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Bridging the AI Gap: How Organizational Literacy and Individual Competencies Drive Implementation Success Across Industries

Lucie Depoo[1*], Lenka Hajerová-Mullerová[2], Zdeněk Kronberger[2], Gabriela Říhová[2], Marek Stříteský[2], Marie Hořáková[2], Kateřina Legnerová[2], Marcela Palíšková[2], Otakar Němec[2], David Šmíd[2], Tomáš Jurčík[2], Martin Kopecký[2]

1 Department of Human Resources, Faculty of Business Administration, Prague University of Economics and Business, W. Churchilla 1938/4, Prague, 12000, Czechia, lucie.depoo@vse.cz (*corresponding author)*

2 Department of Human Resources, Faculty of Business Administration, Prague University of Economics and Business, W. Churchilla 1938/4, Prague, 12000, Czechia, lenka.hajerova@vse.cz, zdenek.kronberger@vse.cz, gabriela.rihova@vse.cz, marek.stritesky@vse.cz, marie.horakova@vse.cz, katerina.legnerova@vse.cz, marcela.paliskova@vse.cz, otakar.nemec@vse.cz, david.smid@vse.cz, tomas.jurcik@vse.cz, martin.kopecky@vse.cz

Abstract

This study examines artificial intelligence adoption patterns and competency requirements across economic sectors in the Czech Republic. The research investigates sectoral differences in AI implementation, required competencies, and organizational impacts. Data were collected via computer-assisted web interviewing and analyzed using descriptive statistics, correlation analysis, and chi-square testing. Results reveal intensive AI usage (78%). Significant sectoral variations emerged: primary sectors focus on general AI tools, secondary sectors emphasize manufacturing-specific applications including quality control and predictive maintenance, while tertiary sector organizations employ the broadest range of AI solutions encompassing specialized finance, healthcare, and legal applications. All sectors invest heavily in employee training and reskilling, though tertiary sector organizations experience the most significant structural transformations including workforce redeployment and role redesign. Statistical analysis confirms significant sectoral differences in AI adoption patterns and validates that higher organizational AI literacy correlates with superior implementation outcomes. These findings contribute to understanding sector-specific AI adoption strategies and inform competency development frameworks for successful organizational AI integration.

Keywords: artificial intelligence; transformation; human resources; sector; competence

1. Introduction

AI is having an exponential impact on the global economy, organizations and society (Suciu et al., 2023). Competitiveness is being achieved through the implementation of advanced technologies such as artificial intelligence (AI), big data analytics, robotics, machine learning, Internet of Things (IoT) (Wittenberg, 2016, Monostori et al., 2016). These disruptive changes are leading experts to predict that the nature of work will change dramatically in the coming decade (Butler, 2016; Davenport & Kirby, 2016).

Based on the experience of the 1990s, when personal computers redefined work in the workplace, the emergence of artificial intelligence could be analogous (Li & Kim, 2024). Just as computer literacy has become a basic requirement for many jobs, the proliferation and sophistication of AI across industries suggests that AI-related readiness could soon become equally essential (Uren and Edwards 2023).

The discussion about the future of work brings conflicting views (Jaiswal et al., 2022). While critics of AI firmly believe that advanced technologies will replace humans in many jobs, advocates of advanced technology envision new jobs with value creation (Ågerfalk, 2020; Sullivan et al., 2020). The International Labor Organization (2023) states that 24% of white-collar jobs will be highly likely to be exposed to technological change. For example, in the USA, approximately 47% of jobs are in the upper risk zone of potential automation (Frey and Osborne, 2017). In Germany, although AI-based robotization has not had a major impact on employment, it has reduced the employment of young people (World Bank Group, 2019). The consensus is clear, advanced technologies will disrupt the balance in employment (Bughin et al., 2017; Østerlund et al., 2021).

As artificially intelligent machines gradually take over tedious, mechanical, and mundane human tasks such as documentation, planning, equipment inspection, data collection, and preliminary analysis (Huang et al., 2019; Huang & Rust, 2018), AI systems augment human capabilities by perceiving, understanding, learning, and acting (Daugherty & Wilson, 2018).

According to Li & Kim (2024), with the increasing integration of AI technologies, employees will be expected to engage, use, and collaborate with them in their daily work routines.

