The Impact of AI Implementation on Job Transformation and Competency Requirements: Prioritising Reskilling and Soft Skills Development

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

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ABSTRACT

Purpose: This research contributes to understanding how organisations are navigating AI-driven workforce transformation by prioritising human-centric competencies and strategic reskilling to improve the quality of human resources rather than widespread job elimination.

Methodology/Approach: This case study investigates the real impact of AI implementation on job transformation within the top 100 Czech companies.

Findings: The study found a strong negative correlation between employee training and new recruitment, suggesting organisations prefer upskilling to replacement. Industry-specific approaches vary significantly.

Research Limitation/implication: As AI continues to reshape work, these insights can guide organisations in developing effective strategies that leverage both technological capabilities and uniquely human skills.

Originality/Value of paper: These findings provide evidence that while AI is transforming jobs in Czech companies, organisations are strategically adapting through reskilling rather than widespread job cancellations, with soft skills becoming increasingly valued as technical tasks are automated.

Category: Research paper

Keywords: artificial intelligence; job redesign; quality of human resources; management; competence; employees' performance quality

Research area: Strategic Quality Management; Management of Technology and Innovation

1 INTRODUCTION

Technological change is unprecedented in its pace, scope, and impact. Innovation is changing the rules of the game. Organisations are reshaping themselves at an exponential rate to remain relevant while trying to stay ahead of the competition. Innovation in Artificial Intelligence (AI) technology requires developing competencies related to learning and adopting new technologies. Sophisticated AI technologies reduce the need for human resources, but connecting these technologies to organisational needs and outcomes requires a deep understanding of the organisational capabilities of organisation members (Davenport and Kirby, 2016).

The large-scale adoption of AI technologies is a global phenomenon impacting the quality of work, and attention needs to be paid to cultural differences, government policies and other socio-economic factors influencing the integration and perception of AI, so that the benefits of AI technology are accessible across different geographical, economic and cultural contexts. The rapid development of AI will lead to fundamental changes in the labour market, performance and quality of work. Therefore, this study focuses on the adoption and use of AI in the Czech Republic, specifically in a sample of the Top 100 Czech companies.

This paper connects to the concept of quality through a fundamental shift in how organisations define and cultivate human resource quality in the AI era. Rather than viewing quality purely through traditional metrics of efficiency or technical competence, the research demonstrates that companies are redefining quality to emphasise uniquely human attributes - interpersonal skills, emotional intelligence, and collaborative abilities - that AI cannot replicate. The study reveals a strategic approach to quality enhancement where organisations invest in reskilling existing employees rather than pursuing wholesale replacement, suggesting they recognise that quality lies not just in immediate productivity but in the adaptable, relationship-building capabilities that create long-term organisational value. This represents a maturation in understanding quality as multidimensional, encompassing both human potential and technological integration, where the highest quality workforce emerges from thoughtful development of irreplaceable human competencies alongside AI capabilities.

Tschang and Mezquita (2020) highlight the currently ambivalent view among scholars. Some argue that AI can lead to unemployment, while others believe that AI could be used to expand existing jobs and improve the quality of employees' outputs. These conflicting views are not surprising, as understanding how and to what extent AI affects human resources is still in its infancy (Pereira and Malik, 2015). This paper identifies the shift of job descriptions and job transformations due to the application of AI into company processes and job descriptions.

Technological advances and successes are possible thanks to data science, analytics and machine learning, which are becoming central to the functioning of AI. A key characteristic of artificially intelligent machines is to draw on continuous learning and manage the adaptation process (Akerkar, 2019; Lecun et al., 2015). The International Labour Organisation (ILO, 2023) reports that already today, 24% of office jobs are highly exposed to technological change, 58% are affected by medium levels of technological change. The McKinsey (2019) estimates that up to 375 million workers worldwide (14% of the global workforce) will need to transition to new occupations and acquire new skills to keep up with the new quality standards. Brougham and Haar (2020) point out that the opportunity to develop skills in areas in demand in the labour market related to AI can increase labour mobility. Conversely, if workers' transition to new jobs is slow, unemployment may increase, and wage growth may be dampened. Hancock et al. (2020) report that around 30-40% of workers will need to significantly upgrade their skills over the next decade, as the expected quality of outputs is shifting along with the AI use.

