Journal of Theoretical and Applied Information Technology
15th March 2026. Vol.104. No.5

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

AVAILABILITY AND IMPACT OF ARTIFICIAL INTELLIGENCE SYSTEMS ON DECISION MAKING SUPPORT IN U.S. SMALL AND MEDIUM-SIZED BUSINESSES

KATERYNA HALAN[1*]

[1]The Walt Disney Company, Burbank, USA.

E-mail: [1]vitaeconscn18@gmail.com

ABSTRACT

Artificial intelligence (AI) systems are becoming a critical tool for digital transformation, but their availability to small and medium-sized businesses (SMBs) remains limited and uneven. High cost, lack of human resources (HR), and low digital maturity create barriers that hinder the implementation of innovations in enterprises in this segment. The aim of the research is to assess how the availability of AI-based decision support systems (DSS) affects the likelihood of their implementation in the United States (USA). The study also determines how such technologies change labour productivity, operating costs, forecast accuracy, and the speed of management decisions in SMBs. The methodology is based on panel data from 2022–2024 from The Business Trends and Outlook Survey (BTOS), Annual Business Survey (ABS), and the Federal Reserve Small Business Credit Survey. An AI Availability Index (AIAI) is proposed, created using the principal components method, which combines indicators of cost, digital maturity, integration, HR, and telecommunications infrastructure. The results show that availability significantly increases the likelihood of AI-DSS implementation in SMBs in the USA. Empirical estimates show an increase in labour productivity by about five percent and a decrease in the share of operating costs by more than three percentage points. The accuracy of forecasts improves, and the speed of management decisions increases because of the integration of AI systems. The effects are significantly stronger for high AIAI values, confirming the key role of infrastructure and digital maturity. Practical conclusions include the development of quick-start roadmaps for SMBs and the implementation of risk management protocols under the NIST AI Risk Management Framework (RMF). The academic novelty is the creation of a unique AIAI and conducting a causal analysis of the effects on key performance indicators (KPIs), taking into account heterogeneity.

Keywords: *Artificial Intelligence, Decision Support Systems, Small and Medium-Sized Business, Availability, Digital Transformation, Productivity, Econometric Modelling.*

1. INTRODUCTION

The modern digital economy is defined by the growing role of AI systems, which are becoming key tools for improving business efficiency and competitiveness. SMBs in the USA provide more than 43% of Gross Domestic Product (GDP) and almost half of jobs, but they face barriers to innovation [1]. The main constraints remain high cost, lack of qualified personnel, complexity of integration, and insufficient digital maturity, which pose the problem of technology accessibility. This creates inequality between large corporations and small businesses in terms of digital transformation.

The aim of the study is to assess how the availability of AI-DSS affects the level of their implementation in U.S. SMBs. The problem is the lack of comprehensive quantitative assessments that take into account accessibility and its relationship with financial and operational results. *The research objectives* include developing an AIAI, identifying determinants of adoption, assessing effects on productivity, costs, forecast accuracy, and management cycle length, as well as international comparison.

The research hypothesis assumes that accessibility is a determining factor of adoption, and its high level significantly enhances the positive impact of AI-DSS on KPIs of enterprises. *The research questions* are specified as follows: what availability factors (cost, infrastructure, personnel, digital maturity)

affect the implementation of AI? What is the causal effect of AI-DSS on productivity, costs, and forecast accuracy in SMBs? Are there differences in effects between SMBs? How do the U.S. results correlate with the international practices of the United Kingdom (UK) and Canada?

The academic novelty is a new AIAI created for SMBs and the use of an econometric model with fixed effects and an event approach. The practical significance is determined by the possibility of creating roadmaps for the implementation of AI, minimizing risks within the NIST AI RMF and increasing the competitiveness of enterprises in the digital economy.

2. LITERATURE REVIEW

The literature review shows that research on AI in SMEs is structured around several interrelated themes: ethical governance, organizational challenges, functional applications, sustainable growth, compliance, and data governance. While the authors agree on the importance of AI-DSS for business competitiveness, they offer different emphases and assess the benefits and risks differently. This allows for a critical comparison of the results.

Štrukelj and Dankova [2] emphasize that ethical leadership is the foundation of trust in AI solutions in SMBs. Their position is consistent with the findings of Melnyk et al. [3], who emphasize the importance of transparency and regulatory control in digital processes. Both studies argue that without an ethical and legal framework, technologies can increase risks rather than reduce them. In contrast, Le Dinh et al. [4] focus more on the practical benefits of functional applications, leaving the ethical aspect on the periphery of the analysis.

Le Dinh et al. [4] demonstrate how AI improves marketing, finance and logistics, emphasizing accessibility through low-/no-code solutions. This functional perspective is supported by Machucho and Ortiz [5], but they add that without overcoming organizational barriers and data scarcity, the benefits may remain declarative. In this sense, Le Dinh et al. [4] are more optimistic, while Machucho and Ortiz [5] emphasize realistic limitations, revealing the risks of superficial integration. This contrast shows the tension between technical potential and organizational readiness.

Khan et al. [6] and Farmanesh et al. [7] consider AI as a driver of sustainable development, but their approaches are different. Khan et al. [6] focus on supply chain resilience and blockchain, arguing that AI reduces vulnerability and supports closed loops. Farmanesh et al. [7] emphasize the role of AI in green innovation, which enhances competitiveness and environmental efficiency. Both approaches converge in concluding that AI helps to achieve the Sustainable Development Goals (SDGs), but Khan et al. [6] emphasizes operational benefits, while Farmanesh et al. [7] emphasizes strategic ones.

Sánchez et al. [8] explain adoption through the TOE–DOI framework and emphasize that accessibility barriers determine the success of AI integration. Their findings have something in common with those of Machucho and Ortiz [5], who also emphasize the importance of organizational and technological factors. At the same time, Sánchez et al.'s [8] approach is more structured and formalized, while Machucho and Ortiz [5] focus on practical challenges and behavioural aspects. This indicates the need to combine conceptual and applied models to fully understand adoption.

