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TRENDY A VÝZVY RODINNÉHO PODNIKANIA A NÁSTUPNÍCTVA X.

Umelá inteligencia a jej akceptácia v podnikovom manažmente

TRENDS AND CHALLENGES OF FAMILY BUSINESS AND SUCCESSION X.

Artificial intelligence and its acceptance in business management

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Zborník vedeckých statí prezentuje názory autorov na vybrané problémy ekonomiky a manažmentu, ktoré sa prejavujú v rodinných podnikoch, dotýkajú sa ich fungovania a v procese podnikového nástupníctva môžu pozitívne/negatívne ovplyvniť ich ďalšiu existenciu.

The collection of scientific papers presents the authors' opinions on selected problems of economics and management, which are reflected in family businesses, affect their functioning and can positively/negatively affect their further existence in the process of business succession.

Rozsah: 9,50 AH.

OBSAH
(CONTENT)

MEASURING PERSONAL CHARACTERISTICS IN THE CONTEXT OF AI ADOPTION: A REVIEW OF AVAILABLE INSTRUMENTS

Andriana Baziuk

Abstract

The increasing need to implement artificial intelligence in work processes has led to growing research interest in factors and barriers influencing AI adoption. In response, several AI adoption models have been proposed, among which Khanfar's model is one of the most comprehensive, as it incorporates factors at both the individual and organizational levels. However, certain factors - particularly personal characteristics - remain underexplored, especially from a measurement perspective. The aim of this study is to is to examine the role of personal characteristics in the adoption of AI technologies within the framework of Khanfar's model and to identify the most robust measurement tools by evaluating their validity and reliability. Based on a review of peer-reviewed empirical studies, the analysis identified a range of measurement tools applicable to this research context. The findings indicate that self-efficacy is the most frequently measured personal characteristic, supported by several well-established and psychometrically tested scales. In contrast, other characteristics – particularly personal self-image and personal development concern – are addressed far less frequently, revealing significant gaps in the existing measurement literature. These results highlight the need for further research focusing on the development and validation of robust measurement instruments for underexplored personal characteristics related to AI adoption.

JEL classification: *J24, O31, O33*
Keywords: *artificial intelligence, AI adoption, technology acceptance*

Introduction

The rapid development of artificial intelligence and the expanding capabilities that AI tools offer organizations have generated increasing interest in their implementation. However, decisions regarding AI adoption are influenced by a wide range of factors. Some of these emerge from the external environment, such as competitive pressure or customer demand for AI-based solutions, while others – such as the level of organizational readiness – are internal.

One of the most comprehensive approaches to systematizing these factors is the model proposed by Khanfar (2025), which builds on the Technology-Organization-Environment (TOE) framework. In Khanfar's model, these determinants are further developed across two levels of analysis: the organizational level and the individual level, each accompanied by specific examples of relevant variables.

But knowing about these influences is not enough. Companies need not only to understand which factors affect AI adoption but also to have tools to measure them and identify the areas where improvement is needed. Technological factors usually receive more attention because companies can influence them directly. By contrast, individual-level factors are measured much less often, even though personal characteristics strongly shape how employees accept and use AI. Therefore, this article focuses on identifying and reviewing measurement instruments for individual-level factors of AI adoption – specifically personal characteristics – based on the categories defined in Khanfar's model.

1 Current State of the Solved Problem at Home and Abroad

The potential benefits and opportunities of Artificial Intelligence (AI) have led to its rapid growth in the workplace, as confirmed by Eurostat (2025) data showing that 19.95% of EU enterprises used AI technologies in 2025. This represents a significant increase of 6.47 percentage points compared to 2024. However, a major gap remains between large corporations and small businesses; while 55.03% of large companies have adopted AI, only 17% of small enterprises have done the same (Eurostat, 2025). This disparity suggests that AI adoption, especially at the organizational level, remains challenging due to limited financial and human resources, as well as a lack of specialized knowledge. Several models explain the factors driving AI adoption at work, most of which categorize these drivers into technological factors, such as costs and ROI, organizational factors like readiness and culture, and environmental factors like competitive pressure. One of the most comprehensive recent frameworks is the model developed by Khanfar et al. (2025), which integrates both firm-level and individual-level factors based on a systematic literature review. These factors are deeply interconnected, as firm-level environments impact employee behavior, while individual traits like self-efficacy and AI literacy shape the overall organizational readiness for AI (Liu et al., 2025).

In Khanfar's model, individual factors are divided into three groups: individual perceptions and feelings, social factors, and personal characteristics. The most researched group is perceptions and feelings, often explored through classic theories like the Technology Acceptance Model (TAM), which includes perceived usefulness, ease of use, and trust in AI systems. While companies can influence these through training or hiring experienced staff, Khanfar's model suggests that this influence is moderated by personal characteristics, which remain the least studied group. This lack of research may be because these traits are often excluded from classic models like TAM or Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), making them harder to measure during the adoption process. However, researching them is vital because these factors are difficult to change and can act as serious barriers. For instance, self-efficacy positively impacts AI adoption (Ren, Guo, & Li, 2025) and boosts the willingness to take risks with AI to gain more benefits (Han et al., 2025). Similarly, individuals with high personal innovativeness are more likely to use AI products (Zhang et al., 2025). A willingness to acquire and transfer knowledge also improves performance and effort expectancy (Qahl & Yahya, 2024), much like previous ICT competence. Conversely, a lack of knowledge leads to resistance to change and skepticism about benefits (Alqaissi & Qtait, 2025). Finally, personal development plays a dual role; some employees avoid AI tools if they see them as a threat to their career growth, while others embrace them as an opportunity to develop new skills.

2 Research design and methodology

The aim of this article is to examine the role of personal characteristics in the adoption of AI technologies within the framework of Khanfar's model and to identify the most robust measurement tools by evaluating their validity and reliability. To achieve this aim, the following research questions were formulated:

- RQ1: What impact do the personal characteristics defined by Khanfar have on the process of AI adoption?
- RQ2: What measurement tools are currently available to quantify these characteristics, and which of them demonstrate the highest quality?

The object of analysis consists of measurement scales assessing personal characteristics included in Khanfar's model, namely: self-efficacy, personal innovativeness, knowledge sharing tendency, personal self-image, personal development concern, system use experience, ICT/AI knowledge, and ICT competence.

As a first step, the original study by Khanfar et al. (2025) was examined, and the primary sources referenced by the authors were reviewed to identify the measurement instruments used for these personal characteristics. Subsequently, an additional literature search was conducted to identify further relevant scales not explicitly mentioned in the original model. The literature search was carried out using the following databases: EBSCO, Web of Science, Scopus, and Google Scholar. Combinations of keywords related to AI adoption and individual characteristics were used, including terms such as AI adoption, personal characteristics, self-efficacy, personal innovativeness, ICT competence, measurement scale, and instrument. In addition, a manual search was performed by reviewing the reference lists of selected articles (cross-referencing method) to identify further relevant studies.

Only peer-reviewed journal articles published in English were included in the review. As the focus of this study was on specific measurement instruments, literature review articles were excluded. Only empirical studies that explicitly reported the use or development of measurement scales for the examined personal characteristics were considered. This methodological approach enabled a comprehensive and systematic coverage of the existing literature related to the measurement of personal characteristics in the context of AI adoption.

3 Research results

The analysis of the available literature reveals that personal characteristics are not equally represented in scientific research. While the influence of self-efficacy on AI adoption is extensively documented, other traits such as personal self-image or personal development concern are mentioned far less frequently, leading to fewer identified constructs for their measurement. The search results and the identified instruments are summarized in Table 1.

A notable trend in analyzed literature is the heavy reliance on adapted scales from general technology models rather than the creation of new, AI-specific instruments. While this approach keeps the theory consistent and shows high validity and reliability across studies, it might miss some unique AI features.

Self-efficacy

Among all personal characteristics, self-efficacy is the most frequently cited in the context of AI adoption. Numerous studies confirm both its direct and indirect positive impact. For instance, self-efficacy influences Perceived Ease of Use, which, according to TAM, indirectly affects the intention to use AI (Bröhl et al., 2019). It also significantly predicts Perceived Usefulness, the strongest driver of AI adoption (Liu et al., 2025). However, general self-efficacy does not always show a strong impact (Latikka et al., 2019). Consequently, researchers often specify Computer or Technological self-efficacy (Falebita & Kok, 2024). To address AI's unique nature, specialized tools like the AI Self-Efficacy Scale (AISES) (Wang et al., 2024) and professional-specific scales, such as the Teacher AI Competence Self-Efficacy (TAICS) (Chiu et al., 2024) have been developed. While these specialized scales show high reliability, many studies still rely on general scales adapted for specific contexts (Han et al., 2025), while some even measure it as a barrier, such as the "Lack of computer self-efficacy" (Gupta & Bhaskar, 2020).

Personal innovativeness

Personal innovativeness also demonstrates a significant direct positive influence on AI adoption and acts as a partial mediator between social influence and usage intention (Kandoth & Sekhar, 2022). Furthermore, personal innovativeness strengthens the impact of other factors like relative advantage and top management support (Pizam et al., 2022). In the analyzed studies, it was typically measured using adapted 4-item or 6-item scales.

Knowledge sharing tendency

Knowledge sharing tendency has a positive effect on key constructs like performance expectancy and directly affects behavioral intention (Gupta & Bhaskar, 2020). This relationship is complex and mutual: AI adoption can foster knowledge sharing, while a tendency to share knowledge acts as a crucial enabler for effective AI use (Hu et al., 2024). Most studies measured this construct using 7-point Likert scales adapted from previous research (Hu et al., 2024; Zamrudi et al., 2024).

Personal self-image

Research suggests that users are more likely to adopt AI innovations that align with their self-perception and enhance their status. In the workplace, perceived personal image fully mediates the negative impact of job insecurity on AI adoption (Dabbous et al., 2022). Researchers typically measure this using 3-item or 7-point Likert scales adapted from the TAM2 model (Bröhl et al., 2019).

Table 1
Overview of measurement scales used in AI adoption research

Study	Characteristics measured and measurement scale	Sample	Theoretical background	Validity
Wang et al, (2024)	AI Self-Efficacy (7-point Likert scale)	314 Internet users in Taiwan	Social cognitive theory (SCT)	Cronbach's α = 0.958
Ren et al, (2025)	Self-efficacy (IROWSE - 4-point Likert scale and SE-HRI -6-point Likert scale), Digital competence (5-point scale)	921 Chinese university students	Constructivist Learning Theory, TAM, Cognitive Load Theory, Identical Elements Theory, Control–Value Theory of Achievement Emotions.	Cronbach's α: 0.94 for Digital competence scale; 0.91 for SE-HRI; 0.90 for IROWSE.
Falebita & Kok (2024)	Technological self-efficacy (5-point Likert scale)	176 undergraduate students from a public university in Nigeria	TAM	Cronbach's α: 0.814,
Chiu et al., (2024)	Self-efficacy (5-point scale)	434 teachers from Hong Kong schools	Bandura's Self-Efficacy Theory	Cronbach's α values > 0.87
Latikka et al. (2019)	General Self-efficacy (6-point scale)	Care work staff (n = 501 experienced users) in Finland.	Bandura's theory of self-efficacy	Cronbach's α = 0.814
Han et al. (2025)	AI usage and Self-efficacy (5-point scale)	442 employees in China	SCT	Cronbach's α: 0.845 for AI Usage; 0.804 for SE;
Bröhl et al., (2019)	Self-efficacy, Image (7-point Likert scale)	1326 operational production workers (Germany, Japan, China, USA).	TAM, TAM 2, TAM 3, UTAUT	Not mentioned
Gupta & Bhaskar (2020)	Lack of computer self-efficacy, Personal innovativeness, Personal development concern, Lack of AI knowledge (Saaty's nine-point scale for pair-wise comparisons)	32 teachers from higher educational institutions in India	Conceptual frameworks developed from existing ICT adoption literature.	Consistency ratio <0.10
Pizam et al. (2022)	Innovativeness (7-point Likert scale)	1077 hotel managers across 11 countries	TOE framework	Composite Reliability > 0.8
Kandoth & Sekhar (2022)	Personal innovativeness (4-point scale)	440 students from Indian universities	Theory of Reasoned Action (TRA), TAM, UTAUT.	Cronbach's α = 0.751

Zamrudi et al. (2024)	Knowledge Sharing, Tech Savvy (7-point Likert scale)	213 business students	Conceptual frameworks developed from existing ICT adoption literature.	Cronbach's α = 0.924 - 0.976
Qahl & Yahya (2024)	Knowledge Sharing (Closed-ended survey/ Qualitative interviews)	Saudi faculty members in higher education institutions	UTAUT 2	X
Hu et al. (2024)	Knowledge Sharing (5-point sca	364 employees from a large Chinese travel company	SCT	Cronbach's α = 0.925
Dabbous et al. (2022)	Self-image (7-point scale)	203 employees working in Lebanon	TAM and TRA	Cronbach's α = 0.952
Haq et al, (2025)	Personal development concern (7-point Likert scale)	285 university students in the UAE	Integrated AI acceptance-avoidance model (IAAAM), Technology Threat Avoidance Theory (TTAT),.	Cronbach's α = 0.90
Cao et al. (2021)	Personal development concern (7-point Likert scale)	269 UK business managers	UTAUT, TTAT, IAAAM	Cronbach's α = 0.88
Nazaretsky et al. (2022)	ICT/AI knowledge (Experiment)	6 high school biology teachers from Israel	TAM, resistance to organizational change theory	Inter-rater agreement ~95%
Caner-Yıldırım (2025)	Information and Data Literacy, Habit (5-point Likert scale)	404 undergraduate students	DigComp, UTAUT2	Cronbach's α = 0.866 - 0.948
Vichitkraivin & Naenna (2021)	Lack of technical knowledge (5-point Likert scale)	466 medical staff in Thai government hospitals	UTAUT and Pagani's barrier model	Cronbach's α > 0.76
Liu et al. (2025)	Self-efficacy, Multimodal Literacy (5-point Likert scale)	498 university students in China	TAM	Cronbach's α > 0.88

Source: Authors' own work

Personal development concern

Personal development concern – the fear that AI might prevent learning from one's own experience ⍰ generally has a negative impact on intention to use AI (Haq et al., 2025). However, this hypothesis was not confirmed in a study of UK business managers (Cao, 2021), where authors used self-developed indicators focusing on career development and loss of control over personal growth.

System use experience

System use experience refers to a person's prior experience with AI. While there is no single established name for this construct, with some researchers calling it "AI usage" (Han et al., 2025), its importance is well-documented. For instance, Han et al. (2025) confirmed that experience influences AI adoption through self-efficacy and risk perception, using a 3-item scale adapted from Tang et al. (2023). Similarly, students with past experience tend to show higher enthusiasm and confidence when interacting with AI tools (Alqaissi & Qtait, 2025).

ICT/AI knowledge and ICT competence

These constructs have a significant impact on the behavioral intention to use AI and can act as either a barrier (in the case of a lack of knowledge) or a driving force (in the case of high competence) (Gupta & Bhaskar, 2020). Most studies confirm that a high level of ICT or digital competence correlates positively with AI adoption, as this competence reduces perceived complexity and increases user confidence (Liu et al., 2025). It has also been confirmed that digital competence often serves as the foundation for building confidence, which directly affects interaction with AI (Zhang et al., 2025). Since ICT/AI knowledge and ICT competence are closely interrelated, many scales measure both constructs simultaneously or focus specifically on competencies that reflect practical skills, as theoretical ICT knowledge is a prerequisite for them.

To measure these, researchers typically use comprehensive scales employed in many international studies, such as DigComp (Vuorikari et al., 2022), the Digital Competence Scale for University Students (Caner-Yıldırım 2025), or the adapted Multimodal Literacy scale by Bulut et al. (2015). However, researchers note that while general ICT competence is useful, the successful adoption of Generative AI requires new, more advanced digital skills than those provided by traditional frameworks. These include skills such as prompt-writing and the critical evaluation of AI-generated content (Caner-Yıldırım, 2025), suggesting that existing scales need further refinement.

4 Discussion

The analysis shows that the study of how personal traits affect AI adoption is growing fast, with the majority of identified studies published after 2022. With the constant use of AI in many areas, this trend is expected to continue. Our review found a wide range of scales, most of which show good reliability and are based on well-known theories. However, there is a gap in how different traits are covered.

Self-efficacy remains the most frequently measured construct, with authors distinguishing between general, technological, and AI-specific self-efficacy. Our findings confirm that it significantly predict AI adoption behaviors. While the instruments used generally demonstrate high internal consistency (Cronbach's alpha often exceeding 0.8), they vary substantially in item count and scoring formats (primarily 5-point vs. 7-point Likert scales), which poses challenges for cross-study syntheses.

Furthermore, personal innovativeness continues to be a central variable, often analyzed through the lens of traditional adoption theories such as TAM, TOE, or UTAUT. Along with innovativeness, AI literacy and digital competence have emerged as critical predictors; users with higher ICT knowledge and literacy demonstrate a significantly higher intention for AI tools use.

The least studied personal characteristics are those that act as barriers to AI adoption, such as a lack of AI knowledge and personal development concerns. Including these factors in models like TTAT or IAAAM gives a better picture of why people avoid AI, not just why they adopt it. Still, these negative factors are not researched enough, and there is a lack of standard scales to measure them.

This study contributes by providing a summary of measurement tools that help track how personal characteristics influence the intention to use AI. However, there are some limits to consider: since the field is changing so fast, our review focuses on very recent data and English-language papers. Also, the variety of scales makes it hard to compare the results directly.

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POROVNÁVACIA ANALÝZA NÁSTROJOV NA MERANIE FAKTOROV OSVOJENIA UMELEJ INTELIGENCIE

Karol Csiffáry – Matúš Hornáček

Abstract
V posledných rokoch sa umelá inteligencia stáva integrálnou súčasťou fungovania ľudskej spoločnosti nakoľko jej pozitívne pôsobenie pri správnom riadení prináša všeobecný osoh. V rámci fungovania spoločností poskytuje veľké úspory z nákladov a zvyšuje konkurenčnú výhodu tých spoločností, ktoré úspešne zvládli jej implementáciu do svojej štruktúry a zavedených procesov. Publikácia sa venuje štúdiu nástrojov na porovnanie faktorov, ktoré môžu slúžiť ako vhodné indikátory pre posúdenie úspešnosti zavedenia umelej inteligencie do spoločnosti v jej úvodných fázach, kedy dochádza k takzvanému osvojeniu umelej inteligencie spoločnosťou.

JEL classification: *M11, M15*
Keywords*: umelá inteligencia, osvojenie umelej inteligencie, faktory osvojenia, nástroje na meranie faktorov osvojenia*

Úvod

Umelá inteligencia sa stala v posledných rokoch neoddeliteľnou súčasťou našich životov. V súčasnosti už našla uplatnenie v rôznych oblastiach nášho každodenného života ako sú napríklad zdravotníctvo, financie alebo verejná správa. Od umelej inteligencie (z anglického Artificial Intelligence alebo tiež AI) sa očakáva zvyšovanie efektívnosti, skvalitňovanie rozhodovania a vytváranie ekonomickej hodnoty (Davenport a Ronanki, 2018). Napriek uvedeným pozitívnym vlastnostiam však adopcia AI v organizáciách stále čelí významným prekážkam. Dlhodobejšie štúdie poukazujú na skutočnosť, že samotná dostupnosť technológie vo všeobecnosti nepostačuje na jej úspešné zavedenie v rámci organizácie (Rogers, 2003). V súvislosti s umelou inteligenciou je problém ešte zložitejší nakoľko v konkrétnej organizácii už predpokladá zavedenú IT infraštruktúru (Alsheibani a kol., 2018). Aj na základe uvedeného preto spoločnosti dôsledne zvažujú viacero faktorov, ktoré im dajú odpoveď˝ o možnosti osvojenia si technológie umelej inteligencie. Medzi skúmané faktory patrí návratnosť investícií, ďalej očakávané prínosy systémov umelej inteligencie, technologická vyspelosť riešenia, kompatibilita s existujúcou IT infraštruktúrou, spoľahlivosť a presnosť systémov, náklady spojené s implementáciou a prevádzkou a schopnosť organizácie integrovať umelú inteligenciu do už fungujúcich procesov (Bughin a kol., 2019; Rai a kol., 2020). Uvedené faktory sa objavujú vo viacerých teoretických modeloch osvojenia rôznych technológií, avšak použité metodiky ich merania sa rôznia v závislosti od autora štúdie. Autori týchto výskumov sa doteraz zameriavali prevažne na identifikáciu faktorov osvojenia a ich vzťahov k zámerom osvojenia alebo organizačnému výkonu, avšak nástroje merania vďaka ktorým sú uvedené faktory zaznamenávané sú skúmané menej čo sťažuje objektívne porovnávanie použitých metodík. Cieľom nášho článku je poskytnúť aktuálny literárny prehľad z oblasti identifikácie a analýzy nástrojov merania faktorov osvojenia umelej inteligencie v organizáciách. Za kľúčové sme zvolili nasledovné faktory: návratnosť investícií, výhody systémov umelej inteligencie, zrelosť systému, kompatibilita s IT infraštruktúrou, spoľahlivosť a presnosť systému, náklady na integráciu systémov umelej inteligencie a technológií. Náš článok analyzuje vybrané publikácie, ktoré práve vyššie uvedené faktory skúmali prostredníctvom kvantitatívnych, kvalitatívnych alebo zmiešaných metodologických prístupov.

1 Súčasný stav riešenej problematiky doma a v zahraničí

Súčasný stav výskumu osvojovania umelej inteligencie organizáciami poskytuje značnú rôznorodosť v metodológii a preto bola na vytvorenie vhodného literárneho prehľadu študovanej oblasti použitá technika scoping review, ktoré umožňuje analyzovať dostupnú literatúru bez potreby striktného hodnotenia kvality skúmaných štúdií typickej pre systematické prehľady (Arksey a O'Malley, 2005). Uvedený prístup je vhodný pre dynamické oblasti ako je osvojovanie umelej inteligencie, ktoré zahŕňa veľké množstvo prístupov a metodológií. V súčasnosti sa osvojovanie umelej inteligencie modeluje prevažne prostredníctvom troch modelov, ktorými sú TOE, DOI a UTAUT/TAM. TOE je skratka z „Technology, Organization, Environment" alebo tiež „Technológia, Organizácia, Prostredie" a hodnotí technologické a organizačné determinanty osvojenia technológií. DOI je skratka zo sloveného spojenia „Diffusion of Innovations" alebo tiež „Šírenie inovácií" a nachádza faktory ako relatívna výhoda, kompatibilita a zložitosť nových technológií. UTAUT/TAM sú skratky zo slovných spojení „Unified Theory of Acceptance and Use of Technology" (UTAUT) alebo tiež „Jednotná teória akceptácie a používania technológií" a „Technology Acceptance Model" (TAM), čo znamená „Model akceptácie technológií", ktoré objasňujú užívateľské úmysly a správanie pri prijímaní technológií. Viaceré z týchto modelov neboli pôvodne navrhnuté pre štúdium umelej inteligencie avšak ukázali sa ako vhodné a preto sa v súčasnosti používajú. Mnohé štúdie tieto modely adaptovali a zároveň rozšírili o faktory relevantné pre umelú inteligenciu. Ich použitie umožňuje systematické meranie faktorov osvojenia si umelej inteligencie organizáciami.

2 Výskumný dizajn a metodológia

V príspevku nás vzhľadom na povahu prehľadového článku v štýle scoping review zaujímali tieto otázky:

1. Ktoré publikácie skúmajú faktory osvojenia umelej inteligencie v organizáciách?
2. Ktoré z metodologických prístupov v nich boli použité?
3. Ktoré nástroje a škály sa v súčasnosti používajú na meranie faktorov osvojenia umelej inteligencie?
4. Z ktorých teoretických rámcov vychádzajú uvedené publikácie?

Do prehľadu boli zahrnuté len štúdie, ktoré spĺňali kritériá empirického výskumu, explicitné zameranie sa na osvojenie alebo zavedenie umelej inteligencie v organizáciách, skúmanie minimálne jedného z uvedených faktorov osvojenia si umelej inteligencie, publikácia musela byť v recenzovanom vedeckom časopise alebo konferenčnom zborníku, publikácia bola napísaná v anglickom jazyku. Vybrané publikácie boli analyzované pomocou deskriptívnej a tematickej analýzy. U každej publikácie boli zaznamenané informácie ako názov štúdie, metodológia, nástroje merania, vzorka objektov, cieľ výskumu a teoretické východiská.

3 Výsledku výskumu

Faktory merania osvojenia umelej inteligencie

Rámec technológia–organizácia–prostredie (Technology–Organization–Environment Framework, TOE)

Tento rámec vychádza v podmienkach osvojenia umelej inteligencie z predpokladu, že je ovplyvnené technologickými charakteristikami ako je napríklad kompatibilita, komplexnosť, relatívna výhoda a organizačnými faktormi ako je veľkosť organizácie, podpora manažmentu spoločnosti, prípadne tiež environmentálnymi podmienkami (Tornatzky a Fleischer, 1990). Niekedy býva tiež rozšírený o parametre ako je napríklad systémová vyspelosť a integrácia s existujúcou IT infraštruktúrou.

Šírenie inovácií (Diffusion of Innovations, DOI)

Táto teória vysvetľuje osvojenie technológií prostredníctvom vlastností konkrétnej inovácie ako môže byť napríklad relatívna výhoda poskytovaná danou inováciou, kompatibilita, zložitosť inovácie a pozorovateľnosť (Rogers, 2003). Viaceré publikáciu ju používajú na presnejší popis prínosov systémov umelej inteligencie a ich kompatibility s existujúcimi technológiami.

Model akceptácie technológií (Technology Acceptance Model, TAM) a Akceptácia informačných technológií používateľmi (User acceptance of information technology, UTAUT)

Hoci boli TAM (Davis, 1989) a UTAUT (Venkatesh a kol., 2003) pôvodne navrhnuté na individuálnej úrovni, viaceré štúdie ich adaptovali na štúdium organizovania umelej inteligencie. Hoci boli oba uvedené modely pôvodne navrhnuté samostatne, v súčasnosti sa používajú v kontexte adaptácie na organizačný kontext a vnímaných prínosov umelej inteligencie, na čo sa používajú konštrukty očakávaný výkon a vnímaná užitočnosť.

Rozšírenia špecifické pre prijatie umelej inteligencie (AI-specific Adoption Extensions)

V reakcii na špecifiká AI vznikajú rozšírené modely osvojenia, ktoré zohľadňujú faktory ako spoľahlivosť algoritmov, presnosť výstupov, transparentnosť rozhodovania a dátovú pripravenosť organizácie (Rai a kol., 2020). Tieto prístupy poukazujú na potrebu špecifických meracích nástrojov, ktoré presahujú tradičné modely osvojenia informačných technológií organizáciami.

Návratnosť investícií (Return on Investment, ROI)

Predstavuje jeden z najvýznamnejších faktorov vplývajúcich na osvojenie umelej inteligencie v organizáciách. Je to pomer medzi finančným príspevkom vytvoreným umelou inteligenciou a nákladmi spojenými s jej spustením a údržbou (Bughin a kol., 2019). Veľká časť prínosov umelej inteligencie v organizácii sa však nedá priamo vyčísliť, nakoľko ide o zlepšenie fungovania vnútorných procesov spoločnosti (Davenport a Ronanki, 2018). Zaujímavým prístupom bolo meranie návratnosti investícií prostredníctvom Likertových škál, kde sa hodnotilo očakávané zníženie nákladov, zvýšenie produktivity a zlepšenie finančnej výkonnosti spoločnosti (Wamba a kol., 2021). Uvedený faktor je však nutné používať so zreteľom na konkrétnu oblasť, na ktorú má byť aplikovaný. Napríklad v podmienkach zdravotníctva bola použitá kombinácia objektívnych a subjektívnych metrík, kde sa hodnotila miera splnenia plánovaných finančných cieľov a úspora nákladov (Adler-Milstein a kol., 2023). Významné využitie má ROI ako heuristický nástroj pri rozhodovaní v skorých fázach osvojenia umelej inteligencie (Alsheibani a kol., 2018).

Výhody systémov umelej inteligencie (Benefits of AI Systems)

Výhody umelej inteligencie možno definovať ako zvýšenie výkonnosti systému, respektíve organizácie, zvýšenie kvality procesov a zlepšenie strategickej pozície organizácie (Rai a kol., 2020). Uvedené zlepšenia môžu spočívať v lepšej automatizácii, vyššej rýchlosti alebo lepšom rozhodovaní a v konečnom dôsledku tak poskytujú svojej organizácii konkurenčnú výhodu. Umelá inteligencia sa môže implementovať aj napríklad na zvýšenie presnosti predpovedí a zlepšenie zákazníckych služieb (Ransbotham a kol., 2020). Pri analýze rozhovorov v kvalitatívnych publikácií sú prínosy umelej inteligencie identifikované induktívne (napr. Davenport a kol., 2020). V kvantitatívnych výskumných publikáciách sú prínosy umelej inteligencie vnímané predovšetkým prostredníctvom vnímanej užitočnosti a zlepšenia výkonu (Davis, 1989; Rogers, 2003).

Vyspelosť systému (Maturity of the System)

Vyspelosť systému poukazuje na technologickú a procesnú úroveň pripravenosti implementácie umelej inteligencie v organizácii (Gartner, 2021). Pokročilé systémy umelej inteligencie sú stabilne zainkorporované interných procesov spoločností a dajú sa škálovať. Na meranie vyspelosti systému sa v súčasnosti najviac používajú modely, ktoré hodnotia všetky fázy implementácie a prevádzky umelej inteligencie, od fázy experimentovania až po jej plnú integráciu (Alsheibani a kol., 2018). V kvantitatívnych štúdiách sa môžu úrovne vyspelosti systému transformovať do Likertových škál, čím sa dajú použiť v SEM modeloch (Wamba a kol., 2021). Lichtenthaler použil pri multisektorovej analýze osvojenia umelej inteligencie ako nástroj merania stupne vyspelosti umelej inteligencie (Lichtenthaler, 2020).

Kompatibilita s IT infraštruktúrou (Compatibility with IT Infrastructure)

Kompatibilita je definovaná ako rozsah, v ktorom sa nová technológia zhoduje s už existujúcimi systémami, procesmi a hodnotami spoločnosti (Rogers, 2003). V rámci umelej inteligencie iba o schopnosť prepojenia s už existujúcou informačnou štruktúrou, kam patrí softvér, databázy a zabezpečené dátové toky (Kamble a kol., 2020). Nekompatibilita s uvedenými typmi už existujúcej infraštruktúry v rámci spoločnosti často vedie k značným problémom v procese osvojenia umelej inteligencie organizáciou (Alsheibani a kol., 2018). V jednej výskumnej publikácii autori merali mieru kompatibility osvojenia umelou inteligenciou v rámci výrobnej spoločnosti prostredníctvom analýzy technologickej úrovne prepojenia a jej potreby s už existujúcou IT a dátovou infraštruktúrou v rámci uvedenej spoločnosti (Kamble a kol., 2020). Kompatibilita môže byť tiež meraná napríklad ako schopnosť systémov umelej inteligencie prepojiť sa v rámci spoločnosti s platformami plánovania podnikových zdrojov a riadením dodávateľského reťazca (Queiroz a kol., 2021). Kompatibilita je v súčasnosti chápaná ako dynamický, meniaci sa a vyvíjajúci proces, ktorý závisí od technologickej rozvinutosti organizácie a stupňa osvojenia si umelej inteligencie (Kinkel a kol., 2022).

Spoľahlivosť a presnosť systému (System Reliability and Accuracy)

Ide o špeciálne faktory osvojenia umelej inteligencie, ktoré prekonávajú modely osvojenia bežných IT technológií. Sleduje sa u nich predovšetkým stabilita a identickosť prejavov umelej inteligencie v kontexte výkonu systémov a taktiež správnosť generovaných algoritmov (Rai a kol., 2020). Uvedené faktory sú kľúčové v sektoroch s vysokými nárokmi na bezpečnosť a presnosť, kam patria napríklad financie alebo zdravotníctvo (Adler-Milstein a kol., 2023). Ako prediktory osvojenia umelej inteligencie v rámci takzvaného SEM modelu (Modelovania štrukturálnych rovníc, SEM) sú zahrnuté konštrukty hodnotiace dôveru vo výstupy umelej inteligencie, stabilitu systému a konzistentnosť výkonu (Kumar a kol., 2021). Hybridným prístupom je v tomto prípade zase hodnotenie spoľahlivosti systémov umelej inteligencie v zdravotníctve na základe miery výskytu chýb a potreby ich opravy človekom (Adler-Milstein a kol., 2023). Algoritmová dôvera identifikovaná Sarkerom a jeho tímom je považovaná za kľúčový predpoklad pre úspešné osvojenie umelej inteligencie. V kontexte toho sú pri vzniku dôvery voči umelej inteligencii kľúčové spoľahlivosť a presnosť (2022).

Náklady na systémy umelej inteligencie (Cost of AI Systems)

Predovšetkým pre malé a stredné podniky predstavujú náklady na implementáciu a prevádzku jednu z výrazných bariér pri zavedení systémov umelej inteligencie v spoločnosti (Bughin a kol., 2019). V modeloch osvojenia umelej inteligencie sú náklady chápané ako negatívny prediktor (Kamble a kol., 2020). Niektorí autori tiež merali náklady na osvojenie umelej inteligencie v spoločnosti pomocou položiek z oblasti finančnej náročnosti zavedenia, dostupných zdrojov a nákladov na zapojenie do systémov spoločnosti (Zhang a kol., 2022). Negatívny vplyv na úspešné osvojenie umelej inteligencie v rámci spoločnosti majú tiež takzvané vnímané náklady, pričom ich vplyv závisí od veľkosti spoločnosti a úrovne jej zavedených technológií (Chatterjee a kol., 2021). Mnohé projekty z oblasti osvojenia umelej inteligencie bývajú tiež v časovom harmonograme posunuté, nakoľko spoločnosti v úvodnej fáze plánovania častokrát podcenia náklady na vývoj a prevádzku umelej inteligencie (Alsheibani a kol., 2018).

Integrácia technológií (Technology Integration)

V prípade osvojenia umelej inteligencie ide o schopnosť spoločnosti efektívne zaviesť a spojiť systémy umelej inteligencie s existujúcou vnútornou organizačnou štruktúrou a procesmi spoločnosti (Rai a kol., 2020). Úspešné zavedenie umelej inteligencie vedie k zmene vnútorných pracovných a rozhodovacích procesov v organizácii (Sarker a kol., 2022). Zaujímavá je publikácia venujúca sa schopnosti plne aplikovať umelú inteligenciu do systémov informačných technológií v rámci spoločnosti pôsobiacej v rámci dodávateľských reťazcov (Queiroz a kol., 2021). Zaujímavý je poznatok, že vyššia technologická komplexnosť v rámci organizácie naopak znižuje pravdepodobnosť osvojenia umelej inteligencie uvedenou organizáciou (Kamble a kol., 2020). Pre úspešnú implementáciu umelej inteligencie v rámci organizácie je potrebné zabezpečiť rovnaký rozvoj ako technológií, tak aj školenie personálu aby nedošlo k odporu zamestnancov k implementácii umelej inteligencie (Sarker a kol., 2022).