Therefore, according to Adams et al. (2023), Chai et al. (2023), Jang, Jeon and Jung (2022), the skills gaps of existing workers and organisations need to be addressed. The ways in which workers develop their skills are creating labour market imbalances that are deepening and are reflected in high and long-term structural unemployment rates (Cedefop, 2017).

This paper is drawn on theories that have been specifically selected because they help identify skill sets that can potentially help IT MNCs and their employees prepare for sustainable AI design and quality implementation due to technological change:

(1) Dynamic Skills Theory (Fischer et al., 2003): views skill development as a network of activities that are context-specific and outcome-oriented (Kunnen and Bosma, 2003). In a dynamic world, individuals need to be proficient in a variety of skills, such as social, emotional, technological, and physical skills, in order to perform well or exhibit appropriate behaviour depending on the context or situation. A skill network captures the interconnected complexity of skills across contexts. Dynamic Skills Theory is a theory of adult cognitive development, and the authors refer to it in relation to employee skill development in the AI era.

(2) Neohuman Capital Theory (NHCT): highlights the increasing demand for technology-induced skills and the development of human capital in times of rapid technological change (Pereira and Malik, 2015). NHCT officials argue that individuals with higher levels of human capital concentration (higher levels of education, training experience, openness to learning and exploration) are more likely to adopt technological change and develop new skills (Bartel and Lichtenberg, 1987; Wozniak, 1984, 1987). Conversely, the need for employee training will not decrease with higher levels of technological knowledge (Pereira and Malik, 2015, p. 154). Rather, as AI-enabled technologies spread across industries, the demand for new skills and higher levels of human capital concentration will increase. While AI's ability to perform more and more tasks is indeed a major source of innovation and value creation, it is also increasingly threatening to lose jobs.

(3) AI Job Replacement Theory (Huang and Rust, 2018): assumes that AI job replacement occurs primarily at the task level rather than at the job level. More specifically, the changing nature of work concerns tasks that are easy and repetitive and that involve mechanical intelligence. Once AI has completed the lower-level tasks and then the higher-level mechanical tasks that make up the workplace, it will progress to replace labour in the area of analytical intelligence, i.e., tasks that require logical thinking. AI is increasingly changing the nature of work by performing various tasks and becoming a major source of innovation (Rust and Huang, 2014).

The coming era requires people to acquire the appropriate skills for newly defined jobs and work closely with AI technologies (Bondarouk et al., 2017; Pereira and Malik, 2015). While technologies enable organisational outcomes, employees are the key drivers of value creation and a source of sustainable competitive advantage. Today's MNCs focus not only on developing physical and organisational capital but also on developing human capital, which is extremely important for organisational sustainability and success, even more so in the coming era of AI and the changing nature of work. Most jobs in MNCs involve mechanical tasks (such as managing daily routines and tracking attendance), thinking tasks (such as analysing customer preferences and planning logistics), and feeling tasks (such as empathising with customers, advising patients, etc.). As AI takes over mechanical human work, humans must increase their focus on tasks that are difficult for AI to take over, i.e. tasks requiring thinking and feeling (Huang et al., 2019; Huang and Rust, 2018).

With the advancement of AI-based technologies, the concept of AI-Readiness needs to be addressed, which reflects an organisation's capabilities to implement and leverage AI in a way that generates added value through digital transformation (Rust and Huang, 2014). The impact of AI on human resource development functions, such as learning and development, professional development, and organisational development, will be critical for employees and organisations. There will be a need to understand how individuals adopt and apply AI technologies in their workplace (Ardichvili 2022; Guenole and Feinzig 2018; Hughes et al. 2019; Upadhyay and Khandelwal 2019).

Strategic adoption of AI technologies requires consideration of the specific technologies, the individuals who use them, and the processes that facilitate adoption (Thite, 2022). Organisations that succeed in adopting and scaling up AI technologies strengthen their competitiveness (Logg et al., 2019). At the institutional level, the European Commission (2021) strongly encourages Member States to improve their knowledge and skills in the area of a portfolio of specific competences for the development and implementation of AI. The OECD (2022) states that governments should work with stakeholders in the field in a way that enables people to use and interact with AI, including the development of the necessary competences. UNESCO (2021) also suggests the development of mechanisms and tools to anticipate current and future needs for AI-related competences in the context of relevant curricula for the labour market.