This study aims to investigate the role of AI literacy as a determinant of successful AI implementation in organizations, examining both organizational-level literacy effects and competency impacts on technology acceptance and usage. Additionally, this research seeks to identify sector-specific variations in AI competency requirements to provide targeted insights for specific AI adoption.

2. Literature review

AI is expected to be the fastest growing business opportunity in today's growing economy. AI's contribution to the global economy is projected to reach $15.7 trillion by 2030, more than the current combined output of China and India (Rao & Verweij, 2017). According to a report by McKinsey & Company, the potential impact of AI technologies on the global economy is estimated at $17.1 to $25.6 trillion (Chui et al. 2023). Accoring to current literature, the main industries and sectors where there are opportunities to create added value through increased digitalization include: manufacturing (Al Suwaidan, 2021, García-Muiña et al., 2020), agri-food industry (Al Suwaidan, 2021, Oltra-Mestre et al., 2021), automotive industry, fast-moving consumer goods, logistics, retail trade and business services (Demeter et al., 2020), financial sector (Wyrwa, 2020, Zhang et al., 2020).

AI-based technological solutions are commonly used, for example more efficient data collection, more efficient sorting of relevant data for further decision-making, improving logistics operations, reducing manual labor, increasing labor productivity (Srivastav, 2019). According to Bhalerao et al. (2022), organizations should understand the importance of AI, strive to overcome obstacles, and leverage strategic advantages. As Suciu et al. (2023) pointed out that digitalization and technological advances affect labor market stability, both directly, such as by displacing traditional jobs, resulting in layoffs, and indirectly, by increasing labor demand in industries that are being transformed by technological advances.

AI technologies introduce innovative changes that increase efficiency and productivity and revolutionize how people work (Borana, 2016; Chen & Lin, 2023; Jarrahi, 2018) and how they communicate in a digitalized work environment (Ismail & Hassan 2019; Rymarczyk 2020).

Implementation of new advanced technologies according to Becker-Ritterspach & Gröger (2018), Chen & Zhou (2020), Janssen et al. (2017) lead to the need to develop technical skills such as programming, data analysis, system integration, etc., the need for new technical skills, development of soft skills such as critical thinking, creativity, problem solving, adaptability (Krings et al., 2017, Naciri et al., 2018, Paulraj et al., 2017, Stojanovic & Sostaric, 2018), development of lifelong learning to remain competitive in the labour market (EESC, 2017), and changes in organizational structure (Suciu et al., 2023).

Understanding the competencies required for AI applications is becoming more important than ever for human resource development practitioners and scholars (Li & Kim, 2024). The multidimensional approach defining individual competencies (Le Deist & Winterton, 2005) intended to guide individuals to perform their jobs effectively and successfully. In addition, workers should also acquire new competencies that will enable them to meet the changing demands of the labor market. For example, Fareri et al. (2020) identify not only the need to integrate existing competencies into professional models, but also the creation of completely new competencies adapted to the trends of the transition from Industry 4.0. to Industry 5.0. Thus, the main competency seems to be the digital skills of individuals, which include the functional use of AI, but also the recognition of its ethical consequences (Kong, Cheung & Zhang, 2023; Williams et al., 2022; Zhang et al., 2022).

Kim (2022) proposes an approach to new competencies that focuses on the individual who uses new technologies - the strategic focus is on the competencies that employees need to adopt and adopt AI technologies; and on the application, use of new tools - competencies for learning and development in relation to AI (e.g. the development of an AI-based educational system). In this sense, Industry 5.0 places considerable emphasis on human-machine cooperation (Suciu et al., 2023).

Issa et al. (2022) define AI competencies under the influence of (1) the approach to human-machine collaboration, (2) the ability to anticipate the strategic impact of AI, respectively the technological infrastructure, and (3) data management capabilities. In contrast, Younnis and Adel (2020) define five categories of competencies needed in connection with the adoption of AI solutions: (1) hard and soft, (2) cognitive (problem solving, creativity, judgment and critical thinking), (3) social and emotional (teamwork, leadership and communication), (4) technological and (5) research. Furthermore, the model proposed by Jaiswal et al. (2021) as a prerequisite for improving the human-AI relationship emphasizes the need to develop cognitive and technological competencies at a higher level and includes five critical competencies: data analysis, digital, complex cognitive, decision-making, continuous learning. In this regard, Qureshi et al. (2021) reveal a critical place between the available information and the competencies that are needed to meet the requirements of AI technologies.