Porovnávacia analýza nástrojov na meranie faktorov

Z analyzovaných štúdií vyplýva jasná preferencia autorov používať v rámci kvantitatívnych výskumných dizajnov predovšetkým dotazníkové metódy, predovšetkým pri štúdiu faktorov ako je návratnosť investícií, náklady na systémy umelej inteligencie, kompatibilita s existujúcou technologickou infraštruktúrou a výhody systémov umelej inteligencie. V rámci kvalitatívneho výskumného dizajnu boli pri analýze integrácie technológií a presnosti systému použité predovšetkým rozhovory a prípadové štúdie. Použitými dominantnými meracími nástrojmi boli Likertove škály, proxy ukazovatele ako vnímaná užitočnosť a zložitosť implementácie a v špeciálnych prípadoch ako je zdravotníctvo aj hybridné prístupy, kombinujúce oba predchádzajúce.

Tabuľka 1
Zjednocujúci prehľad výskumných publikácií o faktoroch osvojenia umelej inteligencie

Publikácia	Metodika	Nástroje na meranie	Vzorka	Cieľ štúdie	Teoretický základ
Adler-Milstein a kol., 2023.	Kvantitatívny prieskum	Položky vnímanej návratnosti investícií, spoľahlivosti a finančného vplyvu	Manažéri v systémoch zdravotnej starostlivosti v Spojených štátoch amerických	Ocenenie hodnoty a výsledkov umelej inteligencie v zdravotníctve	Zavádzanie informačných technológií v zdravotníctve, organizačná výkonnosť
Alsheibani a kol., 2018.	Kvalitatívna (rozhovory, prípadová štúdia)	Rámec pripravenosti umelej inteligencie, tematické kódovanie	21 viacsektorových organizácií	Posúdenie pripravenosti umelej inteligencie a bariér jej prijatia	Rámec technológia-organizácia-prostredie (TOE)
Bughin a kol., 2019.	Zmiešaná (prieskum / ekonomické modelovanie)	Ukazovatele ekonomického vplyvu, aproximácie návratnosti investícií	Globálne medziodvetvové spoločnosti	Odhad vplyvu umelej inteligencie na makro a firemnej úrovni	Tvorba ekonomickej hodnoty, digitálna transformácia
Chatterjee a kol., 2021.	Kvantitatívna (analýza založená na literatúre)	Schéma kódovania bariér a hnacích síl prijatia	Predchádzajúce empirické štúdie	Syntetizovanie determinantov prijatia umelej inteligencie	Rámec technológia-organizácia-prostredie (TOE), model akceptácie technológie (TAM), Šírenie inovácií (DOI)
Davenport a Ronanki, 2018.	Kvalitatívna (analýza prípadov)	Deskriptívne ukazovatele výkonnosti	Veľké spoločnosti	Identifikácia praktických prípadov použitia a výhod umelej inteligencie	Teória inovácií založená na praxi
Davenport a kol., 2020.	Zmiešané (prieskum / rozhovory)	Stupnica vnímaných výhod umelej inteligencie	Marketingoví manažéri	Preskúmanie vplyvu umelej inteligencie na marketingovú výkonnosť	Model akceptácie technológie (TAM), Šírenie inovácií (DOI)
Gartner, 2021.	Koncepčné / aplikované	Úrovne vyspelosti umelej inteligencie	Referenčné hodnoty v odvetví	Vypracovanie modelu hodnotenia vyspelosti umelej inteligencie	Teória vyspelosti modelu
Kamble a kol., 2020.	Kvantitatívne (Modelovanie štrukturálnych rovníc metódou parciálnych	Kompatibilita, náklady, zložitosť Likertových škál	194 výrobných spoločností v Indii	Identifikácia faktorov a bariér pri zavádzaní umelej inteligencie	Rámec technológia-organizácia-prostredie (TOE)

	najmenších štvorcov, PLS-SEM)				
Kinkel a kol., 2022.	Kvalitatívne (prípadové štúdie)	Analýza procesu, protokol pohovoru	Výrobné spoločnosti v Európskej únii	Analyzovanie integrácie umelej inteligencie v produkčnom prostredí	Teória sociotechnických systémov
Kumar a kol., 2021.	Kvantitatívne (Modelovanie štrukturálnych rovníc, SEM)	Škály vnímanej spoľahlivosti, presnosti a dôvery	312 manažérov z oblastí obchodu a informačných technológií	Preskúmanie dôvery a spoľahlivosti systémov umelej inteligencie	Rozšírenie modelu akceptácie technológie (TAM), teória dôvery
Lichtenthaler, 2020.	Zmiešané (koncepčné / empirické)	Fázy vyspelosti umelej inteligencie	Multisektorové organizácie	Štúdium strategickej transformácie umelej inteligencie	Teória dynamických schopností
Queiroz a kol., 2021.	Kvantitatívne (Modelovanie štrukturálnych rovníc, SEM)	Integrácia technológií, škály kompatibility	201 manažérov z oblasti riadenia dodávateľského reťazca (SCM)	Preskúmanie zavádzania umelej inteligencie v dodávateľských reťazcoch	Rámec technológia-organizácia-prostredie (TOE), Šírenie inovácií (DOI)
Rai a kol., 2020.	Koncepčný	Koncepčný rámec	-	Definovanie hybridných systémov človeka a umelej inteligencie	Teória digitálnych platforiem
Ransbotham a kol., 2020.	Kvantitatívny (rozsiahly prieskum)	Vnímané výhody umelej inteligencie, škály schopností učenia	3000 manažérov	Posúdenie organizačnej hodnoty umelej inteligencie	Teória organizačného učenia
Rogers, 2003.	Koncepčný	Konštrukcie atribútov inovácie	-	Vysvetlenie šírenia inovácií	Šírenie inovácií (DOI)
Sarker a kol., 2022.	Kvalitatívne (rozhovory)	Algoritmické konštrukty dôvery	Manažéri a používatelia umelej inteligencie	Analyzovanie formovania dôvery v umelej inteligencii	Sociotechnická a dôveryhodná teória
Tornatzky a Fleischer, 1990.	Konceptuálna	Škála podľa Rámca technológia-organizácia-prostredie (TOE)	-	Vysvetlenie zavádzania organizačných technológií	Rámec technológia-organizácia-prostredie (TOE)
Venkatesh a kol., 2003.	Kvantitatívna (validácia modelu)	Škála podľa jednotnej teórie akceptácie a	Individuálni používatelia	Vysvetlenie akceptácie technológie	Jednotná teória akceptácie a používania technológií (UTAUT)

		používania technológií (UTAUT)			
Wamba a kol., 2021.	Kvantitatívna (Modelovanie štrukturálnych rovníc metódou parciálnych najmenších štvorcov, PLS-SEM)	Návratnosť investícií, zrelosť, ukazovatele výkonnosti	297 manažérov	Prepojenie prijatia umelej inteligencie s výkonnosťou firmy	Rámec technológia-organizácia-prostredie (TOE), model založený na zdrojoch (RBV)
Zhang a kol., 2022.	Kvantitatívna (Modelovanie štrukturálnych rovníc metódou parciálnych najmenších štvorcov, PLS-SEM)	Vnímané náklady, stupnice pripravenosti	268 manažérov malých a stredných podnikov (SME)	Identifikácia prekážok brániacich prijatiu umelej inteligencie	Rámec technológia-organizácia-prostredie (TOE)

Zdroj: vlastné spracovanie

Tabuľka 2
Mapovanie faktorov osvojenia umelej inteligencie vo výskumných publikáciách (matica: Publikácie × Faktory osvojenia umelej inteligencie)

Publikácia	Návratnosť investícií	Výhody umelej inteligencie	Vyspelosť systému	Kompatibilita s IT	Spoľahlivosť a presnosť	Náklady na umelú inteligenciu	Technologická Integrácia
Adler-Milstein a kol., 2023.	▲	▲	∗	∗	▲	∗	∗
Alsheibani a kol., 2018.	∗	∗	▲	▲	□	▲	▲
Bughin a kol., 2019.	▲	▲	∗	□	□	∗	□
Chatterjee a kol., 2021.	∗	▲	□	▲	□	▲	∗
Davenport a Ronanki, 2018.	∗	▲	∗	□	□	□	∗
Davenport a kol., 2020.	□	▲	□	□	□	□	∗
Gartner, 2021.	□	□	▲	∗	□	□	▲
Kamble a kol., 2020.	∗	▲	□	▲	□	▲	∗
Kinkel a kol., 2022.	□	∗	▲	▲	□	□	▲
Kumar a kol., 2021.	□	∗	□	□	▲	□	∗
Lichtenthaler, 2020.	∗	▲	▲	□	□	□	▲
Queiroz a kol., 2021.	∗	▲	□	▲	□	▲	▲
Rai a kol., 2020.	□	□	□	□	∗	□	▲
Ransbotham a kol., 2020.	∗	▲	□	□	□	□	∗
Sarker a kol., 2022.	□	□	□	□	▲	□	▲
Tornatzky a Fleischer, 1990.	□	□	□	▲	□	□	□
Venkatesh a kol., 2003.	□	▲	□	□	□	□	□
Wamba a kol., 2021.	▲	▲	▲	▲	□	∗	∗
Zhang a kol., 2022.	□	∗	∗	▲	□	▲	∗

Zdroj: vlastné spracovanie

Legenda:

▲ = faktor bol meraný explicitne
∗ = faktor bol meraný implicitne / proxy meranie
□ = faktor nebol skúmaný

Tabuľka 3
Porovnanie faktorov osvojenia umelej inteligencie

Faktor	Typ merania	Dominantná metodológia	Hlavné obmedzenia
Návratnosť investícií	Vnímaný ekonomický prínos	Kvantitatívna	Nedostatok objektívnych dát
Výhody umelej inteligencie	Vnímaná užitočnosť / poskytovaná výhoda	Kvantitatívna	Subjektívnosť
Vyspelosť systému	Modely vyspelosti systému / pripravenosť škály	Kombinovaná	Neštandardizované modely
Kompatibilita s IT	Likertove škály	Kvantitatívna	Technologická generalizácia
Spoľahlivosť a presnosť	Vnímaná spoľahlivosť	Kombinovaná	Slabá validácia
Náklady na umelú inteligenciu	Vnímané náklady	Kvantitatívna	Absencia celkových nákladov na vlastníctvo
Technologická Integrácia	Komplexita / pripravenosť	Kombinovaná	Statické merania

Zdroj: vlastné spracovanie

Z vyššie uvedenej tabuľky porovnaní faktorov osvojenia umelej inteligencie vyplýva, že ekonomické a technologické faktory sú v doteraz publikovaných výskumoch metodologicky lepšie uchopené než faktory spojené s dôverou, presnosťou a integráciou AI do organizačných procesov čo môže byť spôsobené prirodzene vyššou mierou exaktnosti a ľahšou merateľnosťou a z toho vyplývajúcou porovnateľnosťou výsledkov u technologických a ekonomických faktorov než u faktorov zameraných viac na subjektívne hodnotenie.

Záver

Na základe analýzy uvedených literárnych zdrojov sa nám podarilo nájsť niektoré medzery v rámci záberu súčasného výskumu v oblasti osvojenia umelej inteligencie. Patria medzi ne absencia štandardizovaných meracích nástrojov, neplnohodnotné meranie nákladov a návratnosť investícií, slabé spoľahlivosť a presnosť a nízku mieru spoľahlivosti a presnosti. Veľmi častým slabým miestom analyzovaných publikácií je neprítomnosť štandardizovaných škál a meraní navrhnutých pre adopciu umelej inteligencie tak aby plne zachytili všetky špecifiká systémov umelej inteligencie ako je napríklad učenie sa v čase a algoritmická autonómia. Na to nadväzuje ďalšia slabina a to je nedostatočne objektívne meranie návratnosti investícií a nákladov, ktoré je vyslovene subjektívne a neumožňuje objektívne zmerať ekonomický prínos umelej inteligencie. Spoľahlivosť a presnosť systémov patria medzi najdôležitejšie no zároveň najmenej metodicky rozvinuté faktory merania osvojenia umelej inteligencie. U väčšiny štúdií tiež chýba silnejší podporný aparát použitých analytických technických metrík. Ďalším nedostatkom uvedených štúdií sa ukazuje byť malý počet dlhodobejších výskumov, ktoré by sledovali uvedené faktory v čase. Nakoľko ide o dynamický proces, je dôležité sledovať všetky uvedené faktory v čase a najmä v súvislosti napríklad s technologickou integráciou. Na základe uvedených zistení môžeme navrhnúť niektoré možné smery ďalšieho empirického výskumu faktorov osvojenia umelej inteligencie. Za veľmi dôležité pokladáme zavedenie meracích škál vhodných pre umelú inteligenciu, ďalej spojenie subjektívnych a objektívnych metrík ako sú návrat investícií, nákladov a spoľahlivosť umelej inteligencie. Bude taktiež potrebné zaviesť dlhodobé modely sledovania osvojenia umelej inteligencie v čase a odvetvovo špecifické hodnotiace parametre pre odvetvia s vysokými požiadavkami na presnosť a bezpečnosť umelej inteligencie. Veľmi dôležitým faktorom taktiež bude sociotechnická interakcia medzi umelou inteligenciou ako technológiou a organizáciou s jej pracovníkmi ako ľudskými bytosťami. Vyššie uvedené zistenia teda poukazujú na dominanciu prevažne subjektívnych meraní, silnú závislosť od tradičných modelov adopcie v rámci všeobecnej oblasti informačných technológií a nedostatočné zohľadnenie špecifík systémov umelej inteligencie. Napriek týmto obmedzeniam poskytuje existujúca literatúra pevný základ pre ďalší výskum, ktorý by sa mal zamerať na vývoj robustných, validovaných a porovnateľných meracích nástrojov osvojenia umelej inteligencie.

Poznámka

Text publikácie, vyhľadanie zdrojov, analýzu zdrojov aj štruktúru publikácie vypracovali autori publikácie. Pri návrhu štruktúry publikácie o umelej inteligencii sa autori inšpirovali návrhom štruktúry práce poskytnutým umelou inteligenciou ChatGPT, keďže išlo o primárny zdroj viažuci sa priamo k riešenej téme publikácie.

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DIGITALISATION AND SME TURNOVER PERFORMANCE IN EUROPEAN COUNTRIES: EVIDENCE FROM AI ADOPTION AND E-COMMERCE USE

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Abstract
This paper examines the relationship between selected dimensions of digitalisation and SME turnover performance in European countries. The analysis covers enterprises with 10–249 employees during the period 2021–2024 and focuses on the adoption of artificial intelligence technologies and the use of e-commerce sales channels. SME performance is measured as net turnover relative to national gross domestic product, allowing comparisons between countries of different economic sizes. The study uses secondary data from Eurostat and applies descriptive statistics, correlation analysis and regression analysis. The results show that e-commerce was more widely adopted than artificial intelligence, while AI use increased substantially in several countries in 2024. However, the empirical findings do not confirm a positive relationship between digitalisation and SME turnover relative to GDP. Artificial intelligence use was not statistically significantly associated with SME turnover performance. E-commerce showed a statistically significant but negative relationship, which remained significant after controlling for AI adoption. The findings indicate that the relationship between digitalisation and SME performance is complex and may depend on sectoral structure, technological maturity, organisational capabilities and national economic conditions.

JEL classification: *L25, L81, M15, O33*
Keywords: *digitalization, Artificial intelligence, E-commerce, Net turnover, business performance, SMEs, EU*

Introduction

Digitalization is one of the key innovations for small and medium-sized enterprises. The extent to which SMEs implement digital innovations has a significant impact on their competitiveness, performance, and internal and external communication (Broccardo et al., 2024). However, the rate of adoption of digital innovations in small and medium-sized enterprises remains lower than that of large enterprises. This is primarily due to the fact that business digitization entails additional costs for small and medium-sized enterprises (Kyshakevych et al., 2024). As confirmed by Broccardo et al. (2024), financial resources, along with top management and human resources, are among the main drivers of digitalization. Small and medium-sized enterprises are at a disadvantage in this regard, as they are characterized by limited access to external capital and insufficient financial support from the government.

However, the adoption of digital innovations is also influenced by the entrepreneur's own optimism and innovative behavior (Sangosanya et al., 2025). Arroyabe et al. (2024) emphasize that the synergy between support for the entrepreneurial environment and digital innovation capabilities is key to the adoption of digital innovations in SMEs, with internal digital capabilities having a greater influence on innovation adoption than external factors. The adoption of digital innovations itself brings benefits to SMEs, such as increased operational efficiency and a better customer experience, and also has a positive impact on their annual revenue (Gao et al., 2026). While the general benefits of digital transformation are documented, there is a need to better explore how specific advanced technologies, such as artificial intelligence (AI) and e-commerce platforms, systematically influence SME performance across different macroeconomic contexts in Europe. This article focuses specifically on the impact of the adoption of digital technologies, namely the implementation of AI into business processes and sales through e-commerce, on SME turnover performance.

The aim of the empirical part of the article is to examine the relationship between selected dimensions of enterprise digitalization and SME turnover performance in European countries. The empirical part uses a combination of analytical methods, such as descriptive statistics, correlation analysis, and regression analysis. The main objective is to determine whether a higher level of digital maturity, measured by the use of artificial intelligence technologies and e-commerce sales, is associated with higher SME turnover relative to national economic output.

1 Current state of the solved problem at home and abroad

1.1 Specifics and Barriers of Digitalisation in SMEs

Small and medium-sized enterprises play a crucial role in the economic growth of individual countries (Varga, 2021). They also have a major impact on individual regions, including their rural areas, where they bring not only economic but also social benefits (Kubíčková et al., 2017). Furthermore, they play an important role in sustainable development and in supporting innovation. At the same time, they help prevent the depopulation of rural areas by creating jobs and supporting local communities (Beckmann et al., 2023). Within local communities, they contribute to improving lifestyles and support sustainable livelihoods (Tabares et al., 2022).

SMEs are characterised by the fact that it is more difficult for them to maintain a competitive advantage than it is for large enterprises. They are most threatened by a more limited use of data and a lack of competence in digitalisation (Spaltini et al., 2024). However, digital transformation generally has a major positive impact on enterprises. Segarra-Blasco et al. (2025) found that interest in using digital technologies is growing. Unfortunately, many SMEs face difficulties when deciding whether to implement digital innovations. They are uncertain about the digitalisation process itself, and at the same time, they face significant barriers (Kallmeunzer et al., 2025; Rojas-Cabezas et al., 2026; Sonar et al., 2025). These barriers are of an internal and external nature (Segarra-Blasco et al., 2025). Internal barriers mainly include the absence of pro-innovative behaviour, organisational culture, insufficient digital knowledge, and low financial resources, which prevent the adoption of digital innovations. Many SMEs also face structural obstacles in the form of old technological infrastructure, or an absence of strategic management, which hinders the development of digitalisation. External barriers mainly include limited access to external financial capital, and the availability of digital skills and infrastructure (Sonar et al., 2025; Segarra-Blasco, 2025). The above-mentioned barriers confirm the Resource-Based View theory, which states that a firm's competitive advantage is determined by its internal resources and capabilities. In the context of SMEs, it explains their reduced ability to implement digital innovations and to cope with technological challenges compared to large enterprises, which have a significantly larger capacity of human and financial resources, and highlights their specific resource poverty (Samara et al., 2026; Rasdi and Baki, 2025).

An important factor for overcoming these barriers is the behaviour of the entrepreneur or manager, especially their own optimism and innovative behaviour (Sangosanya et al., 2025). Arroyabe et al. (2024) emphasise that the synergy between the support of the business environment and digital in-novation capabilities is also crucial, with internal digital capabilities having a greater impact on in-novation adoption than external factors (EL Abiad et al., 2025; Gao et al., 2026). The adoption of digital innovations itself brings advantages to small and medium-sized enterprises, such as increased operational efficiency and better customer experience, and it also has a positive impact on their annual revenues (Gao et al., 2026; Chen et al., 2024).

1.2 Internal and External Dimensions of Digitalisation: AI and E-commerce

Digitalisation, together with AI innovations and the introduction of business processes, generally falls under ICT innovations. Moussa et al. (2025) revealed that the implementation of ICT innovations is mainly influenced by factors such as the need to provide complete and timely information, under-standing the impact of IT systems on organisational efficiency, structure, transparency and relation-ships, addressing limitations in computer information systems, supporting change and innovation, keeping pace with technological progress, and ensuring the correct use of technologies through effective policy communication. The OECD defines the ICT sector as a sector of information and communication technologies that includes all products and services that allow the collection, storage, processing, transmission and display of information by electronic means. Based on the OECD definition, ICT innovations can be more precisely defined as innovations that consist in the creation, application or improvement of technologies and systems enabling the electronic capture, processing, transmission and display of information, and which bring new or significantly improved products, services or processes (OECD, 2025). Within digitalisation, artificial intelligence and e-commerce have played an important role in recent years in increasing the efficiency of business processes.

Artificial intelligence has become one of the internal innovations not only in SMEs, utilizing tools like big data analytics, pattern recognition, consumer behaviour prediction, and process automation (Turcic et al., 2025). The implementation of AI in SMEs brings a number of benefits. It improves decision-making and competitiveness of the enterprise, helps increase operational efficiency, innovates product offerings, and optimises logistical processes. It also has a positive impact on the environmental and social sustainability of SMEs (Mumcu and Brieger, 2026). Despite this, SMEs prefer to introduce artificial intelligence more gradually (Rasdi and Baki, 2025). This is mainly because some of the specific tools require custom development and specific personnel, which is not as available, especially for small enterprises (Silva et al., 2022). Furthermore, internal challenges arise for SMEs, for example, in change management, acceptance by employees, limited resources, and infrastructure (Rasdi and Baki, 2025).

The second mentioned tool is E-commerce. It is a tool for digital sales and expansion, which helps cross borders and opens new opportunities in international trade (Feng, 2025). E-commerce functions as a central hub that connects digital marketing, logistics, financial technologies, and international trade (Kumar et al., 2025). It has a direct positive impact on SME performance and an indirect positive impact on operational efficiency (Santos-Jaén et al., 2023). However, SMEs also face barriers when implementing e-commerce, mainly in connection with the mentioned financial limitations (Pareek et al., 2026). Research by Dallocchio et al. (2024) suggested a possible solution resulting from the financial demands of setting up private e-commerce websites. They mention that it is more efficient for SMEs to use existing marketplaces such as Amazon or Alibaba, rather than owning their own e-commerce websites. Daoud and Kammoun (2024) defined individual factors that influence the implementation of e-commerce in SMEs. These include the support of IT vendors, the degree of complexity of the adopted technology, the innovativeness of the chief executive officer, technological readiness, customer pressure, firm size, infrastructure compatibility, and the relative advantage perceived by the innovative technology.

1.3 The Relationship Between Digitalisation and Financial Performance

The above text shows several advantages for SMEs resulting from the introduction of digitalisation. One of the most significant advantages is the increase in enterprise performance (Hussain et al., 2022; Tolstoy et al., 2022), especially regarding their annual turnover, business resilience, and success (Kumar, 2025). However, Constangiora et al. (2025) emphasise that the use of these innovations generates value and increases performance only when they are strategically integrated into organisational processes. Ballerini et al. (2023) also point out that a successful increase in firm performance is conditional on the ability to generate knowledge about consumers and to succeed internationally. In this regard, the introduction of AI tools can help SMEs, as they can more effectively analyze product reviews, local features, and give suggestions for product improvement or efficiency increase in connection with the improvement of e-commerce (Feng, 2025). Likewise, market-driving orientation is crucial for increasing performance in the international market (Vu and Tolstoy, 2025), ideally in combination with marketing ambidexterity (Tolstoy et al., 2022).

So far, mainly internal factors influencing the increase of enterprise performance have been mentioned. However, Yang et al. (2022) revealed that a key moderator is the external readiness of the surrounding market, which further strengthens the positive impact of human resources and e-commerce functionality on the final results of the enterprise. This suggests that internal capabilities of the enterprise must be in synergy with external market conditions. From the summary above, it follows that to achieve greater enterprise performance, it is necessary to achieve higher digital maturity and transform the entire business model, including the adoption of new organisational processes, generating information about consumers, and adapting to local markets. It is necessary to note that some authors have also found that e-commerce tools in connection with international trade have an unclear impact on enterprise performance (Dallocchio et al., 2024; Adisaksana, 2022). This concerns, for ex-ample, enterprises that had to adopt digital tools as a result of the pandemic or market pressure. For these enterprises, the adoption of digital tools led to inefficiency due to the absence of strategic planning of implementation and the lack of digital skills of employees (Eurofound and Cedefop, 2025)

1.4 Macroeconomic and European Context

The empirical part of this article focuses on the relationship between SME turnover and the national economic output of European countries. The following lines therefore summarise the differences in digital infrastructure and support among EU countries. The implementation of digital technologies by SMEs within European countries is uneven, despite the fact that these enterprises represent a key pillar of European competitiveness. North European countries such as Finland and Denmark perform best in introducing digital innovations, while countries of Southern and Eastern Europe such as Bulgaria, Romania, or the V4 countries lag significantly behind (Eurofound and Cedefop, 2025). In addition to inequalities between individual states, inequalities also arise between SMEs operating in cities and in rural areas, creating an urban-rural digital divide (Holl and Rama, 2023).

These differences between individual countries and regions are mainly caused by the institutional environment, such as laws, government incentives, and the digital ecosystem. Strong government support in the area of digitalisation can have a positive impact on the innovative behaviour of firms and can support easier access to digital technologies (Holl and Rama, 2023; Yesuf and Fields, 2026).

The results of Labhard and Lehtimäki (2022) show that the positive impacts of digital technologies on productivity and economic output are significantly higher in countries with a high-quality institutional framework. Poor quality legislation and weak state support, on the other hand, dampen the effects of digitalisation. For these reasons, in the empirical part of this article, SME turnover is examined relative to national economic output, which allows for controlling macroeconomic differences, market size, and the purchasing power of individual European countries.

2 Research design and methodology

The methodological part of the article explains the empirical design used to examine the relationship between enterprise digitalisation and SME turnover performance. Since the research is based on secondary quantitative data, this section describes the data sources, sample selection, variables, hypotheses, and statistical methods applied in the analysis. Particular attention is paid to the construction of the dependent variable, SME turnover as a percentage of GDP, which enables comparison across countries of different economic sizes.

The analysis focuses on enterprises with 10–249 employees in selected European countries during the period 2021–2024. Digitalisation is measured through two available indicators: the share of enterprises using at least one type of artificial intelligence technology, listed in table 1, and the share of enterprises with e-commerce sales. The following subsections present the research aim, data structure, variables, hypothesis formulation, and analytical procedure used to evaluate the statistical relationships between the selected indicators.

2.1 Research aim and analytical approach

The aim of the empirical part of the article is to examine the relationship between selected dimensions of enterprise digitalisation and SME turnover performance in European countries. The analysis focuses on enterprises with 10–249 employees, which correspond to the SME size category used in the selected Eurostat datasets. The main objective is to determine whether a higher level of digitalisation, measured through the use of artificial intelligence technologies and e-commerce sales, is associated with higher SME turnover relative to national economic output.

The empirical analysis is based on a quantitative cross-country dataset covering the period 2021–2024. The dataset combines information on SME turnover, gross domestic product, the use of artificial intelligence technologies, and the share of enterprises with e-commerce sales. The analytical procedure consists of descriptive statistics, correlation analysis, and regression analysis. This approach makes it possible to describe the distribution of the variables, identify the direction and strength of relationships between them, and test the formulated hypotheses using regression models.

2.2 Data sources and sample

The analysis is based on secondary data obtained from the Eurostat database. SME turnover data were obtained from Structural Business Statistics, while GDP data were obtained from national accounts. Digitalisation indicators were obtained from Eurostat datasets focused on ICT usage and e-commerce in enterprises. The sample includes selected European countries for which all necessary data were available in the examined period.

The observed period covers the years 2021–2024. However, data on the use of artificial intelligence technologies were not available for 2022. Therefore, observations for 2022 are excluded from regression models that include the “AI_use” variable. As a result, the full dataset contains 100 observations for SME turnover relative to GDP and e-commerce, while models involving AI use are estimated on 75 observations. The AI use variable is based on the Eurostat indicator measuring the share of enterprises using at least one artificial intelligence technology.

2.3 Variables

The dependent variable is SME turnover/GDP, which expresses SME turnover as a percentage of gross domestic product. This variable is calculated as follows:

$$SME\ turnover/GDP = \frac{SME\ turnover}{GDP} \times 100$$

This transformation allows SME turnover to be compared across countries with different economic sizes. Since turnover measures the total value of sales and GDP measures value added, the ratio can exceed 100%. Therefore, the variable should be interpreted as SME turnover relative to GDP, not as the contribution of SMEs to GDP.

The explanatory variables are AI use and E-commerce. AI use measures the share of enterprises using at least one artificial intelligence technology. The AI indicator includes technologies such as text mining, speech recognition, natural language generation, image recognition, machine learning, process automation, autonomous robots, and generative AI for pictures, videos, or sound. These technologies are listed in Table 1.

E-commerce measures the share of enterprises with e-commerce sales. This variable captures the extent to which enterprises use digital sales channels and therefore represents a practical dimension of business digitalisation.

2.4 Hypotheses

The empirical analysis tests three pairs of statistical hypotheses. Each hypothesis pair consists of a null hypothesis, which assumes no statistically significant relationship between the analysed variables, and an alternative hypothesis, which assumes the existence of a statistically significant relationship. The hypotheses are formulated in relation to SME turnover as a percentage of GDP, which represents the dependent variable in the regression models.

The first hypothesis pair examines whether enterprise digitalisation, represented by the available digitalisation indicators, is statistically related to SME turnover relative to GDP. The second hypothesis pair focuses specifically on e-commerce sales, while the third hypothesis pair examines the use of artificial intelligence technologies.

- $H0_1$: There is no statistically significant relationship between enterprise digitalisation and SME turnover as a percentage of GDP.
- $H1_1$: There is a statistically significant relationship between enterprise digitalisation and SME turnover as a percentage of GDP.
- $H0_2$: There is no statistically significant relationship between the share of enterprises with e-commerce sales and SME turnover as a percentage of GDP.
- $H1_2$: There is a statistically significant relationship between the share of enterprises with e-commerce sales and SME turnover as a percentage of GDP.

- $H0_3$: There is no statistically significant relationship between the share of enterprises using at least one artificial intelligence technology and SME turnover as a percentage of GDP.
- $H1_3$: There is a statistically significant relationship between the share of enterprises using at least one artificial intelligence technology and SME turnover as a percentage of GDP.

2.5 Analytical procedure

The empirical analysis was conducted in three steps. First, descriptive statistics were calculated for the dependent variable and the explanatory variables. These statistics include the number of observations, mean, median, standard deviation, minimum, and maximum values.

Second, correlation analysis was used to examine the bivariate relationships between SME turnover/GDP, AI use, and e-commerce. This step provides an initial indication of whether the variables move in the expected direction.

Third, regression analysis was used to test the relationships between the selected digitalisation indicators and SME turnover/GDP. Three regression models were estimated. The first model examines the relationship between e-commerce and SME turnover/GDP. The second model examines the relationship between AI use and SME turnover/GDP. The third model includes both AI use and e-commerce as explanatory variables.

2.6 Regression models

The first regression model is specified as follows:

$$SME\ turnover/GDP_i = \beta_0 + \beta_1 E - commerce_i + \varepsilon_i$$

The second model is specified as follows:

$$SME\ turnover/GDP_i = \beta_0 + \beta_1 AI\ use_i + \varepsilon_i$$

The third model includes both digitalisation indicators:

$$SME\ turnover/GDP_i = \beta_0 + \beta_1 AI\ use_i + \beta_2 E - commerce_i + \varepsilon_i$$

where $SME\ turnover/GDP_i$represents SME turnover as a percentage of GDP, $AI\ use_i$represents the share of enterprises using at least one AI technology, $E - commerce_i$represents the share of enterprises with e-commerce sales, and $\varepsilon_i$is the error term.

3 Research results

The results section presents the empirical findings of the analysis. It first describes the structure of the dataset and the development of the main variables across the selected countries and years. The initial tables provide an overview of SME turnover, GDP, AI adoption, and e-commerce use. These descriptive results serve as a basis for the subsequent statistical analysis.

The section then continues with descriptive statistics, correlation analysis, and regression models. The purpose is to examine whether the selected digitalisation indicators are statistically related to SME turnover as a percentage of GDP. The results are interpreted with reference to the formulated hypotheses and are used to assess whether the null hypotheses can be rejected.

Table 1
Net turnover of selected sample of countries and selected time period (values in million euro)

Country	2021	2022	2023	2024
Belgium	730,406 €	925,740 €	885,068 €	897,332 €
Bulgaria	134,870 €	184,043 €	175,406 €	190,691 €
Czechia	362,525 €	493,886 €	471,033 €	447,174 €
Denmark	396,794 €	522,099 €	439,209 €	449,045 €
Germany	3,227,731 €	3,639,621 €	3,608,701 €	3,594,905 €
Estonia	67,137 €	78,596 €	77,013 €	76,230 €
Ireland	474,105 €	555,720 €	599,878 €	616,934 €
Greece	200,597 €	252,313 €	260,221 €	281,371 €
Spain	1,348,897 €	1,616,852 €	1,637,712 €	1,676,878 €
France	1,913,179 €	2,122,626 €	2,202,048 €	2,219,210 €
Croatia	72,131 €	91,149 €	99,223 €	104,629 €
Italy	2,286,824 €	2,736,831 €	2,688,774 €	2,651,137 €
Latvia	55,531 €	62,711 €	59,054 €	58,434 €
Lithuania	82,958 €	101,685 €	103,060 €	104,268 €
Luxembourg	181,808 €	197,483 €	184,516 €	188,494 €
Hungary	219,706 €	250,452 €	253,123 €	254,706 €
Malta	30,362 €	35,378 €	40,113 €	43,638 €
Netherlands	1,309,953 €	1,545,755 €	1,529,133 €	1,535,813 €
Austria	509,708 €	611,430 €	535,312 €	524,397 €
Poland	792,438 €	929,547 €	981,368 €	1,045,314 €
Romania	225,360 €	281,049 €	293,321 €	321,548 €
Slovenia	85,202 €	102,658 €	104,961 €	99,921 €
Slovakia	135,714 €	161,097 €	171,145 €	170,027 €
Finland	268,165 €	296,190 €	286,317 €	280,044 €
Sweden	509,232 €	553,556 €	512,908 €	528,132 €

Source: Own processing based on Eurostat database

Table 1 presents the net turnover of enterprises with 10–249 employees in the selected European countries during the period 2021–2024. The data show considerable differences in the absolute level of SME turnover across countries. The highest values are observed in larger economies such as Germany, Italy, France, Spain, and the Netherlands. This pattern is expected, as these countries have larger domestic markets, a higher number of enterprises, and broader industrial and service structures. At the same time, smaller economies such as Malta, Estonia, Latvia, Lithuania, and Slovenia report substantially lower absolute turnover values. These differences do not necessarily indicate weaker SME performance, but rather reflect the different economic size of the countries. For example, a smaller country may have a relatively strong SME sector, but its absolute turnover will still be lower than that of a large economy.

The development over time also shows that SME turnover generally increased after 2021 in many countries, especially between 2021 and 2022. However, the trend was not uniform. Some countries recorded a decline or stagnation in later years. For instance, Italy, Austria, Latvia, and Slovenia show lower turnover values in 2024 compared with their previous peaks. This indicates that SME turnover was affected not only by digitalisation, but also by broader macroeconomic, sectoral, and country-specific conditions. Because of these differences in country size, the absolute values reported in Table 2 are not directly comparable across countries. Therefore, the empirical analysis uses SME turnover relative to GDP as the main dependent variable. This allows the analysis to compare SME turnover performance in relation to the size of each national economy.