Interventions that reduce the gap between current skills and abilities and those needed in the labour market should be focused on, with a view to improving formal (FE) and non-formal education (NFE) (Chatterjee et al., 2021; Brougham and Haar, 2020; Chowdhury et al. 2022; Da Silva et al. 2022; Varma et al. 2022; Verma and Singh, 2022; Tilibaşa et al., 2023).

The literature reveals two main approaches to competency models for AI: (1) traditional, based on skills mostly related to the use of technology, (2) multidisciplinary, focused on developing models that integrate complex cognitive skills. In traditional approaches, competency models for AI are based primarily on sets of digital competencies, which consist of knowledge, skills and attitudes needed to perform tasks, communicate problems or develop knowledge in an ITandC context (Fernandez Sanz et al., 2017). Digital competencies provide important competitive advantages even for non-IT professions (Chen and Lin, 2023). In multidisciplinary approaches, cognitive skills such as collaboration (Chowdhury et al., 2022), critical evaluation (Liaw et al., 2022) and ethical approach (Varma et al., 2022) are emphasised. Organisational agility is also a factor that facilitates the development of AI competencies necessary for the successful implementation of these technologies (Chatterjee et al., 2021).

According to Clardy (2008), the following appear to be key: understanding the strategic changes of the organisation, which include the introduction of new technologies, identifying the competencies necessary for these strategic changes, and supporting employee adaptation through approaches to continuous competency development. Younis and Adel (2020) define five categories of competencies needed in connection with the adoption of AI solutions: hard and soft, cognitive (problem solving, creativity, judgment and critical thinking), social and emotional (teamwork, leadership and communication), technological, research. The conceptual model of Popa et al. (2024, pp. 33-52) is similar, including five categories of key competencies in the field of AI and documents their mutual relationship: technological, digital, decision-making, personal and social.

Popa et al. (2024, pp. 33-52) demonstrated the relationship between the listed competencies and the effectiveness of using AI tools. Similarly, research by Younis and Adel (2020), Jaiswal et al. (2022) showed that these competencies have a significant impact on the implementation and effectiveness of technology use in organisations: Technological competencies - a deeper understanding of how AI works helps employees increase their confidence in their own abilities (Chowdhury et al., 2022), an effort to contribute to the development and implementation of innovative solutions (Verma and Singh, 2022), and increased optimism in connection with the use of AI tools (Younis and Adel, 2020; Jaiswal et al., 2022). Digital competencies - allow employees to integrate AI tools into their daily work activities (Van Laar et al., 2017). The ability to work with AI tools can have a significant impact on employment opportunities and personal development (European Commission, 2021). Decision-making competencies can play a key role in coordinating and motivating teams working with AI tools (Sousa and Rocha, 2019). Cortellazza et al. (2019) showed that, for example, management and communication competencies can influence the way a team approaches the use of AI. AI increases employees' creativity and innovation capabilities (Verma and Singh, 2022). Employee involvement in innovation activities increases trust levels (Chen and Lin, 2023), creating positive outcomes at the organisational level (Braganza et al., 2020). Personal competencies – focus more on behavioural, cognitive and relational aspects (Fischer et al, 2003). These include critical thinking, adaptability and ethics, which can contribute to greater efficiency and responsible use of AI tools (Younis and Adel, 2020). These competencies can influence not only trust in technology but also the way people understand, use, and manage AI technologies in different contexts (Chowdhury et al., 2023; Verma and Singh, 2022). Social competencies, when using AI, refer to personal competencies and characteristics that enable people to communicate and work effectively in various social and collaborative environments. The use of AI tools leads to faster and more efficient information sharing, the creation of a synergistic work environment, and supports collaboration (Olan et al., 2022). However, the use of AI technologies can also lead to a decrease in interactions and collaboration between people. As a result, implementing AI into the work environment can change the way employees communicate, make decisions, and work in teams.

Torraco and Lundgren (2020) identify a comprehensive competency framework, as learning and adopting AI technologies by employees involves multiple competencies. Therefore, it is necessary to consider not only a learning and development model that cultivates individual development in AI through training programs, but also to think about organisational AI literacy, which Cetindamar et al. (2024) consider as a collective competency of all employees in an organisation. Cetindamar et al. (2024) consider collective AI skills of employees, organisational learning processes involving AI systems, a culture that supports learning in the use of AI, interactions between people and AI, and the mobilisation of AI knowledge. At the organisational level, it is necessary for executives to implement appropriate policies in the form of training programs or support centres to develop AI skills (Chatterjee et al., 2021). There is a need to focus on the ethical aspects of AI use and its broader impact on organisations. Through them, organisations can foster positive employee attitudes and a conducive environment for AI integration.