Kussainov et al. [9] consider AI as a tool to reduce corruption risks in the financial sector, focusing on transaction monitoring and anomaly detection. Melnyk et al. [3] support this idea, but add a systemic analysis of EU regulatory practices, emphasizing that technologies can lose legitimacy without institutional support. Both studies critically correlate with the findings of Le Dinh et al. [4], as the latter barely considers security and compliance issues, focusing on the efficiency of business functions. This demonstrates a certain gap between technical optimism and regulatory reality. These findings coincide with the position of Machucho and Ortiz [5], who also emphasize the risks of data scarcity. Therefore, data management emerges as a fundamental factor determining the effectiveness of AI in SMBs.

Current studies demonstrates different approaches to integrating AI into business practices. Agrawal et al. [10] focus on data quality management in supply chains, emphasizing the need for consistency and standardization. Their analysis identifies structural gaps that hinder the development of sustainable solutions. This approach differs from Al-Surmi et al. [11], who emphasize combined AI strategies for operational management. Their results show that synchronizing strategies yields faster efficiency gains than isolated data management practices.

Åström et al. [12] extend this discussion by analysing AI business models. They propose a three-phase framework for value creation and capture, where data is the starting point and business model innovations determine the scale of the effects. This

has something in common with Agrawal et al. [10], who emphasize data quality but add the economic component of monetization. So, Åström et al. [12] show that data are only important when they are integrated into a value creation strategy.

Bandi et al. [13] and Bengesi et al. [14] are more technical. Bandi et al. [13] systematize the requirements for generative AI, including models, formats, and metrics. They emphasize validation difficulties and risks of bias. On the other hand, Bengesi et al. [14] offer an overview of architectures: GANs, GPTs, autoencoders, transformers, diffusion models. They emphasize resource constraints and scalability. In comparison, Bandi et al. [13] focuses on the evaluation process, while Bengesi et al. [14] focuses more on architectural innovations. Together, they create a complete picture of the challenges of technical development.

Andrew et al. [15] add a social dimension by analysing the use of generative AI (GenAI) by students across subjects. They find low levels of confidence and a need for educational interventions. This contrasts sharply with Bandi et al. [13] and Bengesi et al.'s [14] technical optimism, as even the best models fail to deliver impact without human readiness. Their findings demonstrate that AI adoption depends not only on technical availability but also on the users' skills and culture.

In general, the reviewed literature shows a multi-layered picture: Agrawal et al. [10] and Al-Surmi et al. [11] focus on governance and efficiency, Åström et al. [12] on business models, Bandi et al. [13] and Bengesi et al. [14] on technical challenges, and Andrew et al. [15] on users. Together, they argue that AI availability and effectiveness are determined by the interaction of data, architectures, strategies, and human capital. This is directly consistent with our availability model, which integrates infrastructure, digital maturity, and HR as key moderators of impact.

A critical review of the literature shows that authors agree in recognizing the importance of AI for SMBs, but their emphases differ. Some studies [4] optimistically emphasize functional benefits, while others [5] emphasize challenges and limitations. Some authors [6, 7] emphasize sustainability, while others [3, 9] emphasize transparency and control. The most integrative approaches combine these aspects, proposing AI as a tool for innovation, sustainability and responsible management at the same time.

So, all the reviewed studies strengthen the academic background of the study, proving the relationship between the availability of AI, organizational readiness, ethical standards, and the performance of SMBs. They confirm the need for further interdisciplinary research involving management, information technology, economics, ecology, and government regulation. On the other hand, existing studies do not sufficiently highlight the causal relationship between the availability of AI and specific financial and operational KPIs in SMBs. Most studies focus either on conceptual models of adoption or on the description of functional applications, leaving aside comprehensive econometric tests. There is also a lack of studies that simultaneously take into account the ethical, organizational, regulatory, and environmental dimensions of integrating AI into business practices. Comparative studies with a focus on international contexts that would allow assessing differences in AI implementation between countries remain limited. Therefore, it is necessary to continue and expand such studies on a global scale, relying on comprehensive models and an interdisciplinary approach.

The literature available is mainly a study of the given phenomenon in the form of isolated dimensions with little reference to integrating structural, technological, and performance-related issues. Traditional research usually refers to descriptive or cross-sectional research, and the dynamic and interaction effects are not completely investigated. There is still empirical evidence which is still patchy on how these mechanisms do work together in various institutional or market situations. In this work, the study fills these gaps by using an integrated framework of analysis that fulfils the temporal dynamics of the multivariate interdependencies. In such a manner, the article would be able to bring the body of the literature based on the partial observations to a more systematic and generalized comprehension.

3. METHODS

3.1 Research design

The study was conducted sequentially and included several interconnected stages. The goal was to study the availability of AI solutions and their impact on SMBs in the USA. The period covered 2022–2024, which corresponds to the active wave of digital transformation. The procedure was aimed at testing hypotheses and providing practical recommendations. The research procedure consisted of four interconnected stages (Figure 1).

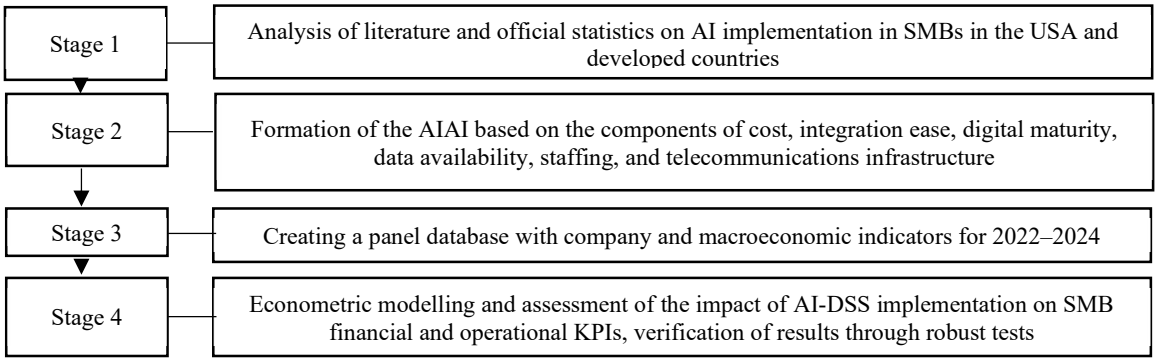

Figure 1: Research stages

Source: developed by the author

The analysis showed that all stages are logically connected and form a coherent procedure. Each stage added a new level of verification and detailing of the study. The procedure ensured the verification of the validity of the data and the consistency of the models. The obtained results can be interpreted in a national and international context.

