Journal of Business Sectors
Volume 04 Issue 02 December 2026
ISSN 2989-3445 www.jobsjournal.eu

Evaluating The Interaction between AI Adoption and Sustainability in Hungarian SME: Owners' and Managers' Perspectives

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ABSTRACT

Research background: Increasing demands for managerial efficiency in the small and medium-sized enterprise (SME) segment are encouraging business owners and managers to explore the potential of artificial intelligence (AI). The integration of AI into risk management and sustainability-oriented decision-making may improve risk identification and assessment, support evidence-based managerial decisions, and strengthen organisational resilience.

Purpose of the article: The aim of this paper is to identify the relationships between AI adoption in corporate settings and (i) enterprise management, (ii) enterprise risk management, and (iii) business sustainability within the SME business environment.

Methods: The questionnaire was designed to examine the attitudes of SME owners and managers towards selected statements. Data were collected in 2025 from a sample of 520 small and medium-sized enterprises operating in Hungary. The Computer-Assisted Web Interviewing (CAWI) method was used for data collection, which was facilitated by an external survey agency. The research hypotheses were tested using a range of statistical methods, including descriptive statistics, contingency tables, reliability and validity assessments, factor analysis, and Spearman's rank correlation analysis.

Findings & Value added: The main findings reveal significant positive associations between (i) the use of AI tools and business sustainability, (ii) AI adoption and effective enterprise management, and (iii) AI adoption and enterprise risk management in the SME segment. These results suggest that, from the perspective of SME owners and managers, greater AI adoption is positively associated with more effective enterprise management and governance. The strongest association was observed between AI adoption and enterprise risk management, whereas a comparatively weaker association was identified between AI adoption and business sustainability. The findings have practical implications for SME owners and managers, who face increasing pressure to improve operational efficiency while ensuring long-term business growth and sustainability. Disseminating these findings among key decision-makers may help raise awareness of the potential applications of AI in managerial decision-making, risk management, and sustainable business development.

RECEIVED: September 8 ⊙ **ACCEPTED:** November 17 ⊙ **PUBLISHED ONLINE:** December 31

KEYWORDS: artificial intelligence, management, perception, sustainability, risk management, case study

JEL CLASSIFICATION: M10, M13, O33, Q01, D81

CITATION: Olah, J. & Dvorsky, J. (2026). Evaluating The Interaction between AI Adoption and Sustainability in Hungarian SME: Owners' and Managers' Perspectives. *Journal of Business Sectors, 4*(2), 83–96. https://doi.org/10.62222/HXZJ2395

INTRODUCTION

Artificial intelligence (AI) is increasingly emerging as an important technological tool supporting decision-making processes in small and medium-sized enterprises (SMEs), which constitute a substantial share of the business sector in Central Europe. Compared with large enterprises, SMEs often have more limited financial, human, and informational resources, which increases the importance of technologies capable of efficiently processing available data and providing managers with rele-

vant information for decision-making (e.g., Malek et al., 2026; Faiz et al., 2024). The application of AI enables the automation of analyses involving large and heterogeneous datasets, the identification of patterns and anomalies, support for forecasting future trends, and reductions in the time required to perform selected managerial tasks. In the Central European context, characterised by a high prevalence of SMEs and an ongoing digital transformation of the business sector, AI therefore represents a potential mechanism for strengthening the information base on which owners and managers make decisions, particularly under conditions of uncertainty and rapid change in the business environment (Kaledinova & Boeldak, 2024).

The importance of AI is particularly evident in enterprise risk management, where owners and managers must identify potential threats, assess their likelihood, and make decisions despite limited information availability (Dvorsky, 2025). AI can facilitate the early identification of risk factors by analysing historical data, financial indicators, market information, and internal business processes, while simultaneously generating predictive scenarios relevant to managerial decision-making (Aldasoro et al., 2025). For SMEs operating in countries such as Slovakia, the Czech Republic, Poland, and Hungary, this aspect is particularly important because of their sensitivity to fluctuations in demand, costs, supplier relationships, regulatory conditions, and resource availability.

However, the integration of AI into management processes is not merely a technological issue. It also involves considerations related to data quality, user competencies, the transparency of algorithmic outputs, and the ability of owners and managers to interpret correctly the information generated by technological systems. Consequently, AI should primarily be viewed as a decision-support tool, while ultimate responsibility for strategic and operational decisions remains with enterprise management (Ispas et al., 2025).

The significance of AI is currently extending beyond traditional management and risk management towards business sustainability (Yu et al., 2026; Arroyabe et al., 2024). More effective use of data can help SMEs optimise business processes, identify resource inefficiencies, forecast consumption, and support decisions related to the environmental, economic, and social dimensions of business activity (Huy & Phuc, 2025). This creates opportunities for Central European enterprises to integrate digital transformation with sustainable development requirements and long-term competitiveness. In this context, AI can be examined as part of a broader managerial framework in which technological capabilities, risk management, the quality of managerial decision-making, and business sustainability are interconnected. Research can therefore focus on the extent to which AI use supports decision-making by SME owners and managers (Dvorsky, 2025), how this relationship translates into enterprise risk management, and whether technology-supported decision-making is associated with conditions supporting the long-term sustainable operation of SMEs in the Central European region (Kumar & Shah, 2025).

The research gap arises from the limited integration of enterprise management, enterprise risk management, and business sustainability within the context of rapidly increasing AI adoption. This provides the main motivation for examining the subjective perspectives of SME owners and managers through a novel questionnaire survey.