Table 2
GDP of selected sample of countries and selected time period (values in million euro)

Country	2021	2022	2023	2024
Belgium	506,047 €	561,678 €	601,867 €	619,914 €
Bulgaria	71,344 €	86,078 €	94,525 €	104,767 €
Czechia	246,012 €	286,977 €	319,099 €	321,231 €
Denmark	343,319 €	380,567 €	373,288 €	400,267 €
Germany	3,682,340 €	3,989,390 €	4,219,310 €	4,328,970 €
Estonia	31,453 €	36,301 €	38,353 €	39,848 €
Ireland	448,469 €	523,248 €	520,792 €	561,941 €
Greece	184,575 €	207,009 €	224,686 €	236,736 €
Spain	1,235,474 €	1,375,863 €	1,497,761 €	1,594,330 €
France	2,508,102 €	2,653,997 €	2,833,826 €	2,935,236 €
Croatia	58,390 €	67,609 €	79,186 €	85,905 €
Italy	1,842,507 €	1,998,073 €	2,142,744 €	2,202,031 €
Latvia	32,284 €	36,089 €	39,564 €	40,652 €
Lithuania	56,709 €	67,081 €	74,317 €	78,996 €
Luxembourg	73,040 €	76,731 €	82,116 €	86,180 €
Hungary	154,972 €	168,546 €	196,984 €	206,156 €
Malta	16,680 €	17,985 €	20,929 €	23,142 €
Netherlands	891,550 €	993,820 €	1,050,133 €	1,115,252 €
Austria	406,232 €	449,382 €	477,837 €	494,088 €
Poland	583,001 €	661,712 €	751,932 €	852,230 €
Romania	240,987 €	280,777 €	321,578 €	353,633 €
Slovenia	52,032 €	56,882 €	64,050 €	67,418 €
Slovakia	101,892 €	109,960 €	123,539 €	130,208 €
Finland	248,764 €	266,135 €	273,005 €	276,151 €
Sweden	533,954 €	547,190 €	535,177 €	563,572 €

Source: Own processing based on Eurostat database

Table 2 presents the share of enterprises with 10–249 employees using at least one artificial intelligence technology. The results show that AI adoption increased in most countries between 2021 and 2024. This confirms that artificial intelligence became more widespread among European SMEs during the analysed period.

Table 3
Use of at least one of the AI technologies by enterprises in selected sample of countries and selected time period

Country	2021	2022	2023	2024
Belgium	9.30%	*Not Available*	12.53%	23.09%
Bulgaria	3.01%	*Not Available*	3.36%	6.13%
Czechia	3.62%	*Not Available*	4.99%	10.10%
Denmark	22.61%	*Not Available*	14.08%	26.43%
Germany	9.87%	*Not Available*	10.75%	18.78%
Estonia	2.35%	*Not Available*	4.74%	13.28%
Ireland	7.17%	*Not Available*	7.17%	13.80%
Greece	2.50%	*Not Available*	3.81%	9.53%
Spain	7.03%	*Not Available*	8.26%	10.30%
France	6.03%	*Not Available*	5.44%	9.25%
Croatia	8.32%	*Not Available*	7.55%	11.31%
Italy	5.84%	*Not Available*	4.68%	7.74%
Latvia	3.41%	*Not Available*	4.14%	8.24%
Lithuania	3.98%	*Not Available*	4.39%	8.01%
Luxembourg	12.12%	*Not Available*	13.51%	22.96%
Hungary	2.69%	*Not Available*	3.31%	6.97%
Malta	9.89%	*Not Available*	12.56%	16.28%
Netherlands	12.10%	*Not Available*	13.11%	21.90%
Austria	8.15%	*Not Available*	10.06%	19.36%
Poland	2.35%	*Not Available*	2.91%	4.92%
Romania	1.19%	*Not Available*	1.28%	2.78%
Slovenia	11.00%	*Not Available*	10.19%	19.81%
Slovakia	4.63%	*Not Available*	6.42%	10.00%
Finland	14.62%	*Not Available*	13.83%	22.81%
Sweden	9.11%	*Not Available*	9.42%	23.96%

Source: Own processing based on Eurostat database

The highest levels of AI adoption in 2024 are observed in Denmark, Sweden, Belgium, Luxembourg, Finland, and the Netherlands. These countries reached adoption rates above 20%, suggesting a stronger integration of AI technologies into SME business processes. These results may reflect more advanced digital infrastructure, higher digital skills, stronger innovation capacity, and greater readiness of enterprises to adopt advanced technologies. In contrast, Romania, Poland, Bulgaria, Hungary, Italy, and Lithuania reported lower levels of AI use. In these countries, the share of SMEs using at least one AI technology remained below 10% in 2024. This indicates that AI adoption is still uneven across European countries and that many SMEs may face barriers related to costs, technical knowledge, digital skills, or organisational readiness. The data also show that AI adoption did not grow at the same pace in all countries. Some countries recorded strong increases between 2023 and 2024, such as Belgium, Denmark, Sweden, Finland, the Netherlands, Austria, and Slovenia. This suggests that 2024 may represent an important acceleration point in the diffusion of AI technologies among SMEs. However, because AI data are not available for 2022, the time trend cannot be evaluated continuously.

Table 4
Use of at least one of the AI technologies by enterprises in selected sample of countries and selected time period

Country	2021	2022	2023	2024
Belgium	30.47%	29.18%	30.79%	32.02%
Bulgaria	11.54%	14.68%	14.79%	14.77%
Czechia	24.36%	23.62%	23.59%	22.68%
Denmark	37.72%	35.30%	35.90%	38.07%
Germany	21.08%	21.86%	21.50%	22.27%
Estonia	21.82%	21.86%	21.58%	24.22%
Ireland	39.47%	42.25%	34.64%	39.14%
Greece	20.35%	17.79%	19.79%	23.04%
Spain	27.44%	32.63%	32.92%	31.49%
France	17.80%	16.15%	16.07%	17.58%
Croatia	29.16%	29.19%	29.66%	31.57%
Italy	17.92%	17.73%	18.54%	19.87%
Latvia	16.48%	17.47%	19.22%	18.91%
Lithuania	35.56%	36.90%	38.31%	41.49%
Luxembourg	11.40%	11.66%	12.86%	11.50%
Hungary	19.71%	21.13%	22.41%	22.06%
Malta	28.95%	31.89%	32.14%	34.23%
Netherlands	27.50%	30.18%	30.03%	29.83%
Austria	28.98%	25.67%	25.16%	30.06%
Poland	17.06%	16.08%	17.04%	16.91%
Romania	12.92%	10.85%	12.50%	14.31%
Slovenia	26.21%	24.75%	22.78%	25.35%
Slovakia	15.82%	16.63%	17.61%	15.81%
Finland	28.49%	31.75%	29.66%	33.29%
Sweden	35.45%	37.62%	37.14%	35.45%

Source: Own processing based on Eurostat database

The results show that AI adoption increased in most countries between 2021 and 2024. This confirms that artificial intelligence became more widespread among European SMEs during the analysed period. The highest levels of AI adoption in 2024 are observed in Denmark, Sweden, Belgium, Luxem-bourg, Finland, and the Netherlands. These countries reached adoption rates above 20%, suggesting a stronger integration of AI technologies into SME business processes. These results may reflect more advanced digital infrastructure, higher digital skills, stronger innovation capacity, and greater readiness of enterprises to adopt advanced technologies. In contrast, Romania, Poland, Bulgaria, Hungary, Italy, and Lithuania reported lower levels of AI use. In these countries, the share of SMEs using at least one AI technology remained below 10% in 2024. This indicates that AI adoption is still uneven across European countries and that many SMEs may face barriers related to costs, technical knowledge, digital skills, or organisational readiness.

The data also show that AI adoption did not grow at the same pace in all countries. Some countries recorded strong increases between 2023 and 2024, such as Belgium, Denmark, Sweden, Finland, the Netherlands, Austria, and Slovenia. This suggests that 2024 may represent an important acceleration point in the diffusion of AI technologies among SMEs. However, because AI data are not available for 2022, the time trend cannot be evaluated continuously.

Table 4 presents the share of enterprises with e-commerce sales in the selected countries. Compared with AI adoption, e-commerce is more widely used among SMEs. This is expected, as e-commerce represents a more established and less technologically complex form of digitalisation than artificial intelligence. The highest e-commerce adoption rates are observed in Lithuania, Ireland, Denmark, Sweden, Finland, Malta, Belgium, Spain, and Croatia. In several of these countries, more than one third of SMEs reported e-commerce sales. This suggests that digital sales channels are an important part of SME business activity, especially in countries with more developed digital markets or stronger online consumer behaviour. The lowest values are observed in Luxembourg, Romania, Bulgaria, Slovakia, Poland, France, and Italy. These results indicate that e-commerce adoption remains uneven across countries. Lower e-commerce use may reflect differences in sectoral structure, market orientation, firm size distribution, consumer behaviour, or the level of digital readiness among SMEs.

The data also show that e-commerce adoption was relatively stable over time in many countries. Unlike AI adoption, which increased strongly in 2024, e-commerce did not show the same dynamic growth pattern. In some countries, such as Czechia, France, Poland, Slovakia, and Slovenia, the values remained broadly stable or even declined slightly. This suggests that e-commerce may already be a more mature digitalisation channel, while AI is still in a faster adoption phase.

Table 5
Descriptive statistics of the variables

Variable	SME turnover/GDP	AI use	E-commerce
N	100	75	100
Mean	137.41	9.64	24.81
Median	132.59	8.32	23.61
Std. dev.	38.86	6.16	8.24
Minimum	75.61	1.19	10.85
Maximum	257.37	26.43	42.25

Source: Own processing using Jamovi

Table 5 reports descriptive statistics for the three main variables used in the empirical analysis. SME turnover/GDP has 100 observations, with a mean value of 137.41 and a median of 132.59. The standard deviation of 38.86 indicates notable cross-country variation in SME turnover relative to GDP. The minimum value is 75.61, while the maximum value reaches 257.37. AI use has 75 observations because data for 2022 were not available. The mean value of AI use is 9.64%, while the median is 8.32%. This indicates that AI adoption among SMEs remained relatively limited during the observed period, although some countries reached much higher values. The minimum value is 1.19% and the maximum value is 26.43%. E-commerce has 100 observations, with a mean value of 24.81% and a median of 23.61%. The standard deviation of 8.24 suggests moderate variation across countries. The minimum value is 10.85%, while the maximum value is 42.25%. Compared with AI use, e-commerce is more widespread among SMEs.

Table 6
Correlation matrix

Variable	SME turnover/GDP	AI use	E-commerce
SME turnover/GDP	1	0.00012	-0.244
AI use	0.00012	1	0.449
E-commerce	-0.244	0.449	1

Source: Own processing using Jamovi

Table 6 presents the correlation matrix. The correlation between AI use and SME turnover/GDP is almost zero, with a coefficient of 0.00012. This indicates no meaningful linear relationship between AI adoption and SME turnover relative to GDP in the analysed sample. The correlation between e-commerce and SME turnover/GDP is negative, with a coefficient of -0.244. This suggests a weak negative relationship between the share of enterprises with e-commerce sales and SME turnover relative to GDP. The result is contrary to the expected positive direction. The correlation between AI use and e-commerce is positive, with a coefficient of 0.449. This indicates a moderate positive relationship between the two digitalisation indicators. Countries with higher e-commerce adoption also tend to report higher AI adoption, although the relationship is not perfect.

Table 7
Regression analysis – model 1 - E-commerce

Model 1: E-commerce only			***N=100; R^2=0.059; Adjusted R^2=0.050***	
Variable	**Coefficient**	**Std. error**	**t-statistic**	**p-value**
Intercept	165,921	12,079	13,737	0,000
E_comm	-1,149	0,462	-2,486	0,015

Source: Own processing using Jamovi

Table 7 presents the first regression model, where SME turnover/GDP is explained by e-commerce. The coefficient for e-commerce is -1.149 and is statistically significant at the 5% level, with a p-value of 0.015. This means that a one percentage point increase in the share of enterprises with e-commerce sales is associated with a decrease of 1.149

percentage points in SME turnover/GDP. The result is statistically significant, but the direction of the relationship is negative, which is contrary to the expected hypothesis.

Table 8
Regression analysis – model 2 – Use of AI technology

Model 2: AI only			***N=75; R^2=0.000; Adjusted R^2 = -0.014***	
Variable	**Coefficient**	**Std. error**	**t-statistic**	**p-value**
Intercept	133,970	8,063	16,615	0,000
AI_use	0,001	0,706	0,001	0,999

Source: Own processing using Jamovi

Table 8 presents the second regression model, where SME turnover/GDP is explained by AI use. The coefficient for AI use is 0.001, with a p-value of 0.999. This result is statistically insignificant and indicates that AI use is not associated with SME turnover/GDP in the analysed sample.

Table 9
Regression analysis – model 3 - E-commerce & Use of AI technology

Model 3: AI and e-commerce			***N=75; R^2=0.072; Adjusted R^2 = 0.047***	
Variable	**Coefficient**	**Std. error**	**t-statistic**	**p-value**
Intercept	160,375	13,613	11,781	0,000
AI_use	0,815	0,766	1,064	0,291
E_comm	-1,377	0,581	-2,370	0,020

Source: Own processing using Jamovi

Table 9 presents the third regression model, which includes both AI use and e-commerce. The coefficient for AI use is positive, at 0.815, but statistically insignificant, with a p-value of 0.291. The coefficient for e-commerce remains negative and statistically significant, with a value of -1.377 and a p-value of 0.020. This suggests that even after controlling for AI use, e-commerce remains negatively associated with SME turnover/GDP.

The regression results do not provide evidence that higher digitalisation, measured through AI use and e-commerce, is associated with higher SME turnover relative to GDP. The only statistically significant relationship is found for e-commerce, but the estimated effect is negative.

4 Discussion

The empirical results provide a mixed picture of the relationship between SME digitalisation and turnover performance. The descriptive analysis confirms that both AI adoption and e-commerce use differ substantially across European countries. E-commerce is more widespread and relatively stable over time, while AI adoption is less common but increased markedly in 2024 in several countries.

However, the correlation and regression results do not confirm the expected positive relationship between digitalisation and SME turnover relative to GDP. AI use shows no statistically significant association with SME turnover/GDP. E-commerce is statistically significant, but its coefficient is negative, which contradicts the expected direction of the relationship. These findings suggest that digitalisation indicators alone do not explain cross-country differences in SME turnover performance. Higher adoption of AI or e-commerce does not automatically translate into higher SME turnover relative to GDP. The results may reflect differences in sectoral structure, market size, productivity, business models, and the maturity of digital technology implementation.

The results should therefore be interpreted cautiously. The analysis identifies statistical associations, not causal effects. Moreover, the available dataset covers only a short period and does not include other important digitalisation indicators, such as cloud computing, ERP systems, ICT investment, or digital skills. Despite these limitations, the results show that the relationship between digitalisation and SME performance is more complex than a simple positive association.

The hypotheses were evaluated on the basis of the regression results reported in Tables 7–9. A significance level of 5% was applied.

Hypothesis 1 examined the relationship between enterprise digitalisation and SME turnover/GDP. Enterprise digitalisation was represented by the available digitalisation indicators, namely AI use and e-commerce. The combined regression model reported in Table 10 shows that e-commerce is statistically significant, while AI use is not statistically significant. Therefore, the null hypothesis $H0_1$ is partially rejected. The results indicate that at least one digitalisation indicator is statistically related to SME turnover/GDP. However, the relationship is not uniformly positive, because the significant coefficient for e-commerce is negative.

Hypothesis 2 examined the relationship between e-commerce and SME turnover/GDP. The regression results in Table 8 show that e-commerce has a statistically significant coefficient, with a p-value of 0.015. In the combined model in Table 10, e-commerce remains statistically significant, with a p-value of 0.020. Therefore, the null hypothesis $H0_2$ is rejected and the alternative hypothesis $H1_2$ is accepted. There is a statistically significant relationship between e-commerce and SME turnover/GDP. However, the coefficient is negative, which means that the relationship is opposite to the expected positive di-rection.

Hypothesis 3 examined the relationship between AI use and SME turnover/GDP. The regression results in Table 9 show that AI use is not statistically significant, with a p-value of 0.999. In the combined model in Table 10, AI use also remains statistically insignificant, with a p-value of 0.291. Therefore, the null hypothesis $H0_3$ is not rejected. The results do not provide evidence of a statistically significant relationship between AI use and SME turnover/GDP.

Based on these results, the analysis confirms a statistically significant relationship only in the case of e-commerce. However, this relationship is negative. AI use does not show a statistically significant association with SME turnover/GDP. Therefore, the empirical results suggest that the relationship between digitalisation and SME turnover performance is not straightforward and cannot be interpreted as a simple positive effect of digital technology adoption.

Conclusion

This paper examined the relationship between selected digitalisation indicators and SME turnover performance in European countries during the period 2021–2024. Digitalisation was measured through the share of enterprises using at least one artificial intelligence technology and the share of enterprises with e-commerce sales. SME performance was expressed as net turnover relative to national GDP, which enabled comparisons between countries with different economic sizes. The descriptive analysis showed substantial differences in digitalisation and SME turnover performance across the selected countries. E-commerce was considerably more widespread than artificial intelligence and remained relatively stable during the analysed period. By contrast, AI adoption was initially limited but increased markedly in several countries in 2024. The highest adoption rates were generally recorded in Northern and Western European countries, while lower values were observed in several Central, Eastern and Southern European economies. The correlation and regression results did not confirm the expected positive relationship between digitalisation and SME turnover relative to GDP. AI adoption showed no statistically significant relationship with the dependent variable. E-commerce was statistically significant in both the individual and combined regression models, but its coefficient was negative. Therefore, the null hypothesis concerning e-commerce was rejected, while the null hypothesis concerning AI use was not rejected. The general hypothesis concerning enterprise digitalisation was only partially supported because one digitalisation indicator was statistically significant, although its relationship with SME turnover performance was opposite to the expected direction.

The findings suggest that the adoption of digital technologies does not automatically translate into higher turnover performance. The economic effects of AI and e-commerce may depend on the quality of their implementation, organisational capabilities, digital skills, sectoral composition, market conditions and the maturity of the adopted technologies. Digitalisation may also require initial investments and organisational changes whose financial benefits become visible only after a longer period.

The study has several limitations. First, the analysis covers a relatively short period, while AI data were unavailable for 2022, reducing the number of observations in the relevant regression models. Second, the research is based on aggregated country-level data and does not allow conclusions about the performance of individual enterprises. Third, the regression models do not control for additional factors such as sectoral structure, labour productivity, enterprise size distribution, ICT investment or institutional quality.

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UMELÁ INTELIGENCIA V HYBRIDNOM RIADENÍ TÍMOV: AKO AI MENÍ MANAŽÉRSKE PRAKTIKY

Lucia Gálová – Peter Bahna – Dávid Rybjanský – Anita Romanová

Abstract
Hybridný model práce, charakterizovaný kombináciou práce z kancelárie a práce na diaľku, sa po pandémii COVID-19 etabloval ako dominantný organizačný model – viac ako 57% organizácií globálne ho dnes využíva (CIPD). Súbežne s týmto trendom nastupuje éra umelej inteligencie (AI), ktorá zásadne transformuje tradičné manažérske praktiky. Cieľom tohto článku je prostredníctvom naratívneho prehľadu vedeckej literatúry identifikovať a analyzovať, ako AI nástroje menia riadenie hybridných tímov. Na základe rešerše publikácií indexovaných v databázach Web of Science a Scopus (2020–2025) článok vymedzuje štyri kľúčové oblasti dopadu AI: (1) komunikácia a koordinácia tímu, (2) monitorovanie a riadenie výkonu, (3) podpora manažérskeho rozhodovania a (4) wellbeing manažment zamestnancov. Teoretickým rámcom je Technology Acceptance Model (TAM) a koncept Human-AI Teaming (HAIT). Výsledky ukazujú, že AI prináša merateľné prínosy v efektivite a koordinácii, no súčasne generuje nové výzvy v oblasti dôvery, transparentnosti, etiky a ochrany súkromia. Kľúčovou výskumnou medzerou zostáva absencia európskej, resp. stredoeurópskej perspektívy na adopciu AI nástrojov v hybridnom manažmente. Článok navrhuje smerovanie budúceho empirického výskumu v tomto kontexte.

JEL classification: *L86, M12, O33*
Keywords: *umelá inteligencia, hybridné tímy, manažérske praktiky, Technology Acceptance Model, Human-AI Teaming*

Úvod

Hybridný model práce – kombinácia práce z kancelárie a práce na diaľku – sa po pandémii COVID-19 etabloval ako nový paradigmatický model organizácie práce vo väčšine odvetví. Podľa Cramarenco et al. (2023) táto transformácia zásadne mení nielen spôsob výkonu práce, ale aj požiadavky na manažérske kompetencie a organizačnú kultúru. Hybridné tímy sa podľa Handke et al. (2024) vyznačujú dynamicky sa meniacimi geografickými konfiguráciami, v ktorých členovia individuálne striedajú prácu z kancelárie a na diaľku – čo vytvára bezprecedentné výzvy pre koordináciu, komunikáciu a hodnotenie výkonu.

Súbežne s nástupom hybridného modelu práce prebieha rozsiahla transformácia organizácií prostredníctvom umelej inteligencie (AI). Dwivedi et al. (2021) v multidisciplinárnom prehľade zdôrazňujú, že AI zásadne ovplyvňuje spôsob, akým organizácie analyzujú, plánujú a vykonávajú svoje procesy. AI nástroje sú čoraz častejšie prezentované ako riešenie výziev hybridného riadenia – od automatizovaného monitorovania výkonu cez AI-asistentov uľahčujúcich koordináciu až po nástroje na podporu manažérskeho rozhodovania. Gupta et al. (2024) identifikujú tri vlny AI integrácie v riadení ľudských zdrojov, pričom súčasná – éra generatívnej AI – predstavuje kvalitatívny skok s dosiaľ nepreskúmaným dosahom na hybridné pracovné prostredia.

Napriek rastúcemu záujmu o túto problematiku zostáva výskum na priesečníku AI a hybridného riadenia tímov fragmentovaný. Bankins et al. (2024) konštatujú, že väčšina štúdií sa zameriava buď na AI v organizáciách všeobecne, alebo na hybridnú prácu samostatne, pričom chýba syntetický pohľad prepájajúci obe oblasti. Obzvlášť výraznou medzerou je absencia európskej a stredoeurópskej perspektívy, kde odlišné regulačné prostredie (napr. GDPR) a kultúrne faktory môžu významne ovplyvňovať vzorce adopcie AI. Práve tu vzniká výskumná medzera, ktorú tento článok adresuje.

Cieľom článku je prostredníctvom prehľadu vedeckej literatúry (databázy Web of Science a Scopus, 2020–2025) identifikovať a analyzovať, ako AI mení manažérske praktiky v hybridnom riadení tímov. Článok si kladie nasledovné výskumné otázky: (RQ1) Aké AI nástroje sú využívané v hybridnom riadení tímov? (RQ2) Ako AI transformuje konkrétne manažérske praktiky? (RQ3) Aké sú prínosy a výzvy implementácie AI v tomto prostredí a kde existujú výskumné medzery? Téma priamo nadväzuje na dizertačný výskum zameraný na inovatívne prístupy k riadeniu podnikových procesov prostredníctvom AI nástrojov.

1 Súčasný stav riešenej problematiky doma a v zahraničí

Nasledujúca kapitola vymedzuje teoretický a kontextuálny základ článku. V prvom rade je charakterizovaný hybridný model práce a jeho kľúčové manažérske výzvy, ktoré vytvárajú potrebu nových nástrojov riadenia. Následne je analyzovaná úloha umelej inteligencie v organizačnom manažmente a jej evolúcia smerom k autonómnym manažérskym funkciám. Na záver je predstavený Technology Acceptance Model (TAM) ako teoretický rámec vysvetľujúci, za akých podmienok manažéri AI nástroje prijímajú a efektívne využívajú.

1.1 Hybridný model práce a manažérske výzvy

Hybridný model práce kombinuje výhody práce z kancelárie a práce na diaľku, pričom zamestnancom umožňuje flexibilitu v mieste a čase výkonu práce. Po pandémii COVID-19 sa stal dominantným organizačným modelom – podľa Chartered Institute of Personnel and Development (CIPD) viac ako 57% organizácií globálne adoptovalo hybridný pracovný model kombinujúci kancelárske dni a pracovné dni z domu. Handke et al. (2024) upresňujú, že hybridný tím sa vyznačuje dynamicky sa meniacimi geografickými konfiguráciami, v ktorých členovia tímu individuálne a v čase striedajú prácu z kancelárie a prácu na diaľku – pričom tieto konfigurácie sa môžu meniť deň po dni aj v priebehu jedného pracovného dňa.

Kraus et al. (2022) identifikujú tri kľúčové manažérske výzvy hybridného modelu: (1) udržanie kohézie a kultúry tímu, (2) spravodlivé a transparentné hodnotenie výkonu zamestnancov, ktorí pracujú z rôznych prostredí a (3) koordinácia a komunikácia v asynchrónnom a geograficky distribuovanom prostredí. Moe et al. (2023) na vzorke 17 agilných tímov empiricky doložili, že tímy s obmedzenou fyzickou spolu-prítomnosťou vykazujú signifikantné problémy s budovaním psychologickej bezpečnosti, zdieľaním znalostí a dôvery – teda s faktormi, ktoré sú základom efektívneho tímového výkonu. Coulston (2025) ďalej dokumentuje, že vedúci hybridných tímov čelia paradoxu: snaha o kompenzáciu obmedzeného fyzického kontaktu nadmernou komunikáciou vedie ku komunikačnému preťaženiu, čo ironicky znižuje efektivitu koordinácie.

Výskum potvrdil, že tradičné manažérske nástroje a prístupy sú v hybridnom prostredí menej účinné. Bankins et al. (2024) vo viacúrovňovom posudzovaní uvádzajú, že hybridné pracovisko vyžaduje nové kompetencie od manažérov: digitálnu gramotnosť, schopnosť riadiť tím bez priameho kontaktu a využívanie technológií na zabezpečenie koordinácie. Osobitnou výzvou je tzv. proximity bias – tendencia manažérov uprednostňovať zamestnancov fyzicky prítomných v kancelárii pri rozhodovaní o odmeňovaní, povyšovaní a zadávaní úloh. Lauring (2025) na základe rozsiahleho prehľadu literatúry zdôrazňuje, že bez cielených organizačných intervencií hybridný model systematicky reprodukuje nerovnosti medzi „viditeľnými“ a „neviditeľnými“ členmi tímu. Práve tieto štrukturálne nedostatky tradičného hybridného manažmentu vytvárajú priestor pre adopciu AI nástrojov v každodenných manažérskych praktikách ako prostriedku na objektivizáciu procesov a kompenzáciu obmedzení ľudského vnímania.

1.2 Umelá inteligencia v organizačnom manažmente

Umelá inteligencia predstavuje spektrum technológií zahŕňajúcich strojové učenie, spracovanie prirodzeného jazyka, počítačové videnie a prediktívnu analytiku (Dwivedi et al., 2021). V kontexte manažmentu organizácií AI prechádza od automatizácie rutinných úloh k pokročilej podpore rozhodovania a autonómnym manažérskym funkciám. Gupta et al. (2024) v systematickom prehľade 73 vedeckých článkov identifikujú tri vlny AI integrácie v HRM: automatizácia procesov (2015–2018), dátová analytika (2018–2021) a generatívna AI a pokročilé rozhodovanie (2021–dnes). Práve príchod generatívnej AI (GenAI) predstavuje kvalitatívny skok: Zhang et al. (2025) dokumentujú, že GenAI zásadne mení manažérske rozhodovanie tým, že efektívne zlučuje interné a externé dáta, znižuje informačnú asymetriu a zvyšuje transparentnosť rozhodovacích procesov. Kronblad et al. (2024) v tomto kontexte upozorňujú, že organizácie stoja pred paradoxom – GenAI ponúka potenciál oslobodiť ľudské kapacity pre kreatívne a strategické úlohy, no zároveň vytvára riziko de-profesionalizácie a nadmernej závislosti od technologickej asistencie.

Hagemann et al. (2023) zaviedli pojem „team-centered AI" – systémy umelej inteligencie navrhnuté tak, aby sa zosúladili s ľudskými cieľmi, komunikačnými vzorcami a rozhodovacími procesmi. Títo autori zdôrazňujú, že optimálny výsledok v hybridných ľudsko-AI tímoch nastáva vtedy, keď AI nepôsobí ako náhrada manažéra, ale ako kognitívny amplifikátor – rozširuje ľudské kapacity bez eliminácie ľudského úsudku. Toto tvrdenie empiricky podporuje Fügener et al. (2022), ktorí v experimentálnom výskume zistili, že ľudia a AI pracujúci spoločne dokázali prekonať výkon AI pracujúcej samostatne – a to aj v prípadoch, keď AI dosahovala objektívne lepšie výsledky ako samotní ľudia. Kľúčovým mechanizmom je teda komplementárnosť, nie substitúcia: AI zvláda spracovanie objemu a rýchlosti dát, kým manažér prispieva kontextuálnym úsudkom, etickým hodnotením a interpersonálnou inteligenciou.

Výskum Berretta et al. (2023) prostredníctvom bibliometrickej analýzy a prehľadovej štúdie identifikoval päť výskumných klastrov v oblasti Human-AI Teaming (HAIT): (1) ľudské premenné (dôvera, kognitívna záťaž), (2) úlohovo závislé premenné, (3) vysvetliteľnosť AI (Explainable AI), (4) AI-riadené robotické systémy a (5) vplyv výkonu AI na ľudské vnímanie. Tento rámec poskytuje základ pre pochopenie komplexnosti vzťahu ľudí a AI v tímovom prostredí. Jiang et al. (2025) v kvantitatívnej štúdii na vzorke 408 respondentov odhalili, že dôvera v AI má duálny efekt na kognitívne procesy: funkčná a emocionálna dôvera podporujú vyššiu kogníciu, no paradoxne transparentnosť AI môže inhibovať kognitívne spracovanie, keďže znižuje motiváciu manažérov k samostatnému analytickému mysleniu. Toto zistenie je obzvlášť relevantné pre hybridné tímy, kde manažér musí vyvažovať závislosť od AI nástrojov s udržaním vlastného úsudku a manažérskej autority.

1.3 Technology Acceptance Model (TAM) ako teoretický rámec

Pre pochopenie adopcie AI nástrojov v hybridnom riadení je kľúčovým teoretickým rámcom Technology Acceptance Model (TAM), ktorý pôvodne navrhol Davis (1989). TAM vysvetľuje akceptáciu technológie prostredníctvom dvoch konštruktov: vnímaná užitočnosť (perceived usefulness) a vnímaná jednoduchosť použitia (perceived ease of use). Davis (1989) preukázal, že tieto dve dimenzie spoľahlivo predikujú zámer a skutočné využívanie informačných technológií v organizáciách.

V kontexte AI nástrojov bol TAM rozšírený o ďalšie dimenzie. Weng et al. (2024) v systematickom prehľade 127 štúdií identifikovali, že okrem pôvodných TAM konštruktov hrajú v prípade AI kľúčovú úlohu aj: dôvera v AI (AI trust), vnímané riziko (perceived risk) a sociálny vplyv (subjective norm). Autori potvrdili, že TAM zostáva jedným z najrobustnejších rámcov pre skúmanie akceptácie AI technológií v organizačnom prostredí, pričom vysvetľuje 60–80 % variancie v zámeroch využívania AI (Weng et al., 2024).

Prezentovaná literatúra naprieč podkapitolami 2.1–2.3 sa zhoduje v jednom kľúčovom bode: hybridný model práce a nástup AI nie sú izolované trendy, ale vzájomne sa podmieňujúce sily transformujúce súčasný manažment (Kraus et al., 2022; Dwivedi et al., 2021; Davis, 1989). Spoločným menovateľom je aj konsenzus o nezastupiteľnosti ľudského úsudku – Hagemann et al. (2023), Fügener et al. (2022) aj Bankins et al. (2024) zhodne odmietajú model substitúcie a obhajujú komplementárnu spoluprácu ľudí a AI. Odlišnosti sa objavujú v miere optimizmu: zatiaľ čo Gupta et al. (2024) a Zhang et al. (2025) zdôrazňujú transformačný potenciál AI, Kronblad et al. (2024) a Jiang et al. (2025) poukazujú na systémové riziká – de-profesionalizáciu, kognitívnu pasivitu a eróziu manažérskej autority. Lauring (2025) a Moe et al. (2023) navyše upozorňujú, že hybridný model bez cielených intervencií sám osebe generuje organizačné nerovnosti, ktoré AI môže buď odstrániť, alebo naopak prehĺbiť. V nadväznosti na tieto poznatky sa v predkladanom článku stotožňujeme s pozíciou, že AI je v kontexte hybridného riadenia najpresnejšie chápať ako kognitívny amplifikátor manažérskych kapacít – nástroj, ktorého prínos je podmienený dôverou, transparentnosťou a organizačným prostredím, v ktorom je implementovaný.

2 Cieľ práce, metodológia a metódy

Hlavným cieľom tohto článku je prostredníctvom prehľadu vedeckej literatúry identifikovať, systematicky analyzovať a syntetizovať poznatky o tom, ako nástroje umelej inteligencie transformujú manažérske praktiky v hybridnom riadení tímov. Výskum sa opiera o teoretický rámec Technology Acceptance Model (TAM; Davis, 1989) a koncept Human-AI Teaming (HAIT; Berretta et al., 2023), pričom adresuje identifikovanú výskumnú medzeru – absenciu syntetického pohľadu prepájajúceho adopciu AI a hybridné pracovné prostredie, osobitne v európskom kontexte.

Na základe hlavného cieľa boli sformulované tri výskumné otázky:

- **RQ1:** Aké AI nástroje sú v súčasnosti využívané v hybridnom riadení tímov?
- **RQ2:** Ako AI transformuje konkrétne manažérske praktiky v hybridnom prostredí?
- **RQ3:** Aké sú kľúčové prínosy, výzvy a výskumné medzery implementácie AI v hybridnom riadení tímov?

Článok má charakter naratívneho prehľadu literatúry. Naratívny prehľad je v literatúre odporúčaný ako vhodný prístup pre oblasť, v ktorej sa výskumná základňa rýchlo rozvíja a kde primárnym cieľom nie je kvantitatívna agregácia výsledkov, ale konceptuálna syntéza a identifikácia vzorcov naprieč heterogénnymi štúdiami (Baumeister & Leary, 1997; Snyder, 2019). Vyhľadávanie zdrojov bolo realizované vo dvoch vedeckých databázach: Web of Science (WOS) a Scopus. Vyhľadávanie prebehlo v období február – marec 2026 a boli použité nasledovné kombinácie kľúčových slov:

- *"artificial intelligence" AND "hybrid team management"*
- *"AI" AND "management practices" AND "hybrid work"*
- *"human-AI teaming"*
- *"algorithmic management" AND "performance monitoring"*
- *"Technology Acceptance Model" AND "artificial intelligence" AND "management"*
- *"AI" AND "well-being" AND "remote work"*
- *"AI decision support" AND "managers"*

Kritériá zahrnutia a vylúčenia zdrojov sú uvedené v tabuľke 1.

Analytický postup po selekcii zdrojov zahŕňal tematické kódovanie (thematic coding) – každý zahrnutý článok bol kódovaný podľa: (a) hlavnej výskumnej témy, (b) metodologického prístupu (empirický/koncepčný/prehľad), (c) geografického kontextu výskumu a (d) priradenej tematickej oblasti dopadu AI (komunikácia, výkon, rozhodovanie, wellbeing). Toto kódovanie umožnilo systematickú syntézu zistení a identifikáciu výskumných medzier. Limitáciami zvoleného prístupu sú naratívny (nie plne systematický) charakter prehľadu a potenciálna selektivita pri výbere zdrojov, ktorá môže vnášať určitú mieru interpretačnej zaujatosti.