Long & Magerko (2020) looked at a set of competencies as literacy (the authors define the set of competencies in the field of AI as AI literacy) that enable individuals to: evaluate AI technologies, communicate and collaborate effectively with AI, use AI (Magerko, 2021; Perchik et al., 2023; Pinski & Benlian, 2023; Wienrich & Carolus, 2021). According to Ng et al. (2021), Steinbauer et al. (2021) AI literacy at the individual level includes: understanding AI technologies, learning to use AI technologies.

It is expected that AI literacy will become a common part of education (Adams et al. 2023; Chai et al. 2023; Jang, Jeon & Jung 2022). This will be particularly important for organizations, as generations with the necessary AI literacy will enter the labor market over time. At the organizational level, success will currently depend on the ability to develop AI literacy among existing employees (Chowdhury et al., 2023). If employees have a certain level of knowledge about the possibilities of AI, they may perceive AI as more accessible and effective, and their readiness to use AI will also reduce pressure and stress in the workplace (Del Giudice et al. 2023).

Cetindamar et al. (2024) view AI organizational competence as a collective capability that can be disseminated as organizational literacy through the interactions of individuals within an organization. Cetindamar et al. (2024) argue that although AI literacy is often viewed as an individual-level competency, it can also be viewed as an organizational capability, where individual competency culminates in a collective organizational strength that enables coordinated tasks and their resolution, efficient use of resources to achieve desired outcomes (Teece, 2007). Understanding the organizational competencies required for interacting with AI is therefore essential. When formulating strategies for developing AI organizational literacy, organizational culture needs to be taken into account (Robinson, 2020), as AI literacy also carries over into the work environment. The importance of ethics in the use of AI technologies needs to be emphasized (Lee et al. 2022; Robinson 2020). By incorporating values-related content, organizations can effectively increase workers' readiness to learn and adopt AI technologies.

The Technology Acceptance Model (TAM) can be used to identify organizational competencies in AI. It distinguishes:

- Skill domain – the real-world use of AI skills (knowledge and understanding of AI, use and application of AI, evaluation and creation of AI, resolution of ethical issues) (Ng et al., 2021).
- Relevance domain – the evaluation and practical use of AI skills (Ng et al., 2021, Cetindamar et al., 2024, Tenório et al., 2023, Schleiss et al., 2022, Yi, 2021). For example, Yi (2021) emphasizes the ability of metacognition, which refers to how to access the information we need to know, with whom and how to engage, what learning strategies to use, how to explore different methods and forms of learning. Relevance can be considered the most critical competency for AI literacy, as it primarily uses the ability to anticipate.
- Ethics – concerns the definition of values, the appreciation of individuals and groups (Cetindamar et al. 2024; Ng et al. 2021; Tenório et al. 2023). For example, Cetindamar et al. (2024) emphasize not only the interaction and understanding of AI systems, including the evaluation of their outputs, but also their limitations. Ethical issues in the use of AI can lead not only to low performance, but also to harm the individual, organization and society (Asaro 2019; Mittelstadt 2019). Ethics is a critical ability for decision-making in everyday routine activities, including the inclusion of privacy, accountability, transparency, etc. (Laupichler et al. 2022; Lee et al. 2022; Perchik et al. 2023; Tenório et al. 2023).
- Knowledge domain – includes not only basic technical knowledge about AI, but also knowledge of principles, decision-making, and critical thinking (Charow et al. 2021; Long and Magerko 2020; Ng et al. 2021; Tenório et al. 2023).

Zhang (2023) defines a competency model for managers involved in the integration of AI solutions. It includes: planning, control regulation, systematic decision justification, initiative behavior, and fairness and impartiality. This model can be complemented by collaborative intelligence (Chowdhury et al., 2022) and critical evaluation (Liaw et al., 2022). Chatterjee et al. (2021) add organizational agility as a crucial factor that facilitates the development of AI competencies, which are necessary for the successful implementation of these technologies. Zhang's competency model represents de facto cross-cutting competencies that are essential for a sustainable, resilient and inclusive transition to a digital workplace that will deliver long-term positive effects. It is considered essential for both leaders and employees to possess them.