The structure of the scientific article is as follows. The introduction outlines the importance of AI adoption and its role in the management of SMEs and explains the motivation for presenting the research findings to the academic community. The theoretical framework draws on recent research examining the application of AI in enterprise management, enterprise risk management, and business sustainability. The research hypotheses are formulated within this section. Subsequently, the methodology section defines the research objective, describes the data collection procedure and statistical methods, and presents the structure of the research sample consisting of SME owners and managers. The empirical findings are presented using tables and figures, and the research hypotheses are evaluated. The discussion compares the findings with international evidence and develops practical implications. Finally, the conclusion addresses the study limitations and outlines directions for future research.

THEORETICAL BACKGROUND

AI Perspectives in the Enterprise

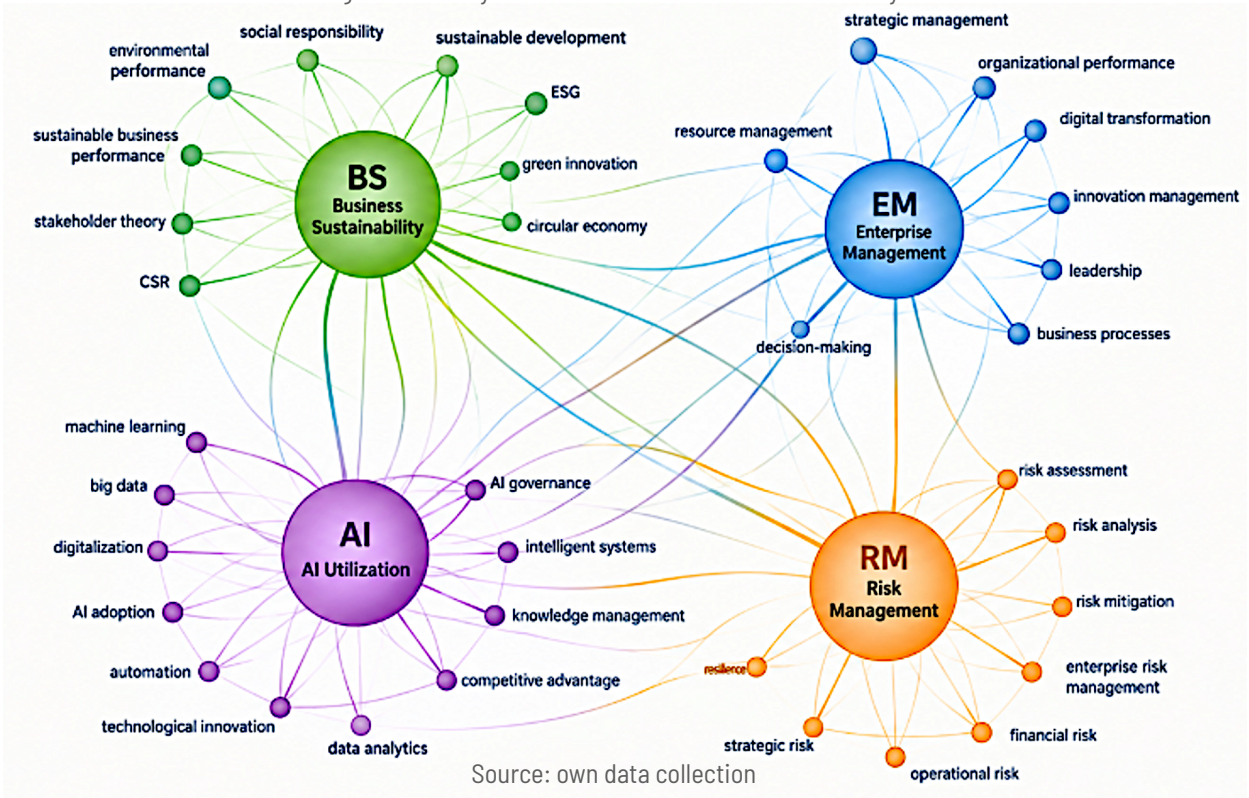
As demonstrated above, AI plays an increasingly important role in contemporary management and technological development. To improve understanding of the relationships between AI and related concepts, a bibliometric analysis was conducted. The all-keywords co-occurrence bibliometric map presented in Figure 1 illustrates the key terms associated with artificial intelligence. The map was constructed using 1,528 scientific articles retrieved from the Web of Science database according to the following criteria: keyword: “Artificial Intelligence”; document type: article; minimum number of keyword occurrences: 36; publication period: 2023–2023; Web of Science category: Management.

Fig. 1 – All-keywords co-occurrence bibliometric analysis.

Source: own data collection

The bibliometric visualisation provides an overview of the most frequently occurring keywords associated with artificial intelligence, which occupies the central position in the map. Each term is represented by a label and a circular node, with node size reflecting the relative importance of the term: the more important the term, the larger the node and its label. Colours indicate thematic clusters, while links between terms represent the strength of their co-occurrence in the analysed literature. Stronger links

Figure 1 – All-keywords co-occurrence bibliometric analysis



Source: own data collection

indicate closer thematic relationships between individual concepts.

The bibliometric analysis identified four dominant thematic areas associated with artificial intelligence research. The red cluster includes concepts related to management, large-scale data processing, and analytics. It includes terms such as "management", "big data", "analytics", and "blockchain", reflecting the role of AI in corporate management and data analysis. The green cluster highlights innovation and related challenges and contains concepts such as "innovation", "knowledge", "entrepreneurship", and "digital transformation". This cluster focuses on the importance of AI in digitalisation and the strategic development of enterprises. The blue cluster includes aspects of AI adoption and trust in technologies and contains concepts such as "trust", "acceptance", "behaviour", and "perception". This thematic area addresses factors influencing the willingness of enterprises and managers to adopt AI. The yellow cluster captures concepts related to technological solutions and machine learning, including "machine learning", "deep learning", "optimisation", and "decision-making". This area focuses on the technological dimensions of AI and its use in the development of algorithms supporting business management.