Tabuľka 1
Kritériá zahrnutia a vylúčenia zdrojov

Kritérium	Zahrnutie	Vylúčenie
Typ zdroja	Recenzované vedecké články (peer-reviewed)	Populárno-vedecké články, blogy, správy bez recenzného procesu
Databáza	Web of Science, Scopus	Zdroje mimo WOS a Scopus
Dostupnosť	Plný text dostupný s DOI odkazom	Abstrakty bez plného textu, zdroje bez DOI
Jazyk	Anglický jazyk	Ostatné jazyky
Časové vymedzenie	2020 – 2025	Publikácie pred rokom 2020 (s výnimkou zakladajúcich prác)
Tematická relevancia	AI v manažmente, hybridná práca, Human-AI Teaming, TAM v kontexte AI	Štúdie bez priamej väzby na manažérske praktiky alebo hybridné prostredie
Výskumný kontext	Organizačný, manažérsky alebo interdisciplinárny kontext	Čisto technické štúdie bez manažérskej implikácie

Zdroj: vlastné spracovanie

3 Výsledky výskumu

Nasledujúca kapitola predstavuje jadro článku a analyzuje štyri kľúčové oblasti, v ktorých AI transformuje manažérske praktiky hybridných tímov. Pre každú oblasť sú identifikované konkrétne AI nástroje, empiricky doložené prínosy a zároveň výzvy, ktoré implementácia AI prináša.

3.1 AI v komunikácii a koordinácii hybridných tímov

Komunikácia a koordinácia predstavujú jednu z najkritickejších výziev hybridných tímov. Keď časť tímu pracuje fyzicky na pracovisku a druhá časť na diaľku, vznikajú asymetrie v prístupe k informáciám, neformálnej komunikácii a kontextuálnym podnetom (Kraus et al., 2022). Hopf et al. (2025) v tejto súvislosti zdôrazňujú, že hybridné tímy s ľudskými a AI členmi vykazujú kvalitatívne odlišné vzorce zdieľania znalostí v porovnaní s čisto ľudskými tímami – AI agenti dokážu spracovať a redistribuovať informácie z rôznych zdrojov rýchlejšie, no nemusia nevyhnutne zachovávať kontextuálne nuansy medziľudskej komunikácie. AI nástroje vstupujú do tejto oblasti prostredníctvom automatizácie a optimalizácie komunikačných procesov.

Zhou a Gorman (2024) v komparatívnej štúdii ľudsko-AI a čisto ľudských tímov zistili, že AI môže signifikantne zlepšiť výkon tímu optimalizáciou načasovania a sekvencie komunikácie. Kým tradičné tímy strácali čas redundantnou komunikáciou, tímy s AI asistenciou dokázali identifikovať kritické informačné potreby a prioritizovať komunikačné toky. Prakticky to zahŕňa nástroje ako automatické transkribovanie a sumarizovanie stretnutí, inteligentné plánovanie a AI-asistovaná príprava agendy. Výskum zároveň ukázal, že hybridné tímy (ľudia + AI) podávali pri nečakaných zmenách kontextu podobný výkon ako čisto ľudské tímy, čo svedčí o schopnosti AI partnerov adaptovať sa na dynamicky sa meniace podmienky – no zároveň odhalil, že práve koordinácia v momente zmeny zostáva kritickým slabým článkom.

Hagemann et al. (2023) zdôrazňujú, že pre efektívne Human-AI Teaming musí AI koordinovať s ľuďmi nielen explicitne, ale aj implicitne – detekovať zlyhania komunikácie a navrhovať korekcie. Táto schopnosť je obzvlášť cenná v hybridnom prostredí, kde manažér nemá priamy vizuálny kontakt so všetkými členmi tímu. Zhu (2025) na základe analýzy zakotvených v teórii sociálnej prítomnosti a teórii mediálnej bohatosti identifikuje, že efektívne hybridné tímy kombinujú synchrónne a asynchrónne komunikačné nástroje podľa charakteru úlohy a vyžadujú explicitne nastavené komunikačné protokoly. Kľúčovým faktorom zostáva transparentnosť AI nástrojov – zamestnanci musia vedieť ako a kedy AI vstupuje do komunikačného procesu (Dwivedi et al., 2021).

3.2 AI v monitorovaní a riadení výkonu

Monitorovanie výkonu predstavuje najkontroverznejšiu oblasť aplikácie AI v hybridnom manažmente. Tradičné metódy hodnotenia výkonu sú v hybridnom prostredí neúčinné – manažéri nemajú priamy dohľad nad zamestnancami a hodnotenie na základe fyzickej prítomnosti je deformované. AI-poháňané systémy hodnotenia výkonu využívajú strojové učenie, prediktívnu analytiku a spracovanie prirodzeného jazyka na priebežnú analýzu výkonnostných dát (Gupta et al., 2024). Cai (2024) v tomto kontexte upozorňuje, že organizačná transparentnosť algoritmického hodnotenia výkonu priamo podmieňuje jeho vnímanú spravodlivosť, efektivitu a motivačný efekt na strane zamestnancov.

Gupta et al. (2024) v systematickom prehľade 73 vedeckých článkov identifikovali, že AI transformuje hodnotenie výkonu smerom k priebežnému, dátami podloženému a menej subjektívnemu procesu. Namiesto ročných hodnotení umožňuje AI kontinuálne sledovanie kvantitatívnych výkonnostných metrík, identifikáciu vzorcov poklesu výkonu a včasné intervencie. Autori však súčasne dokumentujú riziká: technologický stres zamestnancov, narušenie rovnováhy medzi pracovným a súkromným životom a efekt neustáleho sledovania. Emlund et al. (2025) v tejto súvislosti preukázali, že algoritmický dohľad znižuje súlad zamestnancov nie priamym donucovaním, ale prostredníctvom erózie autonómie a vnímanej kontroly – čo má dlhodobé negatívne dopady na intrinsickú motiváciu.

Feuerriegel et al. (2023) zavádzajú koncept algoritmického manažmentu ako automatizáciu manažérskych úloh pomocou AI algoritmov. Výskum OECD (2025) na vzorke viac ako 6 000 firiem zo 6 krajín ukázal, že hoci manažéri vnímajú algoritmické nástroje ako zlepšenie kvality rozhodnutí, až dve tretiny manažérov majú aspoň jednu obavu týkajúcu sa dôveryhodnosti nástrojov – pričom najčastejšie uvádzajú nejasné vymedzenie zodpovednosti pri chybnom rozhodnutí (28%), neschopnosť porozumieť logike algoritmických odporúčaní (27%) a nedostatočnú ochranu fyzického a duševného zdravia zamestnancov (27%). Kľúčovým zistením je, že vnímaná spravodlivosť AI systémov hodnotenia výkonu priamo závisí od miery vysvetliteľnosti ich rozhodnutí (Bankins et al., 2024).

3.3 AI v podpore manažérskeho rozhodovania

Podpora rozhodovania je jednou z najperspektívnejších oblastí aplikácie AI v manažmente. Hybridné prostredie generuje obrovské množstvo dát o tímovej dynamike, komunikačných vzorcoch a výkonnostných metrikách, ktoré ľudský manažér nedokáže efektívne spracovať bez technologickej asistencie. AI decision support systems (AI-DSS) integrujú tieto dáta a poskytujú manažérom odporúčania na základe analýzy komplexných vzorov (Buschmeyer et al., 2024). La Sala et al. (2024) v tomto kontexte zavádzajú pojem „plastické znalosti" (plastic knowledge) – druh adaptabilných kompetencií, ktoré umožňujú manažérom efektívne vyplniť medzery medzi tým, čo AI navrhuje a tým, čo organizačná realita vyžaduje. Tento koncept zdôrazňuje, že adopcia AI v rozhodovaní nie je len technologická, ale predovšetkým kompetenčná výzva.

Buschmeyer et al. (2024) v systematickom prehľade 44 experimentálnych štúdií zistili, že pre optimálny výkon ľudsko-AI rozhodovacej dvojice musia obaja aktéri fungovať na porovnateľnej úrovni kompetentnosti. Ak AI výrazne prevyšuje ľudskú expertízu, hrozí over-reliance – nadmerná závislosť manažéra na AI odporúčaniach bez kritického posúdenia. Naopak, ak manažér AI nedôveruje, výhody AI-DSS sa neutralizujú. Výskum Procedu et al. (2024) ďalej identifikoval, že v multi-rozhodovacích situáciách (keď manažér robí opakované rozhodnutia s AI asistenciou) rastie závislosť od AI s narastajúcou kognitívnou záťažou úlohy, kým nezhoda s predchádzajúcimi AI odporúčaniami spoľahlivosť znižuje – čo naznačuje dynamický a kontextovo citlivý charakter ľudsko-AI vzťahu v rozhodovaní. Optimálnym modelom je augmented decision-making (rozhodovanie s podporou umelej inteligencie): AI spracúva veľké objemy dát a navrhuje alternatívy, kým finálne rozhodnutie zostáva na ľudskom manažérovi.

Dwivedi et al. (2021) zdôrazňujú, že integrácia AI do manažérskych rozhodovacích procesov si vyžaduje súbežné riešenie otázok dôvery, transparentnosti a etiky. Explainable (vysvetliteľná) AI (XAI) – schopnosť AI transparentne prezentovať logiku svojich odporúčaní – je kľúčovým faktorom akceptácie zo strany manažérov. Berretta et al. (2023) potvrdzujú, že vysvetliteľnosť je jedným z piatich kľúčových klastrov výskumu HAIT a má priamy vplyv na dôveru manažérov voči AI systémom. Eisenhardt et al. (2024) v experimentálnom výskume so 53 odborníkmi a 88 manažérmi ďalej preukázali, že kultúrna „prísnosť" (cultural tightness) organizačného prostredia moderuje mieru, do akej manažéri dôverujú AI odporúčaniam – čo implikuje, že adopcia AI v rozhodovaní je silne závislá od organizačného a kultúrneho kontextu.

3.4 AI vo wellbeing manažmente zamestnancov

Wellbeing manažment zamestnancov predstavuje relatívne novú, no rýchlo rastúcu oblasť aplikácie AI v hybridných pracoviskách. Hybridný model práce so sebou prináša špecifické výzvy pre psychologickú pohodu: izoláciu vzdialených pracovníkov, hranicu medzi pracovným a súkromným životom a riziko vyhorenia (Cramarenco et al., 2023). Coulston (2025) v tejto súvislosti dokumentuje, že vedúci hybridných tímov systematicky podceňujú wellbeing problémy vzdialených členov tímu práve z dôvodu obmedzeného vizuálneho kontaktu – čo vytvára silný argument pre AI nástroje schopné detekovať signály poklesu pohody skôr, ako sa stanú viditeľnými pre manažéra. AI nástroje – chatboty pre psychologickú podporu, platformy na sledovanie nálady a systémy na detekciu vyhorenia – reagujú na tieto výzvy.

Virgillito et al. (2025) v prehľadovom článku 21 štúdií potvrdili prínosy AI nástrojov pre zdravie na pracovisku v oblastiach detekcie stresu, vyhorenia a psychologickej pohody zamestnancov. Personalizované AI systémy preukázali schopnosť identifikovať príznaky vyhorenia 3–4 týždne pred tým, ako si ich všimol manažér, čo umožňuje včasnú intervenciu. Autori však identifikujú závažné etické a súkromné obavy: monitorovanie emočného stavu zamestnancov je citlivá oblasť vyžadujúca prísne regulačné rámce. Toto je obzvlášť aktuálne v európskom kontexte, kde nariadenie GDPR stanovuje prísne podmienky pre spracovanie citlivých osobných údajov vrátane údajov o zdravotnom stave – čo môže limitovať implementáciu AI wellbeing nástrojov v porovnaní s inými geografickými oblasťami.

Hu et al. (2025) na vzorke 364 zamestnancov preukázali, že adopcia AI pozitívne ovplyvňuje zdieľanie znalostí a tímovú spoluprácu, pričom kľúčovú moderujúcu úlohu zohráva paradoxné vedenie a technologická nadšenosť zamestnancov. Toto zistenie má priame implikácie pre hybridný manažment: spôsob vedenia tímu (leadership style) a individuálny vzťah zamestnancov k technológiám determinuje, či AI nástroje pre wellbeing prinesú žiaduce výsledky. Emerald (2024) v súvislosti so „závislým" postavením zamestnancov v AI-riadenom HRM prostredí varuje pred tzv. efektmi temnej stránky – situáciami, keď AI-monitorovanie zamestnancov síce zvyšuje krátkodobú produktivitu, no dlhodobo narúša ich autonómiu, dôveru a intrinsickú motiváciu. Akceptácia AI wellbeing nástrojov teda závisí od faktorov priamo zahrnutých v TAM rámci – vnímanej užitočnosti a dôvery (Davis, 1989; Weng et al., 2024).

Tabuľka 2
Prehľad oblastí dopadu AI v hybridnom riadení tímov

Oblasť	Kľúčové AI nástroje	Prínosy	Výzvy
Komunikácia a koordinácia	Automatický prepis, AI plánovanie, chatboty	Zníženie kognitívnej záťaže, optimalizácia komunikácie	Transparentnosť, dôvera
Riadenie výkonu	Prediktívna analytika, algoritmický manažment	Objektívnosť, priebežné hodnotenie	Ochrana súkromia, stres
Podpora rozhodovania	AI-DSS, XAI systémy	Rýchlosť, komplexnosť analýzy	Over-reliance, etika
Wellbeing manažment	AI chatboty, detekcia vyhorenia	Včasná intervencia, personalizácia	Etika, regulácia

Zdroj: vlastné spracovanie podľa Gupta et al. (2024), Hagemann et al. (2023), Berretta et al. (2023).

Tabuľka 2 sumarizuje štyri kľúčové oblasti dopadu AI v hybridnom riadení tímov. Vo všetkých oblastiach možno pozorovať spoločný vzorec: AI nástroje prinášajú merateľné operačné prínosy – od zníženia kognitívnej záťaže v komunikácii cez objektívnejšie hodnotenie výkonu až po včasnú detekciu wellbeing problémov – každá oblasť je zároveň sprevádzaná špecifickými výzvami. Naprieč všetkými štyrmi oblasťami sa ako prierezové témy opakujú transparentnosť, dôvera a etická zodpovednosť, čo potvrdzuje, že technologická implementácia AI bez adekvátneho organizačného rámca a regulačných záruk nestačí na dosiahnutie žiaducich výsledkov.

Analyzovaná literatúra sa rozchádza predovšetkým v otázke miery kontroly a dohľadu, ktorú AI v hybridnom manažmente legitimizuje. Optimistická línia výskumu (Zhou & Gorman, 2024; Hu et al., 2025; Buschmeyer et al., 2024) vníma AI ako kognitívny amplifikátor, ktorý posilňuje manažérske kapacity bez narušenia ľudskej agentúry. Kritickejšia perspektíva (Emlund et al., 2025; Kronblad et al., 2024; Guglielmi et al., 2024) naopak dokumentuje systémové riziká – eróziu autonómie zamestnancov, kognitívnu pasivitu manažérov a dlhodobú de-profesionalizáciu. Geografická dimenzia tohto rozdielu nie je zanedbateľná: anglosaská a ázijská literatúra je voči algoritmickému dohľadu výrazne tolerantnejšia, kým európska perspektíva (OECD, 2025; Cai, 2024) trvá na nevyhnutnosti regulačných záruk a vysvetliteľnosti algoritmov. V predkladanom článku sa stotožňujeme s pozíciou, že tieto dva pohľady nie sú nekompatibilné – AI môže byť súčasne nástrojom efektivity aj zdrojom rizík, pričom výsledok závisí od kvality organizačného dizajnu, v ktorom je implementovaná.

4 Diskusia

Výsledky prehľadu literatúry umožňujú formulovať niekoľko kľúčových záverov s implikáciami pre výskum aj organizačnú prax. Odpoveď na RQ1 je jednoznačná: AI nástroje prenikajú do hybridného riadenia prostredníctvom automatizácie transkripcie a koordinácie (4.1), algoritmického hodnotenia výkonu (4.2), AI-DSS systémov (4.3) a wellbeing platforiem (4.4). Odpoveď na RQ2 ukazuje, že AI nemení manažérske praktiky lineárne – jej dopad je moderovaný dôverou, organizačnou kultúrou a individuálnymi charakteristikami manažérov a zamestnancov (Weng et al., 2024; Eisenhardt et al., 2024).

Kľúčovou teoretickou implikáciou je potvrdenie relevantnosti TAM rámca (Davis, 1989) pre kontextualizáciu adopcie AI v hybridnom prostredí. Weng et al. (2024) preukázali, že pôvodné TAM konštrukty (vnímaná užitočnosť, vnímaná jednoduchosť použitia) vysvetľujú 60–80% variancie v zámeroch využívania AI, pričom v kontexte hybridného manažmentu nadobúdajú osobitný význam rozšírené dimenzie – dôvera v AI a vnímané riziko. Teoretický rámec HAIT (Berretta et al., 2023; Hagemann et al., 2023) zase potvrdzuje, že vzťah ľudí a AI v tímoch nie je jednorozmerný: zahŕňa kognitívne, emocionálne aj kultúrne dimenzie, ktoré determinujú výsledný efekt AI implementácie.

Na úrovni praktických implikácií výsledky konzistentne naznačujú, že organizácie, ktoré zavádzajú AI do hybridného riadenia bez adekvátneho rámca dôvery a transparentnosti, riskujú negatívne vedľajšie efekty – technologický stres, eróziu autonómie a pokles intrinsickej motivácie zamestnancov (Emlund et al., 2025; Guglielmi et al., 2024). Zistenia OECD (2025) poukazujú na to, že tieto riziká sú obzvlášť výrazné v európskom kontexte, kde regulačné prostredie GDPR a kultúrne faktory kladú vyššie nároky na vysvetliteľnosť a etickú správu AI systémov. Odpoveď na RQ3 teda obsahuje varovanie: prínos AI je podmienený kvalitou organizačného dizajnu.

Najvýznamnejším prínosom tohto prehľadu je identifikácia výskumnej medzery: výskum v tejto oblasti je dominantne vedený v anglosaskom a ázijskom kontexte, kým stredoeurópska perspektíva adopcie AI nástrojov v hybridnom manažmente je nedostatočne zastúpená (Cramarenco et al., 2023; Bankins et al., 2024). Kultúrne faktory, špecifiká slovenského a stredoeurópskeho pracovného trhu a odlišný regulačný rámec EÚ môžu signifikantne ovplyvniť vzorce adopcie AI, čo vyžaduje cielený empirický výskum.

Záver

Tento prehľad literatúry dokumentuje, že AI transformuje hybridné riadenie tímov vo štyroch kľúčových oblastiach: komunikácii a koordinácii, monitorovaní výkonu, podpore rozhodovania a wellbeing manažmente. Technology Acceptance Model (Davis, 1989) a koncept Human-AI Teaming (Berretta et al., 2023; Hagemann et al., 2023) poskytujú teoretický rámec pre pochopenie podmienok úspešnej adopcie AI v manažérskej praxi. Prierezovými témami naprieč všetkými skúmanými oblasťami sú dôvera, transparentnosť a etická zodpovednosť – faktory, ktoré determinujú, či AI implementácia prinesie žiaduce výsledky alebo naopak prehĺbi existujúce organizačné problémy (OECD, 2025; Bankins et al., 2024).

Najvýznamnejším prínosom článku je identifikácia výskumnej medzery v podobe chýbajúcej európskej a stredoeurópskej perspektívy na adopciu AI v hybridnom manažmente. Budúci výskum by mal využiť systematickú rešerš s PRISMA protokolom a kvantitatívnu empirickú metodológiu – napríklad dotazníkový prieskum skúmajúci, ako manažéri hybridných tímov na Slovensku vnímajú a využívajú AI nástroje, pričom TAM môže slúžiť ako explanačný model adopcie. Praktické odporúčania pre organizácie sú zrejmé: úspešná implementácia AI v hybridnom manažmente si vyžaduje nielen technologické investície, ale predovšetkým budovanie kultúry dôvery, vzdelávanie manažérov v oblasti AI gramotnosti, jasné etické rámce a dodržiavanie regulačných požiadaviek – len tak môže AI skutočne plniť svoju úlohu kognitívneho amplifikátora ľudských manažérskych kapacít.

Poznámka o riešenom projekte

Tento článok je jedným z výstupov výskumného projektu IGMP Ekonomickej univerzity v Bratislave č. I-26-105-00 s názvom „Implementácia umelej inteligencie do slovenských podnikov: Kľúčové kompetencie, procesy a úspešné postupy integrácie AI“.

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VYUŽITIE UMELEJ INTELIGENCIE PRI TVORBE PLÁNU NÁSTUPNÍCTVA V RODINNOM PODNIKU

Peter Kuchár

Abstract
Succession planning is a critical challenge for family businesses, ensuring long-term sustainability and the seamless transfer of leadership across generations. Traditional succession planning often relies on subjective decision-making and personal biases, which may hinder the selection of the most suitable successors. This study explores the application of artificial intelligence (AI) in optimizing succession planning processes within family businesses. AI-driven analytics, predictive modeling, and machine learning techniques can enhance decision-making by identifying key leadership traits, assessing potential candidates, and forecasting business outcomes under various scenarios. Moreover, AI can mitigate emotional influences by providing data-driven insights, thereby promoting fairness and transparency in successor selection. The research also examines potential challenges, such as ethical considerations, data privacy, and the need for human oversight in AI-driven decision-making. By integrating AI into succession planning, family businesses can improve strategic workforce planning, reduce risks associated with leadership transitions, and ensure the continuity of their legacy. This paper contributes to the growing body of knowledge on AI applications in business management and provides practical implications for family enterprises seeking to enhance their succession planning strategies.

JEL classification*:* D83, M41, O33
Keywords*:* succession plan, succession planning, artificial intelligence in business

Úvod

V súčasnosti je významná časť slovenskej ekonomiky tvorená rodinnými podnikmi, pričom sa odhaduje, že ich podiel na celkovom výkone ekonomiky predstavuje 60 až 80 %. Podľa údajov Slovak Business Agency nie je 70 % rodinných firiem schopných úspešne zvládnuť proces odovzdania riadenia a transferu majetku na druhú generáciu. Nedávny výskum poradenskej spoločnosti PricewaterhouseCoopers preukázal, že miera neúspešnosti prechodu na druhú generáciu dosahuje u mileniálov až 81 %. Tento trend je negatívny, pričom možno pozorovať postupné zvyšovanie miery neúspešnosti pri firemnom nástupníctve v rodinných podnikoch. Plánovanie nástupníctva v rodinných podnikoch je definované ako strategický proces, prostredníctvom ktorého sa zabezpečuje prechod vedenia a vlastníctva medzi generáciami v rámci podniku. Tento proces je považovaný za kľúčový pre dlhodobú kontinuitu a udržateľnosť podniku. Ako sa však ukazuje, jeho význam je ešte viac podčiarknutý jedinečnými výzvami, ktorým tieto podniky čelia, pričom jednou z najvýznamnejších je potreba včasného plánovania. Bolo preukázané, že včasné plánovanie nástupníctva výrazne prispieva k úspešnému prechodu vedenia. V tejto súvislosti sa zdôrazňuje, že identifikácia a príprava potenciálnych nástupcov v dostatočnom predstihu môže minimalizovať riziká spojené s náhlymi zmenami vo vedení (Kechli, 2023). Napriek tomu má formálny plán nástupníctva vypracovaných len približne 15 % rodinných podnikov (Saymaz & Lambert, 2019).

Na základe uvedených skutočností možno konštatovať, že rodinné podniky zohrávajú v slovenskej ekonomike významnú úlohu, avšak transfer majetku a odovzdanie riadenia medzi generáciami je len zriedkavo realizovaný úspešne. Jedným z možných dôvodov je absencia vypracovaného plánu nástupníctva v podnikoch.

Cieľom tohto príspevku je analyzovať, či a akým spôsobom by umelá inteligencia mohla prispieť k efektívnemu vytvoreniu plánu nástupníctva v rodinnom podniku.

1 Súčasný stav riešenej problematiky doma a v zahraničí

1.1 Plánovanie nástupníctva v rodinných podnikoch

Rodinný podnik je definovaný ako podnik, v ktorom sa ako vlastníci podieľajú viacerí členovia rodiny a ktorý je ovplyvňovaný rodinou alebo rodinnými vzťahmi a ktorý sám seba vníma ako rodinný podnik (Tang a Hussin 2020). Pre Slovensko je dôležitá novelizácia zákona č. 112/2018 Z. z. o sociálnej ekonomike a sociálnych podnikoch, ktorá nadobudla účinnosť 1. júla 2023. Táto novela priniesla definíciu rodinného podniku, ktorá zahŕňa nielen obchodné spoločnosti a družstvá, ale aj fyzické osoby – podnikateľov, no len za predpokladu, že členovia spoločnej rodiny spĺňajú zákonné požiadavky. Koľko je rodinných podnikov na Slovensku, nie je presne známe. V novelizácii zákona je síce možnosť dobrovoľnej registrácie alebo evidencie rodinného podniku a to cez formulár s rôznymi prílohami, no podľa Združenia podnikateľov Slovenska tento zákon nemá pre rodinné firmy žiaden prínos, skôr naopak a výsledkom registrácie je len ďalšia administratívna záťaž a aj ďalšia možnosť následných kontrol zo strany štátu napríklad o čom rodinné podniky rokujú na rodinnej rade. Rodinný podnik je dominantná forma hospodárskej organizácie na celom svete (Desbois, 2016; Renuka & Marath 2023). Podľa Európskej komisie rodinné podniky tvoria viac ako 60 % všetkých podnikov v Európe.

Plánovanie nástupníctva je zámerné a systematické úsilie organizácie zabezpečiť kontinuitu vedenia na kľúčových pozíciách, udržať a rozvíjať intelektuálny a znalostný kapitál pre budúcnosť a podporovať individuálny postup (Rothwell, 2015). Je to kľúčová diskusia v rámci strategického plánovania podniku (Mohamad a Yahya, 2010). Cieľom plánovania nástupníctva je zabezpečiť trvalú efektívnu výkonnosť organizácie prostredníctvom strategického rozvoja, výmeny a uplatnenia kľúčových ľudí v priebehu času (Rothwell, 2015). Systémy plánovania nástupníctva by mali byť navrhnuté tak, aby boli jednoduché, flexibilné a otvorené neustálemu zlepšovaniu (Barnett a Davis, 2008). Rodinné podniky majú jedinečné charakteristiky, ktoré významne ovplyvňujú ich procesy nástupníctva (Desbois, 2016). Na rozdiel od nerodinných podnikov sa v rodinných podnikoch prelína osobná rodinná dynamika s podnikateľskou činnosťou, čo vytvára špecifické výzvy (Rothwell, 2015).

Možno konštatovať, že kľúčovou výzvou rodinných podnikov je plánovanie nástupníctva, ktoré ovplyvňujú rodinné vzťahy, generačné rozdiely, emocionálne väzby a osobné ambície členov rodiny, čo môže viesť k náročným rozhodovacím procesom a potenciálnym konfliktom v rámci podniku.

1.2 Umelá inteligencia

Umelá inteligencia zahŕňa technológie, ako sú strojové učenie (ML), spracovanie prirodzeného jazyka (NLP), počítačové videnie, rozpoznávanie reči a robotika (Kumar & Ratten, 2024). Umelá inteligencia (AI) je transformačná technológia, ktorá simuluje procesy ľudskej inteligencie prostredníctvom strojov alebo počítačových systémov, vrátane učenia, uvažovania, riešenia problémov, vnímania a porozumenia jazyku (Sawang & Kivits, 2024). Možno ju definovať ako strojový systém schopný robiť predpovede, odporúčania alebo rozhodnutia, ktoré môžu ovplyvňovať reálne alebo virtuálne prostredie na základe cieľov definovaných človekom (Kumar & Ratten, 2024).

Autori Sawang a Kivits (2024) uvádzajú tieto hlavné výhody AI:

- Zvýšenie efektívnosti a produktivity automatizáciou opakujúcich sa úloh.
- Zlepšenie rozhodovania prostredníctvom analýzy obrovského množstva údajov a prediktívneho modelovania.
- Personalizované zákaznícke skúsenosti prostredníctvom technológií, ako sú chatboty.
- Zjednodušenie operácií v oblastiach, ako je riadenie dodávateľského reťazca a ľudské zdroje.
- Identifikácia nových trhových príležitostí a predvídanie potrieb.

Aplikácie umelej inteligencie možno vo všeobecnosti rozdeliť do dvoch kategórií. (Enholm et al., 2022). Prvou je AI na automatizáciu, ktorá nahrádza ľudskú prácu a druhou je AI na rozšírenie, ktorá zvyšuje ľudskú inteligenciu poskytovaním poznatkov na lepšie rozhodovanie.

AI sa môže uplatniť v rôznych podnikových funkciách vrátane marketingu, riadenia výroby, riadenia podniku a služieb zákazníkom. AI sa využíva aj na zlepšenie interných podnikových procesov a na zefektívnenie týchto procesov (Enholm et al., 2022). V oblasti riadenia ľudských zdrojov sa AI môže využívať na získavanie a udržanie talentov, analýzu prieskumov a vytváranie virtuálnych asistentov pre ľudské zdroje (Konovalova et al., 2022).

Technológie umelej inteligencie vrátane strojového učenia, spracovania prirodzeného jazyka a expertných systémov ponúkajú rôzne aplikácie na zlepšenie plánovania nástupníctva v organizáciách (Ghedabna et al., 2024; Kumar & Ratten, 2024; Anuradha & Rani, 2024).

Strojové učenie (ML)

Strojové učenie je jednou z najrozšírenejších foriem umelej inteligencie, ktorá sa v súčasnosti vyvíja na použitie v podnikaní (Bharadiya, Thomas a Ahmed, 2023). Algoritmy ML môžu analyzovať obrovské množstvo údajov o zamestnancoch, ako sú hodnotenia výkonnosti, hodnotenia zručností, záznamy o školeniach a vzory kariérneho postupu, s cieľom identifikovať zamestnancov s vysokým potenciálom a pravdepodobnosťou postupu (Anuradha & Rani, 2024; Attamimi, Abidin & Amiruddin, 2024). To pomáha organizáciám prijímať rozhodnutia založené na údajoch o stratégiách udržania zamestnancov a identifikovať zamestnancov, ktorým hrozí odchod (Anuradha & Rani, 2024). Algoritmy ML dokážu spracovať veľké objemy údajov s cieľom identifikovať vzory a predpovedať úspešnosť zamestnancov, čo vedie k efektívnejším a presnejším rozhodnutiam o rozvoji a riadení (Ekuma, 2024). Využitím algoritmov strojového učenia a prediktívnej analýzy môžu organizácie predpovedať výkonnosť, možnosti povýšenia a potenciálne riziká fluktuácie zamestnancov (Attamimi, Abidin & Amiruddin, 2024). AI sa používa na posúdenie pripravenosti zamestnancov na vedenie, čím sa zabezpečí, že kritické funkcie majú kvalifikovaných nástupcov a udrží sa stabilita počas zmien vo vedení (Anuradha & Rani, 2024).

Spracovanie prirodzeného jazyka (NLP)

NLP môže analyzovať textové údaje zo zdrojov, ako sú hodnotenia výkonnosti, prieskumy zamestnancov a výstupné rozhovory, s cieľom identifikovať kľúčové témy a pocity súvisiace so spokojnosťou zamestnancov, ich angažovanosťou a potenciálnymi rizikami fluktuácie (Enholm et al., 2022; Ghedabna et al., 2024; Kumar & Ratten, 2024). NLP môže pomôcť pri vývoji vzdelávacích nástrojov na báze umelej inteligencie prispôsobených špecifickým potrebám rodinných podnikov (Sawang & Kivits, 2024). NLP umožňuje chatbotom porozumieť a komunikovať pomocou ľudského jazyka, čo uľahčuje učenie a vývoj s prístupom k väčšiemu množstvu údajov (Enholm et al., 2022).

Expertné systémy

Expertné systémy môžu napodobňovať ľudské rozhodovanie tým, že zachytávajú a reprezentujú odborné znalosti expertov, ktoré môžu využívať ostatní členovia organizácie, a slúžia ako znalostná báza (Enholm et al., 2022). Očakáva sa, že technológie AI pomôžu identifikovať potenciálne zaujatosti pri prijímaní zamestnancov a zabrániť diskriminácii na základe pohlavia, veku, rasy a etnického pôvodu, čím sa zníži ľudská zaujatosť a poskytne sa objektívne zastúpenie založené na údajoch (Konovalova et al., 2022). Plánovanie nástupníctva riadené umelou inteligenciou môže organizáciám ponúknuť presnejší, efektívnejší a prispôsobivejší prístup k rozvoju a kontinuite vedenia (Anuradha & Rani, 2024).

1.3 Využitie AI pri plánovaní nástupníctva

1.3.1 Potencionálne výhody AI pre plánovanie nástupníctva

Umelá inteligencia ponúka niekoľko potenciálnych výhod pre plánovanie nástupníctva vrátane rozhodovania založeného na údajoch, objektívnych hodnotení a personalizovaných plánov rozvoja. (Anuradha & Rani, 2024; Ghedabna et al., 2024).

Rozhodovanie založené na údajoch

AI dokáže analyzovať obrovské množstvo údajov týkajúcich sa výkonu, potenciálu a charakteristík zamestnancov s cieľom predpovedať výkon, možnosti povýšenia a potenciálne riziká fluktuácie zamestnancov (Attamimi, Abidin & Amiruddin, 2024). Prediktívna analýza dokáže identifikovať vzory a trendy v správaní zamestnancov, čo uľahčuje proaktívne rozhodovanie s cieľom udržať si špičkové talenty a zabezpečiť kontinuitu na kľúčových pozíciách (Anuradha & Rani, 2024). Analytika talentov riadená umelou inteligenciou umožňuje organizáciám efektívnejšie a účinnejšie zhromažďovať, analyzovať a využívať údaje o zamestnancoch, čo podporuje strategické rozhodnutia týkajúce sa talentov, ako je nábor, rozvoj a riadenie nástupníctva (Attamimi, Abidin & Amiruddin, 2024). Umelá inteligencia poskytuje cenné poznatky o správaní zákazníkov, trendoch na trhu a výkonnosti podniku, čo rodinným podnikom umožňuje prijímať strategické rozhodnutia na základe dôkazov založených na údajoch (Kumar & Ratten, 2024). AI uľahčuje vytváranie spoľahlivých obchodných prognóz a scenárov, čo umožňuje podnikom strategicky pružne sa orientovať v dynamike trhu (Kumar & Ratten, 2024). AI ponúka organizáciám presnejší, efektívnejší a prispôsobivejší prístup k rozvoju a kontinuite vedenia, čím zabezpečuje strategickejší prístup k riadeniu talentového potrubia a stabilite pracovnej sily (Anuradha & Rani, 2024). Umelá inteligencia dokáže analyzovať údaje a identifikovať potenciálne riziká pre rodinné podniky, čím im pomáha rozvíjať odolnejšie stratégie (Kumar & Ratten, 2024).