According to Suciu et al. (2023), the most important transversal competencies include the ability to use, monitor and control technological devices; analytical and innovative thinking; lifelong learning; development of technological and programmatic solutions; creativity, originality and initiative; emotional intelligence; leadership; ability to solve complex problems. By developing transversal competencies, individuals will be better prepared for jobs (e.g. software developer, robotics engineer, Internet of Things specialist, digital marketing specialist, database and network specialist, artificial intelligence specialist, materials engineer, information security analyst, renewable energy engineer, process automation specialist, etc.).

Currently, the competencies needed to hold these positions are not widely shared among individuals. This is a significant problem. According to Suciu et al. (2023), managers need to focus more on aspects such as employee safety, working conditions, physical and mental well-being or satisfaction of employees integrated into a digitalized work environment.

Relatively few studies have examined competencies related to positive attitudes and intrinsic motivation (self-motivation). Such workers are strongly focused on achieving their goals and proactively adapt to new AI technologies. They recognize that competencies related to AI education are crucial. Martinez-Plumed et al. (2021) defined them at the level of seven classes: knowledge representation, learning, communication, perception, planning, robotics, and collective intelligence.

Success in the AI era depends on acquiring the competencies needed to effectively collaborate with and use AI (Borana et al. 2016; Chen and Lin 2023; Jarrahi 2018), which go beyond simply understanding AI, but also include other areas such as application, evaluation, creation, and even the ethical dimension of AI (Ng et al. 2021).

3. Research goal and hypotheses

This study aims to investigate the role of AI literacy as a determinant of successful AI implementation in organizations, examining both organizational-level literacy effects and competency impacts on technology acceptance and usage. Additionally, this research seeks to identify sector-specific variations in AI competency requirements to provide targeted insights for specific AI adoption.

Based on the literature review, we can identify several promising research hypotheses that emerge from the gaps and relationships discussed.

H1: The use of AI competencies varies significantly across industry sectors.

H2: Organizations with higher levels of AI literacy demonstrate significantly better AI implementation compared to organizations with lower AI literacy levels.

H3: Higher AI competency levels positively correlate with effective use of AI technologies in the workplace.

These hypotheses address the key gaps in the literature review, particularly around empirical testing of the relationships between competencies, barriers, and implementation success. They allow formulation of practical implications for organizations seeking to improve their AI adoption outcomes.

4. Materials and methods

This study employed a quantitative research approach utilizing empirical data collected from 40 organizations selected from the top one hundred companies operating in the Czech Republic. Only organizations listed in the Czech Top 100 were included in the survey. The response rate was 40%. The primary data were obtained through a structured questionnaire administered via computer-assisted web interviewing (CAWI) methodology. The research instrument was designed to examine multiple dimensions of organizational AI adoption, including current AI utilization patterns, specific AI tools and application areas, competencies required for effective AI implementation, and organizational changes related to AI integration such as employee reskilling, training initiatives, recruitment strategies, workforce transitions, job transformations, and skill requirements in the AI era. The questionnaire development was grounded in established theoretical frameworks and validated by previous empirical studies, particularly those conducted by Long et al. (2021) and Perchik et al. (2023). Competency assessment items were systematically reviewed and refined based on relevant literature and theoretical foundations established in this research.

The sampling frame comprised organizations specifically engaged in AI utilization, ensuring relevance to the research objectives. Organizations were strategically selected across diverse industries and geographic regions within the Czech Republic's top one hundred companies to achieve sample representativeness. The selection criteria included organizational location, size, business sector classification, and ownership structure. Each participating organization was represented by a single respondent holding senior-level positions, specifically general managers, human resources managers, or specialized professionals working full-time in AI-related capacities.

The final sample distribution reflected the actual economic structure, with primary sector organizations comprising 7%, secondary sector organizations representing 17%, and tertiary sector organizations constituting 76% of the total sample. This distribution closely mirrors the real-world economic sector composition in the Czech Republic, enhancing the external validity of the findings.

Data collection procedures involved initial email contact with target organizations, followed by distribution of the online questionnaire. Respondents were specifically instructed to identify competencies deemed necessary for successful AI implementation within their work environments. The resulting dataset underwent systematic cleaning and processing to ensure data quality and analytical reliability.