Interaction between Artificial Intelligence and Enterprise Management

AI-driven tools are improving predictive analytics, supply chain management, and customer relationship management while simultaneously introducing challenges related to ethical governance and workforce adaptation. Fnu and Modh (2023) discuss how AI, combined with cloud computing, drives digital transformation in fintech enterprises. Their study highlights the role of AI in strengthening consumer confidence and automating financial processes, thereby making enterprise operations more efficient and scalable.

Lämmermann et al. (2024) developed an AI Application Management Model (AIAMA) aimed at improving stakeholder communication and reducing decision-making uncertainty in the management of AI within the healthcare sector. The study was based on 11 expert interviews. According to the authors, effective AI management in healthcare depends on communication among different stakeholders, alignment of strategic objectives, cross-functional teams, and active monitoring of AI applications. The study contributes a holistic AI management framework.

Gong et al. (2024) examined the integration of AI into human resource management (HRM) and identified four potential research streams: AI-enhanced collaboration, AI-driven workplaces, AI-enabled business models, and AI-driven innovation. Their work highlights the benefits of AI in HRM, particularly in informed decision-making, so-called "algorithmic management", and automation. At the same time, it raises concerns and risks related to job displacement and associated ethical issues.

In this context, Kong and Yuen (2025) found that AI capabilities significantly enhance sustainability-related knowledge management capabilities in maritime firms. Based on survey data from 157 maritime professionals and structural equation modelling, the study highlights the role of AI in strengthening organisations' ability to acquire, process, and apply sustainability-related know-

ledge, thereby supporting more effective sustainability risk management. The findings emphasise the importance of integrating AI capabilities into organisational processes to improve the management of complex sustainability risks and support long-term business viability.

Santos and Carvalho (2025) analysed the integration of AI into participatory environmental management, highlighting its role in developing adaptation strategies, strengthening stakeholder collaboration, and supporting the achievement of sustainable development goals. The study applied text mining and bibliometric analysis to 80 articles using VOSviewer software and identified 10 clusters representing interconnected key concepts. The findings suggest that AI-powered chatbots, digital twins, and the Internet of Things can be particularly useful for real-time monitoring and collaborative decision-making.

Grohmann and Decker (2024) examined the impact of AI implementation on livestock management and highlighted a shift from reactive towards proactive decision-making enabled by predictive analytics and real-time monitoring. Their study also emphasised the synergies between AI and the Internet of Things. Konovalova et al. (2022) examined the impact of AI on human resource management and identified its potential to increase humanisation, for example by reducing bias, personalising training, and improving employee comfort in the workplace. The study also identified current trends in human resource management.

Vergara et al. (2024) presented a bibliometric analysis of the integration of AI into learning management systems based on 256 documents published between 2004 and 2023. According to the authors, AI can facilitate employee evaluation, although its application also raises ethical challenges related to algorithmic transparency and objectivity.

Taherdoost and Madanchian (2023) analysed the impact of AI on knowledge management and examined how AI can improve knowledge acquisition and dissemination and influence organisational learning. According to the authors, AI can improve knowledge acquisition by reducing information asymmetries and enabling real-time knowledge updates. However, challenges remain in relation to ethical issues and security.

Corvello (2024) examined the application of generative AI in innovation management. Unlike traditional AI, which focuses primarily on automation and prediction, generative AI facilitates problem-solving activities requiring a creative approach. The author identified several challenges, including organisational resistance and shortages of appropriately trained employees.

Arévalo and Jurado (2024) examined the impact of AI on the planning, operation, and management of distributed energy systems in smart grids. The results indicate that AI can improve network stability and fault detection through machine learning and neural networks, although implementation costs remain high and cybersecurity represents a major risk.

Marques et al. (2024) investigated the impact of AI, big data, and IoT-based analytics on management accounting. The authors found that AI accelerates data processing, improves the accuracy of financial forecasts, and strengthens financial risk management, while also requiring appropriate oversight to ensure accuracy and ethical managerial decision-making.

Morita et al. (2024) analysed the effects of AI-powered chatbots in infodemic management within the healthcare sector. Their results indicate that chatbots have the potential to reduce and detect misinformation, personalise health information, and improve communication with patients.

Ray and Majumder (2023) examined the use of ChatGPT in infectious disease management. According to the authors, ChatGPT can support patient education but requires continuous information updates and carries risks related to misinformation. The authors also highlight the potential usefulness of ChatGPT in scientific research.

Gatea (2024) examined the impact of AI on financial accounting disclosure and identified effects on managerial decision-making, transparency, and the accuracy of financial reporting. The research was based on a survey of 168 stock market participants and 22 in-depth interviews.

Isabella et al. (2023) examined the impact of AI on scientific knowledge in management and explored the possibilities for automating research-related activities through AI. According to the authors, potential applications include automating literature reviews, generating summaries, and supporting hypothesis development. The study also documented the increasing importance of generative AI models.

Interaction between Artificial Intelligence and Enterprise Risk Management

Schuett (2024) investigated Article 9 of the EU AI Act, focusing on risk management requirements for high-risk AI systems. Article 9 requires AI providers to implement risk management systems incorporating risk identification, assessment, and continuous monitoring throughout the AI system lifecycle.

Granata et al. (2023) examined the role of AI in risk assessment within diagnostic management in the healthcare sector, focusing on early detection and patient stratification. The study discusses various AI-based models for risk assessment.