3.2 Sampling

The sample covered US SMEs with up to 499 employees. The sample covered 48,720 U.S. SMBs with up to 499 employees. The enterprises were selected based on official surveys and statistical databases. The largest number of SMBs is concentrated in the states of California, Texas, Florida, New York, and Illinois. These five states together form more than 45% of the total sample. Such coverage ensures representativeness and takes into account regional differences in digital infrastructure and levels of maturity of enterprises. The data for the UK and Canada were additionally used for comparison. The analysis covered the period of 2022–2024. The sources included official surveys, national databases and open-source infrastructure statistics. The main variables were: AI-DSS implementation level, availability index, productivity per employee, cost share, forecast accuracy, inventory turnover, and decision cycle. Additional characteristics described the digital maturity of enterprises, industry affiliation, and the availability of specialists in the regions. The choice of countries was justified by a similar level of digitalization and openness to new technologies. This ensured international representativeness and the possibility of comparative analysis.

3.3 Research methodology

Fixed-effects panel econometric models were used. The main model assessed the impact of AI-DSS on productivity, costs, forecasts, inventories, and decision speed. Interactions were used to test the moderating effect of the availability index. The determinants of adoption were estimated using a logit model with time lags. Fixed effects accounted for constant company characteristics and time trends. Endogeneity was limited by using tools related to the accessibility of digital infrastructure. Robustness checks were performed using alternative models and PSM-DiD and IV methods. The dynamics of effects were studied using an event-based approach.

Baseline model:

$$Y_{it} = \alpha + \beta_1 AI\_DSS_{it} + \beta_2(AI\_DSS_{it} \times Access_{it}) + \beta_3 Access_{it} + \beta_4 DigitalMaturity_{it} + \beta_5 Talent_{it} + \gamma X_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (1)$$

where:

- Y_{it} – performance indicators of enterprise i in period t: ProdLab (productivity per employee), OpExRate (share of operating expenses), ForecastMAPE (average forecast error), InvTurn (inventory turnover), DecisionCycle (duration of the management cycle);
- α – model constant reflecting the baseline level of performance indicators in the absence of the influence of explanatory variables;
- β_1 – coefficient showing the direct impact of AI-DSS implementation on enterprise efficiency;
- β_2 – interaction coefficient assessing how the AIAI enhances or weakens the effect of AI-DSS implementation;
- β_3 – coefficient reflecting the autonomous impact of the AIAI on enterprise results regardless of the fact of using AI-DSS;
- β_4 – coefficient showing the impact of the enterprise's digital maturity on its efficiency;
- β_5 – coefficient assessing the role of the density of data and machine learning (ML) specialists in the region for business results;

- AI_DSS_{it} – AI decision support system implementation variable;
- $Access_{it}$ – AI availability index;
- $DigitalMaturity_{it}$ – the level of digital maturity of the enterprise;
- $Talent_{it}$ – the density of data and ML specialists in the region;
- γ – vector of coefficients for control variables (X_{it}), which include the size of the enterprise, its age, industry affiliation, regional characteristics and macroeconomic conditions;
- X_{it} – control variables (size, age, industry, region, macroeconomic conditions);
- μ_i – individual fixed effects, which take into account the constant characteristics of specific enterprises that do not change over time;
- τ_t – time fixed effects, which take into account general macroeconomic and technological changes in certain years;
- ε_{it} – random error, which reflects the influence of uncontrolled and unmeasured factors.

Model for AI-DSS implementation determinants:

$$P(AI\_adopt_{it=1}) = F(\beta_0 + \beta_1 Access_{it-1} + \beta_2 DigitalMaturity_{it-1} + \beta_3 Talent_{it-1} + \beta_4 X_{it-1}) \quad (2)$$

where:

- $P(AI\_adopt_{it=1})$ – probability that enterprise i will implement AI-DSS in period t;
- $F(\cdot)$ – logistic distribution function;
- β_0 – model constant;
- β_1 – impact of AIAI in the previous period;
- β_2 – impact of enterprise digital maturity on the probability of implementing AI-DSS;u54ghgbv;
- β_3 – impact of density of data and machine learning specialists in the region;
- β_4 – vector of coefficients for control variables describing enterprise characteristics in the previous period.

Research hypotheses:

1. $\beta_1>0$: Availability is a key factor in AI adoption in SMBs.
2. $\beta_1>0$, $\beta_2>0$: adoption has a positive impact on productivity and cost reduction, and availability amplifies this effect.
3. $\beta_3>0$: Higher levels of digital maturity and talent availability amplify the adoption effect.
4. The effects are more pronounced for small companies due to higher marginal benefits.

The formula is used to quantify the impact of key factors on performance, it enables summarizing relationships and checking the statistical significance of indicators. Its application helps to identify dominant factors, determine the strength of their influence, and assess the potential for management decisions. Calculations based on the formula give grounds to compare different scenarios, confirm hypotheses and draw practical conclusions about the effectiveness of the strategy. So, the formula is not only a mathematical tool, but also as an analytical basis for drawing conclusions and providing recommendations.

3.4 Data availability

The data for analysis were obtained from official open sources. The main sets are:

1) U.S. Census Bureau – Annual Business Survey (ABS) and Business Trends and Outlook Survey (BTOS);
2) Federal Reserve Banks – Small Business Credit Survey (SBCS);
3) Federal Communications Commission (FCC) – Broadband Data;
4) OECD Digital Economy Outlook (2024);
5) World Bank World Development Indicators [1];
6) Office for National Statistics (UK) – UK Business: Activity, Size and Location;
7) Statistics Canada – Survey on Business Conditions.

All data are publicly available to researchers through the appropriate references provided in the bibliography. The author did not have access to confidential or proprietary sources.

3.5 Tools

Data collection was based on the U.S. Census, Federal Reserve Surveys, FCC Broadband Data, and national statistics for the UK and Canada. Python with pandas, statsmodels, and linearmodels libraries was used for analysis. The robustness of estimates was tested in Stata with clustered errors. Visualization was performed in Microsoft Excel for tables and graphs.

The AIAI was created using the principal components method. The reliability of the models was tested using Wald, Hausman, and Broich-Pagan tests. Standard errors were clustered at the enterprise level. The results were interpreted taking into account industry and regional specifics.

