochberg false discovery rate correction. Effect size was calculated as $r = |Z| / \sqrt{N}$.

Source: the authors

The results of the Mann–Whitney U test (Table 6) show statistically significant differences between respondents performing physical and mental work for all twelve AI-related statements. These differences remained statistically significant after applying the Benjamini–Hochberg correction for multiple testing. Taking into account the mean rank values presented in Table 5, respondents performing mental work evaluated the expected effects of artificial intelligence more positively than respondents performing physical work. The effect sizes were generally small to moderate. The strongest effect was observed for “Greater efficiency and faster processes” ($r = 0.331$), followed by “More efficient decision-making and data analysis” ($r = 0.293$) and “Increasing training

needs” ($r = 0.251$). These findings suggest that the type of work is related to employees’ perceptions of AI, with mental workers showing more positive expectations regarding AI-related workplace changes. Therefore, H2 is supported.

The final hypothesis of the research is: “H3: People with different job positions will have different perceptions of the future impact of AI on business.”

In testing this hypothesis, we examined the relationship between job position (independent nominal variable) and perceptions of the future impact of AI (dependent ordinal variables).

To decide which statistical method to use, a normality test (Table 7) was used again:

Table 7 Test of Normality – H3 (n = 260)

Statements	Position	Kolmogorov - Smirnov			Shapiro - Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
Increasing training needs	Owner	0.191	79	0.000	0.871	79	0.000
	Manager	0.321	57	0.000	0.830	57	0.000
	Employee	0.259	124	0.000	0.869	124	0.000
Greater efficiency and faster processes	Owner	0.249	79	0.000	0.872	79	0.000
	Manager	0.307	57	0.000	0.800	57	0.000
	Employee	0.262	124	0.000	0.853	124	0.000
Disadvantage compared to competitors	Owner	0.232	79	0.000	0.862	79	0.000
	Manager	0.231	57	0.000	0.868	57	0.000
	Employee	0.237	124	0.000	0.867	124	0.000
A challenge for workers to adapt	Owner	0.218	79	0.000	0.880	79	0.000
	Manager	0.275	57	0.000	0.859	57	0.000
	Employee	0.252	124	0.000	0.868	124	0.000
Increasing productivity	Owner	0.220	79	0.000	0.879	79	0.000
	Manager	0.300	57	0.000	0.840	57	0.000
	Employee	0.253	124	0.000	0.869	124	0.000
Innovation and competitiveness growth	Owner	0.244	79	0.000	0.875	79	0.000
	Manager	0.313	57	0.000	0.809	57	0.000
	Employee	0.280	124	0.000	0.854	124	0.000
More efficient decision-making and data analysis	Owner	0.249	79	0.000	0.870	79	0.000
	Manager	0.275	57	0.000	0.816	57	0.000
	Employee	0.277	124	0.000	0.858	124	0.000
Creation of new products and services	Owner	0.266	79	0.000	0.863	79	0.000
	Manager	0.278	57	0.000	0.852	57	0.000
	Employee	0.221	124	0.000	0.876	124	0.000
Automation of manual tasks and workflows	Owner	0.194	79	0.000	0.878	79	0.000
	Manager	0.262	57	0.000	0.836	57	0.000
	Employee	0.244	124	0.000	0.867	124	0.000
Changing work organization methods	Owner	0.223	79	0.000	0.870	79	0.000
	Manager	0.242	57	0.000	0.861	57	0.000
	Employee	0.220	124	0.000	0.878	124	0.000
Improving the quality of customer service	Owner	0.236	79	0.000	0.875	79	0.000
	Manager	0.253	57	0.000	0.867	57	0.000
	Employee	0.276	124	0.000	0.851	124	0.000
Reducing operating costs	Owner	0.219	79	0.000	0.865	79	0.000
	Manager	0.243	57	0.000	0.858	57	0.000
	Employee	0.260	124	0.000	0.867	124	0.000

Source: the authors

Based on the results presented in Table 7, the data were not normally distributed for any of the

examined items; therefore, a Kruskal-Wallis test (Table 8) was performed.