Velev and Zlateva (2023) analysed challenges associated with applying AI to disaster risk management. Their findings indicate that AI can improve the accuracy of disaster prediction through early-warning systems and support response coordination. The study also discusses tools for assessing the consequences of disasters.

Izquierdo-Bueno et al. (2024) examined the application of AI in agriculture, focusing on its potential to reduce risks associated with grapevine diseases and support the early detection of emerging diseases. The authors found

that AI-supported risk management can reduce pesticide use and associated costs.

Guerra (2024) examined the impact and potential applications of AI in patient risk management within healthcare. According to the author, AI can support the early identification and reduction of patient risks, facilitate the prevention of adverse events, and enable more personalised patient management. AI can also identify high-risk patients and treatment errors, thereby potentially reducing the burden on hospitals.

Ghaffarian et al. (2023) analysed the role of AI in disaster risk management. The authors found that AI improves prediction accuracy and supports early-warning systems. However, the "black-box" nature of many AI systems limits interpretability and may reduce stakeholder trust.

Yazdi et al. (2024) examined the role of AI in risk management, with a particular focus on comparing traditional risk management approaches with methods based on AI integration. Using a comparative case study approach, the authors showed that AI-supported risk management combines machine learning, big data analytics, and predictive modelling. At the same time, they emphasised the need for human oversight to mitigate AI-related errors and ethical concerns.

Žigienė et al. (2019) proposed a conceptual framework for integrating AI, big data, and machine learning into commercial risk management in SMEs. Their main finding is that AI-based solutions can support the identification and assessment of complex commercial risks by processing large volumes of internal and external data, thereby improving managerial decision-making and potentially strengthening SME competitiveness and sustainable development. The authors also emphasise that providing these capabilities through shared external services may help reduce the financial and human resource constraints faced by individual SMEs.

Zhu (2024) investigated the application of data mining and AI in enterprise risk management and proposed an enterprise management risk assessment (EMRA) model. According to the author, AI improves the identification, classification, and prediction of risks, particularly in financial risk assessment, client credibility evaluation, and operational decision-making.

Darwiesh et al. (2023) proposed a risk management model based on AI and big data analysis for the healthcare sector. The model analyses patient tweets to identify and assess operational, financial, and technological risks. The proposed model is intended to improve decision-making and support institutional sustainability.

Ferrara et al. (2024) conducted a review of the role of AI in clinical risk management and patient safety. The authors demonstrated that AI applications can improve decision-making, support the detection of medical errors, reduce risk, and enhance patient safety. They also identified several challenges, including AI bias, insufficient human oversight, and difficulties integrating AI with existing healthcare IT systems.

Durlik et al. (2024) also investigated the potential of AI in risk management using data from the maritime transport sector. Their results showed that AI can improve predictive capabilities and enable real-time hazard identification, thereby helping to prevent accidents and improve maritime safety.

Kong and Yuen (2024) explored the potential of AI in sustainability risk management in the maritime industry based on a survey of 157 maritime professionals. Their findings indicate that AI significantly improves risk assessment, increases operational efficiency, and supports sustainability.

Faqihi and Miah (2023) and Dvorsky (2025) examined risks and opportunities associated with AI-supported talent management systems. Their findings indicate that AI can improve talent acquisition and support career development. At the same time, risks include bias in AI-driven decision-making, data loss, and dehumanisation.

Zhang et al. (2023) investigated the use of AI and numerical simulation in emergency risk management in geology. The authors integrated remote sensing with AI-based management approaches, resulting in more accurate assessments of geospatial risks and infrastructure resilience. AI proved particularly effective when combined with numerical simulation.

Wang et al. (2024) investigated the use of AI in big data analysis for risk management and enterprise information security. The authors compared traditional encryption methods with AI-driven systems and proposed a mobile payment signature scheme that improves authentication speed and security while increasing resistance to attacks.

Interaction between Artificial Intelligence and Sustainable Enterprise Development

Syafrudin et al. (2024) examined the importance of applied AI for sustainability, focusing specifically on its use in product eco-design, predictive maintenance of renewable energy systems, and resource optimisation.

Takas et al. (2024) investigated the use of AI in predicting the sustainability of start-ups. Their work resulted in the development of a decision-support system for predicting start-up success based on various indicators. The study also identified key challenges associated with AI adoption in start-ups.

Guo and Li (2024) highlight that integrating AI into enterprise risk management transforms reactive risk controls into proactive, data-driven frameworks. Their key finding emphasises that AI-driven risk mitigation can strengthen long-term business resilience and act as an important catalyst for sustainable enterprise development in dynamic market environments.

Ta et al. (2024) examined the effects of AI across the food supply chain, focusing on waste reduction and sustainability. AI was used primarily for food-quality control through machine-learning-based image analysis. The study applied a documentary systematic review and con-

firmed the relationship between AI application and sustainability outcomes.

Rohde et al. (2024) presented a framework of sustainability criteria and indicators for artificial intelligence systems (SCAIS). Using this framework, the authors categorised sustainability impacts across different stages of the business lifecycle.

König et al. (2023) analysed citizens' regulatory preferences regarding the sustainability of AI using survey data from the German population. The study demonstrated moderate to strong support for AI regulation, with energy efficiency emerging as a particularly important regulatory concern. The results also showed that respondents considered sustainability an important issue in AI use.

Bermejo and Juiz (2023) conducted a comprehensive review of the role of AI in improving cloud sustainability, reducing CO_2 emissions, and increasing energy efficiency. The authors divided AI applications for sustainability into different categories and compared their effectiveness. Machine learning and deep learning produced the strongest results.

Tariq et al. (2024) examined AI models for improving energy sustainability in educational buildings. The authors identified several factors influencing energy sustainability, including building size and air-conditioning capacity. The AI models were trained using data from 352 schools.