4. RESULTS

Analysis of the U.S. SMB panel data for 2022-2024 provided a detailed picture of the availability and impact of AI-DSS on key metrics. Table 1 provides descriptive statistics for variables reflecting adoption, availability, digital maturity, staffing, as well as financial and operational performance. The metrics enable assessing the scale of the barriers and potential for digital transformation in the SMB sector.

Table 1: Descriptive statistics for variables for 2022-2024

Variable	Mean	SD	P25	Median	P75	N
AI_DSS adoption (0/1)	0.284	0.451	0	0	1	48,720
Access Index (0–100)	57.6	14.9	48.1	57.2	67.0	48,720
Digital Maturity (0–1)	0.42	0.23	0.28	0.39	0.55	48,720
Talent density (per 10k)	7.3	4.1	4.4	6.5	9.3	48,720
ProdLab (ths USD/empl.)	189.5	84.1	126.4	175.6	233.8	48,720
OpExRate (%)	71.2	11.6	64.0	71.5	78.2	46,008
Forecast MAPE (%)	23.7	9.8	16.9	22.4	29.1	18,362
Inventory turns	4.1	2.3	2.6	3.7	5.1	21,905
Decision cycle (days)	12.8	6.2	8	11	16	19,447

Source: developed by the authors based on the results of an econometric model using the data [1, 16–19]

Only 28.4% of companies have implemented AI-DSS, indicating that SMBs lag behind in technological integration compared to corporations. The average AIAI of 57.6 confirms the average level, but the spread shows significant differences between enterprises. High variance in productivity and costs indicates heterogeneity of effects, which requires further causal analysis.

Table 2 shows the results of a logit model that identifies determinants of AI-DSS adoption in U.S. SMBs. The analysis found that accessibility and digital maturity have the greatest impact on adoption, increasing the likelihood of implementation by several times. The presence of cloud ERP/CRM systems and high-speed internet also confirmed the importance of infrastructure factors.

Table 2: Determinants of AI-DSS Adoption (AME)

Covariate	AME	Std.Err.
Access Index (per 10 pts)	0.041***	0.006
Digital Maturity (0–1)	0.137***	0.023
Talent density (per 5)	0.019**	0.008
Firm size 100–249	0.072***	0.014
Firm size 250–499	0.089***	0.017
Age (log years)	−0.012*	0.007
Cloud ERP/CRM	0.058***	0.011
Broadband speed	0.015**	0.007

Source: developed by the authors based on the results of an econometric model using the data [1, 16–19]
Notes: *** p < 0.01, ** p < 0.05, * p < 0.1

Each 10-point increase in the AIAI increases the probability of adoption by 4.1 percentage points, and digital maturity by almost 14 percentage points. The presence of cloud ERP/CRM adds another 5.8 percentage points, emphasizing the importance of business readiness for integrations. Older enterprises demonstrate a lower probability of adoption, indicating institutional inertia. Table 3 shows the results of the causal impact of AI-DSS on productivity, costs, and operational KPIs. The DiD model confirms that AI-DSS has economically significant positive effects. The fact that interaction with accessibility significantly amplifies the effects is of particular importance.

Table 3: The impact of AI-DSS on KPIs (DiD)

Indicator	AI_DSS (β)	SE	AI×Availab (θ)	SE	N
ProdLab (% change)	0.054***	0.012	0.018**	0.007	31,602
OpExRate (pp)	−3.10***	0.68	−0.92**	0.37	29,947
Forecast MAPE (pp)	−3.8***	0.9	−1.7**	0.7	11,085
Inventory turns	0.41**	0.17	0.19*	0.10	13,204
Decision cycle (%)	−0.21***	0.05	−0.06**	0.03	12,377

Source: developed by the authors based on the results of an econometric model using the data [1, 16–19]
Notes: *** p < 0.01, ** p < 0.05, * p < 0.1

Implementing AI-DSS increases productivity by 5.4%, reduces costs by 3.1 pp, and reduces forecast errors by almost 4 pp. Inventory turnover is accelerated and the management cycle is shortened by 21%. The additional effect of the AIAI confirms the synergistic relationship between technology and infrastructure.

Tables 4.1 and 4.2 present the results of heterogeneity by enterprise size and sector. This gives grounds to assess which SMB groups benefit the most from AI integration. It is found that smaller companies have more pronounced marginal benefits, while medium-sized enterprises integrate technologies more often.

Table 4.1: Effects by enterprise size

Indicator	Small (<100)	SE	Medium (100–499)	SE	p-diff
ProdLab (%)	0.062***	0.015	0.043***	0.013	0.048
OpExRate (pp)	−3.6***	0.9	−2.4***	0.8	0.091
Decision cycle (%)	−0.24***	0.06	−0.17***	0.05	0.112

Source: developed by the authors based on the results of an econometric model using the data [1, 16–19]
Notes: *** p < 0.01, ** p < 0.05, * p < 0.1

Table 4.2: Effects by sector

Indicator	Retail & Trade	SE	Manufacturing	SE	Services	SE
ProdLab (%)	0.049***	0.018	0.061***	0.020	0.052***	0.014
OpExRate (pp)	−2.7***	0.9	−3.9***	1.1	−3.0***	0.7
Forecast MAPE (pp)	−4.5***	1.4	−3.1**	1.5	−3.7***	1.0

Source: developed by the authors based on the results of an econometric model using the data [1, 16–19]
Notes: *** p < 0.01, ** p < 0.05, * p < 0.1

Small firms experience greater productivity gains and cost reductions, while manufacturing has the strongest effects due to the complexity of processes and the need for forecasting. Retail shows the largest reduction in forecast errors, which is explained by the extensive use of AI in demand and inventory. The difference between sectors confirms the flexibility of the technology in different contexts.

The dynamics of the effects are presented in Table 5, which shows the change in indicators over time from the moment of adoption. The results demonstrate that the effects emerge quickly and intensify in the medium term. This confirms that AI-DSS is effective not only in the short term, but also in the long term.