Learning and acceptance of AI technologies vary depending on personal beliefs and attitudes (Gado et al. 2022; Kelly, Kaye, and Oviedo-Trespalacios 2023; Sohn and Kwon 2020), and individuals' values toward AI should be a key topic for human resource development. The importance of individual values in the use of AI lies in ethical considerations and attitudes—including subjective norms, interests, motivation, and self-efficacy—that can influence the adoption of AI technologies.

The aim of this paper is to investigate how AI implementation is affecting organisational competencies, job transformations, and human resource strategies across different industries. Based on the theoretical background provided, the research focuses on: (1) Identify which human competencies remain irreplaceable as AI adoption increases in organisations; (2) Examine how organisations are responding to AI integration through their human resource practices, (3) Analyse which job categories are most vulnerable to transformation or elimination due to AI; (4) Determine industry-specific approaches to managing workforce transitions during AI implementation and (5) Identify correlations between AI usage in specific business functions and the development of particular employee competencies.

The strong focus on communication skills and other soft competencies suggests that the research is particularly interested in understanding which unique human capabilities will remain valuable in an increasingly AI-driven workplace. The statistical correlations between training approaches and employment outcomes indicate that the research aimed to provide evidence-based guidance for organisations navigating workforce transitions during technological change. Overall, the research aims at helping organisations develop effective strategies for maintaining workforce capabilities and managing job transformations as they incorporate AI into their operations.

2 METHODOLOGY

This study examines the impact of AI implementation on organisational competencies, job transformations, and human resource strategies across Czech Top 100 companies. Primary data were collected through a quantitative research approach utilising web-based questionnaires. The survey instrument was designed based on theoretical models derived from the literature review, with particular focus on competencies necessary for AI use, relationships between competencies and AI implementation, management approaches, and impacts on various job categories across different business areas.

Data collection employed Computer-Assisted Web Interviewing (CAWI) methodology, followed by systematic data cleaning and processing. The final data matrix was analysed according to identification questions using statistical methods, including Spearman's Rho correlations, to examine relationships between variables such as reskilling approaches and employment outcomes.

The sample comprised 34 respondents, with one respondent per organisation. Participating organisations were specifically selected based on their active engagement with AI implementation. To ensure representativeness, the sample was stratified across diverse sectors and regions within the Czech Republic's top 100 companies. Potential respondents were contacted via email with requests to complete the online questionnaire. Organisations were selected according to their operational location, size, business sector, and ownership structure. Only top managers or HR managers participated in the survey, with a single respondent representing each organisation. This sampling approach ensured that the final sample accurately represented the corporate landscape of AI-implementing organisations in the Czech Republic. The survey focused exclusively on organisational approaches rather than individual respondent characteristics.

The research aimed to investigate how AI implementation affects organisational competencies, job transformations, and human resource strategies. Respondents were asked to identify competencies necessary for successful AI integration across various job positions. Table 1 presents the distribution of surveyed companies by sector and AI use, reflecting the actual sectoral distribution in the Czech Republic's business environment.

Table 1 shows the current division of surveyed companies on AI use and distribution among sectors. This distribution reflects and represents the actual distribution of sectors in the Czech Republic.

Table 1 – Data sample general information

Sector	Frequency	Percent
I. sector	2	6.25
II. sector	5	15.62
III. sector	25	78.13

For the evaluation of results, tools of descriptive statistics were used. Two-dimensional statistics, including correlation and association tests, were used. The Spearman´s Rho was used to test the dependencies due to the nature of the data. To test the results, SPSS Statistics was used.

3 RESULTS AND DISCUSSION

According to respondents, searched organisations' irreplicable competencies with regard to the increasing use of AI are interpersonal competencies (87.5%), emotional competencies (84.375%) and team competencies (59.375%). It is possible to see a higher importance of interpersonal and team skills compared to technical skills, which are being replaced by AI. To keep up with these competencies and support development of these among employees, the surveyed organisations are mostly train and retrain or reskill their employees (50%), 21.9% are combining training and hiring of new employees, 6.25% of organisations are changing their job positions or moving employees to different jobs and 12.5% of organisations do not apply any tools to train or change their HR practices with regard to the AI skills and AI use. Only one organisation referred that they had to cancel some jobs due to AI use.