Objektívne hodnotenia

AI poskytuje objektívne hodnotenia založené na údajoch, ktoré zabezpečujú jednotnosť vývoja v celej organizácii (Ghedabna et al., 2024). Umelá inteligencia zvyšuje rozmanitosť a inkluzívnosť pri plánovaní nástupníctva tým, že minimalizuje nevedomé predsudky pri výbere kandidátov (Anuradha a Rani, 2024). Umelá inteligencia umožňuje komplexnú analýzu výkonnosti, kompetencií a preferencií zamestnancov s využitím prediktívnych modelov na identifikáciu potenciálnych kandidátov a formulovanie efektívnejších stratégií riadenia talentov (Attamimi, Abidin & Amiruddin, 2024). Tímy ľudských zdrojov sa môžu zamerať výlučne na objektívne ukazovatele výkonnosti, čo pomáha zabezpečiť, aby boli identifikovaní najlepší kandidáti bez ohľadu na pohlavie, vek alebo iné demografické faktory (Anuradha & Rani, 2024). Hodnotenia založené na umelej inteligencii môžu poukázať na schopnosti, obmedzenia a oblasti rastu jednotlivca na pracovisku. Tieto hodnotenia podrobne skúmajú technické schopnosti aj osobné vlastnosti, načrtávajú vhodnosť jednotlivca pre určenú pozíciu a poukazujú na oblasti zrelé na rozvoj (Vapiwala & Pandita, 2024).

Personalizované plány rozvoja

AI uľahčuje personalizované plány rozvoja zamestnancov, identifikuje nedostatky v zručnostiach a odporúča na mieru šité vzdelávacie programy, ktoré sú v súlade s individuálnymi aj organizačnými cieľmi (Ghedabna et al., 2024). AI dokáže analyzovať údaje o výkonnosti zamestnancov, ich preferenciách a histórii osobného rozvoja s cieľom odhaliť nedostatky v zručnostiach a poskytnúť odporúčania pre vhodné vzdelávacie programy (Attamimi et al., 2024). Nástroje založené na AI v oblasti vzdelávania a rozvoja využívajú analýzu údajov na vytvorenie vzdelávacích programov šitých na mieru zamestnancom (Siradhana, N. K. 2023). AI dokáže prispôsobiť programy odbornej prípravy a rozvoja individuálnym potrebám zamestnancov, čím sa zabezpečí, že vzdelávanie bude efektívnejšie a relevantnejšie (Joe & Suganya, 2022). Algoritmy AI sa využívajú aj pri zamestnancovi v organizácii na vytvorenie účinných individualizovaných rozvojových plánov zameraných na rôzne spôsoby vzdelávania, ciele a údaje o zlepšovaní zamestnancov (Ghedabna a kol., 2024). Analýza kariérnych dráh a medzier v zručnostiach na báze AI môže organizáciám pomôcť zmapovať potenciálne kariérne dráhy zamestnancov na základe ich súčasných zručností a kompetencií (Attamimi, Abidin & Amiruddin, 2024). Personalizácia zvyšuje spokojnosť zamestnancov a znižuje fluktuáciu (Ghedabna et al., 2024). Nástroje AI môžu klientom navrhnúť, ako by mohli zvládať stres, rovnováhu medzi pracovným a súkromným životom a dokonca aj svoju pohodu (Ghedabna et al., 2024). AI dokáže analyzovať údaje o učení a poskytovať personalizované návrhy na zlepšenie výsledkov učenia (Attamimi, Abidin a Amiruddin, 2024).

V súhrne možno konštatovať, že AI má potenciál transformovať plánovanie nástupníctva tým, že umožňuje rozhodovanie založené na údajoch, objektívne hodnotenie a personalizované rozvojové plány.

1.3.2 Výzvy a obmedzenia AI pri plánovaní nástupníctva

Využívanie AI v organizačných procesoch predstavuje niekoľko potenciálnych výziev a obmedzení vrátane obáv o ochranu osobných údajov, etických aspektov a predpojatosti algoritmov (Enholm et al., 2022; Ghedabna et al., 2024).

Ochrana osobných údajov

Robustné protokoly o bezpečnosti údajov a jasné zásady manipulácie s údajmi sú kľúčové pre zabezpečenie dôvernosti a ochrany informácií o zamestnancoch (Anuradha & Rani, 2024; Attamimi, Abidin & Amiruddin, 2024). Organizácie sa musia orientovať vo vyvíjajúcom sa prostredí predpisov o ochrane údajov, ako je všeobecné nariadenie o ochrane údajov (GDPR), ktoré vyžaduje zabezpečenie „práva na vysvetlenie" automatizovaných rozhodnutí s vplyvom na jednotlivcov (Enholm et al., 2022). Pri práci s citlivými informáciami týkajúcimi sa rodiny v rodinných podnikoch sa zodpovedné používanie údajov zhromaždených prostredníctvom aplikácií umelej inteligencie stáva etickým aspektom (Kumar & Ratten, 2024).

Etické aspekty

Transparentnosť, racionalita a zodpovednosť pri nasadzovaní AI v rozhodovaní sú nevyhnutné pre etické využívanie AI v oblasti ľudských zdrojov (Ghedabna et al., 2024). Keďže sa AI čoraz viac integruje do procesov ľudských zdrojov, vyvoláva to otázky týkajúce sa ochrany súkromia, spravodlivosti a ľudského prístupu v personálnom riadení (Joe & Suganya, 2022). Organizácie musia pri začleňovaní AI do svojich obchodných modelov zvážiť otázky súvisiace so súkromím, zaujatosťou, transparentnosťou a zodpovednosťou (Moro-Visconti, Cruz Rambaud & López Pascual, 2023). Etické rámce sú kľúčové na zabezpečenie súladu implementácie AI so spoločenskými hodnotami a normami (Islami a Mulolli, 2024). Autori Enholm a kol. uvádzajú, že jedným z najvýraznejších príkladov je zlyhanie organizácií pri identifikácii a odstraňovaní zaujatosti v údajoch alebo algoritmoch AI, čo môže viesť k diskriminácii alebo nepriaznivým výsledkom pre určité etnické skupiny, pohlavia alebo skupiny obyvateľstva. Takisto konštatujú, že systémy AI nerozumejú ani vstupom, ktoré spracúvajú, ani svojim výstupom. Učia sa tak, že interpretujú vzory v predchádzajúcich údajoch s cieľom predpovedať budúcnosť. Výsledky tak môžu odrážať podozrivé vzory, ako napríklad sexizmus a rasizmus, ktoré sa nachádzajú v základných údajoch.

Predpojatosť algoritmu

Algoritmy môžu uprednostňovať niektoré trendy alebo vlastnosti pred inými. (Londhe et al., 2025). Algoritmy AI môžu zdediť predpojatosť z historických údajov (Joe & Suganya, 2022). Systémy riadenia ľudských zdrojov musia byť starostlivo monitorované, aby sa znížilo riziko neúmyselnej zaujatosti a zabezpečila sa spravodlivosť (Anuradha & Rani, 2024). Ak systém umelej inteligencie skúma súčasný spôsob zamestnávania a zistí, že mu chýba akákoľvek heterogenita (vďaka charakteristikám, ako je vek a rasa), jeho výsledok bude naďalej podporovať tento základný typ predsudkov (Tairov a kol., 2024). Systémy umelej inteligencie môžu udržiavať predsudky prítomné v ich tréningových údajoch, čo vedie k diskriminačným praktikám pri prijímaní do zamestnania (Islami a Mulolli, 2024). Organizácie musia zaviesť spoľahlivé mechanizmy na zmiernenie týchto negatívnych vplyvov vrátane zabezpečenia transparentnosti a zodpovednosti v nástrojoch riadených AI (Ekuma, 2024). Pravidelné audity a rozmanité súbory údajov môžu pomôcť minimalizovať tieto riziká (Anuradha & Rani, 2024). Budúce trendy budú zahŕňať vývoj modelov AI, ktoré budú vysvetliteľné a kontrolovateľné, čím sa zabezpečí, že tímy ľudských zdrojov (HR) a zamestnanci pochopia, ako sa predpovede vytvárajú (Anuradha & Rani, 2024).

Ďalšie výzvy a obmedzenia

Zabezpečenie kvality údajov je nevyhnutné na zachovanie etickej a presnej analýzy. Zneužívanie alebo nadmerné spoliehanie sa na údaje môže viesť k nekalým praktikám, preto sú transparentnosť a etické aspekty pri zavádzaní prediktívnych stratégií stability pracovnej sily kľúčové (Anuradha & Rani, 2024). Rozhodovanie v rodinnom podniku môže byť náročné z dôvodu chýbajúcich jasných hraníc medzi rodinou a podnikom, potenciálnych konfliktov záujmov medzi členmi rodiny, plánovania nástupníctva a otázok riadenia (Sawang & Kivits, 2024). Umelá inteligencia dosahuje svoje limity pri riešení jedinečných problémov, čo si vyžaduje zásah človeka (Babashahi et al., 2024). Hoci prediktívna analýza ponúka cenné poznatky, prílišné spoliehanie sa na algoritmy môže viesť k prehliadaniu kvalitatívnych faktorov, ktoré majú vplyv na stabilitu pracovnej sily (Anuradha & Rani, 2024). Konflikty medzi akcionármi a manažérmi by mohli mať významné dôsledky na skutočné využívanie AI v prevádzke, konkrétne, protichodné názory, keď akcionári podporujú automatizáciu na zníženie nákladov, zatiaľ čo manažéri presadzujú augmentáciu, môžu spôsobiť paralýzu pri skutočnom nasadení (Enholm et al., 2022). Prediktívne nástroje sa najlepšie používajú ako doplnok k ľudskému úsudku, a nie ako jeho náhrada, pretože algoritmom môže chýbať kontextové porozumenie potrebné na prijímanie diferencovaných rozhodnutí v oblasti ľudských zdrojov (Anuradha & Rani, 2024). AI môže zmeniť základnú povahu práce a predstavovať vážnu hrozbu pre zamestnanosť (Konovalova et al., 2022). Povaha „čiernej skrinky“ mnohých prediktívnych algoritmov predstavuje etickú výzvu, keďže zamestnanci a manažéri môžu mať problém pochopiť základ predpovedí, čo vedie k nedôvere a spochybňovaniu platnosti poznatkov riadených umelou inteligenciou (Anuradha & Rani, 2024). Zavedenie AI a vytlačenie alebo presun viacerých tradičných pracovných rolí pravdepodobne povedie k zvýšeniu napätia, konfliktov a pocitov nedôvery voči samotnej technológii a útvarom, ktoré podporujú jej nasadenie (Enholm et al., 2022).

Na zmiernenie týchto výziev by organizácie mali zaviesť opatrenia na ochranu súkromia zamestnancov, minimalizovať zaujatosť a zachovať transparentnosť procesov AI (Anuradha a Rani, 2024). To zahŕňa pravidelný audit algoritmov AI na zaujatosť, školenie modelov na rôznych súboroch údajov a integráciu etických aspektov do návrhu a nasadenia systémov AI (Enholm et al., 2022; Ghedabna et al., 2024). Okrem toho je nevyhnutné dosiahnuť rovnováhu medzi poznatkami riadenými AI a ľudským úsudkom, čím sa zabezpečí, že AI posilní, a nie nahradí ľudské rozhodovanie (Anuradha & Rani, 2024).

2 Výskumný dizajn

Výskumná otázka príspevku je: Či a ako by vedela umelá inteligencia pomôcť pri vytvorení plánu nástupníctva v rodinnom podniku?

Cieľom príspevku je preskúmať súčasné poznanie o využití umelej inteligencie pri plánovaní firemného nástupníctva.

Obsahom príspevku je literárna rešerš o využití umelej inteligencie pri plánovaní firemného nástupníctva.

Za účelom vypracovania praktickej časti som študoval a analyzoval zdroje o firemnom nástupníctve, rodinných podnikoch, o umelej inteligencii a jej možnému využitiu pri plánovaní firemného nástupníctva. Zdroje som vyberal podľa kľúčových slov a podľa relevantnosti. Príspevky, ktoré neboli v anglickom jazyku alebo ktorých abstrakty neboli v súlade s hlavnou výskumnou otázkou, boli vylúčené z analýzy. Duplicity v zdrojoch boli odstránené na základe abecedného zoradenia zdrojov, pričom príspevky s rovnakým názvom a číslom na konci boli porovnané a duplicitné záznamy boli eliminované. Následne boli príspevky zoradené podľa veľkosti, pričom v prípade rovnakej veľkosti boli jednotlivé položky porovnané a duplicitné boli odstránené.

V príspevku sú použité zahraničné literárne zdroje, za využitia google scholar, web od science, scopus a proguest. Medzi autorov, ktorí sa zaoberajú skúmanou témou patria okrem iných Abidin , Amiruddin , Anuradha, Attamimi, Enholm, Ghedabna, Kumar a Ratten.

Výsledkom príspevku je návrh na ďalší výskum o využití umelej inteligencie pri plánovaní firemného nástupníctva.

3 Výsledky práce a diskusia

Cieľom tejto práce bolo zodpovedať otázku, či a akým spôsobom by mohla byť umelá inteligencia využitá pri tvorbe plánu nástupníctva v rodinnom podniku.

Táto otázka sa považuje za relevantnú nakoľko možno konštatovať, že rodinné podniky predstavujú základný pilier ekonomiky a preto je dôležité zachovať ich kontinuitu.

Z dostupnej literatúry sa zistilo, že transfér majetku a riadenia na ďalšiu generáciu býva málokedy úspešný. Nedostatok formálneho plánovania nástupníctva, ktoré je prítomné len u približne 15% rodinných podnikov, predstavuje zásadný rizikový faktor pre ich udržateľnosť.

Prepojenie AI s procesom plánovania nástupníctva predstavuje perspektívny prístup k riešeniu problémov spojených s prechodom majetku a vedenia. Výskum poukazuje na tri hlavné výhody, ktoré prináša využitie AI pri plánovaní nástupníctva. Ide o rozhodovanie založené na údajoch, objektívne hodnotenia a personalizované plány rozvoja. Výsledky literárnej rešerše naznačujú, že implementácia AI do procesu plánovania nástupníctva by mohla výrazne zlepšiť efektivitu a kvalitu rozhodovacích procesov v rodinných podnikoch. Rozhodnutia založené na rozsiahlych údajoch spracovaných AI sú opreté o empirické dáta a prediktívne analýzy, čo môže viesť k efektívnejšiemu identifikovaniu a rozvoju kandidátov s vysokým potenciálom pre budúce vedúce pozície. Objektívne hodnotenia pomocou technológie AI môžu eliminovať subjektívne faktory, ktoré často skresľujú tradičné hodnotenia kandidátov. Takéto objektívne prístupy napomáhajú spravodlivejšiemu výberu nástupcov. AI nástroje môžu na základe analýzy individuálnych údajov navrhovať konkrétne vzdelávacie a rozvojové programy, čím podporujú kontinuálny rast a adaptáciu na meniace sa podmienky trhu.

Napriek výrazným prínosom prináša integrácia AI so sebou aj niekoľko zásadných výziev ako sú ochrana osobných údajov a etické aspekty, predpojatosť algoritmov a nutnosť zachovania ľudského úsudku. Využívanie AI vyžaduje prísnu ochranu osobných údajov, najmä v kontexte rodinných podnikov, kde sú často spracovávané citlivé informácie. Súčasné legislatívne rámce kladú dôraz na transparentnosť a ochranu práv zamestnancov. Algoritmy môžu dedične odrážať historické predsudky obsiahnuté v dátach na ktorých AI trénuje. To môže viesť k diskriminačným praktikám, ak nie je zabezpečená pravidelná kontrola a audit algoritmických modelov. AI by mala slúžiť ako podporný nástroj. Pre dosiahnutie optimálneho rozhodovacieho procesu je nevyhnutné synergické prepojenie expertného ľudského úsudku s prediktívnymi analýzami generovanými umelou inteligenciou.

Na základe dostupnej literatúry možno konštatovať, že aj keď rodinné podniky čelia výrazným problémom v procese nástupníctva, integrácia umelej inteligencie môže priniesť inovatívne riešenia v oblasti plánovania nástupníctva. Úspešná implementácia AI však závisí od vyriešenia etických a legislatívnych otázok a zabráneniu predpojatosti algoritmu. Pritom je nevyhnutné, aby technológia posilnila a nie nahradila ľudský úsudok.

Táto analýza poskytuje dôležité východisko pre ďalšie skúmanie využitia umelej inteligencie pri tvorbe plánu nástupníctva v rodinnom podniku, pričom zdôrazňuje jej potenciál pri optimalizácii rozhodovacích procesov a zabezpečení kontinuity riadenia v dynamickom podnikateľskom prostredí.

3.1 Komparatívna analýza využitia nástrojov umelej inteligencie pri tvorbe plánu nástupníctva v rodinných podnikoch

Plánovanie nástupníctva v rodinných podnikoch predstavuje komplexný a multidimenzionálny proces, ktorý integruje strategické, personálne, finančné, právne a psychosociálne dimenzie podnikania. Ide o oblasť, v ktorej sa prelínajú ekonomické racionality s rodinnou dynamikou, hodnotami a emóciami, čo výrazne zvyšuje nároky na kvalitu analytických nástrojov a rozhodovacích procesov. V tomto kontexte sa využitie nástrojov umelej inteligencie (AI) javí ako potenciálne významný faktor zvyšovania systematickosti, konzistentnosti a transparentnosti plánovania nástupníctva.

Aplikácia AI v procese nástupníctva môže prispieť najmä k lepšej štrukturalizácii problému, identifikácii rizík, podpore rozhodovania a k dokumentácii jednotlivých krokov procesu. Zároveň však platí, že nevhodný výber alebo nesprávna implementácia AI nástroja môže viesť k nadmernému zjednodušeniu komplexných vzťahov, opomenutiu kritických oblastí alebo dokonca k eskalácii latentných rodinných konfliktov. Z tohto dôvodu je nevyhnutné pristupovať k využívaniu AI v oblasti rodinného nástupníctva metodicky a kriticky.

Cieľom tejto časti príspevku je navrhnúť systematický a reprodukovateľný postup hodnotenia a výberu AI nástrojov v závislosti od jednotlivých fáz procesu nástupníctva a špecifických potrieb rodinných podnikov. Pozornosť je zameraná predovšetkým na schopnosť AI systémov podporovať proces prostredníctvom riadeného dialógu, analytických otázok a generovania prakticky využiteľných výstupov.

3.1.1 Metodika hodnotenia AI nástrojov

V rámci empirickej časti výskumu bolo analyzované využitie piatich súčasných generatívnych AI systémov: Gemini 3 Pro, Claude Sonnet 4.5, ChatGPT (GPT-4o), Perplexity a Grok 3. Testovanie bolo realizované prostredníctvom verejne dostupných (bezplatných) verzií týchto nástrojov po registrácii používateľa, pričom bola využitá aj funkcionalita deep research.

Za účelom zabezpečenia porovnateľnosti výstupov bol všetkým AI systémom zadaný identický vstupný prompt. Prompt bol koncipovaný tak, aby simuloval úlohu vedeckého pracovníka s cieľom navrhnúť otázkový rámec pre tvorbu a aktualizáciu plánu nástupníctva v rodinnom podniku, pričom sa vyžadovalo predchádzajúce identifikovanie obsahových náležitostí takéhoto plánu.

Vygenerované návrhy promptov boli následne podrobené kvalitatívnej komparatívnej analýze. Hodnotenie bolo realizované na desaťbodovej škále (1–10), kde vyššia hodnota indikovala vyššiu mieru naplnenia daného kritéria. Hodnotiaci rámec pozostával z deviatich analytických kritérií reflektujúcich kľúčové dimenzie plánovania nástupníctva.

3.2 Výsledky komparatívnej analýzy

3.2.1 Komplexnosť pokrytia problematiky

Prvým hodnotiacim kritériom bola miera, do akej jednotlivé AI nástroje pokrývali kľúčové oblasti plánovania nástupníctva, vrátane strategickej vízie, výberu a rozvoja nástupcu, leadershipu, vlastníckych a finančných vzťahov, právnych mechanizmov, rodinnej governance, riešenia konfliktov, časového harmonogramu, krízových scenárov a implementácie.

Najvyššiu mieru komplexnosti dosiahli nástroje Grok 3 a Claude Sonnet 4.5, ktoré ponúkli systematické a široké tematické pokrytie vrátane oblastí rodinnej governance a krízového plánovania. ChatGPT (GPT-4o) poskytol robustné jadro problematiky, avšak s menšou hĺbkou v oblasti dlhodobej kontinuity podnikania. Gemini 3 Pro a Perplexity síce pokryli hlavné tematické okruhy, avšak niektoré oblasti boli spracované skôr sumarizačne alebo s dôrazom na diskusiu než na implementáciu.

Nasledujúce hodnotiace kritériá – štruktúrovanosť procesu, praktická použiteľnosť, práca s emóciami a konfliktmi, právne a daňové aspekty, finančné plánovanie, riadenie používateľa, flexibilita a vhodnosť pre formálny dokument – boli analyzované analogickým spôsobom, pričom výsledky sú sumarizované v tabuľke 1.

Tabuľka 1
Hodnotenie komplexnosti AI-nástrojov

Kritérium	Grok 3	ChatGPT (GPT-4o)	Claude Sonnet 4.5	Gemini 3 Pro	Perplexity
Komplexnosť pokrytia témy	9	8	9	7	8
Štruktúrovanosť procesu	10	8	8	9	7
Praktická použiteľnosť	8	10	9	8	7
Práca s emóciami a konfliktmi	8	6	8	6	10
Právne a daňové aspekty	9	8	8	7	7
Finančné plánovanie	8	8	8	7	7
Riadenie používateľa	10	7	8	9	6
Flexibilita a adaptabilita	6	8	8	7	9
Vhodnosť pre formálny dokument	10	8	9	8	6
CELKOVÉ SKÓRE	**78**	**71**	**75**	**68**	**67**

Zdroj: vlastné spracovanie

3.3 Súhrnné hodnotenie

Súhrnné výsledky komparatívnej analýzy, prezentované v tabuľke 1, poukazujú na to, že najvyššie celkové skóre dosiahol nástroj Grok 3. Zároveň však analýza jednoznačne naznačuje, že neexistuje univerzálne „najlepší“ AI nástroj vhodný pre celý proces plánovania nástupníctva v rodinných podnikoch. Jednotlivé systémy sa líšia svojimi silnými stránkami v závislosti od konkrétnej fázy procesu a typu požadovaného výstupu.

Na základe týchto zistení sa ako optimálny javí kombinovaný prístup, založený na fázovaní procesu nástupníctva a selektívnom využívaní špecifických silných stránok jednotlivých AI nástrojov. Tento prístup umožňuje maximalizovať prínosy AI pri súčasnom minimalizovaní rizík spojených s jej nekritickým alebo plošným využívaním.

Záver

Možno konštatovať, že hoci je implementácia AI v rodinných podnikoch zatiaľ v počiatočnej fáze, predstavuje významný potenciál na zvýšenie ich konkurencieschopnosti a zabezpečenie dlhodobej udržateľnosti. Plánovanie nástupníctva môže byť transformované umelou inteligenciou prostredníctvom umožnenia rozhodovania založeného na údajoch, objektívneho hodnotenia a tvorby personalizovaných rozvojových plánov. Podniky by však mali mať na pamäti výzvy a etické aspekty spojené so zavádzaním AI a prijať opatrenia na zabezpečenie spravodlivosti, transparentnosti a ochrany osobných údajov. V budúcich výskumoch by sa malo skúmať, akým spôsobom prebieha prijímanie AI v rodinných podnikoch, aký dlhodobý vplyv môže mať jej implementácia a aké osvedčené postupy by mohli byť vypracované na zabezpečenie jej etického a efektívneho využitia. Taktiež by mohol byť realizovaný výskum zameraný na využitie AI pri tvorbe konkrétneho plánu nástupníctva, prispôsobeného špecifikám jednotlivých rodinných podnikov. Tento proces by mohol byť založený na komplexnom systéme otázok, v rámci ktorého by AI získavala informácie o rodinnom podniku, jeho vízii a potenciálnych nástupcoch a na základe toho by bol následne vypracovaný formálny plán nástupníctva. Moje odporúčanie pre podnikateľov je, aby si pripravovali plán nástupníctva a nebáli a využili pomoc AI pri jeho tvorbe. Moje odporúčanie pre vládu je investovať do vlastnej AI, ako sa ukázalo v prípade modelu Deepseek, je to možné aj z nižšími nákladmi. Predpokladám, že v budúcnosti vzniknú tisíce modelov AI a je žiadúce, aby mali aj jednotlivé štáty svoju vlastnú. Týmto opatrením sa zabráni spracovaniu údajov v zahraničí, a zároveň sa podporí vzdelávanie domácich odborníkov v oblasti umelej inteligencie. Táto “domáca“ umelá inteligencia by mohla byť lepšie prispôsobená špecifikám konkrétnej krajiny.

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ANALYSIS OF AI ADOPTION AND ITS KEY DETERMINANTS IN EU COUNTRIES

Diana Pallérová – Kristián Drugda

Abstract
Artificial intelligence adoption is increasingly understood as a capability driven process shaped by firms' digital foundations, human capital, and innovation environment. This study examines business level AI adoption across EU countries in a cross-country cross-sectional framework covering 2023 to 2025. Using Eurostat indicators, it combines enterprise level measures for firms with macro structural variables to assess both the evolution of AI uptake and its key correlates. The analysis maps changes in AI adoption over time and cross-country differences in adoption dynamics, documents the 2025 dispersion of AI adoption and its potential determinants within the domains of technological readiness, digital human capital, and the macro level innovation environment, and evaluates the direction and strength of associations between AI adoption and these determinants using correlation analysis. The results show a pronounced increase in enterprise AI adoption across the EU, alongside persistent heterogeneity in both adoption levels and growth trajectories. The strongest relationships with AI adoption are observed for digital human capital, particularly the availability of ICT specialists and higher population digital skills, suggesting that skills and talent supply remain central constraints and enablers. Indicators of technological readiness, notably cloud service uptake and the use of enterprise business software, are also positively and robustly associated with AI adoption, while business sector R&D intensity provides additional support through a more favourable innovation input environment. The findings indicate that AI diffusion is driven by complementarities between skills, enterprise digital infrastructure, and innovation investment rather than by any single factor, offering policy and managerial implications for accelerating AI uptake in lagging EU economies.

JEL classification: *J24, O32, O33*
Keywords: *AI adoption, Digital human capital, European Union*

Introduction

Artificial intelligence (AI) has emerged as one of the most influential general-purpose technologies shaping contemporary economic systems and firm-level competitiveness. Unlike earlier waves of digitalisation that focused primarily on automation or information processing, AI enables predictive, adaptive, and learning-based functionalities that can fundamentally transform how firms organise production, manage resources, and generate value. From an economic perspective, AI is increasingly understood as a productivity-enhancing technology with the potential to reshape industry structures, alter labour demand, and influence long-term growth trajectories (OECD, 2025). At the enterprise level, AI adoption is therefore no longer viewed as an isolated technological upgrade but rather as a strategic investment decision that affects competitiveness, innovation capacity, and resilience in dynamic market environments (Lee et al., 2022).

The literature increasingly emphasises that AI adoption should be understood as a capability-driven process rather than a purely technological choice. Firms' decisions to adopt and scale AI are shaped by the presence of complementary assets, including digital infrastructure, organisational readiness, and human capital. Technological readiness, such as the availability of scalable computing resources and integrated enterprise software systems, provides the necessary foundation for deploying AI applications. Equally important is digital human capital, encompassing both specialised ICT professionals and broader workforce digital skills, which determines whether firms can effectively implement, adapt, and maintain AI solutions (Cubric, 2020; Oldemeyer, Jede, & Teuteberg, 2025). At a higher level, the macroeconomic innovation environment, particularly investment in research and development, further conditions firms' absorptive capacity and willingness to experiment with advanced technologies (Lee et al., 2022).

Although a growing body of research has examined individual drivers and barriers to AI adoption, comparative cross-country analyses that integrate enterprise-level digital readiness, human capital conditions, and macro-level innovation inputs remain limited, particularly in the EU context. Much of the existing literature focuses either on firm-level determinants within single countries or on narrow subsets of enabling factors, leaving an incomplete picture of how these elements interact at the national level. Moreover, rapidly evolving digital conditions and recent acceleration in AI uptake call for updated evidence that reflects the current stage of diffusion. Against this background, this study contributes by providing an integrated cross-country assessment of business-level AI adoption across EU member states, explicitly linking adoption outcomes to technological readiness, digital human capital, and the innovation environment within a unified analytical framework. The empirical analysis draws on open Eurostat data for the EU 27, tracks AI adoption over 2023 to 2025, and operationalises enabling conditions through the most recent available indicators on digital technologies, skills, and innovation inputs. Methodologically, we combine adoption growth indexing with descriptive analysis and correlation testing using Pearson and Spearman to assess the robustness of the relationships. The findings point to a strong acceleration of AI adoption in the EU alongside persistent differences across countries, with the strongest associations related to the availability of ICT specialists and overall digital skills, while business R&D intensity and core digital foundations such as cloud use and enterprise software also appear to matter.

1 Current State of the Solved Problem at Home and Abroad

1.1 The concept of AI adoption and innovation diffusion

In management and innovation research, enterprise AI adoption is increasingly framed as a multistage process in which the pivotal transition is the move from experimentation to scaling. Haefner et al. (2023) show that implementation and expansion unfold across distinct phases and that, beyond the initial technical deployment, successful progression depends on building robust data foundations, reconfiguring processes, and establishing governance capabilities that enable production grade use and the replication of solutions across multiple organisational domains. This process-oriented view aligns with a rapidly expanding empirical and review-based literature that treats AI adoption as a central determinant of competitiveness, productivity, and innovation performance.

International evidence consistently indicates that uptake remains selective and uneven, concentrated among larger enterprises, technology intensive sectors, and firms with stronger innovation capabilities (Cubric, 2020; Oldemeyer, Jede, and Teuteberg, 2025). While early narratives often anticipated rapid diffusion, more recent studies emphasise persistent constraints rooted in organisational complexity, high implementation costs, data availability and quality challenges, and shortages of relevant skills, which keep many firms in pilot mode rather than fully embedding AI into core business processes (OECD, 2025). EU focused comparative research similarly finds systematically higher adoption in countries with more advanced digital ecosystems, stronger innovation systems, and more developed ICT labour markets (Ionașcu, 2025; Laitsou, Gerogiannis, and Savvas, 2025).

These studies highlight the importance of national context, since institutional quality, policy frameworks, and accumulated digital capabilities shape firms' readiness to engage with AI, even as EU enterprises face shared structural frictions such as regulatory uncertainty, limited access to specialised talent, and difficulties integrating AI with legacy systems, which collectively slow diffusion despite rising awareness of AI's potential benefits (OECD, 2025).

1.2 Technological readiness and digital infrastructure as determinants of AI adoption

A recurring conclusion in the recent literature is that enterprise AI adoption is strongly path dependent and builds on firms' technological readiness and the maturity of their digital foundations. Systematic evidence suggests that organisations are more likely to adopt and especially to scale AI when they already operate interoperable enterprise systems and data infrastructures that support reliable data access, integration, and reuse, because these reduce implementation frictions and the fixed costs of deployment (Oldemeyer, Jede, & Teuteberg, 2025). Empirical work in the European context similarly links AI uptake to broader digital capabilities and complementary investments, indicating that AI is more often adopted where firms have already progressed in digitalisation and innovation-oriented capability building (Arroyabe et al., 2024). Survey based studies grounded in TOE and diffusion perspectives further underline the importance of infrastructure readiness, compatibility with existing systems, and organisational capacity as practical preconditions for adoption (Sánchez et al., 2025). OECD highlights cloud computing as a key enabling platform that lowers entry barriers by providing flexible access to computing resources and scalable infrastructure, which can make experimentation and deployment feasible even for firms with limited upfront investment capacity (OECD, 2025).

From a European perspective, technological readiness has been identified as a key differentiating factor between high- and low-adoption countries. Research indicates that enterprises operating in digitally mature environments are better positioned to experiment with and scale AI, as complementary technologies are already embedded in routine business processes (Ionașcu, 2025). However, the literature also cautions that technological infrastructure alone is insufficient. While digital foundations are a necessary condition, they do not automatically translate into AI adoption unless combined with appropriate organisational and human capabilities (Cubric, 2020). This insight reinforces the view that AI diffusion reflects cumulative digital development rather than isolated technology choices.

1.3 Digital human capital and skills constraints

Digital human capital is widely regarded as one of the most critical determinants of AI adoption. Numerous studies identify shortages of ICT specialists and limited digital skills among the workforce as primary barriers preventing firms from implementing AI solutions effectively (Hunady, 2025; Oldemeyer et al., 2025). AI systems require not only technical expertise for development and maintenance but also managerial and operational competencies that enable firms to integrate AI into decision-making and workflows. As a result, firms operating in labour markets with limited digital talent face higher adoption costs and greater implementation risks.

In the EU context, disparities in digital skills and ICT labour supply contribute significantly to cross-country differences in AI uptake. Comparative analyses show that countries with a higher share of ICT specialists and stronger general digital skills among the population tend to exhibit higher levels of enterprise AI adoption (Ionașcu, 2025; Laitsou et al., 2025). Firm-level investment in ICT training is also highlighted as an important mechanism for overcoming skill constraints, particularly for small and medium-sized enterprises that may struggle to attract specialised talent (Badghish & Soomro, 2024). These findings support the interpretation that human capital constraints represent a structural bottleneck for AI diffusion and that skills development plays a central role in enabling sustainable adoption.

1.4 Innovation environment, R&D, and synthesis of the literature

Beyond firm-level capabilities, the broader innovation environment shapes incentives and capacities for AI adoption. Investment in research and development enhances firms' absorptive capacity, supports experimentation, and facilitates the integration of advanced technologies into production and innovation processes. Empirical evidence demonstrates that AI adoption is more prevalent in environments characterised by higher R&D intensity and stronger innovation systems, as these conditions reduce uncertainty and encourage long-term strategic investment (Lee et al., 2022; European Commission, 2024). AI adoption is therefore closely linked to national innovation performance and the availability of complementary knowledge assets.

The literature increasingly converges on the view that AI adoption is driven by complementarities rather than by single determinants. Technological readiness, digital human capital, and innovation inputs jointly shape the conditions that support AI diffusion, and shortcomings in any one of these domains can substantially constrain adoption outcomes (Cubric, 2020; Ćukušić, 2025). Configurational and firm-level studies further suggest that multiple pathways to AI adoption exist, but successful implementation consistently relies on bundles of capabilities rather than isolated investments. This synthesis provides the conceptual foundation for analysing AI adoption across EU countries by jointly considering enterprise digital infrastructure, human capital conditions, and the macro-level innovation environment.

2 Research design and methodology

2.1 Object of the research and research sample

The main objective of this paper is to theoretically ground and empirically assess which determinants within the domains of enterprises' technological readiness, digital human capital, and the macro level innovation environment are most strongly associated with business level artificial intelligence adoption across EU countries, and thereby to identify the factors that best account for cross country differences in AI uptake, including its evolution over the 2023 to 2025 period.

Building on the main objective, the following research questions are formulated:

- RQ1: What is the current level of business-level AI adoption across EU countries, and how has it evolved over the 2023–2025 period, including cross-country differences in the pace of growth?
- RQ2: What are the current levels and dispersion of AI adoption and its associated key determinants across EU, and which indicators within the domains of technological readiness, human capital, and the macro-level innovation environment exhibit the greatest cross-country variability?
- RQ3: What is the direction and strength of the correlation between business-level AI adoption and its determinants in the domains of technological readiness, digital human capital, and the macro-level innovation environment across EU countries?

The dataset was retrieved from Eurostat's open-access database (Eurostat, 2025). Indicator selection was informed by two criteria – conceptual relevance to the research topic as established in the literature, and cross-country availability and comparability across European economies. Given that not all countries had complete data for the same periods, latest available data were utilized to maintain the highest possible representativeness of the sample.