Table 5: Event analysis of effects

Horizon	ProdLab (%)	SE	OpExRate (pp)	SE	Decision cycle (%)	SE
t−2	0.004	0.010	0.2	0.5	−0.01	0.03
t+1	0.021**	0.010	−1.4**	0.6	−0.12**	0.05
t+3	0.047***	0.013	−2.6***	0.7	−0.18***	0.05
t+6	0.071***	0.019	−3.3***	0.9	−0.24***	0.06

Source: developed by the authors based on the results of an econometric model using the data [1, 16–19]
Notes: *** p < 0.01, ** p < 0.05, * p < 0.1

Just a quarter after adoption, productivity increases by 2.1%, and costs decrease by 1.4 pp. After a year, productivity gains reach more than 7%. This confirms that AI-DSS creates a stable positive effect that accumulates over time.

Table 6 shows the results of robustness tests, which confirm the stability of the findings across different specifications. The use of alternative models preserved the positive effects of AI-DSS on productivity and costs. This reduces the risk of bias and increases the reliability of the results.

Table 6: Robustness of estimates

Specification	ProdLab (%)	SE	OpExRate (pp)	SE	Notes
Baseline FE-DiD	0.054***	0.012	−3.10***	0.68	Baseline model
+Firm trends	0.048***	0.013	−2.85***	0.72	Trends by firm
PSM-DiD (ATT)	0.051***	0.015	−2.77***	0.83	Matching
2SLS (IV-FE)	0.059**	0.024	−3.41**	1.36	Tools
Oster δ	1.87	—	1.64	—	Factors not considered

Source: developed by the authors based on the results of an econometric model using the data [1, 16–19]
Notes: *** p < 0.01, ** p < 0.05, * p < 0.1

The effects persist even when including trends at the enterprise level, instrumental variables and various selection control methods. This proves the high stability of the models. So, the results can be interpreted as reliable and applicable to real business practices.

The tables are presented as a systematized result of calculations that summarize the relationships between variables and allow us to clearly demonstrate the obtained quantitative results of the analysis. They are formed on the basis of selected indicators that reflect the key factors of the study, enabling to identify their dynamics in time and space. The variables measure specific characteristics of the object, including economic, financial or social aspects that determine the efficiency and sustainability of the processes under study. The generalized results in the tables show the significance of individual factors, giving grounds for making comparisons and drawing conclusions on the confirmation or refutation of hypotheses. Therefore, the tables are an analytical tool that provides a clear interpretation of the results and serves as a basis for practical recommendations.

Finally, Figure 2 presents an international comparison with the UK and Canada. The USA has higher adoption and impact rates, although the trends are generally similar. This confirms the universality of the affordability model and the relevance of the results to other developed countries.

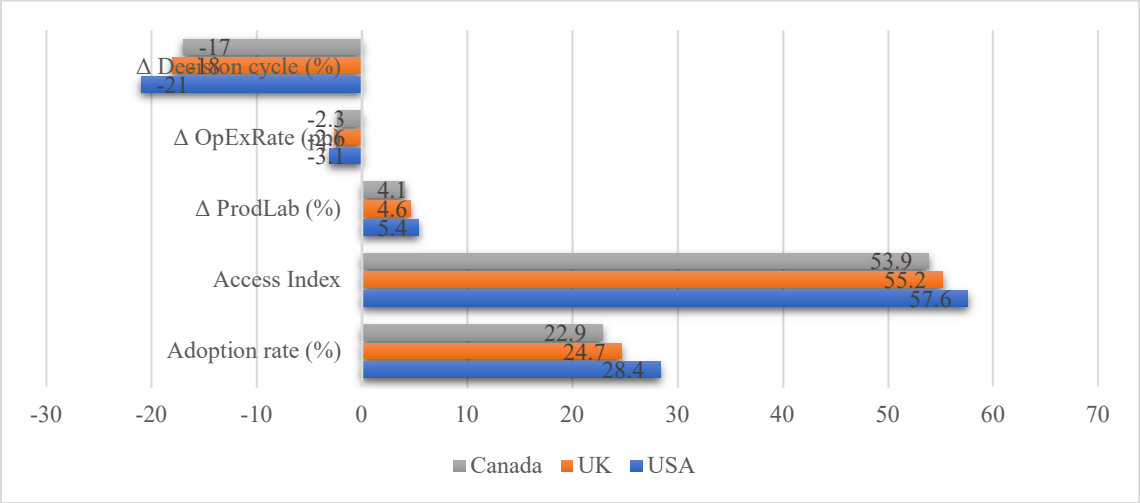

Figure 2: Comparison of the USA, UK, and Canada in 2022-2024

Source: developed by the authors based on the results of an econometric model using the data [1, 16–21]

The USA leads in adoption, but the gap narrows at high levels of availability. This means that availability determines the speed and scale of effects regardless of the country. The comparison confirms the key role of infrastructure and digital maturity in realizing the benefits of AI-DSS.

The availability of AI for enterprises is increasing due to the reduction in the cost of technology, the spread of cloud services and the emergence of ready-made digital platforms. An example is the use of chatbots in the service sector, which significantly reduce costs and increase customer satisfaction. OECD statistics show that more than 40% of EU SMBs used AI-based tools in 2024. Such data demonstrate that even small companies can integrate AI solutions without the need for significant investments. This supports the conclusion that the accessibility of AI has already become a reality that supports the competitiveness and innovation of businesses.

Overall, the results of the study confirmed the hypothesis that availability is a key factor in adoption and enhances the effects of AI-DSS. Small businesses reap the greatest benefits, and the effects grow over time and are confirmed by various specifications. The findings provide a solid foundation for SMB recommendations and government digital transformation policies.

5. DISCUSSION

The discussion of the results of this study demonstrates significant coherence with current approaches to digital business transformation, financial sustainability, and performance management in SMBs. Our findings confirm that accessibility and technological readiness are key moderators of AI-DSS effects, which is consistent with previous research. However, the heterogeneous effects found across company sizes and sectors suggest that AI integration strategies need to be tailored to specific circumstances. This emphasizes the practical relevance of the study for U.S. SMBs and provides a basis for further interdisciplinary work. Our 5.4% productivity increase and 3.1 pp OpEx reduction support the economic relevance of AI-DSS for SMEs.