Statistical analysis was conducted using IBM SPSS Statistics 22 software. The analytical approach incorporated descriptive statistics to characterize sample demographics and response patterns, correlation analysis to examine relationships between variables, and association tests to identify significant connections between organizational factors and AI adoption patterns. Additionally, multivariate factor analysis was employed to identify underlying competency dimensions and reduce data complexity. Chi-square and Spearman´s correlation tests were utilized to examine sectoral differences and relations in AI adoption patterns and competency requirements, with statistical significance set at $p < 0.05$. The chi-square assumptions (e.g., minimum expected counts) were reached in the case of secondary and tertiary sector organizations. Therefore, the chi-square test was used to test the differences between those sectors. The consistency was tested by Cronbach Alpha and the result reached over 0.8, which is satisfactory for further analyses. Factor analysis was not used to test sectors, as there were not enough responses to provide relevant base for such an analysis.

5. Results

The results show that surveyed organizations are using AI on daily basis for in many areas. Intensively use AI 77.8% of respondent organizations. The general AI tools are used by most organizations, such as customer support (68.8%) and data analysis (also 68.8%), content generation (60%), language translations (56.3%) and surprisingly, large use of AI is among human resources (53.9%).

5.1. AI Tool Usage

According to the data, the use of AI is sector specific. The AI tools used by the primary sector cover the most commonly used AI such as customer support and service: e.g., chatbots or virtual assistants, human resources: e.g., recruitment automation, data analysis: e.g. processing of larger amounts of data and predictive analysis, content generation: e.g. automated compilation of data summaries or writing articles, product descriptions, etc. and language translations and localization: e.g. content localization or AI-powered language translations. The secondary sector is specific by using AI for manufacturing and operation management: e.g., quality control or predictive maintenance and supply chain management: e.g., demand forecasts or optimization of distribution routes, which is almost exclusively used by the secondary sector organizations. The tertiary sector organizations in addition use AI for finance and risk management: e.g., automated invoice extraction, fraud detection or algorithmic trading, healthcare management: e.g., assistance in determining a patient's diagnosis and treatment process, and legal services: e.g., contract analysis or legal research in the area of searching for relevant cases and laws. The AI tools used by all three sectors are the general AI tools used by the primary sector. The differences between sectors are statistically significant. The Chi-square test indicated the difference with p=0.000. The use of AI tools is displayed in the Fig. 1.

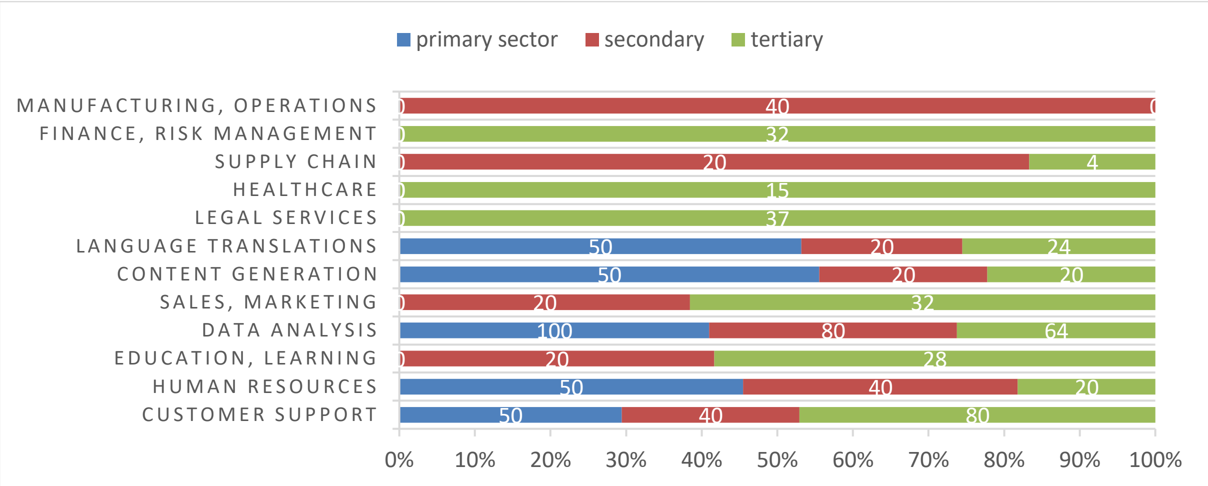

Fig. 1. AI tools among sectors

According to the survey result, the most commonly used AI competencies are analytical competencies (84.38%), followed by digital competencies (78.13%), and critical thinking (65.63%). Strategic competencies are important in relation to AI use in 50% of respondent organizations. The least importance was shown within soft skills.