Table 8 Kruskal-Wallis Test - Ranks – H3 (n = 260)

Statements	Position	N	Mean Rank
Increasing training needs	Owner	79	117.17
	Manager	57	147.90
	Employee	124	130.99
Greater efficiency and faster processes	Owner	79	110.11
	Manager	57	149.40
	Employee	124	134.80
Disadvantage compared to competitors	Owner	79	127.92
	Manager	57	141.52
	Employee	124	127.08
A challenge for workers to adapt	Owner	79	125.02
	Manager	57	143.65
	Employee	124	127.95
Increasing productivity	Owner	79	119.25
	Manager	57	145.44
	Employee	124	130.80
Innovation and competitiveness growth	Owner	79	121.80
	Manager	57	149.11
	Employee	124	127.49
More efficient decision-making and data analysis	Owner	79	123.22
	Manager	57	151.51
	Employee	124	125.48
Creation of new products and services	Owner	79	127.23
	Manager	57	152.40
	Employee	124	122.52
Automation of manual tasks and workflows	Owner	79	115.97
	Manager	57	153.62
	Employee	124	129.13
Changing work organization methods	Owner	79	113.02
	Manager	57	151.39
	Employee	124	132.04
Improving the quality of customer service	Owner	79	134.03
	Manager	57	143.30
	Employee	124	122.37
Reducing operating costs	Owner	79	124.49
	Manager	57	151.73
	Employee	124	124.57

Source: the authors

Based on the mean rank scores (Table 8), managers generally showed the highest level of agreement with the AI-related statements. To test whether these differences were statistically significant across job positions, a Kruskal–Wallis test was conducted for

each of the twelve AI-related statements. The test statistics, adjusted p-values, and effect sizes are presented in Table 9.

Table 9 Kruskal–Wallis test results and effect sizes – H3 (n = 260)

Statements	Kruskal-Wallis H	df	Asymp. Sig.	Adjusted p	ϵ^2
Increasing training needs	6.175	2	0.046*	0.079	0.016
Greater efficiency and faster processes	11.003	2	0.004*	0.040*	0.035
Disadvantage compared to competitors	1.723	2	0.422	0.422	0.000
A challenge for workers to adapt	2.547	2	0.280	0.305	0.002
Increasing productivity	4.491	2	0.106	0.141	0.010
Innovation and competitiveness growth	5.373	2	0.068	0.102	0.013
More efficient decision-making and data analysis	6.531	2	0.038*	0.079	0.018
Creation of new products and services	7.068	2	0.029*	0.079	0.020
Automation of manual tasks and workflows	9.141	2	0.010*	0.040*	0.028
Changing work organization methods	9.648	2	0.008*	0.040*	0.030
Improving the quality of customer service	3.646	2	0.162	0.194	0.006
Reducing operating costs	6.398	2	0.041*	0.079	0.017

Note: Adjusted p-values were calculated using the Benjamini–Hochberg false discovery rate correction. Effect size is reported as epsilon squared (ϵ^2). *p < .05 after correction.

Source: the authors

The results of the Kruskal–Wallis test (Table 9) indicate that, before correction for multiple testing, statistically significant differences appeared for several AI-related statements. However, after applying the Benjamini–Hochberg correction, significant differences remained for three statements: “Greater efficiency and faster

processes” (adjusted p = 0.040), “Automation of manual tasks and workflows” (adjusted p = 0.040), and “Changing work organization methods” (adjusted p = 0.040). Taking into account the mean rank values presented in Table 8, managers generally reported the highest level of agreement with these statements. The effect sizes were small,

indicating that although job position is associated with some differences in AI-related perceptions, the practical magnitude of these differences is limited. Therefore, H3 is only partially supported.

4. Discussion

4.1. Interpretation of the findings

Results related to the first hypothesis (*H1: People with different educational backgrounds have different perceptions of the future impact of AI on business*) show that educational background was associated with AI perceptions only to a limited extent. After correction for multiple testing, a significant difference was identified only in relation to decision-making and data analysis, where respondents with university education expressed more positive expectations. This is in line with previous research (Oksanen et al., 2020; Soulami et al., 2024), which shows that highly educated workers perceive AI as a tool for competitive advantage, while lower educated workers perceive it more as a tool for uncertainty and threat. Research by Duan et al. (2019) also confirms that the adoption of AI is highly dependent on individual knowledge and analytical skills, which are acquired to a greater extent by those with higher education. As these workers are more frequently exposed to AI in decision-support roles, they are more likely to naturally accept its benefits. In contrast, workers with less education may find automation more challenging. Consequently, companies should provide targeted training programs for lower-skilled workers to reduce uncertainty about AI and build confidence in the technology.

However, the role of education should be interpreted carefully, because recent research shows that employees' intentions to adopt AI depend heavily on perceived usefulness, trust, and affective attitudes toward the technology (Nguyen et al., 2026). In addition, effective AI adoption depends on how clearly organizations communicate AI principles, provide training, and help employees understand the purpose and governance of AI systems (Kelley, 2022).