Magableh et al. [22] demonstrate that marketing AI enhances financial sustainability through customer engagement and data-driven decision-making. López-Solís et al. [23] summarize the effects of generative AI for strategic management, highlighting both new opportunities and risks of unpredictability. Both approaches suggest that AI is becoming central to shaping management strategies, but they assess the balance between benefits and risks differently. Our effects on KPIs confirm Magableh et al. [22] on financial sustainability, but clarify that the magnitude of the benefits increases with increasing AIAI. We partially confirm the findings of López-Solís et al. [23]: the effects are persistent, but the risks of unpredictability decrease with higher digital maturity and accessibility.

Popa et al. [24] apply PLS-SEM to model adoption, integrating TAM and UTAUT2, and show the importance of organizational drivers. Similar results were obtained by Jamil et al. [25], who found that technological readiness determines sustainable outcomes in the manufacturing sector of Pakistan.

This confirms that adoption depends not only on technology, but also on contextual factors, which is consistent with our availability model. We confirm Popa et al. [24]: digital maturity significantly increases the probability of adoption (≈+13.7 pp). The results of Jamil et al. [25] are confirmed: our effects are largest in manufacturing, especially with high availability and cloud integration.

Komelina et al. [26] analyse the mechanisms of management adaptation to sustainable development standards in global changes. Their conclusions have something in common with those of Orlov et al. [27], who argue that the strategic success of the company ensures long-term sustainability. Dumanska et al. [28] reinforce this logic by showing the role of information support in strategic investment management. Together, these studies confirm: AI-DSS should be integrated into broader sustainable development strategies. We confirm Komelina et al. [26] and Orlov et al. [27]: the sustainable effects of AI-DSS increase with their integration into corporate strategy. We clarify the conclusion of Dumanska et al. [28] empirically: improved forecasts (–3.8 pp MAPE) strengthen the investment decision of SMBs.

Kobets et al. [29] emphasize that digitalization is shaping new marketing strategies and creating the conditions for integrating AI into business processes. This is in line with the study of Magableh et al. [22], who see marketing AI as the foundation of financial sustainability. However, Kobets et al. [29] focus more on organizational change, while Magableh et al. [22] analyse the customer dimension. The parallel between these works shows that AI simultaneously changes internal processes and external interactions. Our range of benefits in retail (the largest reduction in MAPE) supports both approaches: the customer effect and the need for organizational readiness.

Caiza et al. [30] examine the impact of AI on government decision-making, emphasizing the complexity of policy contexts. Although they analyse the state level, their findings are relevant to SMBs. Similar to business, the effects of AI in public administration are determined by data availability, institutional constraints, and trust. This reinforces the argument that AI-DSS implementation requires consideration of context and regulatory frameworks. We confirm Caiza et al. [30]: infrastructure availability and trust are correlated with adoption; our Availability Index formalizes this relationship for SMBs.

Filippi et al. [31] analyse the use of AI in consulting SMBs and show both benefits and challenges. They emphasize that AI can improve productivity and reduce costs, but integration and ethical issues remain significant. This conclusion has something in common with López-Solís et al. [23], who also emphasize the risks of new technologies. The comparison demonstrates that regardless of the industry, the challenges of adoption are universal. Our robustness tests (PSM-DiD, IV-FE) confirm the benefits of Filippi et al. [31], and also clarify that risks decrease with higher availability and maturity.

Prokopenko et al. [32] analyse the development of blockchain technologies in financial accounting, emphasizing their role in ensuring transparency, security, and data integrity. The authors argue that integrating blockchain with AI can create a new level of automation, where transactions become verifiable in real time. These findings have something in common with the ideas of Koldovskiy [33], who emphasizes the strategic transformation of the financial sector infrastructure to achieve sustainable success. Both studies agree that digital innovations not only optimize processes, but also form the foundation for long-term financial stability. We partially confirm Prokopenko et al. [32]: the effects of AI are amplified in environments with a reliable data infrastructure compatible with DLT. The findings of Koldovskiy [33] are confirmed: strategic infrastructure modernization increases the marginal benefits of AI-DSS in SMBs.

Koldovskiy [33] emphasizes that the strategic transformation of the financial sector infrastructure requires a comprehensive implementation of innovative technologies, including AI and blockchain. He argues that modernizing the governance of the financial system provides increased efficiency, reduced risks, and better adaptation to global challenges. In this sense, his findings are consistent with Prokopenko et al. [32], who also see blockchain and AI as the basis for transparency and trust. Together, these studies confirm that the combination of AI-DSS and blockchain creates a new financial governance architecture capable of ensuring sustainability and innovation in SMBs. Our results confirm this synergy: with high availability, the effects of AI-DSS on productivity and costs are statistically stronger.

So, most studies confirm the relevance of the chosen model and hypotheses. Our study integrates into the modern academic paradigm, which recognizes the close connection between AI availability, digital maturity, and SMB performance. However, some aspects, such as the impact of regulatory policies, ethical standards and the risks of excessive automation, require further study, taking

into account the industry and cultural context. The obtained results can be used by SMBs to build roadmaps for the implementation of AI-DSS and strategic planning of investments in digital infrastructure. The model is also suitable for comparative international studies, allowing to assess the specifics of adoption in different economic environments. We also clarify that the effects are stronger for small firms and increase in dynamics (event analysis t + 6), which is consistent with the literature on the diffusion of innovations.

Farmanesh et al. [7] show that AI stimulates green innovation, creating competitive advantages and contributing to the achievement of sustainable development goals. This confirms the relevance of eco-branding strategy in FMCG, where digital innovations become the basis for attracting and retaining a loyal audience. Hu et al. [34] emphasize the importance of symbolic leadership, which increases staff flexibility and promotes the adoption of new technologies in small businesses. This approach strengthens the implementation of digital strategies in FMCG, where the combination of innovation and management practices determines the success of eco-branding. Such results demonstrate that technological modernization and effective leadership complement each other in creating sustainable competitive advantages.

Although the empirical findings are quite strong, this research has several limitations concerning the access to data and time span of the investigated sample. Although theoretically reasonable, the chosen indicators can be inadequate to measure all the institutional and behavioural variables that can mediate the observed relations. The model applied might contain methodological assumptions that may influence the sensitivity of coefficients in different specifications or with long data sets. Heterogeneity across countries and sectors (though the latter can be controlled to a degree) can result in structural biases, which can be further subjected to disaggregated analysis. The limitations of the study should be overcome in future studies by including longer periods of time, more variables and other modelling methods.