5.2. Competency Patterns

The respondent organizations indicated that the most important AI-related skills are analytical (84.4%), digital (78.8%) and critical thinking (65.6%). However, significant differences among sectors were recorded also in the area of use of competences necessary for AI use in business. All three sectors reported the use of competencies related to digital, critical thinking, and analytical skills. Problem solving skills are used by primary and tertiary sector organizations.

Communication by secondary and tertiary sector organizations and team competencies only by tertiary sector organizations. Again, Chi-square test confirmed significant differences in AI-related competency use among sectors (p=0.000). Details are in Fig. 2.

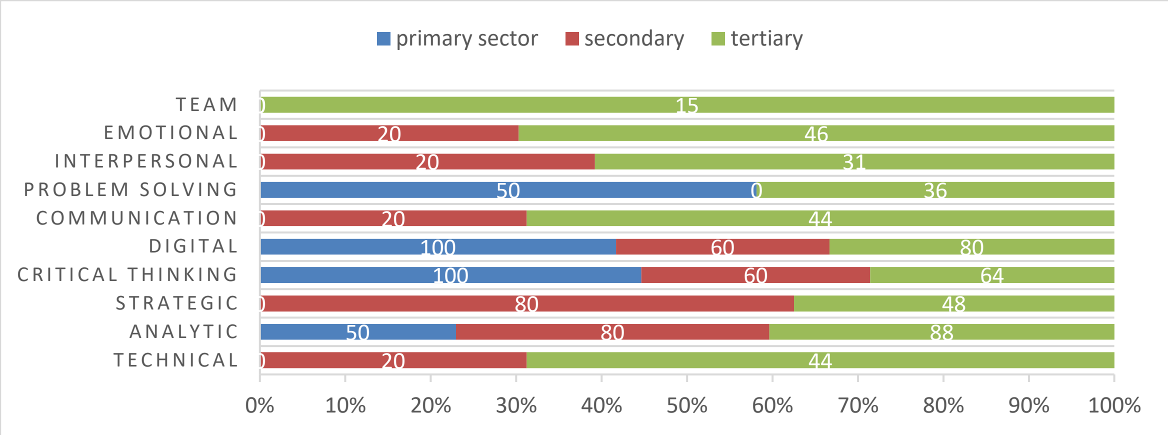

Fig. 2. AI-related competencies among sectors

5.3. *Organizational Impact*

Finally, the impact of AI incorporation into daily procedures has a significantly different impact on organizations based on their sector (p=0.000). As indicated in Fig. 3, all three sectors are focusing on employee training and reskilling. Organizations from secondary and tertiary sector organizations also reported no change in their job structure and no transformation. The tertiary sector organizations are, according to expectations, experiencing the most of the changes in relation to job structure and transformation based on AI use among all sectors, including the need of hiring new employees, outplacement of some employees that are no longer needed and transfer to different tasks.

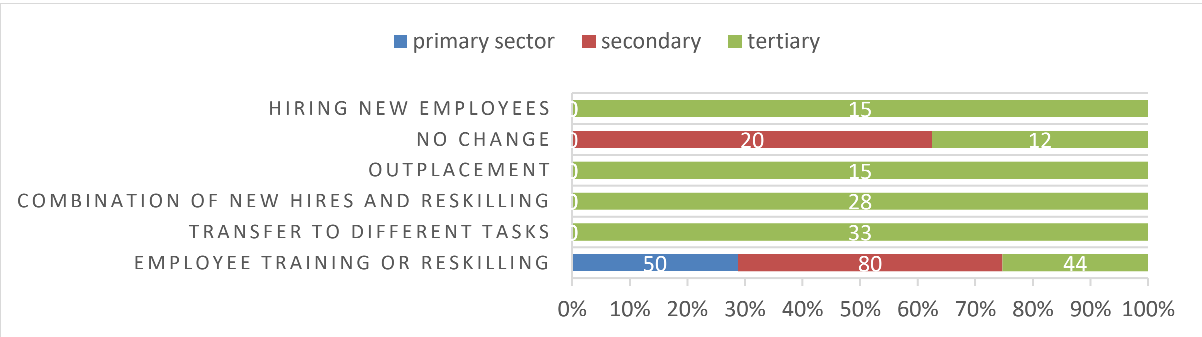

Fig. 3. Impact of AI on jobs among sectors

Based on the results above, the Chi-square test confirmed the H1, as there are statistically significant differences in AI use among sectors (p=0.000). The test also confirmed, that organizations which actively use AI demonstrate significantly better AI implementation compared to organizations with lower AI literacy levels. This concludes that H2 was valid (p=0.000). On the other hand, the H3 was not confirmed. The use of AI indicated a very weak correlation with focus on use of technologies (r=0.129). AI is used by all organizations without their primary focus or the level of use of technologies.