Our results related to the second hypothesis (*H2: People doing mental work value the effects of AI more positively than people doing physical work*) confirm that the two groups of workers have different attitudes towards the role of AI in the firm. Mental workers see AI primarily as a tool for innovation and efficiency, while physical workers show higher levels of uncertainty and concern

about job loss. This difference is in line with previous literature (Makarius et al., 2020; Zheng et al., 2017; Haenlein & Kaplan, 2019), which has shown that AI transforms jobs in different ways. While it serves a decision-support and analytical function for mental workers, automation can often pose a threat to the jobs of manual workers. However, research by Wei & Li (2022) also shows that the application of AI can have a positive impact on the work environment, increasing its safety and flexibility, which can contribute to improving the mental well-being of workers. Therefore, it may be particularly important for companies to implement AI gradually, taking into account employee feedback and involving relevant employees in the planning process of the technology's deployment.

This finding is also consistent with recent studies suggesting that AI may operate as a double-edged sword for employees. While AI can boost engagement when it supports core responsibilities, it tends to reduce engagement when employees perceive that AI substitutes essential task characteristics (Liu & Li, 2025). Similarly, AI-induced job insecurity may reduce psychological safety and increase knowledge-hiding behavior, while AI self-efficacy may mitigate these negative consequences (Kim & Kim, 2024). These findings help explain why physical and mental workers may interpret the expected effects of AI differently.

Results related to the third hypothesis (*H3: People with different job positions will have different perceptions of the future impact of AI on business*) clearly support that employees in different positions have different perceptions of the impact of AI on the company. Senior management tends to be more favorable to the adoption of AI as a strategic and competitive advantage, while for employees the level of adoption depends largely on the practical application of AI, technological transparency and training opportunities. This finding is consistent with previous research (Mikalef & Gupta, 2021; Dong et al., 2024) that suggests that adoption of AI is strongly influenced by organizational culture, openness to innovation, and managers' attitudes towards technology. While top management decisions play a crucial role in the successful corporate integration of AI, the attitudes and skills of employees are key to the effective adoption of new technologies.

This result reinforces the view that AI is a multilevel organizational phenomenon that affects individuals, groups, and organizational structures simultaneously (Bankins et al., 2024). From a

hierarchical perspective, managers may evaluate AI mainly through its strategic, efficiency-related, and decision-support functions, while employees may focus more on its consequences for autonomy, workload, job security, and everyday work practices. This interpretation is further supported by research showing that AI-based technologies can reshape leadership communication and employee performance when they are embedded into organizational communication systems (Florea & Croitoru, 2025).

4.2. Managerial implications

Results show that successful integration of AI in enterprises is not only a technological issue, but also depends to a large extent on the strategies that organizations use to facilitate the adaptation of different groups of employees. In order to reduce attitudinal differences, it is crucial to introduce appropriate retraining and competence development programs, and to create a corporate culture that encourages openness to technological innovation and adaptability.

From a practical managerial perspective, companies should begin AI implementation with an internal assessment of employees' AI-related skills, concerns, and expectations. This assessment should not be limited to formal education level, because employees' attitudes toward AI are also shaped by perceived usefulness, trust, previous experience, organizational communication, and perceived job-related consequences. Based on this assessment, companies can segment employees into groups that require different forms of communication, training, and managerial support.

According to research by Rozman et al. (2023), an AI-based corporate culture, leadership approach and targeted training programs can significantly contribute to reducing employee workload and increasing organizational performance. In particular, AI improves complex decision-making and data analytics, helping managers make faster and more informed choices while cutting down on routine tasks for employees and boosting workplace engagement. Therefore, companies must support AI adoption with transparent communication and detailed training programs to build employee confidence and ease resistance. From a managerial perspective, the findings suggest that companies should not treat AI implementation as a purely technological project. Managers should proactively engage employees in the introduction of AI-based tools, clearly communicate the purpose and expected benefits of

the technology, and provide targeted training programs for different employee groups. Particular attention should be paid to physical workers and lower-level employees, who may perceive AI more as a source of uncertainty or job-related threat. Transparent communication, gradual implementation, and opportunities for reskilling and upskilling can help reduce resistance and increase employee acceptance of AI. In addition, managers should create an organizational culture that supports experimentation, continuous learning, and human-machine collaboration.

More specifically, companies should implement AI gradually through pilot projects rather than through sudden organization-wide changes. Pilot implementation allows managers to test AI-based tools in selected processes, collect employee feedback, identify sources of resistance, and adjust the implementation process before broader deployment. This approach is particularly important for employees who may associate AI with job loss, monitoring, or increased performance pressure.