Schwaeke et al. (2025) examined the impact of AI on corporate sustainability transformation. According to the authors, the principal drivers of this transformation are technological capacity and operational capabilities. Their study was based on 24 empirical observations of companies.

O'Connor et al. (2024) examined the gap between the potential of AI for sustainability and its actual implementation. According to the authors, governments and researchers have high expectations regarding the contribution of AI to sustainability, while evidence of practical implementation in governmental sustainability policymaking remains limited.

Sachithra and Subhashini (2023) conducted a critical literature review examining the contribution of AI to sustainability in the agricultural sector. AI applications included forecasting, crop management, and resource management. The findings indicate that AI can reduce waste, improve efficiency, and mitigate environmental impacts.

Kaledinova and Boeldak (2024) evaluated the impact of AI on sustainability in the transport sector using the Transportation Technology Sustainability Index (TTSI). The assessment incorporated six sustainability dimensions. The results confirmed the potential of AI to support sustainability.

Currie et al. (2024) examined the impact of AI on sustainability in the nuclear medicine sector. Machine-learning and deep-learning models were found to optimise image reconstruction, enable radiation dose reduction, and support automated reporting, thereby improving diagnostic accuracy and reducing human workload. The findings suggest that AI integration can contribute to sustainability in the medical sector.

David and Dadkhah (2023) analysed the impact of AI on sustainable development in tourism through a bibliometric analysis of 1,300 research papers. Their findings indicate that research on AI in tourism has grown rapidly and that AI-supported augmented reality and virtual tourism can contribute to sustainable tourism and support the United Nations Sustainable Development Goals.

Ali et al. (2024) developed an AI-based model for supply chain performance (SCP) using artificial neural networks capable of processing limited, imprecise, and uncertain data. The authors identified 21 key performance indicators for assessing model performance. Their findings demonstrate that AI-supported SCP models can contribute to economic sustainability, particularly in industries characterised by data-quality limitations.

Cardoso et al. (2023) conducted a systematic bibliometric analysis of AI-based tools for assessing sustainability in manufacturing systems. The authors identified three principal applications of AI in sustainable manufacturing: predictive maintenance, process optimisation, and energy efficiency. They also applied a Sustainability Index Function (SIF) to support comprehensive sustainability assessment.

AIM, RESEARCH OBJECTIVE, AND DATA

The aim of the paper is to identified interaction between AI adoption in corporate settings and: (i) enterprise management, (ii) enterprise risk management, and (iii) business sustainability within the market environment. The research was realised in the year of the 2025 in Hungary.

Data collection

The respondent is defined as an owner or manager of a business operating within the business environment of Hungary. As part of a collaboration among researchers focusing on sustainability, risk management, and the quality of the business environment, a need arose to analyze the dependences of AI adoption among owners and managers in Central European countries. In the initial phase, an English version of the questionnaire was developed. The questionnaire was the result of discussions based on: (i) a critical literature review; (ii) the researchers' expertise; and (iii) its completion by 20 respondents, who provided feedback to the research team, including during face-to-face interviews. Subsequently, an external data collection agency was approached to secure data collection using the CAWI (Computer Assisted Web Interviewing) methodology.

A question regarding consent to process respondents' attitudes for scientific purposes was added to the questionnaire. The research sample initially consisted of 533 respondents; however, 13 respondents did not give explicit consent for their questionnaire to be evaluated for

scientific purposes. The final research sample comprised 520 (n; 100%) respondents from the Hungarian business environment. Analysis of the sample size confirmed that the minimum required sample of respondents (n = 384; with using the Cochran´s formula with the following characteristics: confidence level – 95%; margin error – 5%; population proportion = 0-50) was exceeded by more than 35%.

The study is based on a representative sample of SMEs from the Hungarian business environment for the following reasons: (i) the sample size exceeds the minimum required number of respondents; (ii) the demographic structure of SMEs is analysed using more than five demographic characteristics; and (iii) data collection was conducted by an external survey agency.

Questionnaire and formulation of statements

The final version of the questionnaire contained 40 questions. At the beginning of the questionnaire, the motivations for conducting the research were explained to the respondent. Respondents were asked to complete the questionnaire responsibly and truthfully.

Demographic questions were formulated to demonstrate the representativeness of the research sample. They focused on business characteristics (legal form of business, firm size, business sector, and years in business) and respondent characteristics (gender, age, education level, and job position). Subsequently, statements were formulated for the following factors: Corporate Social Responsibility (CSR, 4 items); Human Resource Management (HRM, 4 items); AI utilization in the enterprise (AI, 5 items); Business Sustainability (BS, 4 items); Financial Performance (FR, 4 items); Enterprise Management (EM, 4 items); and Risk Management (RM, 3 items).

The questionnaire also contained a control question to verify the consistency of the respondent's answers. Statements in the questionnaire were presented to the respondent in a randomized order. Respondents were required to answer all questions in the questionnaire. The statements were evaluated using a 5-point Likert scale (1 – strongly disagree, ..., 5 – strongly agree).

Dependent and independent variables

To achieve the objective of the scientific article, the following factors and their corresponding statements were defined.

AI Utilization (AI): Our organization leverages AI capabilities to enhance business performance (AI1). The enterprise uses AI to automate repetitive and time-consuming tasks (e.g., payroll processing, employee data management, shift scheduling, etc.; AI2). The enterprise employs AI in employee selection (e.g., resume screening, candidate assessment, predicting candidate success based on historical data; AI3). The enterprise uses AI to gather feedback, obtain insights into satisfaction, and collect recommendations and advice from employees (AI4). Organizational leadership actively supports the use of AI in employees' daily work activities (AI5).