The indicators considered in this paper can be organised into three analytical domains as technological infrastructure and digital capability at the enterprise level (BUSINESS_SW, CLOUD_COMP, DATA_ANALYTICS), human capital and digital skills

(ICT_TRAINING, ICT_SPECIALISTS, DIG_SKILLS), and macro-level investment in innovation inputs (R&D).

To capture cross-country differences in digitalisation and innovation within a cross-sectional framework, the empirical design combines micro-level enterprise adoption measures with macro-structural national indicators, including population digital skills, the availability of ICT labour, and R&D intensity. Unless stated otherwise, variables expressed as a percentage of enterprises refer to enterprises with at least 10 persons employed (≥10), consistent with Eurostat's ICT usage in enterprises methodology. In contrast, macro-level indicators are reported either as a percentage of GDP (e.g., business-sector R&D expenditure) or as population- and workforce-based shares (e.g., the proportion of individuals with at least basic digital skills and the share of ICT specialists in total employment).

Variable definitions:

- AI_USE (2023-2025) – share of enterprises (%) using at least one artificial intelligence technology. This indicator summarises whether the firm reports adoption of at least one AI technique.
- CLOUD_COMP (2025) – share of enterprises (%) buying cloud computing services used over the internet. Conceptually, it reflects reliance on externally provided computing resources delivered via the internet.
- BUSINESS_SW (2025) – share of enterprises (%) using any business software (ERP, CRM or BI). The variable is coded as adoption of at least one of the three enterprise application types.
- DATA_ANALYTICS (2025) – share of enterprises (%) performing data analytics, either by the enterprise's own employees or by an external provider. The indicator captures whether firms use data-analytics practices as part of their operations, irrespective of whether the capability is internalised or outsourced.
- DIG_SKILLS (2025) – share of individuals aged 16–74 (%) with basic or above basic overall digital skills. Unlike the enterprise indicators, this is a population-based measure of the general digital capability available in each country.
- ICT_TRAINING (2024) – share of enterprises (%) that provided training to develop or upgrade the ICT skills of their personnel in the reference year. In interpretation, this serves as a proxy for firm-level investment in digital human capital.
- ICT_SPECIALISTS (2024) – share of employment accounted for by ICT specialists (%). The indicator approximates the size of the technical workforce that can support diffusion and maintenance of advanced digital technologies in firms.
- R&D (2024) – business enterprise R&D expenditure as a percentage of GDP. This macro-level variable is interpreted as an innovation-input intensity measure at the country level.

2.2 Methodological approach

The dynamics of AI adoption over the 2023 to 2025 period are assessed using a growth index derived from year-on-year changes in the share of enterprises using AI. Based on these annual changes, an average growth index (AVG Growth Index) is computed for each country to provide a synthetic measure of the overall pace of change across the observed time horizon. The results are summarised in a table (Table 1) reporting AI_USE values for 2023, 2024, and 2025 together with the resulting AVG Growth Index for each country. Incidies were calculated using MS Excel.

The analysis then profiles the 2025 cross section through descriptive statistics that characterise the central tendency and dispersion of each indicator across countries (using last available year of each indicator). For each variable, the Shapiro–Wilk test is additionally reported as a diagnostic assessment of departures from normality. This diagnostic evidence informs the selection and interpretation of association measures in the subsequent step, particularly where distributional non normality motivates the use of rank-based statistics.

Finally, the relationship between AI adoption and the selected determinants is examined via correlation analysis to quantify both the direction and magnitude of cross-country associations. Two complementary measures are employed. Pearson's correlation coefficient captures linear association under conventional distributional assumptions, while Spearman's rank correlation coefficient provides a more robust alternative appropriate for non-normal data and monotonic relationships that may be nonlinear.

All descriptive statistics, including measures of central tendency and dispersion, as well as the Shapiro-Wilk normality tests and the correlation analyses, were carried out in the statistical software Jamovi. Calculations related to time development, specifically the year-on-year growth indices and the resulting AVG Growth Index, were conducted in Microsoft Excel.

3 Research Results

This section examines the current level and recent evolution of business-level AI adoption across EU Member States, highlighting cross-country differences and shifts in digital maturity. It then focuses on the key determinants of AI adoption in the EU and assesses the direction and magnitude of their association with AI uptake through correlation analysis. The distribution and cross-country variability of the selected indicators are summarized using descriptive statistics.

3.1 Current state of AI adoption and its development across EU countries

Based on Eurostat data, significant differences in the rate of AI adoption can be observed among EU member states. Table 1 provides an overview of the share of enterprises that use AI technologies in at least one business function in the years 2023, 2024 and 2025. To better illustrate the dynamics of this development, a growth index was also calculated.

Table 1
Percentage of EU enterprises using at least one of the AI technologies

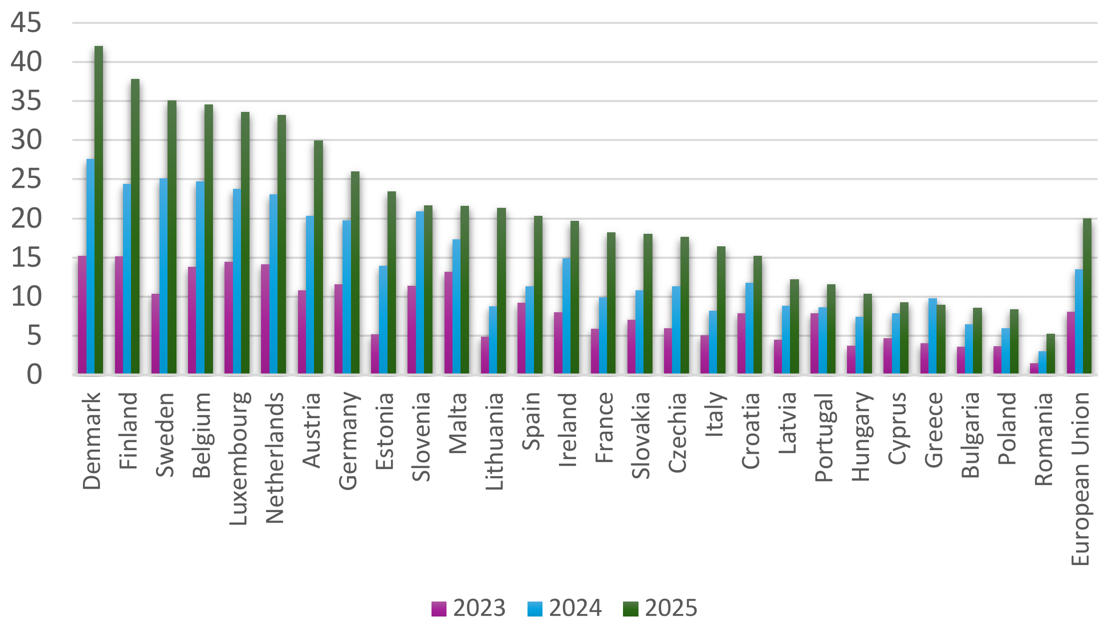
Country	2023	2024	2025	AVG Growth Index
European Union - 27 countries	***8.06***	***13.48***	***19.95***	***1.5762***
Belgium	13.81	24.71	34.54	1.5935
Bulgaria	3.62	6.47	8.55	1.5544
Czechia	5.90	11.26	17.6	1.7358
Denmark	15.17	27.58	42.03	1.6710
Germany	11.55	19.75	25.97	1.5124
Estonia	5.19	13.89	23.4	2.1805
Ireland	8.01	14.90	19.64	1.5891
Greece	3.98	9.81	8.93	1.6876
Spain	9.18	11.31	20.27	1.5121
France	5.88	9.91	18.16	1.7589
Croatia	7.89	11.76	15.19	1.3911
Italy	5.05	8.20	16.4	1.8119
Cyprus	4.67	7.90	9.27	1.4325
Latvia	4.53	8.83	12.21	1.6660
Lithuania	4.86	8.76	21.3	2.1170
Luxembourg	14.45	23.73	33.61	1.5293
Hungary	3.68	7.41	10.37	1.7065
Malta	13.17	17.30	21.56	1.2799
Netherlands	14.10	23.06	33.21	1.5378
Austria	10.79	20.27	29.95	1.6781
Poland	3.67	5.90	8.36	1.5123
Portugal	7.86	8.63	11.54	1.2176
Romania	1.51	3.07	5.21	1.8651
Slovenia	11.37	20.89	21.61	1.4359
Slovakia	**7.04**	**10.78**	**18**	**1.6005**
Finland	15.10	24.37	37.82	1.5829
Sweden	10.37	25.09	35.04	1.9080

Source: own processing based on the statistical data of Eurostat (2025)

Table 1 presents the evolution of AI adoption among enterprises in the European Union between 2023 and 2025, based on projected statistical data from Eurostat (2025). The indicator tracks the percentage of enterprises utilizing at least one AI technology, serving as a proxy for the depth of digital transformation within the corporate sector. The aggregated results for the EU-27 reveal a robust upward trajectory, with the adoption rate rising from 8.06% in 2023 to a projected 19.95% in 2025. This dynamic expansion corresponds to an Average Growth Index of 1.5762 and is consistent with evidence from the European Investment Bank (EIB) that EU firms maintain a strong pace of investment in digitalisation and AI, suggesting that AI is increasingly treated as a mainstream capability rather than a purely experimental tool (EIB, 2025). However, despite this accelerating trend, the absolute adoption levels suggest that full-scale integration of AI remains a challenge for the majority of European firms, reflecting the complexities associated with implementing advanced cognitive systems. (OECD, 2025)

In terms of regional performance, a distinct "multi-speed Europe" pattern emerges. The highest adoption rates projected for 2025 were observed in Denmark (42.03%), Finland (37.82%), Sweden (35.04%), Belgium (34.54%), and the Netherlands (33.21%). These countries constitute the group of digital frontrunners, characterized by mature innovation ecosystems, high availability of venture capital, and a workforce with advanced digital skills (European Commision; 2024). Their high adoption rates can be attributed to a proactive corporate culture that views technology as a primary driver of competitiveness. In stark contrast, the lowest adoption rates are forecasted for Romania (5.21%), Poland (8.36%), Bulgaria (8.55%), and Cyprus (9.27%). This significant lag suggests structural barriers in these regions, such as a more conservative managerial approach, aversion to investment risks associated with emerging technologies, and a shortage of specialized AI talent. The disparity highlights a persistent digital divide between Northern/Western Europe and the Central/Eastern European (CEE) region (McKinsey & Company; 2022).

Figure 1
AI adoption of enterprises (%) of European countries in the period 2023-2025



Source: own processing based on the statistical data of Eurostat (2025)

Figure 1 clearly illustrates a multi speed Europe in enterprise AI adoption. In 2025, the Nordic countries Denmark, Finland and Sweden form the leading cluster, combining the highest adoption levels with consistently above average values already in 2023 and 2024, which points to strong absorptive capacity and an ability to scale AI into core business processes. They are followed by other digitally advanced small open economies such as Belgium, Luxembourg and the Netherlands, while the middle of the distribution reflects gradual convergence among countries with rising but still moderate uptake. At the lower end, Romania, Poland, Bulgaria and Cyprus remain clear laggards: despite incremental year on year increases, their adoption levels stay markedly below the EU average, underscoring a persistent intra EU digital divide.

3.2 Descriptives and Correlation analysis of AI adoption and its key determinants

This section presents the key analysis (correlation analysis) of this paper that explores how business level AI adoption relates to the selected determinants across EU countries. Before reporting the correlation coefficients, Table 2 provides an overview of the descriptive statistics for the variables included in the analysis and provides the baseline for correlation analysis (Table 3).

Table 2
Descriptive statistics of indicators

Variable	Descriptives						Shapiro-Wilk	
	N	Mean	Median	SD	Minimum	Maximum	W	p
AI_USE	27	20.73	19.640	10.259	5.210	42.03	0.945	0.16476
BUSINESS_SW	27	50.74	51.090	12.824	31.050	73.07	0.956	0.30113
CLOUD_COMP	27	52.52	52.080	16.296	17.830	79.21	0.968	0.56250
DATA_ANALYTICS	27	41.18	40.560	9.118	24.500	59.99	0.967	0.53122
DIG_SKILLS	27	60.80	60.840	12.801	31.840	83.61	0.970	0.59962
ICT_TRAINING	27	23.25	21.580	7.998	9.110	38.33	0.970	0.60899
ICT_SPECIALISTS	27	5.31	5.000	1.428	2.500	8.60	0.928	0.06286
R&D	27	1.15	0.990	0.711	0.290	2.61	0.915	0.03068

Source: own processing using JAMOVI software

Table 2 provides a descriptive profile of a sample of 27 EU countries for the variable AI_USE (enterprise AI adoption) and selected digitalisation “enablers” (BUSINESS_SW, CLOUD_COMP, DATA_ANALYTICS, DIG_SKILLS, ICT_TRAINING, ICT_SPECIALISTS, and R&D), while also assessing distributional properties using the Shapiro–Wilk normality test. In terms of level and cross-country heterogeneity, AI_USE is characterised by a mean of 20.73 (median 19.64), relatively high dispersion (SD = 10.26), and a wide range (min 5.21; max 42.03). This degree of variability points to substantial cross-national inequality in enterprise AI uptake, consistent with a “digital divide” interpretation in which a group of high-penetration leaders coexists with countries where adoption remains limited. A similar pattern of uneven development is evident in other indicators, particularly CLOUD_COMP (M = 52.52, SD = 16.30, min 17.83, max 79.21) and BUSINESS_SW (M = 50.74, SD = 12.82), suggesting that firms’ technological capabilities and readiness for digital transformation are highly differentiated across the EU. By contrast, DATA_ANALYTICS (M = 41.18, SD = 9.12) and ICT_TRAINING (M = 23.25, SD = 8.00) exhibit more moderate dispersion, which may indicate a comparatively more even diffusion of certain mid-level digital practices, although notable cross-country gaps persist. Variables expressed as shares of GDP or employment, such as R&D intensity (% of GDP) and ICT specialists (% of employment), naturally exhibit a smaller numerical range than enterprise-level adoption measures. Shapiro–Wilk test (W) was used to assess normality. At $\alpha = 0.05$, most variables do not deviate significantly from normality ($p > 0.05$ for AI_USE, BUSINESS_SW, CLOUD_COMP, DATA_ANALYTICS, DIG_SKILLS, ICT_TRAINING), supporting the use of parametric methods where other assumptions hold. Given that R&D is the only variable that rejects normality ($p < 0.05$), the main bivariate analysis is complemented with Pearson correlation coefficients for comparability with the remaining variables, while also reporting Spearman rank correlations as a robustness check in the subsequent section.

Table 3
Selected correlations (Pearson and Spearman)

Indicator	AI_USE			
BUSINESS_SW	**Pearson's r**	0.648***	**Spearman's rho**	0.576**
	df	25	**df**	25
	p-value	0.00026	**p-value**	0.00201
CLOUD_COMP	**Pearson's r**	0.641***	**Spearman's rho**	0.614***
	df	25	**df**	25
	p-value	0.00031	**p-value**	0.00084
DATA_ANALYTICS	**Pearson's r**	0.485*	**Spearman's rho**	0.408*
	df	25	**df**	25
	p-value	0.01035	**p-value**	0.03538
DIG_SKILLS	**Pearson's r**	0.714***	**Spearman's rho**	0.669***
	df	25	**df**	25
	p-value	0.00003	**p-value**	0.00020
ICT_TRAINING	**Pearson's r**	0.605***	**Spearman's rho**	0.516**
	df	25	**df**	25
	p-value	0.00084	**p-value**	0.00646
ICT_SPECIALISTS	**Pearson's r**	0.748***	**Spearman's rho**	0.779***
	df	25	**df**	25
	p-value	<.00001	**p-value**	<.00001
R&D	**Pearson's r**	0.713***	**Spearman's rho**	0.655***
	df	25	**df**	25
	p-value	0.00003	**p-value**	0.00021

Source: own processing using JAMOVI software
*Notes: *** high correlation, ** moderate correlation, * lower correlation*

Table 3 reports selected bivariate correlations between AI_USE (enterprise AI adoption) and a set of digital "enabler" indicators, presenting both Pearson's r and Spearman's rho (df = 25). Overall, the results show consistently positive and statistically significant associations, indicating that higher national levels of digital readiness tend to coincide with higher levels of AI adoption among enterprises. The strongest relationship is observed for ICT_SPECIALISTS (Pearson $r = 0.748$; Spearman $\rho = 0.779$; $p < 0.00001$), underscoring the central role of specialised human capital in enabling AI deployment. Similarly strong correlations are found for DIG_SKILLS ($r = 0.714$; $\rho = 0.669$; $p \leq 0.00020$)

and R&D ($r = 0.713$; $\rho = 0.655$; $p \leq 0.00021$), suggesting that enterprise AI uptake is closely linked to broader digital skill endowments and innovation capacity. Significant but somewhat weaker associations are evident for BUSINESS_SW ($r = 0.648$; $\rho = 0.576$) and CLOUD_COMP ($r = 0.641$; $\rho = 0.614$), reflecting the relevance of business process digitalisation and cloud maturity, as well as for ICT_TRAINING ($r = 0.605$; $\rho = 0.516$), pointing to the importance of continuous capability development.

The weakest, though still significant, correlation with AI_USE is observed for DATA_ANALYTICS ($r = 0.485$; $\rho = 0.408$; $p < 0.05$), which may indicate that the diffusion of analytics practices alone is not sufficient and that specialised skills, workforce capacity, and innovation inputs are more decisive for AI adoption. The close alignment between Pearson and Spearman coefficients further strengthens the robustness of these findings against potential outliers and minor departures from normality.

4 Discussion

The findings of this study confirm that AI adoption in the European Union is progressing, yet in an uneven manner that reflects persistent regional divides. Business level AI adoption is widely understood as a capability driven process rather than a purely technological decision. It tends to depend on whether firms operate in an environment that provides adequate digital infrastructure, relevant data and software foundations, and a workforce with the skills needed to implement and scale AI applications, while also being supported by a broader innovation ecosystem that incentivises investment and experimentation.

4.1 Answers to research questions

RQ1: What is the current level of business-level AI adoption across EU countries, and how has it evolved over the 2023–2025 period, including cross-country differences in the pace of growth?

AI adoption at the business level has increased markedly across the EU over the 2023–2025 period, indicating that AI is moving from early experimentation toward broader organisational uptake. At the same time, the pattern remains clearly multi speed, with a stable group of leading countries and a set of laggards that continue to trail behind. This cross-country stratification is consistent with EU focused comparative evidence showing persistent clusters of high and low adopters and emphasising that countries differ not only in adoption levels but also in how rapidly adoption accelerates. In this sense, the results point to overall progress combined with incomplete convergence, where some countries are catching up faster while others continue to expand more gradually. Supportive cross-country evidence is provided by Ionașcu et al. (2025), Laitsou et al. (2025), and Lülök, Dobos and Sebestyén (2026), all of whom document substantial differences in AI diffusion across EU member states and highlight the structural nature of these gaps.

RQ2: What are the current levels and dispersion of AI adoption and its associated key determinants across EU, and which indicators within the domains of technological *readiness, human capital, and the macro-level innovation environment exhibit the greatest cross-country variability?*

The cross section descriptive analysis reveals substantial dispersion in both AI adoption and its determinants, suggesting that the EU landscape is characterised by uneven digital maturity and unequal enabling conditions. Variability is especially visible in indicators that represent foundational digital infrastructure and readiness, such as the extent to which enterprises rely on cloud services and integrated business software (ERP systems etc.), indicating that countries differ considerably in the digital backbone that can support AI deployment. Human capital conditions are also uneven, reflecting cross country differences in the availability of ICT specialists, workforce upskilling, and broad digital competence, which collectively shape the capacity to implement and scale AI. Macro level innovation conditions, captured through business sector R&D intensity, further contribute to cross country differentiation by reflecting differences in innovation input environments. These findings align with the EU comparative literature that points to infrastructure, skills, and investment as recurring constraints, determinants and differentiators. Ionașcu et al. (2025) emphasise expertise gaps and the need for infrastructure and training investment. Laitsou et al. (2025) stress that infrastructure and skills matter but are not sufficient in isolation and Lülök, Dobos and Sebestyén (2026) link adoption differences to broader digitalisation and economic disparities. Review evidence likewise supports this framing, as Cubric (2020), Oldemeyer, Jede & Teuteberg (2025), and Khanfar et al. (2024) identify skills, data readiness, infrastructure, and organisational capabilities as the most recurrent drivers and barriers shaping observed variation.

RQ3: What is the direction and strength of the correlation between business-level AI adoption and its determinants in the domains of technological readiness, digital human capital, and the macro-level innovation environment across EU countries?

Across EU countries, AI adoption is positively associated with the proposed determinants, supporting the expectation from the literature that higher adoption tends to co-occur with stronger digital foundations, stronger human capital conditions, and more supportive innovation environments. The strongest relationships are consistently tied to digital human capital, particularly the availability of specialised ICT labour and broader digital skills, indicating that capability constraints remain central to explaining adoption gaps. Technological readiness also shows clear positive associations, reinforcing the interpretation that AI diffusion builds on the prior diffusion of enterprise digital systems and scalable computing resources. The macro level innovation environment contributes in a complementary way, consistent with the view that investment intensity and innovation capacity support the absorption of advanced digital technologies. Importantly, the broader literature also suggests that these factors operate as complements rather than stand-alone drivers. Ćukušić (2025) demonstrates multiple configurational pathways to high adoption, frequently combining cloud, analytics, ICT specialists, and training, which supports the interpretation that AI uptake is enabled by bundles of capabilities. Firm level empirical studies similarly emphasise readiness and capabilities as primary drivers, including Arroyabe et al. (2024), Yang, Blount & Amrollahi

(2024), Badghish & Soomro (2024), Hunady (2025), and Horani, Al Adwan et al. (2023). Finally, the complementarity logic is reinforced by Lee et al. (2022), who show that AI related outcomes are stronger when paired with complementary investments and R&D strategy, providing a coherent explanation for why technological infrastructure indicators and innovation intensity tend to move together with higher AI adoption in cross country comparisons.

Conclusion

This paper provides cross country evidence that business level AI adoption in the EU has advanced rapidly over the 2023 to 2025 period, yet the diffusion remains markedly uneven across member states. The persistence of substantial cross-country gaps suggests that, despite overall progress, AI uptake continues to reflect broader differences in digital maturity and innovation capacity, with countries progressing at different speeds.

The empirical results indicate a clear and predominantly positive association between AI adoption and the proposed determinants. The strongest relationships are observed for variables capturing digital human capital, particularly the availability of ICT specialists and broader population digital skills, pointing to skills and talent supply as central enabling conditions for AI diffusion. Technological readiness indicators, especially cloud service uptake and the use of enterprise business software, also exhibit robust positive correlations with AI adoption, reinforcing the interpretation that AI typically builds on established digital foundations and scalable computing resources. In addition, a supportive innovation environment measured through business sector R&D intensity is positively related to AI uptake, consistent with the view that innovation investment and complementary capabilities facilitate more extensive and sustainable adoption. Taken together, the results highlight that AI diffusion is best understood as a capability and complementarities process: countries achieve higher adoption where digital infrastructure, skills development, and innovation inputs co-exist and mutually reinforce one another.

From a practical perspective, the findings imply that policies and firm strategies aiming to accelerate AI adoption should prioritise expanding specialised ICT labour supply, strengthening broad digital skills, supporting continuous ICT training within enterprises, and encouraging investment in core digital technologies and R&D. Future research could extend these insights by incorporating multivariate modelling, time lags, and sector or firm size disaggregation to further clarify mechanisms behind cross country differences in AI adoption.

This paper has several limitations. The analysis relies exclusively on secondary data from Eurostat, which, while reliable, restricts the ability to capture more nuanced aspects of AI adoption such as firm-level strategies, cultural factors, or organizational practices. Finally, the study is descriptive in nature, and its conclusions are constrained by the availability of comparable quantitative indicators across countries.

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ASSESSING RELATIONS BETWEEN ENTERPRISE INFORMATION SYSTEMS IMPLEMENTATION AND AI IMPLEMENTATION: A SYSTEMATIC LITERATURE REVIEW

Dávid Rybjanský – Róbert Hanák

Abstract

The enterprise implementation literature is split between a mature stream on enterprise information systems (IS) and a newer stream on enterprise artificial intelligence (AI), even though firms often treat AI as a continuation of digital transformation. The aim of this article was to assess how enterprise IS implementation relates to enterprise AI implementation by synthesizing where implementation logics converge, where they diverge, and whether national patterns of AI uptake co vary with IS related adoption proxies across the European Union. Using a dual stream systematic literature review in Web of Science, we applied transparent screening and retained 14 studies on enterprise IS implementation and 14 studies on enterprise AI implementation for comparative thematic synthesis. We then triangulated the literature-based comparison with a Eurostat correlation analysis for 2023 and 2025, relating enterprise AI adoption to proxies for business software use, cloud computing, and data analytics. We find substantial overlap in core implementation priorities, including leadership sponsorship and governance, socio technical change management, strategic and process alignment, data and integration discipline, and staged value realization beyond go live. At the same time, AI implementation introduces distinct requirements tied to data dependency, model opacity, lifecycle management, and responsible governance, alongside stronger sensitivity to AI specific managerial literacy and human machine work redesign. The results provide actionable guidance for managers on which IS implementation lessons plausibly transfer to AI initiatives and identify research directions for integrating the two streams and improving measurement and empirical testing.

JEL classification: *M15, O32, O33*
Keywords: *Information systems, Artificial intelligence, System implementation*

Introduction

This article aims to assess how enterprise information systems implementation relates to enterprise AI implementation by identifying where implementation logics converge and where they diverge, and whether national patterns of AI uptake co vary with IS related adoption proxies across the EU. The topic is motivated by the practical reality that many firms approach AI as a next step in digital transformation, yet the implementation knowledge base remains split between a mature IS implementation stream and a newer AI implementation stream that often emphasizes distinct challenges. IS research has long documented that implementation outcomes depend on leadership commitment, change management, process fit, and post implementation embedding (Dwivedi et al., 2015; Costa et al., 2016; Audzeyeva & Hudson, 2016; Badewi et al., 2018), while recent AI studies stress data dependency, model opacity, lifecycle management, and governance requirements (Paleyes et al., 2022; Weber et al., 2023; Papagiannidis et al., 2025). The literature remains fragmented into two largely parallel streams, IS implementation research with decades of accumulated evidence, and AI implementation research emphasizing distinct constraints such as data dependency and responsible AI.

This study contributes by providing a systematic, side by side synthesis that makes similarities and differences explicit and by adding macro level adoption associations that support the relevance of comparing the two domains. Methodologically, we conduct a systematic literature review in Web of Science using two search streams, one for IS implementation and one for AI implementation, apply transparent screening, and retain 14 studies per stream for comparative synthesis. We then perform a Eurostat based correlation analysis for 2023 and 2025 across EU Member States, relating AI adoption to enterprise level proxies for business software use, cloud computing, and data analytics. The paper is guided by two research questions: What recurring similarities and differences between enterprise IS and enterprise AI implementation are reported in the academic literature? And, at the EU country level, is enterprise AI adoption positively associated with selected indicators that proxy enterprise IS adoption and related digital foundations?

1 Current state of the solved problem at home and abroad

Enterprise AI is increasingly treated as an information-systems phenomenon because it relies on the same socio-technical foundations that determine whether enterprise IS create value: integrated data flows, enterprise architectures, governance, and alignment between digital technologies and organizational goals. AI initiatives are therefore commonly framed as part of broader digital transformation, where "AI readiness" depends not only on algorithms but also on the organization's existing technologies, activities/processes, boundaries (e.g., inter-unit integration), and strategic goals (Holmström, 2022). Likewise, research on the strategic use of AI explicitly highlights that business value from AI depends on IT–business alignment and on embedding AI into organizational strategy and information management practices rather than treating it as a standalone tool (Borges et al., 2021). At the same time, IS scholarship increasingly foregrounds AI-specific governance and responsibility concerns (e.g., accountability, risk, and societal impacts) as issues that must be handled through IS-like design and management choices (Dennehy et al., 2023), and it conceptualizes enterprise AI diffusion as a staged capability-building process (Hansen et al., 2024).

2 Research design and methodology

This study examines how implementation priorities in enterprise information systems (IS) relate to implementation priorities in enterprise AI systems. The goal is to provide a structured comparison of the two implementation domains by synthesizing peer reviewed research from each stream and then identifying their recurring commonalities and differences. In addition, we complement the literature-based comparison with a simple macro level association analysis using Eurostat indicators, which serves as an empirical plausibility check for whether AI adoption tends to co-occur with enterprise digital foundations that are typically linked to enterprise IS deployment.

The review is guided by two research questions. RQ1 asks: What are the recurring similarities and differences between enterprise IS implementation and enterprise AI implementation as described in the academic literature? RQ2 asks: At the country level in the European Union, is enterprise AI adoption positively associated with selected indicators that proxy enterprise IS adoption and related digital foundations?

To ensure a transparent and replicable review process, we follow a structured stepwise procedure based on the Step 0 to Step 5 process described by Opland et al., adapted to our research context. The procedure is applied separately to two literature streams, enterprise IS implementation and enterprise AI implementation, and then combined in a comparative synthesis.

2.1 Data source and search strategy

The literature search was conducted exclusively in the Web of Science on 3.1.2026. We applied inclusion filters and limited the search for both streams to open access articles and reviewed articles in English in research areas: Business Economics or Computer Science or Information Science Library Science. We also limited to search to years 2022-2026 for AI stream and to years 2015-2026 for IS stream to ensure the highest relevance possible. Searches were performed in titles, abstracts, and author keywords to retrieve studies that explicitly address implementation in an organizational or enterprise context.

Two separate search strings were used, one for each stream, and they were applied consistently within Web of Science. The enterprise AI implementation stream used the following search string:

- ("artificial intelligence" OR "AI") AND ("implementation") AND (enterprise OR organization OR firm)

The enterprise IS implementation stream used the following search string:

- ("information system*") AND ("implementation") AND (enterprise OR organization OR firm)

The search yielded 16659 records for the IS stream and 7241 records for the AI stream at Step 0.

2.2 Screening procedure

The screening and selection of studies followed a structured pipeline consisting of six steps, applied to each stream and recorded to enable traceability.

Step 0, database search. Records were retrieved from Web of Science using the predefined search strings and exported for screening and deduplication.

Step 1, application of basic inclusion filters. As mentioned, we applied same initial inclusion filters at the metadata level to both searches, including publication language, document type, except for the defined time window to ensure relevance of publications. After Step 1, the dataset consisted of 1386 IS stream records and 1109 AI stream records.

Table 1
Overview inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Open access and peer reviewed articles	Book chapters, notes, short communications, and similar non article formats
English language	Publications focused on a different level or topic than organizational or enterprise implementation, for example purely technical or non implementation oriented discussions
Research areas: Business Economics, Computer Science, or Information Science and Library Science	
Time window: AI stream 2022–2026; IS stream 2015–2026	

Source: own processing

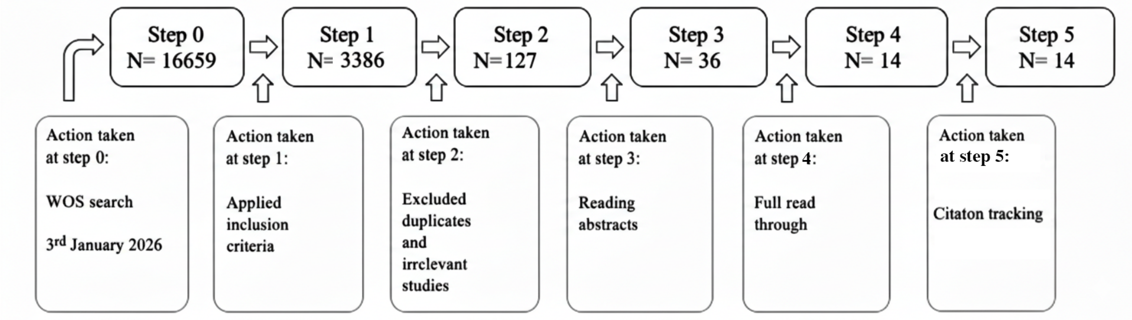
Step 2, removal of duplicates and clearly irrelevant records. Duplicate records were removed within and across streams. We also removed records that were clearly outside the enterprise implementation scope based on bibliographic information and titles. After Step 2, 127 records remained for the IS stream and 105 records remained for the AI stream.

Step 3, abstract screening. The remaining records were screened using titles and abstracts to assess whether they addressed implementation in an organizational or enterprise context. At this stage, we retained studies that provided implementation relevant content, such as implementation stages, governance arrangements, organizational change considerations, integration challenges, capabilities, or implementation outcomes. Records that did not contain organizational implementation content were excluded. After Step 3, 36 IS stream papers and 26 AI stream papers were retained for full text assessment.

Step 4, full text assessment. Full texts were obtained and assessed to confirm that each study met the review scope. Studies were included if they provided substantive evidence or argumentation about implementation priorities, mechanisms, challenges, practices, or success conditions in enterprise IS or enterprise AI implementation. After Step 4, 14 studies were included in the IS stream and 13 studies were included in the AI stream.

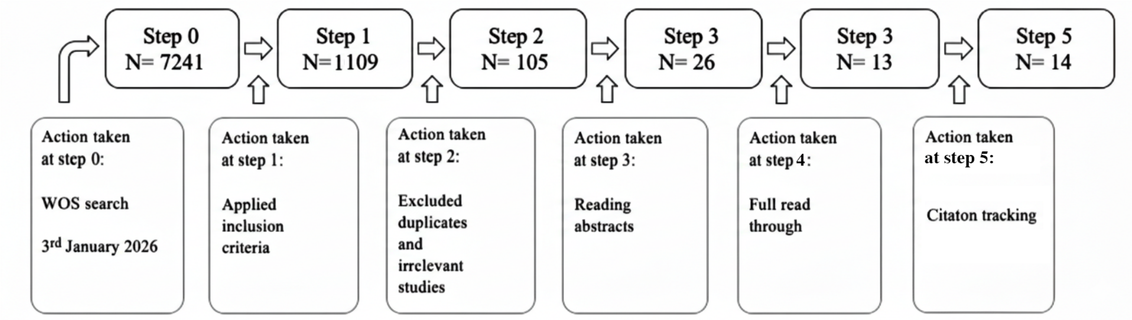
Step 5, citation based enrichment. To reduce the risk of missing relevant papers due to terminology fragmentation across streams, we performed one iteration of citation based enrichment within Web of Science. This consisted of backward reference checking of the Step 4 included studies, supplemented where available by forward citation tracking using the “cited by” functionality in Web of Science. Candidate papers identified through this process were screened using the same Step 3 and Step 4 criteria. After Step 5, the final sample comprised 14 IS stream studies and 14 AI stream studies.

Figure 1
Review process of IS stream



Source: own processing based on Opland et al. (2022)

Figure 2
Review process of AI stream



Source: own processing based on Opland et al. (2022)

Throughout the screening process, borderline cases were resolved through discussion among the authors, and inclusion decisions were applied consistently across the two streams to preserve comparability.

2.3 Comparative synthesis across the IS and AI streams

The analytical objective of the review was not to impose an a priori coding framework, but to derive similarities and differences directly from the synthesized evidence in the two literatures. We therefore conducted a comparative thematic synthesis in two stages.

First, each stream was synthesized separately. For the IS stream, we summarized recurring implementation priorities and challenges reported in enterprise IS implementation research, focusing on the organizational and managerial content rather than on system specific technical details. For the AI stream, we summarized recurring implementation priorities and challenges reported in enterprise AI implementation research, with attention to the interplay between organizational change and AI specific requirements such as data dependence, model lifecycle considerations, and governance issues.