6. LIMITATION

The study has several limitations that need to be considered when interpreting the results:

- the data used only cover the period 2022–2024, which limits the longterm dynamics of AI implementation;
- not all financial and operational indicators are available for the full range of enterprises, which reduces the level of detail of the results;
- the measurement of indicators such as forecast accuracy or decision speed is partly based on surveys, which may introduce subjective errors;
- the model only takes into account formal factors of AI accessibility, while cultural and behavioural barriers remain outside the analysis;
- the international block includes only two countries for comparison, so generalization of the findings requires a wider geographical sample;
- the possibility of endogeneity is not completely eliminated, despite the use of tools and robust checks;
- rapid changes in the field of AI may make the results less relevant in the future.

Despite these limitations, the study provides a solid basis for further work in the field of SMB digital transformation.

7. RECOMMENDATIONS

The research findings provide a number of practical recommendations for U.S. SMBs. Companies should start integrating AI with small pilot projects focused on specific business processes with a clearly measurable impact. The priority should be to automate routine tasks, including inventory management, demand forecasting, and financial analytics. It is recommended to use cloud solutions and low-code tools that reduce implementation costs and simplify integration into existing systems. Companies should invest in increasing digital maturity and training staff in basic skills for working with data and AI platforms. It is necessary to create internal data security protocols and use the NIST AI RMF recommendations to reduce technological and ethical risks.

Companies should form partnerships with educational and consulting organizations to expand access to knowledge and personnel. It is recommended to use a combined approach that combines internal resources with outsourcing solutions to optimize costs and scale faster. It is important to systematically monitor the effects of AI implementation, creating own KPIs and comparing them with industry standards. It is appropriate for the government and regulators to support SMBs with subsidy programmes, digitalization benefits, and expanding access to high-quality digital infrastructure. The recommendations will help companies to develop a realistic digital transformation roadmap and strengthen competitiveness in a dynamic market environment.

8. CONCLUSIONS

The study confirmed the high relevance of the problem of availability and the impact of AI systems on U.S. SMBs. All tasks were completed in full, which ensured the comprehensiveness and logical completion of the study. Key factors that shape the accessibility of AI solutions were identified, including cost, digital maturity, human resources potential and infrastructure availability. The created AIAI made it possible to quantitatively assess the conditions for integrating technologies into business practices of enterprises.

Econometric analysis showed that the implementation of AI-DSS increases productivity by 5.4%, reduces operating costs by 3.1 pp. and reduces forecast errors by 3.8 pp. The probability of adoption increases by 4.1 pp. with each 10-point increase in the AIAI. Digital maturity increases the probability of implementation by almost 14 pp, confirming the crucial role of technological readiness. Small companies gain 6.2% in productivity, while medium-sized companies gain 4.3%, confirming the hypothesis of higher marginal benefits. Dynamic analysis showed that productivity increases by over 7%, and costs decrease by 3.3 percentage points after just one year.

The results showed that enterprises with higher access to AI benefit significantly from the integration of innovative solutions. It was found that small companies demonstrate greater marginal benefits from implementation, while medium-sized businesses are more likely to integrate. Analysis of the data compared to the UK and Canada confirmed the relative advantage of the US in the speed and scale of AI implementation. The results of the study confirm the importance of technology accessibility as a determining factor in the success of the digital transformation of SMBs.

The research proposes a new analytical foundation that combines the application of both empirical modeling and modern digital transformation processes that go beyond the descriptive paradigm that was prevailing in earlier studies. In contrast to the currently available literature, the article quantitatively measures the previously underresearched relationships in a systematic manner, which presents a solid evidence-based on the effects of those mechanisms on the performance and structural outcomes. The results are valuable contributions to the existing body of knowledge as they show that the effects, identified, remain consistent across contexts, which invalidates the premises made by fixed or one-factor models. The article represents a methodological advancement to be offered in empirical studies into the relevant fields in the future since it relates theoretical constructs to the measurable indicators. In general, the research contributes to the academic literature by providing generalizable results to accomplish not only the creation of academic theory but also the implementation of evidence-based choices in practice.

The findings have practical implications for the development of company strategies and government digitalization policies. The study demonstrates that supporting SMBs in the field of AI is an important prerequisite for their competitiveness. Further studies should include a wider set of countries for international comparisons and a longer time period. It is necessary to focus on analysing the cultural, behavioural, and ethical aspects of AI integration, which were left beyond the scope of this study. Further work can also expand the set of performance indicators and include new areas of application of AI in business practices. Overall, the study provides a solid academic and practical foundation for developing digital strategies for U.S. SMBs.

DATA AVAILABILITY STATEMENT

Data openly available in a public repository that issues datasets with DOIs.

REFERENCES

[1] World Bank, “World Development Indicators (WDI)”, 2024. https://databank.worldbank.org/source/world-development-indicators

[2] T. Štrukelj and P. Dankova, “Ethical Leadership and Management of Small- and Medium-Sized Enterprises: The Role of AI in Decision Making”, *Administrative Sciences,* Vol. 15, No. 7, 2025, pp. 274. https://doi.org/10.3390/admsci15070274

[3] D. S. Melnyk, O. A. Parfylo, O. V. Butenko, O. V. Tykhonova and V. O. Zarosylo, “Practice of the member states of the european union in the field of anti-corruption regulation”, *Journal of Financial Crime,* Vol. 29, No. 3, 2022, pp. 853-863. https://doi.org/10.1108/JFC-03-2021-0050

[4] T. Le Dinh, M.-C. Vu and G. T. C. Tran, “Artificial Intelligence in SMEs: Enhancing Business Functions Through Technologies and Applications”, *Information,* Vol. 16, No. 5, 2025, p. 415. https://doi.org/10.3390/info16050415

[5] R. Machucho and D. Ortiz, "The Impacts of Artificial Intelligence on Business Innovation: A Comprehensive Review of Applications, Organizational Challenges, and Ethical Considerations", *Systems,* Vol. 13, No. 4, 2025, p. 264. https://doi.org/10.3390/systems13040264

[6] S. A. R. Khan, A. A. Sheikh, I. R. A. Shamsi and Z. Yu, "The Implications of Artificial Intelligence for Small and Medium-Sized Enterprises' Sustainable Development in the Areas of Blockchain Technology, Supply Chain Resilience, and Closed-Loop Supply Chains", *Sustainability,* Vol. 17, No. 1, 2025, p. 334. https://doi.org/10.3390/su17010334