Business Sustainability (BS): The business strives to maintain long-term growth by diversifying its portfolio to increase resilience against market changes and risks (BS1). The business takes measures to optimize its energy resources and seeks ways to reduce energy consumption associated with its business activities (BS2). The business attempts to improve its environmental and social impacts by making decisions that take long-term sustainability into account (BS3). I consider my business to be sustainable (BS4).

Enterprise Management (EM): The manager is deeply committed to the business (managing the company for more than 8 hours a day; EM1). I employ a participatory management style that involves employees in decision-making processes (EM2). I consider human capital within the firm to be the most important resource (EM3). The business owner (manager) should regularly evaluate the performance of their subordinates and motivate them to innovate work processes (EM4).

Risk management (RM): Strong competition in our industry does not fundamentally affect our business (RM1). Consumer spending has a positive impact on our business (RM2). Our company faces no difficulties in distributing our products or services (RM3).

Statistical hypotheses and methods

To address and evaluate the objective of the scientific article, the following statistical hypotheses (SHs) were formulated:

- SH1: There is a statistically significant dependences between the use of AI and enterprise management on the base of the Hungarian respondents' subjective attitudes.
- SH2: There is a statistically significant dependences between the use of AI and business sustainability on the base of the Hungarian respondents' subjective attitudes.
- SH3: There is a statistically significant dependences between the use of AI and risk management on the base of the Hungarian respondents' subjective attitudes.

Statistical hypotheses were verified using the following methods. In the first step, descriptive statistics were applied to obtain an initial overview of respondents' attitudes. Subsequently, the reliability and validity of the defined factors (AI, HRM, BS, ME) were verified using factor analysis in the analytical software IBM SPSS Statistics. In the third step, IBM SPSS AMOS software was applied to analyze the relationships between the factors. The chosen sequence of statistical methods is frequently used in quantitative research utilizing survey-based data collection.

Demographic structure of owners and managers

The research sample consisted of 520 Hungarian respondents (n = 520; 100%) who fulfilled questionnaire. The demographic structure of respondents is as follows.

Business characteristics. Enterprise Size: Micro-enterprises constituted the largest proportion (45.8%), followed by small enterprises (24.2%) and medium-sized enterprises (30.0%). Legal Form: Limited liability companies accounted for 50.2% of the firms, sole proprietorships represented 27.1%, joint-stock companies constituted 14.6%, and other legal forms accounted for 8.1%. Business sector: The majority of enterprises operated in the services sector (43.7%), followed by trade (17.1%), manufacturing (14.6%), construction (7.7%), transport (5.6%), and other sectors (11.4%). Time period in Business: Regarding operating history, 16.2% of enterprises had been operating for less than 5 years, 52.5% for 5 to 20 years, and 31.3% for more than 20 years.

Characteristics of respondents. i. Gender: Men represented 50.8% of the respondents, while women accounted for 49.2%. ii. Age: The largest age group was respondents aged 29–43 years (49.8%), followed by those aged 44–59 years (39.2%). Respondents aged 28 and under constituted 6.2%, and those aged 60 and over represented 4.8%. iii. Education: A university degree was held by 77.7% of the respondents, whereas 22.3% had completed secondary education with a school-leaving exam. No respondents fell into the lower education categories. iv. Job Position: Managers made up 56.2% of the sample, while business owners represented 43.8%.

RESULTS

In the first phase of the analytical evaluation of respondents' attitudes, absolute and relative frequencies of respondents were utilized based on one and two statistical variables. The results are presented in contingency tables (see Table 1).

The pivot tables and descriptive statistics results (absolute perception and relative perception) confirmed that respondents answered most positively to statements regarding enterprise management (Mean = 3.667). Conversely, the lowest agreement among respondents was observed in the evaluation of statements regarding AI utilization (Mean = 2.559). The differences in the mean evaluation of factors are significant. The largest variance

Table 1: Contingency tables of items

TA	AI1		AI2		AI3		AI4	
	No	%	No	%	No	%	No	%
1	140	26.9%	140	26.9%	147	28.3%	131	25.2%
2	104	20.0%	97	18.7%	135	26.0%	120	23.1%
3	173	33.3%	154	29.6%	135	26.0%	137	26.3%
4	74	14.2%	103	19.8%	83	16.0%	106	20.4%
5	29	5.6%	26	5.0%	20	3.8%	26	5.0%
N	520	100 %	520	100 %	520	100 %	520	100 %
TA	EM1		EM2		EM3		EM4	
	No	%	No	%	No	%	No	%
1	33	6.3%	59	11.3%	20	3.8%	13	2.5%
2	46	8.8%	46	8.8%	22	4.2%	38	7.3%
3	93	17.9%	194	37.3%	111	21.3%	110	21.2%
4	199	38.3%	177	34.0%	197	37.9%	227	43.7%
5	149	28.7%	44	8.5%	170	32.7%	132	25.4%
N	520	100 %	520	100 %	520	100 %	520	100 %
TA	BS1		BS2		BS3		BS4	
	No	%	No	%	No	%	No	%
1	33	6.3%	32	6.2%	32	6.2%	11	2.1%
2	52	10.0%	56	10.8%	46	8.8%	31	6.0%
3	156	30.0%	143	27.5%	172	33.1%	147	28.3%
4	201	38.7%	184	35.4%	198	38.1%	234	45.0%
5	78	15.0%	105	20.2%	72	13.8%	97	18.7%
n	520	100 %	520	100 %	520	100 %	520	100 %
TA	RM1		RM2		RM3		AI5	
	No	%	No	%	No	%	No	%
1	48	9.2%	20	3.8%	16	3.1%	111	21.3%
2	126	24.2%	55	10.6%	39	7.5%	97	18.7%
3	171	32.9%	213	41.0%	125	24.0%	171	32.9%
4	126	24.2%	187	36.0%	207	39.8%	105	20.2%
5	49	9.4%	45	8.7%	133	25.6%	36	6.9%
N	520	100 %	520	100 %	520	100 %	520	100 %