Training programs should also be differentiated by employee group. For physical workers, training should focus on how AI will change specific tasks, how safety and work organization may improve, and what reskilling opportunities will be available. For mental workers, training should focus more on AI-supported decision-making, data analysis, productivity tools, innovation, and human-machine collaboration. For managers, training should include AI strategy, ethical governance, communication, change management, and the management of employee attitudes toward AI.

The role of managers in promoting the adoption of AI is becoming more important, while corporate culture and employee attitudes are also becoming key factors. In the future, it will be particularly important to develop effective human-machine collaboration that not only increases efficiency but also improves employee satisfaction and engagement. The success of AI implementation will therefore be not only a technological issue, but also a strategic and organizational one.

Managers should therefore actively manage employees' attitudes toward AI by creating transparent communication channels, regular feedback mechanisms, and opportunities for employee participation. Coaching-oriented leadership may be especially useful during AI-related transitions, because it can reduce job stress and buffer negative effects on employee health (Jeong et al., 2024). In addition, perceived

organizational support may reduce the risk that AI awareness leads to burnout or negative employee reactions (Wang & Zhou, 2025).

Ethical governance should also be part of practical AI implementation. Since AI-augmented HRM may raise concerns related to fairness, transparency, responsibility, and employee protection, companies should clearly define how AI systems are used, what types of decisions they support, and where human oversight remains necessary (Priksht et al., 2022). This is particularly important for maintaining employee trust and preventing resistance to AI-based organizational change.

Finally, companies should evaluate AI implementation not only through efficiency and cost indicators, but also through employee-related indicators such as perceived job security, work engagement, well-being, skill development, and trust in AI. This is important because AI adoption may improve employee well-being only indirectly, especially when it contributes to task optimization and workplace safety (Valtonen et al., 2025).

4.3. Limitations and future research

This study has several limitations that should be considered when interpreting the findings. First, the research was based on convenience sampling, which may limit the representativeness of the sample and the generalizability of the results to the broader population of employees in Slovakia. Second, the sample size was relatively limited, and therefore the findings should be interpreted with caution. Third, the study employed a cross-sectional research design, capturing respondents' perceptions at a single point in time. Consequently, it was not possible to examine changes in attitudes toward artificial intelligence over time or establish causal relationships between the investigated variables.

In addition, the study focused on selected group differences based on education, type of work, and job position. Future research could extend this approach by examining additional psychological and organizational factors, such as AI anxiety, perceived usefulness, trust in AI, perceived organizational support, AI self-efficacy, and job insecurity. Recent studies show that these factors may influence how employees respond to AI-related changes (Bai et al., 2024; Feng et al., 2025; Kim & Kim, 2024).

Despite these limitations, the integration of artificial intelligence into the enterprise will continue to accelerate in the coming years, creating

new opportunities and challenges in the labor market. The evolution of AI is expected to not only transform decision-making and data analysis processes, but also play an increasing role in automation and customer relationship management. To adapt successfully, companies will need to proactively develop their training strategies to ensure that employees have the necessary technological and analytical skills.

The rapid development of AI adoption in the enterprise warrants further research on the long-term impact of AI adoption. Future studies may focus on the dynamics of AI adoption, especially in relation to how different industries and corporate cultures adapt to technological changes.

Optimizing the interaction between AI and human work could also be an important research direction, especially among manual workers, where automation is seen as a threat. Further empirical studies are needed to explore the impact of AI on worker satisfaction, engagement and performance, and what training programs can facilitate adaptation.

Future studies could also use longitudinal research designs to examine how employee attitudes toward AI change over time as workers gain more direct experience with AI-based systems. Comparative research across industries, countries, and organizational cultures would also help clarify whether the differences identified in this study are specific to the Slovak context or reflect broader patterns of AI adoption in organizations.

Conclusion

In this research, we aimed to determine how people with different educational and professional backgrounds perceive the impact of AI in the near future. We looked at the extent to which people with manual and mental jobs feel affected and the differences in their views. Our aim was to use statistical methods to empirically test our hypotheses and to gain deeper insights into how AI affects business operations.

The findings indicate that perceptions of AI are not homogeneous across employee groups. Educational background appears to play a limited but relevant role, particularly in relation to decision-making and data analysis, while the type of work and job position show clearer differences in how employees evaluate the future impact of AI.

Overall, the study highlights that AI implementation should be understood not only as a technological transformation but also as a

managerial and organizational challenge. Companies need to combine technological investment with transparent communication, differentiated training, employee involvement, ethical governance, and leadership support in order to increase employee acceptance and reduce resistance to AI-related change.

Declarations

Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

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Use of Artificial Intelligence (AI) Tools

No AI tools or Large Language models (LLMs) were used in the preparation of this manuscript.

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