A more detailed impact of AI use on job transformation is shown in Chart 1 below. Chart 1 clearly identifies administrative jobs as the most impacted by AI use, as one-third of organisations reported either job cancellations or transformation. Similarly, unqualified positions are the most affected by job cancellations or transformations due to the use of AI in surveyed organisations. Employees in agriculture, craftsmen, services and sales do not seem to be threatened by job cancellations at all. The organisations reported only job transformations of 10% in the case of craftsmen and agriculture, and over 50% of sales and services. As expected, jobs in agriculture and craftsmen are the least impacted by the use of AI. On the other hand, managers, specialists, technicians and craftsmen are experiencing job transformations in one third of organisations.

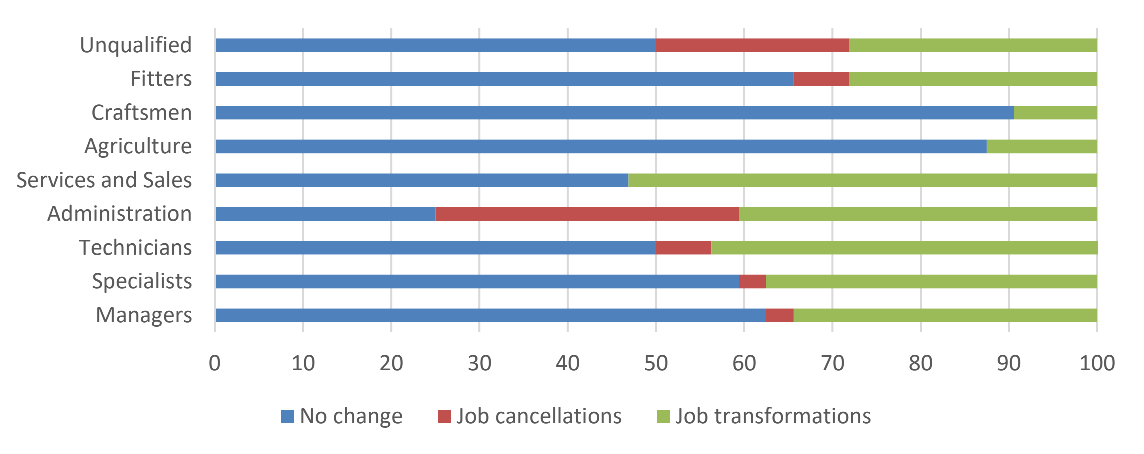

Figure 1 – Job transformations in surveyed organisations

The surveyed organisations are dedicated to keeping and reskilling their employees. It was confirmed also by Spearman´s Rho correlations, which showed a strong negative correlation between employee training and recruitment of new employees (r=-0.529, p=0.002). The results also show that reskilling is helping with the ability to keep employees at the current job positions (r=0.238, p=0.05).

The most used approaches with different organisations were found. Organisations specialising in marketing mostly use a combination of reskilling and hiring of new employees (r=0.447, p=0.01). Organisations providing security services are using personalised training (r=0.667, p=0.000), as well as organisations providing HR services (r=0.398, p=0.024). Reskilling of employees is being used also in logistics (r=0.436, p=0.013), production and operations, e.g. quality control or predictive maintenance (r=0.557, p=0.001), finance and risk management: e.g. automated invoice mining, fraud detection or algorithmic trading (r=0.389, p=0.028) and construction and engineering: e.g. project management, quality control or planning (0.447, p=0.010).

The use of AI in specific areas is shown in Table 2 below. The surveyed companies are using AI to monitor security in production and operations or to predict maintenance, as well as to automate financial administration regarding operational processes. Other organisations are using AI for transportation management, construction project management, or quality controls. The third area of relations between the use of AI in specific activities was found between security and education, to personalise learning or simplify administrative tasks. Detailed correlations are shown in Table 2 below.