Note: TA – Type of answer. Source: own research results

Table 2: Reliability and validity of factors (AI, BS, ME, RM)

F/I	Utilization of AI (AI)					Risk management (RM)		
	AI1	AI2	AI3	AI4	AI5	RM1	RM2	RM3
IL	0.806	0.866	0.813	0.877	0.841	0.855	0.807	0.712
CA	0.896					0.820		
CR	0.921					0.874		
AVE	0.751					0.714		
F/I	**Enterprise management (EM)**				**Business sustainability (BS)**			
	EM1	EM2	EM3	EM4	BS1	BS2	BS3	BS4
IL	0.759	0.783	0.729	0.831	0.748	0.752	0.774	0.680
CA	0.738				0.722			
CR	0.792				0.788			
AVE	0.619				0.602			

Note: IL – Item loading; CA – Cronbach alpha; CR – Composite reliability; AVE – Average variance explained; F – Factor; I – Item. Source: own research results

in responses was also identified when evaluating statements regarding AI (Standard deviation = 0.052).

The results of the reliability and validity verification of the individual factors (AI, BS, ME, RM) are presented in Table 2.

The results regarding the validity and reliability of the defined factors confirmed their existence. The internal relationships among the items with respect to the factor are strong, and the factors are clearly identified. The values of CA, CR, and AVE are at acceptable levels (Morse et al., 2002).

The following table (see table 3) presents the primary output of the factor analysis, illustrating the factor loadings of the items onto their respective factors, with a minimum cutoff value of 0.300.

Table 3: Rotated component Matrix and component transformation matrix

Items	Factors			
	AI	EM	BS	RM
AI1	0.775			
AI2	0.841			
AI3	0.815			
AI4	0.836			
AI5	0.794			
EM1		0.639		0.368
EM2	0.434	0.551		
EM3		0.661		
EM4		0.574	0.356	
BS1		0.324	0.621	
BS2			0.693	
BS3			0.633	
BS4		0.414	0.677	
RM1				0.846
RM2			0.386	0.860
RM3		0.362	0.305	0.607
Component transformation matrix				
	AI	EM	BS	RM
AI	0.717	0.470	0.498	0.128
EM	0.277	0.828	0.385	0.013
BS	0.086	0.219	0.848	0.185
RM	0.143	0.120	0.263	0.914

Note: Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization; Rotation converged in 6 iterations. Source: own research results

In addition to the aforementioned findings regarding the relationships between the items and the factor, it is necessary to provide information on factor validity. The verification of discriminant validity between factors are evaluated in table 4.

Table 4: Heterotrait–Monotrait Ratio of Correlations

	AI	EM	BS	RM
AI	-			
EM	0.681	-		
BS	0.546	0.819	-	
RM	0.643	0.785	0.753	-

Source: own research

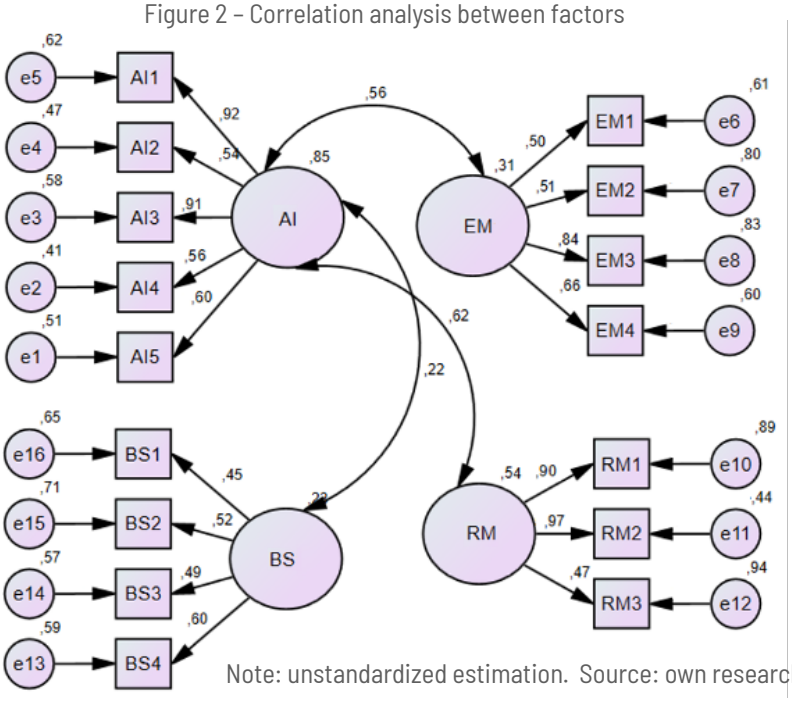
The results of the discriminant validity (see Table 4) assessment using the HTMT approach confirmed that the factors are mutually independent (HTMT values between factors are less than the critical value 0.850).

Figure 2 presents the correlation results among the examined factors (AI, EM, BS, and RM). These results confirmed that the dependences (with using Spearman coefficient of correlation) between: i. AI and EM; ii. AI and BS; iii. AI and RM are positive and strong. The verification of estimation of correlation was realised with t-test. The p-values of t-Stat were lower than the level of significance 0.05 (i. AI and EM – p-value is less than 0.001; ii. AI and BS – p-value = 0.004; iii. AI and RM – p-value is less than 0.001). The statistical hypotheses SH1, SH2, and SH3 are accepted.