6. Discussion

The research findings align closely with the theoretical framework suggesting that AI represents the fastest growing business opportunity in today's economy, with projections indicating its contribution to the global economy (Rao & Verweij, 2017; Chui et al. 2023). The intensive daily use of AI by 77.8% of surveyed organizations demonstrates that this theoretical potential is being actively realized across various sectors, confirming that AI-based technological solutions are becoming integral to organizational operations for more efficient data collection, improved decision-making processes, enhanced logistics operations, and increased labor productivity (Srivastav, 2019).

The sectoral differences observed in AI implementation patterns reflect the literature's identification of key industries where digitalization creates added value, including manufacturing, agri-food industry, automotive, logistics, retail trade, and financial services (Al Suwaidan, 2021; García-Muiña et al., 2020; Demeter et al., 2020; Wyrwa, 2020; Zhang et al., 2020). The secondary sector's focus on manufacturing-specific AI applications such as quality control and predictive maintenance directly corresponds to the theoretical expectation that manufacturing would be among the primary beneficiaries of AI integration. Similarly, the tertiary sector organizations adoption of specialized AI tools for finance, healthcare, and legal services validates the theoretical framework's emphasis on these sectors as key areas for AI value creation.

The competency requirements identified in the study strongly support the theoretical model proposed by various scholars regarding the multidimensional nature of AI-related skills. The prominence of analytical competencies (84.4%) and digital competencies (78.1%) among surveyed organizations aligns with Jaiswal et al.'s (2021) model emphasizing data analysis and digital skills as critical competencies for improving human-AI relationships. The importance of critical thinking (65.6%) mirrors the theoretical emphasis on cognitive competencies including problem solving, creativity, judgment and critical thinking as defined by Younnis and Adel (2020). The relatively lower priority given to soft skills in the survey results contrasts somewhat with theoretical frameworks that emphasize social and emotional competencies such as teamwork, leadership, and communication as essential for AI adoption.

The sectoral variations in required competencies reflect the theoretical understanding that AI implementation necessitates different skill sets depending on the organizational context. The Technology Acceptance Model's distinction between skill domain, relevance domain, ethics, and knowledge domain (Ng et al., 2021; Cetindamar et al., 2024) provides a framework for understanding why different sectors prioritize different competencies. The tertiary sector organizations emphasis on team competencies and communication skills aligns with the theoretical expectation that service-oriented industries would require stronger collaborative intelligence (Chowdhury et al., 2022) and human-machine cooperation capabilities as emphasized in Industry 5.0 transitions (Suciu et al., 2023). Therefore, the tertiary sector could consider incorporating employee trainings specifically focusing on these areas.

The organizational impacts observed, particularly the focus on employee training and reskilling across all sectors, directly support theoretical predictions that AI implementation leads to fundamental changes in workforce requirements and organizational structures (Becker-Ritterspach & Gröger, 2018; Chen & Zhou, 2020; Janssen et al., 2017). The tertiary sector organizations experience of more significant transformations, including workforce redeployment and role reassignment, validates theoretical frameworks suggesting that AI technologies introduce innovative changes that revolutionize how people work and communicate in digitalized environments (Borana, 2016; Chen & Lin, 2023; Jarrahi, 2018; Ismail & Hassan, 2019; Rymarczyk, 2020).

The confirmation of Hypothesis 2, demonstrating that organizations with active AI use show superior implementation compared to those with lower AI literacy levels, strongly supports the theoretical framework of AI literacy as both an individual and organizational capability (Long & Magerko, 2020; Cetindamar et al., 2024). This finding validates the theoretical proposition that AI literacy enables individuals to evaluate AI technologies, communicate effectively with AI systems, and use AI tools efficiently (Magerko, 2021; Perchik et al., 2023; Pinski & Benlian, 2023; Wienrich & Carolus, 2021). The organizational perspective of AI literacy as a collective capability that emerges through individual interactions within organizations (Cetindamar et al., 2024) is supported by the research findings showing that higher organizational AI literacy correlates with better implementation outcomes.