Table 2 – Areas of AI use in companies

Hypotheses	Spearman's rho	Sig.
Security: e.g. anomaly detection or facial recognition - production and operation: e.g. quality control or predictive maintenance	0.557**	0.000
Finance and risk management: e.g. automated invoice mining, fraud detection or algorithmic trading - production and operations	0.477**	0.006
Transportation: e.g. traffic management - construction and engineering: e.g. project management, quality control or planning	0.803**	0.000
Security: e.g. anomaly detection - education: e.g. personalised learning or connected administrative tasks	0.667**	0.000

To investigate the necessary competencies for AI use, the main competence indicated by all searched organisations was communication. Table 3 shows significant correlations found between the use of communication and other competencies used to successfully manage AI in organisations.

Table 3 – Necessary competencies for AI use in companies

Hypotheses	Spearman's rho	Sig.
Communication – strategic thinking	0.437*	0.012
Communication – problem-solving	0.380*	0.032
Communication – team skills	0.498**	0.004

As it is possible to note from Table 3, the most important competencies are communication among team members related to strategic thinking and team cohesion and management. As stated in theory, soft and team skills will gain importance as businesses increase their use of AI.

The research findings on AI's impact on organisational competencies and job transformations reveal several important trends. Organisations have identified three irreplaceable competencies as AI usage increases: interpersonal, emotional and team competencies. These "soft skills" are becoming more important than technical skills that AI can replace. Job impact analysis shows that administrative positions are most affected, with one-third of organisations reporting cancellations or transformations. Unqualified positions also face a significant impact.

The study's findings align with several key theoretical frameworks regarding AI's impact on organisational competencies and job transformation. The strong emphasis on interpersonal (87.5%), emotional (84.375%), and team competencies (59.375%) as irreplaceable skills supports Huang and Rust's (2018) AI Job Replacement Theory, which proposes that AI primarily replaces mechanical administrative positions that require human workers to focus on tasks that require thinking and feeling capabilities. This is evident in our findings, which show that administrative positions are most affected by AI transformation.

The Dynamic Skills Theory (Fischer et al., 2003) is reflected in our results, showing that organisations are developing interconnected skill networks, with communication emerging as the universal essential competency strongly correlated with strategic thinking and team management. This aligns with Popa et al.'s (2024) conceptual model of AI competencies, particularly the importance of social competencies in creating synergistic work environments.

Our finding that 50% of organisations are training and reskilling employees rather than eliminating positions supports the Neohuman Capital Theory (Pereira and Malik, 2015), which suggests that as AI technologies spread, the demand for new skills and higher human capital concentration increases. The strong negative correlation between employee training and recruitment ($r=-0.529$, $p=0.002$) validates this theoretical perspective.

The industry-specific approaches we identified align with Cetindamar et al.'s (2024) view of organisational AI literacy as a collective competency. Organisations in security and HR services emphasising personalised training ($r=0.667$, $p=0.000$ and $r=0.398$, $p=0.024$) demonstrate how different sectors are developing collective AI skills tailored to their specific needs.

Our results show minimal job cancellations due to AI implementation, contradicting some pessimistic predictions. Instead, we see evidence of Brougham and Haar's (2020) assertion that developing AI-related skills can increase labour mobility. The significant job transformations in sales and services (over 50%) without cancellations demonstrate organisational adaptation.

McKinsey (2019) estimated that 14% of the global workforce would need to transition to new occupations. Our findings suggest Czech organisations are proactively addressing this through reskilling rather than replacement, potentially mitigating Hancock et al.'s (2020) concern that 30-40% of workers will need significant skill upgrades.

Finally, our results support Chatterjee et al.'s (2021) argument that executives must implement appropriate policies to develop AI skills. The correlation between reskilling and maintaining current employment ($r=0.238$, $p=0.05$) suggests organisations are successfully implementing such policies, creating what Thite (2022) described as strategic adoption of AI technologies, considering both the technologies and the individuals who use them.

4 CONCLUSION

This study provides valuable insights into how AI is transforming jobs and competency requirements in top Czech companies. The findings reveal that organisations are prioritising the development of interpersonal, emotional, and team competencies (87.5%, 84.375%, and 59.375% respectively) as these human-centric skills remain irreplaceable in the AI era. While administrative and unqualified positions face the highest risk of transformation, most companies are responding through reskilling rather than job elimination, with 50% of organisations actively training existing employees and only one organisation reporting job cancellations.