Second, we conducted a structured comparison across the two stream level syntheses to identify convergence and divergence patterns. Similarities were defined as implementation priorities that appear consistently in both literatures, even if expressed with different terminology. Differences were defined as priorities that are prominent in one stream but absent or only marginal in the other, or priorities that share a label but imply materially different implementation actions. The comparative synthesis was then used to formulate a set of evidence grounded statements about which IS implementation lessons plausibly transfer to AI implementations and which areas require distinct AI specific practices.

2.4 Eurostat correlation analysis as empirical triangulation

To complement the literature-based comparison with a simple empirical plausibility check, we conducted a country level association analysis using Eurostat indicators. Enterprise AI adoption was measured using the Eurostat dataset isoc_eb_ai with the indicator "enterprises using at least one AI technology" and the enterprise segment 10 persons employed or more for the years 2023 and 2025. To proxy enterprise IS adoption and related digital foundations, we used three Eurostat indicators: tin00116 (business software use), isoc_cicce_use (cloud computing use), and isoc_eb_das (use of data analytics), aligned by country and year to the extent permitted by data availability.

We computed Pearson correlation coefficients between the AI adoption indicator and each proxy variable. Where appropriate, we also computed Spearman correlations as a robustness check for potential non linearities and outlier sensitivity. Results are interpreted strictly as descriptive associations at the country level. This analysis does not identify causal effects and does not measure implementation strategy quality directly. Its purpose is to assess whether the comparative focus of the review is consistent with observable co variation patterns between AI adoption and enterprise digital foundations across EU countries.

3 Research results and discussion

This chapter reports the findings from both components of the study. First, we synthesize implementation priorities in the enterprise IS stream and in the enterprise AI stream, and then compare them to identify where implementation logics converge and where they diverge. Second, we triangulate the literature-based insights with a Eurostat correlation analysis to assess whether enterprise AI adoption co-varies with country-level proxies of enterprise IS adoption and related digital foundations across EU Member States.

3.1 Synthesis of Enterprise information system implementation priorities

A recurring similarity across the IS implementation literature is the centrality of senior leadership sponsorship and governance. ERP adoption and satisfaction work explicitly models top management support as a determinant of usage and satisfaction (Costa et al., 2016), while implementation challenge evidence also frames leadership commitment and knowledge transfer from top management as necessary to align competencies, vision, and willingness to change (Zuma & Sibindi, 2023).

Table 2
Overview of IS stream publications

Authors	Year	Paper focus	Contribution to the comparison
Aldossari & Mokhtar	2020	Model for ERP & BI adoption; qualitative study; identifies factors: system/service/information quality, change management, communication, training, clear vision, competitive pressure & government role.	Highlights critical success factors (quality, change management, training); emphasises organisational and external influences; supports shared themes relevant for comparing IS and AI implementation.
Arnott, Lizama & Song	2017	BI systems use patterns; case studies using Gorry & Scott Morton framework; shows enterprise and functional BI systems co-exist to support different decision types.	Emphasises organisational scope (enterprise vs functional) and decision-level differences; shows that decision-support frameworks need empirical tailoring; informs comparison by illustrating complex usage patterns beyond basic adoption.
Audzeyeva & Hudson	2016	Post-implementation BI benefits; deep-structure transformation framework; stresses dynamic interaction between BI and organisational deep structure and overcoming inertia for long-term benefits.	Underlines importance of organisational deep structure and feedback loops; parallels AI implementation's need for organisational integration and continuous adaptation; emphasises long-term success beyond initial rollout.
Badewi, Shehab, Zeng & Mostafa	2018	ERP benefits capability framework; orchestration theory; classifies benefits (automation, planning, innovation); matches ERP resources & organisational complementary resources; warns against pursuing innovation benefits without planning/automation maturity.	Shows interplay between technical resources and organisational capabilities; emphasises sequential capability building; relevant to compare with AI implementation that also depends on data readiness and organisational maturity.
Costa, Ferreira, Bento & Aparicio	2016	ERP adoption & satisfaction determinants; survey-based model; finds top management support, training & system quality influence behavioural intention and user satisfaction.	Highlights role of management support, training and system quality in successful ERP adoption; user-centred perspective; these factors are likely applicable to AI adoption and satisfaction.
Dwivedi et al.	2015	IS failures & successes review; notes complex multi-factor reasons, high failure rates, need to study multiple perspectives and underexplored contexts.	Emphasises complexity and multi-stakeholder nature of IS implementations; highlights high failure rates; encourages research beyond narrow technical focus; lessons useful for AI implementation caution.
Ferrer-Gilabert, Forés & Lapiedra	2025	ERP implementation stages & critical success factors; expert survey and case studies; proposes life cycle model; emphasises dynamics and complexity of each stage and contextual success factors.	Provides stage-wise understanding of ERP life cycle and critical success factors; emphasises dynamic and contextual elements; framework can be contrasted with AI implementation stages and success factors.

Authors	Year	Paper focus	Contribution to the comparison
Zuma & Sibindi	2023	ERP-implementation challenges at the National Youth Development Agency (case study); identifies problems such as misaligned processes, product-quality issues, lack of helpdesk and pilot testing, insufficient top-management support and user training, resistance to change, poor integration and technology planning; stresses the need for knowledge management and change management.	Shows that ERP projects fail without organisational alignment, strong change management and user training; emphasises knowledge management and top-management support as critical, themes likely to reappear in AI implementations.
Skafi et al.	2020	Survey of Lebanese SMEs on cloud computing adoption using TOE framework; finds complexity and security, top management support and prior IT experience as positive determinants; poor infrastructure and lack of government support hinder adoption.	Demonstrates that technical and organisational factors, together with environmental context, drive adoption of enterprise digital services; underlines the role of top management and external infrastructure-parallels AI adoption drivers.
Lutfi	2022	UTAUT-based survey of Jordanian SMEs on continuance intention to use accounting information systems; reports that effort and performance expectancy and facilitating conditions drive continuance; top-management support shows a negative effect; social influence and self-efficacy matter.	Highlights the importance of user expectations, organisational support and self-efficacy for sustained use of enterprise IS; such user-centric factors are relevant when comparing long-term AI adoption and usage.
Lázár & Madaras	2024	Logistic-regression study (374 CEO interviews) on ERP adoption in Romanian SMEs; uses TOE framework; finds ERP seen as a necessary transaction tool rather than cutting-edge innovation; adoption positively influenced by wider market scope (business partnerships) and top-management support; business-performance indicators do not affect adoption.	Shows that environmental and organisational factors (market scope, partnerships, competitive pressure, top-management support) rather than performance metrics drive ERP adoption; useful for comparing how external context influences AI adoption strategies.
Kim	2022	Develops CSF-MCDM framework for strategic information system planning; uses PEST-SWOT and causal-layered analysis to identify critical success factors for a next-generation business system; evaluates CSF dimensions via multi-criteria decision-making; aims to provide replicable strategic priorities for IS planning.	Provides a mixed-methods approach for evaluating and prioritising success factors; emphasises strategic alignment of IT with business goals; such evaluation frameworks can inform AI-implementation planning and prioritisation.
Kapler	2021	Study of barriers to implementing innovative information-management solutions in service SMEs; finds mental barrier not always crucial; necessity for document-exchange acceleration drives adoption; success linked to technological	Points out that adoption barriers can be necessity-driven and that technological capabilities are critical; highlights that employees may be motivated despite mental barriers; these insights help compare organisational and technological obstacles in IS versus AI implementations.

Authors	Year	Paper focus	Contribution to the comparison
		capabilities; technological barriers are especially important in financial-services SMEs.	

Source: own processing based on data from database WOS (2026)

Broader IS success and failure discussions treat managerial commitment as part of the conventional “core conditions” for implementation outcomes (Dwivedi et al., 2015).

A second shared theme is that implementation is fundamentally an organizational change process, not only a technical rollout. User training is repeatedly positioned as a key lever for acceptance and effective use (Costa et al., 2016), and field evidence highlights that inadequate training, weak communication, and limited participation increase resistance to change and degrade transition quality (Zuma & Sibindi, 2023). Post implementation research similarly emphasizes that realizing value depends on embedding the system into the organization and managing inertia factors over time (Audzeyeva & Hudson, 2016).

A third similarity is the need for strategic and process alignment, often operationalized via fit between the system and organizational processes. ERP implementation accounts stress strategic alignment as crucial and link success to process integration, customisation, and configuration choices (Zuma & Sibindi, 2023). Related benefit oriented theorizing treats performance as an outcome of fit among organizational factors, assets, and capabilities, including the evolving fit between ERP and organizational function (Badewi et al., 2018). In BI contexts, alignment is also framed as dynamic, requiring recurrent realignment as conditions change (Audzeyeva & Hudson, 2016).

A fourth cross cutting issue is data and integration quality as a technical organizational interface problem. Empirical accounts identify data accuracy, validation, and migration quality as critical because ERP systems are highly integrated and depend on reliable inputs (Zuma & Sibindi, 2023). Capability oriented work similarly foregrounds the integration platform needed to collect current, accurate data and synchronize information across the organization and supply chain (Badewi et al., 2018). Adoption research also treats system quality as a core construct shaping perceived ease of use, behavioural intention, and satisfaction (Costa et al., 2016).

A fifth similarity is that value realization is staged and extends beyond go live, requiring continuous monitoring, adaptation, and benefit management. Post implementation BI research shows that long term benefits depend on processes that embed the application into the organization, maintain adaptability, and include feedback mechanisms that counter inertia (Audzeyeva & Hudson, 2016). ERP evidence likewise emphasizes post implementation performance monitoring to assess ongoing alignment with processes and to improve process quality and outcomes (Zuma & Sibindi, 2023). Capability process models also treat benefits as dependent on when and how firms invest in resources and complementary resources over time (Badewi et al., 2018).

A sixth shared pattern is that implementation outcomes are conditioned by organizational capabilities and resource constraints, which shape both adoption and sustained use. Post implementation work stresses the need for a strategically positioned system owner, adequate resources, and a match between user skills and system needs (Audzeyeva & Hudson, 2016). Complementary resource arguments similarly position management’s orchestration of resources and capabilities as central to achieving higher level benefits (Badewi et al., 2018). Empirical implementation accounts also show how limited skills, weak technology initiatives, and security threats emerge as practical constraints during ERP deployment (Zuma & Sibindi, 2023).

3.2 Synthesis of AI implementation priorities

A recurring similarity across the reviewed studies is that they treat enterprise AI implementation as continuous with established IS governance concerns: senior sponsorship, clear decision rights, and accountability structures remain central preconditions for implementation quality. Governance-focused reviews argue that organizations must translate principles into operational arrangements (formal roles, escalation paths, and procedural controls) so that development, deployment, and use are steered across the full system lifecycle (Birkstedt et al., 2023; Papagiannidis et al., 2025). This framing mirrors classic IS implementation logic in which governance is not an "add-on" but a coordinating mechanism that shapes implementation discipline and outcomes (Yi et al., 2024).

A second shared theme is that implementation is fundamentally socio-technical change rather than a purely technical rollout. Adoption-oriented work explains uptake through organizational, technological, and environmental conditions and through end users' perceptions, implying that communication, training, and readiness shape whether systems become routinely used (Na et al., 2022). Studies of AI-based systems in professional work similarly describe implementation as reconfiguring tasks and coordination as automation and augmentation alter roles, responsibilities, and workflows (Spring et al., 2022). In this sense, "implementation" is treated as organizational transformation with a technology component, not the other way around.

A third similarity is the prominence of data, integration, and process alignment as the technical–organizational interface problem. Across the papers, AI systems are framed as dependent on enterprise data flows and therefore inheriting familiar IS implementation challenges around data quality, interoperability, and cross-process coordination (Weber et al., 2022; Yi et al., 2024). Governance perspectives likewise foreground data governance, transparency, and robustness as implementation-relevant concerns because weaknesses in upstream data and integration propagate into unstable or unreliable system behavior (Birkstedt et al., 2023; Papagiannidis et al., 2025). Implementation success is therefore repeatedly linked to aligning models, data pipelines, and operational processes into a coherent socio-technical system.

A fourth cross-cutting issue is that implementation success is conditioned by organizational capabilities and resource constraints, not only by selecting the "right" technology. Capability-focused analyses stress the need for complementary resources (skills, routines, and governance capabilities) to cope with AI-specific dependencies such as data reliance and limited explainability (Weber et al., 2022). Work synthesizing machine-learning deployment challenges similarly highlights that implementation is constrained by practical capability gaps (e.g., operational expertise, evaluation practices, and deployment know-how) that must be developed or acquired (Paleyes et al., 2022). This mirrors a recurring IS implementation insight: capabilities and complementary investments are often the binding constraint on realizing value.

Table 3
Overview of AI stream publications

Authors	Year	Paper focus	Contribution to the comparison
Van Phuoc	2022	Survey of 193 managers in Vietnam identifies ten critical factors for AI adoption using the technology–organisation–environment framework; factors include technical compatibility, relative advantage, complexity, technical and managerial capability, organisational readiness, government involvement, market uncertainty and vendor partnership.	Shows that AI adoption depends on a mix of technical, organisational and contextual factors, mirroring the multi-dimensional determinants seen in IS implementation research; highlights that organisation size is not significant.
Ayinaddis	2025	Systematic review and bibliometric analysis of AI adoption in SMEs versus large firms; groups drivers into ten dimensions (technology readiness, customisation, AI tools and needs, data requirements, skills, financial readiness, management support, market pressure, partnership/collaboration and regulatory compliance).	Provides a taxonomy of adoption determinants, enabling comparison of AI and IS implementation across firm sizes; underscores that management support and resources remain central but data and AI-specific requirements introduce new dimensions.
Birkstedt et al.	2023	Systematic literature review on AI governance identifies four themes (technology, stakeholders and context, regulation and processes); notes limited understanding of implementation and calls for future research; emphasises training, awareness, stakeholder management and organisational culture.	Highlights governance and ethical considerations unique to AI; points out gaps in knowledge about implementation processes and stresses the need for senior management commitment and cultural readiness, linking governance to both AI and IS contexts.
Madanchian & Taherdoost	2025	Conceptual paper examining barriers and enablers of AI adoption in human-resource management; identifies change aversion, data security, integration costs and ethical challenges as barriers; highlights digital leadership, supportive culture, and advances in natural language processing as enablers.	Shows that organisational culture and ethical considerations are critical for AI adoption; underscores that power dynamics and employee perceptions influence implementation, extending IS lessons on change management to AI.
Maragno et al.	2023	Case study of eight European public-sector organisations; uses TOE framework and Technology Affordances and Constraints Theory to map how contextual factors afford or constrain AI use; emphasises that AI implementation emerges from interactions between people, organisations and technology.	Demonstrates that AI implementation in public sector is shaped by interrelated organisational, technological and environmental factors; reinforces the idea from IS literature that integration and contextual alignment are essential, while noting AI adds unique affordances and constraints.
Na et al.	2022	Survey of construction-industry end users applying the technology acceptance model and TOE framework; finds technological factors	Illustrates how AI acceptance depends on both perceived usefulness and organisational support; identifies social influence

Authors	Year	Paper focus	Contribution to the comparison
		and individual traits positively influence perceived usefulness and ease of use; organisational support, culture and participation are important, while social suggestions can disrupt acceptance.	as a potential barrier; these insights parallel user-centric determinants in IS adoption and highlight additional sociocultural factors.
Paleyes et al.	2022	Survey of case studies on ML deployment; maps challenges across stages of the deployment workflow and cross-cutting issues such as ethics, bias, fairness, accountability, legal compliance, user trust and security.	Highlights AI-specific challenges and cross-cutting concerns (e.g., ethics, bias, governance, MLOps) that rarely appear in IS implementation; shows how AI deployment requires continuous monitoring and accountability beyond typical IS projects.
Papagiannidis et al.	2025	Scoping review of responsible AI governance; synthesizes literature and proposes a conceptual framework across structural, relational and procedural governance practices; notes the gap between high-level principles and operational implementation.	Introduces responsible AI governance as a critical dimension; emphasizes translating ethical principles into operational practices across the AI lifecycle—extending traditional IS governance to include ethics, transparency and accountability.
Peretz-Andersson et al.	2024	Empirical study of AI implementation in manufacturing SMEs using resource orchestration theory; shows how firms acquire, bundle and leverage AI resources, building learning and governance capabilities and coordinating processes and people.	Demonstrates that successful AI implementation requires orchestrating resources and dynamic capabilities (learning, governance, process integration); parallels IS implementation's reliance on resource alignment but highlights AI-specific capability bundling in SMEs.
Pinski et al.	2024	Quantitative study using upper-echelons theory; finds that top-management-team AI literacy enhances corporate AI orientation and implementation ability, with AI orientation mediating this relationship and effects stronger in start-ups.	Stresses the role of AI-specific managerial knowledge; extends the IS concept of top-management support to highlight the need for AI literacy and strategic orientation in leadership for effective AI implementation.
Sánchez et al.	2025	Review applying Technology-Organization-Environment and Diffusion-of-Innovations frameworks to AI adoption in SMEs; identifies ten critical challenges (data access, skills shortages, cultural resistance, infrastructure limitations, weak governance) and proposes a six-phase roadmap incorporating responsible and generative AI.	Uses IS adoption frameworks to map AI-specific obstacles; shows that AI adoption shares organisational and environmental drivers with IS but introduces new concerns (data governance, responsible AI, generative AI); provides structured roadmap useful for comparing stages.
Weber et al.	2023	Qualitative study with 25 interviews; identifies four organisational capabilities for AI implementation to cope with inscrutability and data dependency: AI project planning, co-development, data management and AI model lifecycle management; stresses that	Highlights capabilities needed to manage AI's complexity and data dependency; emphasises planning, co-development and continuous model lifecycle management—capabilities distinct from typical IS implementation.

Authors	Year	Paper focus	Contribution to the comparison
		many AI projects fail and that AI implementation differs from traditional IT.	
Spring et al.	2022	Case-based study in law and accountancy firms; develops a model showing how AI-based systems automate high-volume tasks and augment professional work, enabling process improvement and service extension; identifies research questions about automation, augmentation and competitiveness.	Shows AI as both automation and augmentation; illustrates selective AI use in knowledge-intensive services and the interplay between human expertise and AI systems; contrasts with traditional IS that focus mainly on automation and process standardisation.

Source: own processing based on data from database WOS (2026)

A fifth shared pattern is that implementation extends beyond go-live and requires monitoring, learning, and continuous adaptation. Lifecycle perspectives frame deployment as iterative evaluation and improvement, where feedback loops and control mechanisms are needed to sustain performance and legitimacy as contexts shift and models drift (Papagiannidis et al., 2025). Analytical review work also emphasizes that implementation problems unfold across phases and can interact causally, implying sustained managerial attention after initial rollout rather than treating implementation as a single event (Yi et al., 2024). Overall, these studies converge on the view that value realization is post-implementation work, consistent with long-standing IS implementation thinking applied to AI-enabled systems.

3.3 Similarities and differences between enterprise IS and AI implementation

This subchapter compares the two literature streams to clarify which implementation priorities are broadly shared across enterprise information systems (IS) and enterprise AI, and which priorities appear distinctive to AI. Building on the synthesized evidence in Sections 4.1–4.2, the goal is to make explicit the transferable "IS implementation lessons" and the additional requirements introduced by AI-specific properties.

3.3.1 Similarities in enterprise IS and AI implementation strategies

A first similarity is the centrality of leadership, governance, and clear ownership. In the IS stream, top management support repeatedly predicts adoption, use, and satisfaction (Costa et al., 2016) and weak leadership commitment is associated with implementation breakdowns (Zuma & Sibindi, 2023; Dwivedi et al., 2015). In the AI stream, governance reviews emphasize that responsible AI requires formal roles, decision rights, and operational controls that steer development and deployment across the lifecycle (Birkstedt et al., 2023; Papagiannidis et al., 2025). Related empirical work shows that AI-specific managerial capability (e.g., AI literacy) strengthens organizational orientation toward AI and implementation ability (Pinski et al., 2024), echoing the leadership capability logic present in IS implementation studies.

A second shared theme is that implementation is fundamentally socio-technical change rather than a purely technical rollout. IS evidence frames training, communication, and participation as levers that shape acceptance and reduce resistance during transitions (Costa et al., 2016; Zuma & Sibindi, 2023), while post-implementation BI research argues that value depends on embedding the system into organizational structures and managing inertia over time (Audzeyeva & Hudson, 2016). Similarly, AI acceptance research links perceived usefulness and ease of use to organizational support, culture, and participation (Na et al., 2022), and professional-service evidence depicts implementation as reconfiguring tasks and coordination as systems automate and augment work (Spring et al., 2022). Across both streams, "implementation" therefore extends into organizational redesign and capability building, not only system installation.

Third, strategic alignment and process fit recur as core implementation logics. ERP studies link implementation success to process integration, configuration choices, and alignment between the system and organizational workflows (Zuma & Sibindi, 2023), and benefits-oriented theorizing frames performance as dependent on fit between technical resources and complementary organizational resources (Badewi et al., 2018). BI work similarly portrays alignment as dynamic, requiring recurrent realignment as conditions change (Audzeyeva & Hudson, 2016) and differentiates enterprise versus functional BI designs to match decision contexts (Arnott et al., 2017). AI studies adopt comparable alignment logic through TOE-based explanations of adoption (Nguyen, 2022; Maragno et al., 2023) and through resource orchestration accounts that emphasize bundling and leveraging AI resources in ways that match processes and organizational needs (Peretz-Andersson et al., 2024).

Fourth, data and integration quality appear in both streams as a critical technical–organizational interface problem. In IS implementations, data accuracy, validation, and migration are emphasized because ERP systems are highly integrated and depend on reliable inputs (Zuma & Sibindi, 2023), while system quality shapes perceived ease of use, intentions, and satisfaction (Costa et al., 2016). Cloud adoption evidence likewise highlights security and complexity alongside organizational and environmental enablers and constraints (Skafi et al., 2020). AI literature intensifies these concerns by repeatedly foregrounding data access, data requirements, and governance as determinants and constraints (Nguyen, 2022; Sánchez et al., 2025; Weber et al., 2023). Despite different technologies, both streams converge on the idea that implementation succeeds when organizations can ensure dependable information flows and integrate the system into enterprise data and process architectures.

Fifth, both streams treat value realization as staged and extending beyond go-live, requiring monitoring, learning, and benefit management. Post-implementation BI research stresses long-term benefits depend on adaptability, feedback mechanisms, and ongoing embedding of the application (Audzeyeva & Hudson, 2016). ERP evidence also emphasizes post-implementation monitoring and continuous improvement (Zuma & Sibindi, 2023), and capability frameworks describe benefits as dependent on the timing and sequencing of investments into resources and complementary resources (Badewi et al., 2018). AI governance work similarly frames implementation as lifecycle governance, where organizations must operationalize principles, maintain controls, and adapt practices over time (Papagiannidis et al., 2025; Birkstedt et al., 2023). Across both literatures, a "go-live mindset" is treated as insufficient for sustained performance and legitimacy.

3.3.2 Key differences between enterprise IS and AI implementation

The most fundamental difference concerns system behavior: enterprise IS are typically engineered to execute predefined rules and standardized processes, whereas AI systems often exhibit probabilistic behavior and depend on training data and model assumptions. As a result, AI implementation places heavier emphasis on coping with inscrutability and data dependency through dedicated capabilities, including AI project planning, co-development, data management, and model lifecycle management (Weber et al., 2023). This contrasts with the IS stream where implementation challenges center more on process fit, training, integration, and organizational adoption. Complex, but generally within a more deterministic system paradigm (Zuma & Sibindi, 2023; Costa et al., 2016).

A second difference is the prominence of ethics, accountability, and responsible governance as first-order implementation requirements in AI. While IS research recognizes failure risks and multi-factor success conditions (Dwivedi et al., 2015), AI governance reviews foreground ethics, stakeholder impacts, regulatory pressures, and the operationalization gap between principles and practice (Birkstedt et al., 2023; Papagiannidis et al., 2025). ML deployment syntheses also treat fairness, bias, legal compliance, user trust, and security as cross-cutting challenges throughout the workflow (Paleyes et al., 2022). These themes are not absent from IS implementation, but they are more central and implementation-defining in the AI stream.

Third, AI implementation appears to require more specialized human capital and leadership cognition than many traditional IS projects. In the IS stream, managerial support matters, but adoption can be driven by transactional necessity and market scope rather than performance metrics (Lázár & Madaras, 2024), and user continuance depends on expectancy and facilitating conditions (Lutfi, 2022). In AI, studies emphasize AI literacy and AI-oriented strategic cognition at the top-management level (Pinski et al., 2024), and systematic reviews of SME adoption identify distinctive requirements around data, skills, and AI-specific tools and needs (Ayinaddis, 2025; Sánchez et al., 2025). This suggests that, relative to many enterprise IS implementations, AI projects are more sensitive to the depth of AI-specific expertise and the organization's ability to interpret and govern model-driven outputs.

Fourth, the locus of value differs: enterprise IS implementations often emphasize process standardization, integration, and transaction efficiency, whereas AI implementations more frequently emphasize automation-plus-augmentation and the redesign of knowledge work. ERP benefits frameworks distinguish automation, planning, and innovation benefits and warn against attempting higher-level innovation before foundational capabilities mature (Badewi et al., 2018). In AI, professional-service evidence highlights how AI augments professionals while automating lower-value tasks, changing work allocation and service offerings (Spring et al., 2022). This "augmentation" emphasis implies that AI implementation may demand deeper attention to task boundaries, decision rights, and human–machine coordination than many ERP-like rollouts.

Finally, AI implementation appears more exposed to environmental uncertainty and evolving technology trajectories (including generative AI), motivating roadmaps and iterative experimentation logic. AI adoption work highlights market uncertainty, vendor partnerships, and government involvement (Nguyen, 2022), and SME-focused reviews identify regulatory compliance and rapid tool evolution as salient dimensions (Ayinaddis, 2025; Sánchez et al., 2025). While IS implementation also depends on external context (Skafi et al., 2020; Aldossari & Mokhtar, 2020), the AI stream more strongly portrays implementation as a moving target that requires continuous updating of governance, capabilities, and operating procedures as models, data, and regulations evolve (Papagiannidis et al., 2025; Weber et al., 2023).

3.4 Eurostat based correlation analysis between AI adoption and enterprise IS proxies

To complement the dual-stream literature comparison, we use Eurostat data to provide a descriptive "sanity check" of whether enterprise AI adoption co-varies with proxies of enterprise IS and related digitalisation practices. The underlying logic is simple: if countries where firms are more active users of enterprise IS-related technologies also tend to report higher AI uptake, this supports the relevance of comparing IS and AI implementation as related organisational phenomena rather than as fully disconnected domains.

The correlation analysis was conducted for all 27 EU Member States (excluding the EU aggregate). For the years 2023 and 2025, we combined the share of enterprises using at least one AI technology with three IS-side proxies available in Eurostat such as use of cloud computing services, use of data analytics (big data analytics), and use of any business software (a broad proxy for enterprise software use). We calculated Pearson's correlation coefficient r, the coefficient of determination R^2, and the corresponding p value for each year-proxy pair.

Table 4
Eurostat based correlation analysis between AI adoption and enterprise IS proxies in the EU

Year	Countries (n)	IS proxy	Pearson r	R squared	p value
2023	27	Cloud computing (any cloud services)	0.55	0.30	0.0032
2023	27	Data analytics (any big data analytics)	0.41	0.17	0.0344
2023	27	Business software (any)	0.78	0.60	0.0000
2025	27	Cloud computing (any cloud services)	0.64	0.41	0.0003
2025	27	Data analytics (any big data analytics)	0.48	0.24	0.0103
2025	27	Business software (any)	0.65	0.42	0.0003

Source: own processing based on statistical data from database EUROSTAT (2026)

Across EU Member States, the association between AI adoption and IS-related proxies is consistently positive and statistically significant for all tested pairs in both observed years. In 2023, the strongest relationship appears between AI adoption and the broad "business software" proxy ($r = 0.78$; $R^2 = 0.60$), indicating that countries with higher enterprise software usage also tend to exhibit substantially higher AI uptake. Cloud computing shows a moderate positive association ($r = 0.55$; $R^2 = 0.30$), while data analytics presents a weaker but still significant relationship ($r = 0.41$; $R^2 = 0.17$). This pattern aligns with macro-level EU evidence showing that foundational digital enablers, drawn from DESI and Eurostat, are positively and significantly associated with enterprise AI adoption, supporting the interpretation that AI uptake tends to rise where broader digital maturity is higher (Laitsou et al., 2025).

In 2025, the relationships remain positive and in two cases strengthen. The AI–cloud association increases to r = 0.64 (R^2 = 0.41), suggesting that as cloud becomes more widespread, it increasingly co-varies with enterprise AI uptake. The AI–data-analytics relationship also strengthens modestly (r = 0.48; R^2 = 0.24). The AI–business-software association remains strong (r = 0.65; R^2 = 0.42), although the linear explanatory share is lower than in 2023, indicating that AI adoption becomes somewhat less "captured" by this single proxy as AI diffuses.

These results should be interpreted as correlational rather than causal. The observed co-variation can plausibly reflect shared underlying drivers such as national digital maturity, enterprise investment capacity, sectoral structure, digital infrastructure, management capabilities, and complementary skills. Nevertheless, the pattern provides supportive evidence for the premise of this paper: AI adoption tends to be higher in environments where enterprise IS-related practices are already more prevalent, which strengthens the rationale for comparing implementation priorities and transferring applicable lessons from enterprise IS implementation to enterprise AI implementation.

Conclusion

The aim of this paper was to assess how enterprise AI implementation priorities relate to enterprise information systems (IS) implementation priorities. We addressed this aim through a dual-stream systematic literature review (14 IS studies and 14 AI studies) and complemented the qualitative comparison with a Eurostat-based correlation analysis that tests whether AI adoption co-varies with country-level proxies of enterprise IS adoption and related digital foundations.

RQ1: The literature synthesis shows substantial overlap between IS and AI implementation as socio-technical transformation. Both streams stress leadership and governance, change management, strategic/process alignment, data and integration quality, and staged value realization beyond go-live. At the same time, AI implementation adds distinct requirements tied to model-based and data-dependent behavior: coping with inscrutability and data dependency (including model lifecycle management), responsible-AI governance (ethics, accountability, transparency), and a stronger dependence on AI-specific leadership competence and human–machine work redesign.

RQ2: The Eurostat correlation analysis provides a macro-level plausibility check for our comparison. Across EU Member States, enterprise AI adoption is positively and statistically significantly associated with IS-related proxies in both observed years, with the strongest link to business software and moderate links to cloud computing and data analytics. These correlational patterns suggest that AI uptake tends to be higher where broader enterprise digitalization and IS-related practices are already more prevalent.

For practice, the findings imply that many "core" IS implementation lessons remain applicable to AI: strong governance and ownership, active change management, process/data integration discipline, and staged benefit management. However, organisations should not treat AI as a standard IS rollout: AI implementation requires additional capabilities for data management and model lifecycle oversight, explicit responsible-AI governance, and leadership competence that can translate AI opportunities and risks into operational controls. For policy, the co-variation patterns suggest that raising AI adoption may depend not only on AI-specific initiatives but also on strengthening the broader enterprise digital base (e.g., enterprise software diffusion, cloud readiness, analytics capability, and skills).

This study has several limitations. The review relies on a single database (Web of Science), English-language open-access records, and bounded time windows, which may omit relevant evidence. The comparative synthesis is literature-grounded but not based on a formal coding framework, which can introduce interpretive subjectivity. The Eurostat analysis is country-level and uses proxy indicators rather than direct measures of implementation strategy quality; the correlations do not permit causal inference and may reflect omitted drivers such as sectoral structure, productivity, investment intensity, regulation, and skills. Future research should extend the evidence base with additional databases and non-open-access sources, apply more formal comparative coding, and triangulate with firm-level and panel designs. Empirically, future work could test predictive models (e.g., regression/panel approaches), incorporate richer IS proxies and structural controls, and distinguish AI adoption by application domain and IS implementation by system type to refine which IS lessons transfer to which AI implementation contexts.

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THE INTEGRATION OF AI-SUPPORTED SYSTEMS IN MEDICAL PRACTICE – EFFECTS ON WORK PROCESSES AND LABOUR DIVISION

Murat Tetik – Peter Markovič

Abstract
The increasing integration of artificial intelligence (AI) in medical organizations is fundamentally changing work processes and the division of labour. While much of the research to date examines individual acceptance factors of AI systems, there is still a deficit of systematic analyses of technological influencing factors at the company level. Organizational decisions on the selection, implementation and integration of AI-supported systems determine whether they are only used as a support or lead to a sustainable transformation of medical work.
This article analyses the integration of AI-supported systems in medical practice with a focus on technological influencing factors at the company level and their effects on work processes and division of labour. The adoption model of Khanfar (2025) serves as a theoretical frame of reference, particularly the cluster of firm-level influencing technological factors. Methodologically, the work is based on a systematic, theory-driven literature review of empirical studies from the health care sector as well as from comparable knowledge-intensive organizations.
The results show that factors such as return on investment, perceived benefits of AI systems, system maturity, IT compatibility, system reliability, cost, and the degree of technology integration are decisive for the depth of AI implementation. High system maturity, reliable results and close embedding in existing IT infrastructures favour a sustainable redesign of work processes and lead to a shift in the division of labour towards more coordinating, monitoring and interpreting roles of medical professionals. The article is closely linked to a dissertation thesis and provides a conceptual basis for the empirical operationalization of technological influencing factors as well as for further investigations on the transformation of medical work through AI.

JEL classification *I11, I18, L86, M15, O32, O33*
Keywords: *Artificial intelligence, medical practice, AI adoption, technological influencing factors, company level, Work processes, division of labour, Healthcare organizations*

Introduction

In recent years, the ongoing digitalization of the healthcare sector has led to an increasing implementation of AI-supported systems in medical organizations. Artificial intelligence is used in a variety of medical and administrative areas, including image-based diagnostics, clinical decision support systems, predictive analytics, and the automation of documentation and billing-related processes. Data-intensive and standardizable activities are considered particularly suitable for the use of AI-based technologies, as they are based on large amounts of data and can be easily mapped algorithmically (Topol, 2018) (Jiang et al., 2017).

At the same time, medical organizations are under considerable structural pressure. Demographic change, the increasing shortage of skilled workers and increasing regulatory and economic requirements mean that existing work processes are reaching their limits. Against this background, AI is not only discussed as a technological innovation, but increasingly as an organizational transformation tool (Jiang et al., 2017).

In parallel with technological development, medical organizations are under considerable structural pressure. Demographic change is leading to an increasing demand for medical services, while at the same time an increasing shortage of skilled workers is limiting human resources. In addition, there are growing regulatory requirements, rising costs and an increasing documentation and coordination effort, which binds medical professionals from patient-related activities (Ethics and governance of artificial intelligence for health, n.d.) In this area of tension, AI is no longer seen exclusively as a technological innovation. but increasingly as a potential instrument for reorganizing and relieving medical work.

Against this background, the use of AI-supported systems is increasingly being discussed as an organizational transformation tool. AI can not only automate individual activities but also restructure work processes in the long term and change existing divisions of labour between occupational groups. Studies indicate that the use of AI can be accompanied by a shift in professional role models as medical activities increasingly shift from operational decision-making to monitoring, interpreting and coordinating tasks (Reddy et al., 2019).

Despite the growing relevance of these developments, much of the research to date has focused primarily on individual acceptance factors such as user trust, perceived user-friendliness or ethical concerns when dealing with AI systems. On the other hand, there is still a research gap regarding determinants of AI integration related to company levels. Technological decisions at the organizational level – for example about system maturity, IT compatibility, investment costs or expected return on investment – have a significant influence on whether AI systems are only used as a supplement or have a structurally transformative effect on work processes and the division of labour (Khanfar et al., 2025).