DISCUSSION

Most notably, the results indicate that AI adoption is most strongly associated with enterprise risk management (RM). This finding is consistent with recent empirical literature from the European context. Studies examining

Figure 2 – Correlation analysis between factors



Note: unstandardized estimation. Source: own research results

SME resilience and AI-supported risk management (Dvorsky, 2025; Izquierdo-Bueno et al., 2024; Yazdi et al., 2024) suggest that AI-driven predictive analytics and real-time data processing can improve early risk identification and support greater operational agility. Given that SMEs typically operate under considerable resource constraints, AI-enabled monitoring and analytical functions may help compensate for limited managerial and analytical capacity and reduce vulnerability to market volatility, operational disruptions, and supply chain risks.

By contrast, although the relationship between AI adoption and business sustainability was positive and statistically significant, it was comparatively weaker than the association between AI adoption and risk management. Similar observations have been reported in studies examining digital transformation and sustainability in SMEs (e.g., Huy & Phuc, 2025; Kumar & Shah, 2025; Faiz et al., 2024). This may indicate that SMEs tend to prioritise the immediate operational benefits of AI, such as efficiency improvements, risk identification, and decision support, over longer-term sustainability-oriented applications. Although European policy frameworks increasingly encourage enterprises to incorporate sustainability considerations into business practices, the integration of AI into sustainability management may require additional resources, capabilities, and organisational maturity.

The strong positive relationship between AI adoption and effective enterprise management further supports the broader findings of contemporary management research (e.g., Santos & Carvalho, 2025; Grohmann & Decker, 2024). Existing studies indicate that AI tools can streamline administrative processes, support managerial decision-making, improve information processing, and facilitate more proactive management practices. The present findings therefore suggest that higher levels of AI adoption among SME owners and managers are associated with perceptions of more effective enterprise management and organisational governance. However, given the correlational nature of the research design, these relationships should not be interpreted as evidence of direct causal effects.

According to Microsoft's Global AI Diffusion Report, Hungary ranked first among the Visegrád Four (V4) countries in generative AI adoption among the working-age population in the second quarter of 2026, with 33.3% of the population using generative AI, compared with 32.3% in Poland, 31.2% in Czechia, and 27.1% in Slovakia (Microsoft AI Economy Institute, 2026). However, this relatively high level of individual AI use does not necessarily translate into a leading position in enterprise-level adoption. Eurostat data for 2025 indicate that approximately 10.4% of Hungarian enterprises with at least 10 employees used AI technologies, compared with 18.0% in Slovakia, 17.6% in Czechia, and 8.4% in Poland.

These figures suggest that relatively widespread individual engagement with generative AI in Hungary coexists with more limited integration of AI into business operations (MTI-Hungary Today, 2026). This distinction reinforces the importance of examining not only general awareness and use of AI, but also its practical integration into managerial decision-making, enterprise risk management, and sustainability-oriented business practices..

CONCLUSION

The aim of this scientific article was to identify and quantify the key factors determining public participation in regional territorial development.

The main finding of the research is that the territorial identity of space users, attachment to the city, and perceptions of cultural heritage represent statistically significant determinants of public participation.

By integrating cultural heritage and regional development, the study addresses the fragmentation identified in the existing literature and quantifies the relationships among the examined constructs through a validated structural model. A key theoretical contribution lies in demonstrating the role of civic participation as an important mechanism linking heritage-related factors with broader socio-economic development outcomes. The application of the model in the Slovak Republic further provides evidence from the specific post-transformation context of Central and Eastern European countries, thereby extending the empirical basis of participatory approaches to cultural heritage management. From a methodological perspective, the study contributes through the validation of measurement models for latent variables and provides a basis for further quantitative research in regional and heritage studies.

The empirical findings are relevant to local and national authorities as well as business support organisations, as they indicate underutilised potential in linking cultural heritage management with the active involvement of local residents. The findings may also be relevant to business entities, since activities associated with stronger public participation in the local environment, when combined with cultural heritage, may contribute to competitive advantage and enhance customer satisfaction and loyalty.

The study has several limitations. First, the geographical scope was limited, as respondents were drawn from a single country. Second, the findings were based on respondents' subjective attitudes and perceptions. Third, the hypotheses were verified using a limited range of statistical techniques. Fourth, data were collected through an online questionnaire, which may have influenced the composition of the sample. Finally, given the breadth and complexity of the topic, a single period of data collection provides only a partial view of the relationships examined.

Future research should therefore extend data collection to other countries in the region, include larger and more diverse samples, and adopt a longitudinal design covering multiple time periods. An equally important direction for future research is to link the examined relationships with regional economic indicators, the business and economic potential of individual regions, and the sustainable development of both regional and national economies.

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AUTHOR CONTRIBUTIONS STATEMENT

Conceptualization, J.O.; methodology, J.O.; software, J.D.; validation, J.D.; formal analysis, J.O.; investigation, J.D., resources, J.O.; data curation, J.O.; writing – original draft preparation, J.O. and J.D.; writing – review and editing, J.O. and J.D.; visualization, J.O.; supervision, J.O. and J.D. All authors have read and agreed to the published version of the manuscript.

DATA AVAILABILITY STATEMENT

The datasets used and analyzed in this study are available from the corresponding author upon reasonable request.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

AI DISCLOSURE

The authors disclose that AI-assisted technology (ChatGPT, Geminy) was used strictly for English-language refinement and proofreading. No generative AI was employed for data processing, statistical analysis, or content synthesis. The authors have reviewed and vetted all output to ensure academic accuracy.

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