The research highlights communication as the universal essential competency, strongly correlating with strategic thinking and team management capabilities. This supports theoretical perspectives that as AI takes over mechanical and analytical tasks, human workers must focus on tasks requiring thinking and feeling capabilities (Huang and Rust, 2018). The strong negative correlation between employee training and recruitment (r=-0.529, p=0.002) suggests that organisations prefer upskilling to replacement, aligning with Neohuman Capital Theory's prediction that AI adoption increases demand for new skills rather than decreasing employment (Pereira and Malik, 2015).

Industry-specific approaches to AI integration vary significantly, with security and HR services emphasising personalised training, while marketing combines reskilling with new hiring. These differentiated strategies reflect organisational efforts to develop collective AI literacy tailored to specific sector needs.

Several limitations must be acknowledged. First, the study focused exclusively on top Czech companies, limiting generalisability to other organisations or different national contexts. Second, the research captured a snapshot during ongoing AI implementation, while longitudinal data would better reveal evolving trends. Third, the study relied on organisational perspectives without examining employee experiences directly, potentially missing important insights about how workers perceive AI-driven transformations.

Future research should explore several promising avenues. Longitudinal studies could track how job transformations and competency requirements evolve as AI implementation matures. Comparative research across different organisational sizes, industries, and national contexts would enhance understanding of contextual factors influencing AI adoption strategies. Investigation into employee perspectives would complement organisational views, particularly regarding the effectiveness of reskilling programs. Research examining the development of specific AI competency frameworks for different roles could provide practical guidance for organisations. Finally, studies evaluating the return on investment from different AI integration approaches (reskilling versus hiring) would offer valuable insights for strategic decision-making.

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ABOUT AUTHORS

Lucie Depoo ORCID: 0000-0003-4296-875X (L.D.) – Ph.D., Associate Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: lucie.depoo@vse.cz.

Lenka Hajerová-Mullerová ORCID: 0009-0009-2527-7296 (L.H.) – Ph.D., Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: lenka.hajerova@vse.cz.

Zdeněk Kronberger ORCID: 0009-0002-8625-9285 (Z.K.) – Ph.D. candidate, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: zdenek.kronberger@vse.cz.

Gabriela Říhová ORCID: 0000-0001-8796-2656 (G.R.) – Ph.D., Assistant Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: gabriela.rihova@vse.cz.

Marek Stříteský ORCID: 0000-0002-0359-1200 (M.S.) – Ph.D., Assistant Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: marek.stritesky@vse.cz.

Marie Hořáková ORCID: 0009-0002-6931-8626 (M.H.) – Ph.D. candidate, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: marie.horakova@vse.cz.

Kateřina Legnerová ORCID: 0000-0002-3042-8142 (K.L.) – Ph.D., Assistant Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: katerina.legnerova@vse.cz.

Marcela Palíšková ORCID: 0009-0005-0877-3475 (M.P.) – Ph.D., Assistant Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: marcela.paliskova@vse.cz.

Otakar Němec ORCID: 0000-0002-5587-9505 (O.N.) – Ph.D., Associate Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: otakar.nemec@vse.cz.

David Šmíd ORCID: 0000-0001-9133-7837 (D.S.) – JUDr., Assistant Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: david.smid@vse.cz.

Tomáš Jurčík ORCID: 0009-0005-0812-6331 (T.J.) – Ph.D., Assistant Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: tomas.jurcik@vse.cz.

Martin Kopecký ORCID: 0009-0002-1736-1657 (M.K.) – Ph.D., Assistant Professor, Prague University of Economics and Business, Faculty of Business Administration, Department of HR Management, Czech Republic, e-mail: martin.kopecky@vse.cz.

AUTHOR CONTRIBUTIONS

Conceptualisation, L.D., M.S., M.H., K.L., O.N., D.S., T.J., M.K. and Z.K.; Methodology, L.D.; software, L.D.; Validation, L.D., Z.K. and G.R.; Formal analysis, L.D. and Z.K.; Investigation, Z.K. and G.R.; Resources, L.H.; Data curation, Z.K. and G.R.; Original draft preparation, L.D.; Review and editing, L.D.; Visualization, L.D.; Supervision, L.D.; Project administration, L.D., Z.K., M.S., M.H., K.L., O.N., D.S., T.J., M.K.; Funding acquisition, M.S.

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CONFLICTS OF INTEREST

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