This article directly ties in with this research gap and analyzes the integration of AI-supported systems in medical practice with a focus on technological influencing factors at the company level. The aim is to systematically investigate how these factors influence the design of work processes, and the organizational division of labour and what implications arise from them for a sustainable implementation of AI in a medical context.

1 Current state of the solved problem at home and abroad

The scientific debate on the use of artificial intelligence in healthcare has increased consider-ably in recent years. While early work focused primarily on technical performance and algorithmic accuracy, the question of the organizational conditions under which AI systems can be sustainably integrated into medical practice structures is increasingly coming to the fore (Topol, 2018) (Reddy et al., 2019).

A central research focus is on the application of AI-supported systems in medical diagnostics, especially in radiology, pathology and dermatology. Numerous studies show that AI algorithms can achieve diagnostic accuracy comparable to or sometimes superior to human experts in specific use cases (Esteva et al., 2017). At the same time, however, it is emphasized that these results are often achieved under experimental conditions and that their transferability to everyday clinical practice depends strongly on organizational and technological framework conditions (Sendak et al., 2020).

In parallel, a growing strand of research has been working on the integration of AI-powered systems into clinical decision support systems (CDSS). These studies show that AI offers added value, especially in the processing of large, heterogeneous amounts of data, such as risk assessment, therapy planning or prognosis estimation („The Historical Background of Resort Therapy“, 2018a). However, it is also clear here that the benefits of such systems depend largely on their embedding in existing work processes and IT infrastructures.

More recently, the organizational level of AI adoption has increasingly become the focus of research. While individual acceptance models such as the Technology Acceptance Model (TAM) or the Unified Theory of Acceptance and Use of Technology (UTAUT) provide valuable insights into user perceptions, they are only of limited use for the analysis of complex implementation processes in organizations (Venkatesh - 2022 - Adoption and Use of AI Tools A Research Agenda GR | PDF | Artificial Intelligence | Intelligence (AI) & Semantics, n.d.). Technological decisions at the enterprise level – for example regarding investment volume, system maturity or interoperability – are increasingly identified as decisive for the success or failure of AI implementations (Khanfar et al., 2025).

Empirical studies show that the expected return on investment (ROI) is a key driver for the adoption of AI-powered systems. ROI in the healthcare sector is often operationalized not only in monetary terms, but also via qualitative indicators such as time savings, process quality or reduction of administrative burdens (Khanna et al., 2022). Organizations prioritize AI applications especially in areas with high documentation and coordination effort, which has a direct impact on work processes and division of labour.

Another key research finding concerns the maturity and reliability of AI systems. Studies show that low-maturity systems often lead to parallel work structures, as AI results need additional verification. Only with increasing technological stability and validation will there be lasting changes in the division of labour, for example through the delegation of data-intensive tasks to AI systems (Sendak et al., 2020).

Compatibility with existing IT infrastructure is also highlighted in the literature as a decisive success factor. A lack of interoperability between AI systems and existing hospital information systems leads to media discontinuities, increased documentation effort and limited usability, which often means that potential efficiency gains cannot be realized (WHO, 2021). Studies therefore emphasize the importance of early consideration of technological integration aspects in the implementation of AI (Ethics and governance of artificial intelligence for health, n.d.).

In addition, recent work indicates that the use of AI-supported systems can have long-term effects on professional role models and organizational division of labour. Medical and nursing activities are increasingly shifting from surgical tasks to monitoring, interpreting and coordinating tasks, which requires new competence requirements and qualification profiles (Reddy et al., 2020) (Davenport & Kalakota, 2019).

In summary, the current state of research shows that the successful use of AI-supported systems in medical practice depends less on pure technological performance and more on technological decisions related to the company level. Despite growing empirical evidence, there is still a need for systematic analyses that take an integrative view of technological influencing fac-tors, work processes and the division of labour. This is where the present article comes in by systematically examining these aspects based on a theory-driven framework.

2 Research design and methodology

The present work is based on a systematic, theory-driven literature review with a qualitative-analytical focus. The aim of this methodological approach is to identify, analyze and synthesize empirical studies that investigate technological factors influencing the adoption of artificial intelligence at the company level and address their effects on work processes as well as the organizational division of labour in medical institutions. Systematic literature reviews are considered a suitable instrument, especially in interdisciplinary research fields such as AI research in healthcare, to bring together fragmented empirical evidence in a structured way and to classify it in a theory-guided manner (Snyder, 2019).

Table 1 summarizes the key characteristics of the studies included in the literature review, including methodology, measurement tools, samples, research aims, and theoretical backgrounds.

The adoption model of Khanfar (2025), which conceptualizes the introduction and use of AI-supported systems as a multi-stage organizational decision-making and implementation process, serves as an analytical frame of reference. The model integrates individual, organizational and technological influencing factors and thus allows a differentiated analysis of adoption mechanisms at different levels. The focus of this thesis is explicitly on the cluster of firm-level influencing technological factors. This perspective is chosen because technological decisions at the company level significantly determine investment decisions, implementation strategies and the degree of integration of AI systems into existing work and IT structures (Khanfar et al., 2025)

Table 1
Overview of Included Studies

No.	Study	Qualitative or Quantitative methodology	Measurement tool	Sample	Aim of the study	Theoretical background
1	Davenport & Kalakota (2019)	Qualitative (conceptual)	Narrative literature review	Healthcare organizations	Analyze potential AI applications in healthcare and implications for workflows	Sociotechnical systems theory; Digital transformation
2	Reddy et al. (2019)	Qualitative	Conceptual framework development	Healthcare delivery systems	Examine how AI-enabled healthcare reshapes professional roles and care processes	Human–AI collabouration; Sociotechnical perspective
3	Sendak et al. (2020)	Qualitative (implementation study)	Case study, workflow analysis	Large U.S. hospital system	Evaluate real-world integration of a sepsis prediction AI system	Implementation science; Sociotechnical systems theory
4	Wolff et al. (2020)	Qualitative (systematic review)	Systematic literature review	Healthcare organizations	Assess the economic impact of AI adoption in healthcare	Health economics; Technology adoption theory
5	Khanfar et al. (2025)	Qualitative (systematic review)	Systematic literature review	Cross-industry organizations incl. healthcare	Identify firm-level technological factors influencing AI adoption	TOE framework; Technology adoption theory

Source: own presentation

The analysis focuses on technological factors such as return on investment, perceived benefits of AI systems, system maturity, compatibility with existing IT infrastructure, system reliability and accuracy, costs, and the degree of technology integration. These factors are described in the literature as central determinants of whether AI systems are only used as supporting tools or lead to a sustainable reorganization of work processes and division of labour (Reddy et al., 2020; Sendak et al., 2020).

The literature was searched in international scientific databases, in particular PubMed, Scopus and Web of Science, as these ensure a high level of coverage of both medical and organizational and information science research. The search strategy combined controlled keywords and free text terms such as artificial intelligence, healthcare, adoption, technology factors, Organization, workflow and task allocation. The search terms were iteratively adjusted to include both clinical and management-oriented studies. In addition, reference lists of relevant reviews were used (backward snowballing) to identify relevant studies that were not covered by the database-supported search (Booth et al., 2025).

Peer-reviewed empirical studies from the healthcare sector as well as from comparable knowledge-intensive organizations were included, provided that an explicit reference was made to the company level and to technological factors influencing AI adoption. Studies that only examined individual acceptance factors, ethical issues or purely technical performance aspects without an organizational context were excluded. These selection criteria serve to ensure a consistent theoretical orientation as well as direct connection to the higher-level dissertation work.

The evaluation of the identified studies was carried out by means of structured qualitative content analysis according to (Mayring, n.d.). Relevant text passages were first inductively openly coded and then deductively assigned to the technological influencing factors defined in the theoretical framework. In a further step of the analysis, the identified factors were systematically interpreted about their effects on work processes and the organizational division of labour. This approach enables a transparent, rule-driven and at the same time theory-driven condensation of complex empirical findings and supports the derivation of reliable conclusions for research and practice.

3 Research result

Return on investment (ROI)

The expected return on investment (ROI) is a key decision factor for the adoption of AI-powered systems at the enterprise level. In the medical context, however, ROI is often not operationalized exclusively through direct monetary returns, but through indirect and qualitative indicators such as time savings, reduction of administrative activities, process acceleration, and improvements in the quality of care (Davenport & Kalakota, 2019). These enhanced ROI concepts consider the specificity of medical organizations, where efficiency gains are often not directly measurable financially, but have significant organizational impacts.

Empirical studies show that organizations prioritize AI applications especially in areas with high documentation, coordination and administrative effort, such as coding, scheduling or clinical documentation. The automation of these activities relieves the burden on medical professionals and enables the reallocation of personnel resources towards patient-oriented tasks. At the company level, ROI thus acts not only as an investment criterion, but also as a control instrument for the strategic realignment of work processes (Wolff et al., 2020).

Advantages of AI systems

The perceived benefits of AI systems include process standardization, error reduction, improved decision support, and increased transparency of complex data and decision-making processes. At the enterprise level, these benefits act as key drivers of strategic decisions to redesign processes and reorganize medical work (Topol, 2018).

Studies show that organizations with clearly defined objectives for the use of AI, such as in-creasing efficiency, improving quality or reducing variability, achieve significantly stronger effects on work processes and division of labour than organizations with selective or experimental implementations (Reddy et al., 2019). Standardized processes in particular benefit from AI-supported decision support, as they provide consistent recommendations for action and thus strengthen organizational coordination mechanisms.

Maturity of the system

The maturity level of an AI system describes its technological stability, validation, regulatory approval and practicality in everyday clinical practice. Low maturity systems often lead to parallel work structures, as AI results need to be additionally reviewed and validated. This increases the workload in the short term and limits organizational effects (Sendak et al., 2020).

As the system matures, the control and validation effort decreases considerably. As a result, medical activities are increasingly shifting from operational decision-making to monitoring, interpreting and coordinating tasks. This shift in the division of labour represents a central mechanism of organizational transformation through AI (Sendak et al., 2020) (Jiang et al., 2017).

Compatibility with IT infrastructure

The compatibility of AI systems with existing IT infrastructures is a decisive success factor for sustainable integration. Lack of interoperability between AI applications and hospital information systems, electronic patient records or billing systems leads to media discontinuities, redundant data entry and increased documentation effort (Ethics and governance of artificial intelligence for health, n.d.).

Empirical findings show that a high level of IT compatibility enables a deeper integration of AI-supported systems into existing workflows and thus strengthens organizational effects on efficiency, quality and division of labour. Organizations that embrace interoperability early achieve significantly higher utilization rates and more sustainable process changes (Ethics and governance of artificial intelligence for health, n.d.) (Reddy et al., 2019).

System Reliability and Accuracy

System reliability and diagnostic accuracy significantly influence the degree of task shift to AI systems. Only with stable, validated and transparent results are organizations willing to delegate data-intensive and risky tasks to AI („The Historical Background of Resort Therapy“, 2018).

High reliability allows for a clear redefinition of professional roles, with healthcare professionals increasingly taking on coordinating, supervising, and interpreting activities. In the long term, this will lead to a change in the division of labour and new competence requirements with-in medical organizations („The Historical Background of Resort Therapy“, 2018).

Costs of the AI system

In addition to acquisition costs, the costs of AI systems also include implementation, maintenance, update and training costs. High costs act as a limiting factor at the enterprise level and often lead to selective or pilot-like implementations. In such cases, organizational effects on work processes and division of labour are often limited.

Studies show that organizations with long-term investment strategies and clear scaling plans achieve significantly more sustainable effects than organizations with short-term cost focuses (Davenport & Kalakota, 2019).

Technology Integration

The degree of technology integration largely determines whether AI is used as an isolated tool or as an integral part of organizational processes. A high level of integration into existing IT and work structures promotes sustainable changes in work processes and enables new role pro-files such as AI coordinators, digital interface functions or data-responsible specialist roles (Reddy et al., 2019).

Empirical evidence shows that deeply integrated AI systems have significantly stronger effects on division of labour and organizational efficiency than stand-alone solutions. Technology integration is thus proving to be a key factor for the long-term organizational transformation of medical work.

The results show that the introduction and impact of AI-supported systems in medical organizations is largely determined by technological influencing factors at the company level. A key driver is the expected return on investments, which in the healthcare sector is often not primarily assessed in monetary terms, but via indirect effects such as time savings, reduction of administrative activities, process acceleration and quality improvements in care. Accordingly, organizations are prioritizing the use of AI, especially in areas that require documentation, coordination and administration, which relieves the burden on medical professionals and allows personnel resources to be used more for patient-related tasks.

Table 2
Overview of technological influencing factors

Factor	Definition (company level)	Typical measurement approach	Impact on work
ROI	Economic benefits	Cost-benefit analysis	Workflow prioritization
Advantage	Strategic added value	Management surveys	Relocation of tasks
System maturity	Technological stability	The Readiness Scale	Reduction of duplication of work
IT Compatibility	Interoperability	Degree of integration	Efficient prcesses
Reliability	Quality of results	Error rates	Delegation of tasks
Costs	Total Cost of Ownership	TCO analyses	Selective use
Technology Integration	Embedding in processes	Organizational Analyses	New role models

Source: own presentation

In addition, the perceived benefits of AI systems – such as process standardization, error re-duction, and improved decision support – act as central drivers for strategic decisions to rede-sign work processes. Organizations with clearly defined objectives for the use of AI achieve significantly stronger effects on work processes and division of labour than those with selective or experimental implementations.

Another key factor is the maturity of the AI systems used. While systems with a low degree of maturity often lead to parallel work structures and increased control effort, a high level of system maturity enables a sustainable shift in the division of labour. Medical activities are increasingly shifting from operational decision-making to monitoring, interpreting and coordinating tasks.

Compatibility with existing IT infrastructure also proves to be crucial for implementation success. A lack of interoperability leads to media disruptions and additional documentation effort, while a high level of IT compatibility enables deeper integration into existing workflows and increases organizational effects on efficiency, quality and division of labour.

System reliability and accuracy largely determine the degree of task shift to AI systems. Only with stable and transparent results are organizations willing to delegate data-intensive and risky tasks to AI, which in the long-term leads to a redefinition of professional roles and new skill requirements.

Finally, the results show that the cost of AI systems acts as a limiting or enabling factor. High costs favor selective implementations with limited organizational effects, while long-term investment strategies and a high degree of technology integration enable sustainable changes in work processes and division of labour. Overall, the deep integration of AI into organizational structures is proving to be a key factor for a long-term transformation of medical work.

4 Discussion

The aim of this thesis was to analyse the integration of AI-supported systems in medical practice from a company-level perspective and to investigate its effects on work processes and division of labour. The results make it clear that technological influencing factors at the organizational level play a central role in implementation success and are decisive in determining whether AI systems only achieve incremental efficiency gains or enable a sustainable transformation of medical work (von Conta et al., 2025).

A central result of the analysis concerns the importance of the return on investments as a basis for organizational decision-making. The findings show that ROI in healthcare is understood in an expanded form and, in addition to monetary returns, considers qualitative effects such as time savings, process acceleration and improvements in the quality of care. This perspective confirms existing work that indicates that economic evaluations in the medical context are closely linked to quality and efficiency indicators. At the same time, it illustrates why AI implementations often start in administrative and documentation-intensive areas, where efficiency gains are visible in the short term and organizational risks are comparatively low. In the discussion, however, the question arises to what extent this strategic focus enables the transition to a deeper transformation of clinical core processes in the long term or whether it merely optimizes existing structures without bringing about fundamental changes (von Conta et al., 2025).

In addition, the results show that the perceived benefits of AI systems significantly influence strategic decisions on process redesign. Process standardization, error reduction and improved decision support are used as central arguments for the use of AI at the company level. Organizations with clearly defined objectives achieve significantly stronger effects on work processes and division of labour than those with selective implementations. These findings underline the importance of strategically anchoring AI projects and confirm assumptions of current adoption models, which understand technological implementations as the result of conscious organizational decisions.

Another key point of discussion concerns the maturity of the AI systems used. The results show that systems with a low degree of maturity lead to increased control overhead and parallel work structures in the short term, which initially limits potential efficiency gains. Only with in-creasing system maturity will there be a lasting shift in the division of labour, in which medical activities increasingly take on monitoring, interpreting and coordinating functions. This development raises fundamental questions about the future role of medical professions and makes it clear that technological maturity is a prerequisite for organizational transformation but does not automatically lead to it.

The compatibility of AI systems with existing IT infrastructure is also proving to be a key success factor. A lack of interoperability leads to media discontinuities, increased documentation effort and limited usability, which significantly reduces the potential advantages of AI systems. The results underline that technological integration decisions must be included in the implementation process at an early stage to achieve sustainable effects on work processes and division of labour. These findings are in line with international recommendations that consider interoperability to be a prerequisite for the successful use of digital technologies in healthcare.

System reliability and accuracy significantly influence the degree of task shift to AI systems. Only with stable, validated and transparent results are organizations willing to delegate data-intensive and risky tasks to AI. These results confirm the assumption that trust in AI systems is not primarily based on individual acceptance, but on organizational risk assessment. The associated redefinition of professional roles represents one of the most profound effects of AI integration and requires new competence profiles as well as adapted responsibility structures.

Finally, the results make it clear that the costs of AI systems act as a structural framework factor that significantly influences implementation strategies. High acquisition and operating costs often lead to selective or pilot-like implementations with limited organizational effects. In contrast, long-term investment strategies and a high degree of technology integration enable sustainable changes in work processes and division of labour. These findings suggest that success-ful AI integration depends less on individual technology decisions and more on long-term organizational governance and investment models.

In summary, the discussion shows that the integration of AI-supported systems in medical practice must be understood as a multidimensional transformation process that includes techno-logical, organizational and professional aspects in equal measure. The results extend existing adoption models by focusing on the impact of technological decisions on work processes and division of labour. For further research, there is a need for long-term studies that systematically investigate the dynamic interactions between technological maturity, organizational embeddedness and professional practice. In practice, the findings imply that AI implementations will only be effective in the long term if they are strategically planned, technologically integrated and organizationally supported (Wenderott et al., 2024) (Erdal et al., 2023) (You et al., 2025)

Conclusion

The article concludes that the integration of AI in medical practice only goes beyond selective efficiency gains if it is consciously understood as a strategic design task at the company level. AI thus does not unfold its effect in isolation as a technology, but in the way in which organizations plan and control investments, system selection, implementation and embed-ding in existing structures.

Central to this is an expanded concept of ROI, which, in addition to direct financial effects, includes time savings, relief from documentation and coordination tasks, process quality and improvements in the quality of care. This broader ROI framework explains why AI is being introduced primarily in areas with high administrative burdens, where it can contribute to a noticeable redistribution of resources towards patient-oriented activities.

At the same time, the results show that the maturity, reliability and IT compatibility of AI systems are decisive levers for the depth of organizational changes. If systems are still immature and require additional controls, parallel structures will emerge without fundamental relief; only with a high level of system stability and seamless integration into existing IT landscapes does the division of labour shift significantly in the direction of monitoring, interpreting and coordinating roles.

In addition, cost structure and degree of integration are decisive factors in determining whether AI remains as an isolated solution in pilot areas or covers the entire organization. Organizations that pursue long-term investment and scaling strategies, address interoperability at an early stage, and actively build new role and competence profiles, for example for data and AI managers, achieve significantly more lasting effects on processes, division of labour and professional identities.

Overall, the extended conclusion is that the transformation of medical work through AI de-pends less on the technical performance of individual systems and more on the ability of organizations to understand technological influencing factors, work processes, governance and personnel development as a coherent field of design and to control them coherently.

Acknowledgement

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Author's share: 20 %

Project overview

Futurepreneurs and SMEs for a sustainable Central Europe | Certification Scheme

Futurepreneurs are professionals that are driven by purpose and impact. They take on societal challenges and climate change with an entrepreneurial mindset and want to improve our lives. The GREENPACT project sets up partnerships between companies and futurepreneurs. The aim is to develop a certification scheme for a new generation of impact-driven top executives. To this end, the project develops joint action plans, pilot actions and a self-assessment tool.

1,78 m €
Project Budget

80%
of the Budget is funded by ERDF

5
Countries

6
Regions

9
Partners

1
Pilots

Duration

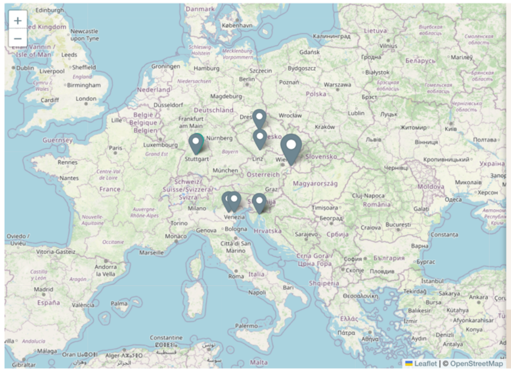
Start date 04.2023

End date 03.2026

Project progress

20%

Project partnership



Project partner

University of Economics in Bratislava

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Address
Dolnozemská cesta 1
85235 Bratislava

Country
Slovakia (SK)

Web
www.euba.sk

Total partner budget
207 200 €

Project partners

Lead partner

Stuttgart Media University

Startup Center

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Nobelstr. 10
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Project partner

- Stuttgart Region Economic Development Corporation
- ENAIP Veneto Social Enterprise
- Region of Veneto - Department of Labour
- STEP RI Science and Technology Park of the University of Rijeka Ltd
- City of Rijeka
- Czech Chamber of Commerce
- Institute of Technology and Business in České Budějovice
- University of Economics in Bratislava

VReduMED

Project partners

Lead partner
South Bohemian Science and Technology Park, corp.

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Web
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Project partner

- University of South Bohemia in České Budějovice
- Business Upper Austria
- Education Group
- University of Economics in Bratislava
- National Institute of Children's Diseases
- Strategic Partnership for Sensor Technologies
- Ostbayerische Technische Hochschule Regensburg
- Innoskart Business Development Nonprofit Ltd.
- Széchenyi István University

Project overview

Virtual Reality Education and Training Solutions for Medicine Sector

Medical interventions are increasingly digitalised but training of health care staff is still lagging behind. The VReduMED project helps to untap the potential of virtual and augmented reality for their education. The partnership develops a roadmap for virtual reality training products and services and will publish a handbook on the integration of virtual reality into health care education. They also set up three regional virtual reality labs to test different virtual reality use cases.

2,20 m € Project Budget

80% of the Budget is funded by ERDF

5 Countries

6 Regions

10 Partners

3 Pilots

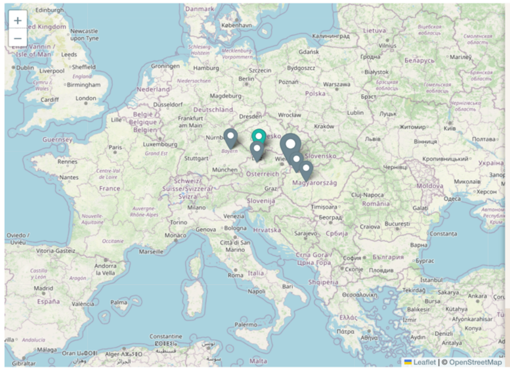
Duration

Start date 04.2023
End date 03.2026

Project progress

20%

Project partnership



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Total partner budget
220 900 €

Interreg Danube Region | Co-funded by the European Union

SReST

Project overview

Start date: 01 January 2024

Status: ongoing

End date: 30 June 2026

€1,540,470 budget

80.00 % funded by Interreg Funds

7 countries

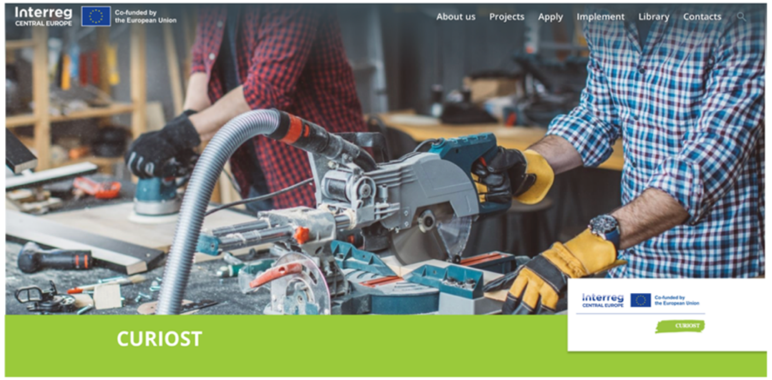
10 partners

SOCIALLY RESPONSIBLE SLOW FOOD TOURISM IN THE DANUBE REGION

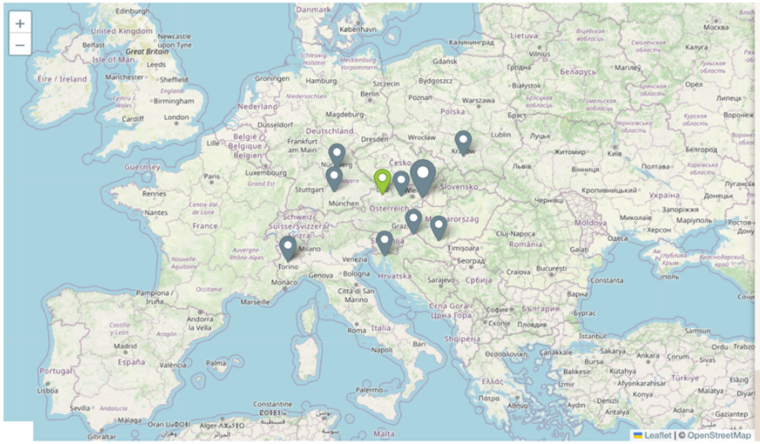
The main objective of the SReST project is to promote "slow food" tourism in the Danube region and enhance the employability of vulnerable groups by providing solutions that enable the valorisation of agrobiodiversity and gastronomic heritage and a fair distribution of generated benefits, including the well-being of the host communities.

By focusing on agro-biodiversity, food heritage and local identity, the goal is to broaden the socially responsible sustainable tourism offer and promote "slow food" tourism based on the exploration of gastronomic traditions and the local communities that preserve them. The project will help enhance local agricultural high-value chains while appreciating natural and cultural diversity of partner regions.

SReST will develop joint solutions to enhance socio-economic development and promote alternative models and competitive new tourism products of "slow food" itineraries grounded in agrobiodiversity and food heritage, tested in different territorial contexts of pilot regions. These solutions will not be limited to the local level, but will have a wider impact in the Danube area. Therefore, the success of the project will be based on close cooperation between partners from different countries and regions. You can learn more about the project partners here.



Project partnership



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Total partner budget
174 020 €

Duration

Start date **06.2024**

End date **11.2026**

Project partners

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Project partner

- **ConPlusUltra Ltd**
- **University of Economics in Bratislava**
- **Chamber of Commerce and Industry of Pécs- Baranya**
- **South Poland Cleantech Cluster Ltd.**
- **STEP RI science and technology park of the University of Rijeka Ltd.**
- **Development and Training Centre for the Metal Industry – Metal Centre Čakovec**
- **MESAP Innovation Cluster**
- **Science and Technology Park - Envipark**
- **Bayern Innovativ**
- **Cluster of Environmental Technologies Bavaria**

Project overview

Circular design and development of Sustainable products in 4 key sectors in Central Europe

The ongoing transition to a circular economy is not only a tedious obligation for the manufacturing industry. It also offers an opportunity to develop innovative sustainable products. The CURIOST project helps small- and medium-sized companies in sectors like mechanics, packaging, plastics, and construction to harvest the potential benefits. They help selected companies to co-develop tailor-made, innovative, sustainable and circular product prototypes. The learnings are then aggregated into a universal strategy and action plans to accelerate the green transition in the manufacturing industry.

1,90 m €
Project Budget

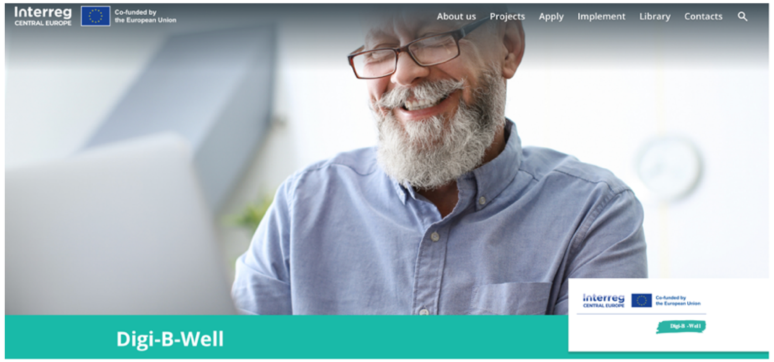
80%
of the Budget is funded by ERDF

7
Countries

10
Regions

11
Partners

1
Pilots

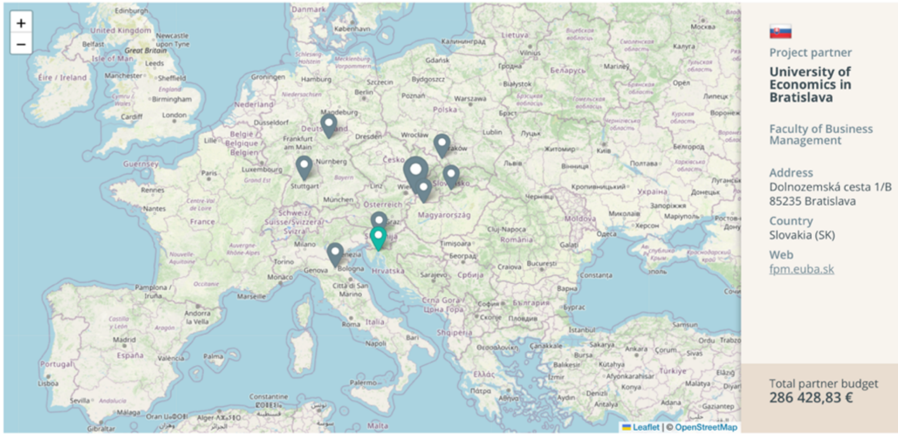


Duration

Start date **06.2024**

End date **05.2027**

Project partnership



Project partners

Lead partner

Primorje-Gorski Kotar County

Administrative Department for Regional Development, Infrastructure and Project Management

Address
Adamićeva 10
51000 Rijeka

Country
Croatia (HR)

Web
www.pgz.hr

Project partner

- **Alma Mater Studiorum - University of Bologna**
- **Technical University Ilmenau**
- **bwcon**
- **Chamber of Commerce and Industry of Slovenia**
- **Pannon Business Network Association**
- **University of Economics in Bratislava**
- **Regional Development Agency in Bielsko-Biała**
- **City Lucenec**

Project overview

Enhancement of capacities of SMEs, public authorities and academia for digitalisation, digital era-fit management and achievement of digital well-being.

The digital transformation offers new opportunities for companies but also increases complexity. Especially employees over 55 can suffer from digital stress or burnout at the workplace. The Digi-B-Well project helps companies to transform and make employees fit for the digital age. The partners upskill competences of managers, public authorities, and academia to better prevent digital stress and burnout. They develop and test new tools to self-assess digital maturity and digital transformation models in companies. In addition, a digitalisation strategy and action plans ensure the uptake of their innovative solutions into broader policy and business practices.

2,19 m € Project Budget

80% of the Budget is funded by ERDF

7 Countries

9 Regions

9 Partners

1 Pilots

Interreg Danube Region

Co-funded by the European Union

PATHS

Our Solution

PATHS introduces the **Life Path Support Service (LPSS)** model – a new approach to career guidance that is local, inclusive, and tailored to the individual.

Instead of one-size-fits-all programs, LPSS offers:

- Free, accessible services in small municipalities
- Career workshops, camps, and internships rooted in **self-awareness**
- Trained local **mentors** who provide personal guidance and support
- A long-term strategy for sustainable regional development

This model is being piloted in communities across Hungary, Slovakia, Czech Republic, Romania, Croatia, and Bosnia & Herzegovina – with expert support from Austria and Slovenia.

Project overview

Start date: 01 April 2025

Status: ongoing

End date: 31 March 2028

€2,516,726 budget

80.00 % funded by Interreg Funds

9 countries

13 partners

Interreg Europe
Co-funded by the European Union

PERSIST

What did this project achieve?

This project will:

- **Strengthen regions' ability** to deliver smart specialisation in a sustainable way.
- **Develop and test new methods** to move from the Entrepreneurial Discovery Process to the Ongoing Discovery Process.
- **Improve cooperation** between authorities, businesses and researchers.
- **Enable inclusive decisions** and make better use of regional resources.
- **Boost innovation capacity** and strengthen regional competitiveness.
- **Create stronger ecosystems** and new opportunities that benefit both the economy and society.

A few numbers

1,793,584 € budget

01 May 2025-31 Jul 2029

12 partners

Project summary

Across Europe, regions face similar challenges. How can we build **innovation systems that endure** – systems that meet today's needs while paving the way for a **sustainable future**, **economically**, **socially**, and **environmentally**?

This project helps **regional authorities and agencies** strengthen **long-term cooperation** around smart specialisation.

Through **practical frameworks and tools**, it supports regions in creating **strong, inclusive networks** with **lasting commitment** from key actors.

The project builds on engagement through the **Entrepreneurial Discovery Process** and other **participatory methods**. This ensures that collaboration is rooted in **real regional needs and ambitions**.

Who we are

Persist brings together nine partners from across Europe – regions, universities, and development agencies working together for smarter, more sustainable regional growth.

- **Region Jönköping County** (Sweden)
- **Podkarpackie Region** (Poland)
- **Regional Development Agency of Khmelnytskyi oblast** (Ukraine)
- **University of Economics in Bratislava** (Slovakia)
- **Ústí Region** (Czech Republic)
- **Regional Management Northern Hessen** (Germany)
- **University of Groningen** (Netherlands)
- **Business Innovation Center of Cartagena** (Spain)
- **Udhëtim i Lirë** (Albania)

Together, we share knowledge, test new ideas, and build long-term cooperation to strengthen smart specialisation across Europe.

Interreg Europe
Co-funded by the European Union

ForYouth

A few numbers

1,617,350 € budget

01 May 2025- 31 Jul 2029

9 partners

Project summary

Youth involvement is essential in all policy areas that affect their lives, as highlighted in the **EU Youth Strategy 2019–2027**. The project aims to develop **mechanisms and instruments** tailored to young people's needs, supporting the strengthening of their **voice in decision-making**, promoting effective use of resources, and fostering **cross-sector collaboration**.

The project's **innovative character** stems both from its **topic** and the **partnership structure**. The topic is highly relevant, as the gap between **urban strategies** and **youth interests** remains visible in the targeted regions. The partnership unites territories with contrasting demographic realities: some face **low birth rates** and an **ageing population**, while others stand out for having a **large youth population**, which is uncommon in many European areas.

The **overall objective** is to improve policies that enable **active youth participation** in community life and decision-making processes. The project seeks to create an environment where young people feel **valued, empowered, and motivated** to contribute to **societal progress and development**.

This objective will be achieved by:

- **Removing barriers and administrative blockages** that prevent young people from feeling appreciated;
- Encouraging them to **remain in or return to their birthplaces** and engage actively in their communities;
- **Engaging key stakeholders** (public institutions, NGOs, education, and private sector);
- **Transferring knowledge and good practices** from advanced regions to those with fewer youth-oriented solutions;
- Developing **tools and mechanisms** based on the gathered experiences;
- Promoting **social inclusion**, with a focus on **young emigrants** and the **youth diaspora**.

The project will be implemented within the framework of **territorial cooperation** among partner regions, through the **exchange of good practices and experiences** on youth participation.