Interestingly, the rejection of Hypothesis 3, showing only weak correlation between AI usage and organizational technology focus, challenges some theoretical assumptions about technology adoption patterns. This finding suggests that AI has transcended traditional technology-focused organizations and has become a universal business tool, supporting the theoretical framework that emphasizes AI's transformative potential across all industries regardless of their primary technological orientation. This universal adoption pattern aligns with theoretical predictions about the pervasive nature of AI technologies and their potential to revolutionize diverse organizational contexts (Bhalerao et al., 2022; Suciu et al., 2023).

7. Conclusions

This study examines artificial intelligence adoption patterns across different economic sectors, revealing significant variations in implementation, required competencies, and organizational impacts. The research demonstrates widespread AI adoption, with 77.8% of surveyed organizations using AI tools intensively on a daily basis. The study reveals distinct sectoral patterns in AI implementation: Primary Sector organizations utilize general AI applications including customer support chatbots, HR recruitment automation, data processing for predictive analysis, automated content generation, and language translation services. Secondary Sector organizations demonstrate unique specialization in manufacturing-focused AI applications, incorporating quality control systems, predictive maintenance tools, and supply chain optimization including demand forecasting and distribution route optimization. Tertiary sector organizations employ the broadest range of AI applications, encompassing all general tools while also implementing specialized solutions for finance and risk management (automated invoice processing, fraud detection, algorithmic trading), healthcare management (diagnostic assistance, treatment planning), and legal services (contract analysis, legal research).

Organizations identified critical AI-related competencies in order of importance: analytical skills (84.4%), digital competencies (78.1%), and critical thinking abilities (65.6%). Strategic competencies were deemed important by 50% of respondents, while soft skills received the lowest priority ratings. Competency requirements also varied by sector, with all sectors emphasizing digital, critical thinking, and analytical skills. Primary and tertiary sector organizations additionally prioritized problem-solving capabilities, while secondary and tertiary sector organizations valued communication skills.

AI implementation has generated varying organizational responses across sectors. All sectors have prioritized employee training and reskilling initiatives. Secondary and tertiary sector organizations reported minimal changes to job structures, while the tertiary sector organizations experienced the most significant transformations, including new employee recruitment, workforce redeployment, and role reassignment.

The research employed tested three hypotheses to provide important insights into AI adoption patterns. The first hypothesis was confirmed, demonstrating that statistically significant differences exist in AI use among economic sectors (p=0.000), which validates the sectoral variations observed in implementation strategies and application focus areas. The second hypothesis was also confirmed, showing that organizations with active AI use demonstrate superior implementation compared to those with lower AI literacy levels (p=0.000). However, the third hypothesis was rejected, as AI usage showed only weak correlation with organizational technology focus (r=0.129), indicating that AI adoption occurs regardless of an organization's primary technological orientation and suggesting that AI has transcended traditional technology-focused sectors to become a universal business tool across diverse organizational contexts. The findings suggest that while AI adoption is widespread across all economic sectors, implementation strategies and impacts are highly sector-dependent. Czech organizations in similar economic contexts may consider developing tailored approaches that align with their sector's specific needs while building appropriate competency frameworks to support successful AI integration.

This research acknowledges several methodological and contextual limitations that may influence the generalizability and interpretation of findings. The relatively small sample size of 40 organizations, while representative of the Czech economic structure, limits the statistical power for detecting nuanced differences between sectors and may restrict the applicability of findings to larger organizational populations. The cross-sectional design captures AI adoption patterns at a single point in time, potentially missing the dynamic nature of technological implementation and organizational adaptation processes that evolve continuously.

Several promising research directions emerge from this study's findings and limitations. Longitudinal research designs would provide valuable insights into the temporal dynamics of AI adoption, tracking how organizational competency requirements, implementation strategies, and sectoral differences evolve over time. Expanding the geographic scope through comparative international studies would enhance understanding of how cultural, regulatory, and economic factors influence AI adoption patterns across different national contexts.

Future research should incorporate larger, more diverse samples including organizations at various stages of AI adoption, from non-adopters to advanced implementers. Mixed-methods approaches combining quantitative surveys with qualitative case studies would provide richer understanding of organizational experiences, implementation challenges, and success factors.

Ethics statement

This article does not involve any original experimental studies with human or animal subjects. Therefore, no ethical approval was required for this work.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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