[7] P. Farmanesh, N. Solati Dehkordi, A. Vehbi and K. Chavali, "Artificial Intelligence and Green Innovation in Small and Medium-Sized Enterprises and Competitive-Advantage Drive Toward Achieving Sustainable Development Goals", *Sustainability,* Vol. 17, No. 5, 2025, 2162. https://doi.org/10.3390/su17052162

[8] E. Sánchez, R. Calderón and F. Herrera, "Artificial Intelligence Adoption in SMEs: Survey Based on TOE–DOI Framework, Primary Methodology and Challenges", *Applied Sciences,* Vol. 15, No. 12, 2025, 6465. https://doi.org/10.3390/app15126465

[9] K. Kussainov, N. Goncharuk, L. Prokopenko, L. Pershko, B. Vyshnivska and O. Akimov, "Anti-corruption management mechanisms and the construction of a security landscape in the financial sector of the EU economic system against the background of challenges to european integration: Implications for artificial intelligence technologies", *Economic Affairs (New Delhi),* Vol. 68, No. 1, 2023, pp. 509-521. https://doi.org/10.46852/0424-2513.1.2023.20

[10] R. Agrawal, V. A. Wankhede, A. Kumar, S. Luthra and K. Kataria, "A systematic and network-based analysis of data driven quality management in supply chains and proposed future research directions", *The TQM Journal,* Vol. 35, 2023, pp. 73–101. https://doi.org/10.1108/TQM-12-2020-0285

[11] A. Al-Surmi, M. Bashiri and I. Koliousis, "AI based decision making combining strategies to improve operational performance", *International Journal of Production Research,* Vol. 60, No. 14, 2022, pp. 4464–4486. https://doi.org/10.1080/00207543.2021.1966540

[12] J. Åström, W. Reim and V. Parida, "Value creation and value capture for AI business model innovation: A three-phase process framework", *Review of Managerial Science,* Vol. 16, No. 7, 2022, pp. 2111–2133. https://doi.org/10.1007/s11846-022-00521-z

[13] A. Bandi, P. V. S. R. Adapa and Y. E. V. P. K. Kuchi, "The power of generative AI: A review of requirements, models, input–output formats, Evaluation metrics, and challenges", *Future Internet,* Vol. 15, No. 8, 2023, p. 260. https://doi.org/10.3390/fi15080260

[14] S. Bengesi, H. El-Sayed, M. K. Sarker, Y. Houkpati, J. Irungu and T. Oladunni, "Advancements in generative AI: A comprehensive review of GANs, GPT, autoencoders, diffusion model, and transformers", *IEEE Access,* Vol. 12, 2024, pp. 69812–69837. https://doi.org/10.48550/arXiv.2311.10242

[15] K. Andrew, M. Sullivan and K. Strampel, "Generative artificial intelligence: University student awareness, experience, and confidence in use across disciplines", *Journal of University Teaching and Learning Practice,* Vol. 20, No. 6, 2023, pp. 1–18. https://doi.org/10.53761/1.20.6.12

[16] U.S. Census Bureau, "Annual Business Survey (ABS)", 2024a. https://www.census.gov/programs-surveys/abs.html

[17] U.S. Census Bureau, "Business Trends and Outlook Survey (BTOS)", 2024b. https://www.census.gov/business-trends-outlook

[18] Federal Reserve Banks, "Small Business Credit Survey (SBCS)", 2024. https://www.fedsmallbusiness.org/survey

[19] Organisation for Economic Co-operation and Development (OECD), *Digital Economy Outlook*. OECD Publishing, 2024. https://www.oecd.org/digital

[20] Office for National Statistics (ONS), "UK Business: Activity, Size and Location", 2024. https://www.ons.gov.uk

[21] Statistics Canada, "Survey on Business Conditions", 2024. https://www.statcan.gc.ca

[22] I. K. Magableh, M. H. Mahrouq, M. A. Ta'Amnha and H. A. Riyadh, "The Role of Marketing Artificial Intelligence in Enhancing Sustainable Financial Performance of Medium-Sized Enterprises Through Customer Engagement and Data-Driven Decision-Making", *Sustainability,* Vol. 16,

No. 24, 2024, 11279. https://doi.org/10.3390/su162411279

[23] O. López-Solís, A. Luzuriaga-Jaramillo, M. Bedoya-Jara, . Naranjo-Jantamaría, D. Bonilla-Jurado and P. Acosta-Vargas, "Effect of Generative Artificial Intelligence on Strategic Decision-Making in Entrepreneurial Business Initiatives: A Systematic Literature Review", *Administrative Sciences,* Vol. 15, No. 2, 2025, p. 66. https://doi.org/10.3390/admsci15020066

[24] R.-G. Popa, I.-C. Popa, D.-F. Ciocodeică and H. Mihălcescu, "Modeling AI Adoption in SMEs for Sustainable Innovation: A PLS-SEM Approach Integrating TAM, UTAUT2, and Contextual Drivers", *Sustainability,* Vol. 17, No. 15, 2025, 6901. https://doi.org/10.3390/su17156901

[25] K. Jamil, W. Zhang, A. Anwar and S. Mustafa, "Exploring the Influence of AI Adoption and Technological Readiness on Sustainable Performance in Pakistani Export Sector Manufacturing Small and Medium-Sized Enterprises", *Sustainability,* Vol. 17, No. 8, 2025, 3599. https://doi.org/10.3390/su17083599

[26] O. Komelina, S. Korobka, H. Kondratieva, O. Lazor and O. Lazor, "Mechanisms of management adaptation to sustainable development standards under the condition of global changes", *Problemy Ekorozwoju,* Vol. 20, No. 2, 2025, pp. 245–254. https://doi.org/10.35784/preko.6941

[27] O. Orlov, K. Dumanska, N. Ponomaryova and D. Kobets, "Company's strategic success as the basis of its potential sustainability", *E3S Web of Conferences,* Vol. 166, 2020, 12002. https://doi.org/10.1051/e3sconf/202016612002

[28] K. Dumanska, I. Chaikovska, L. Vahanova and D. Kobets, "Strategize company's sustainable management of investment project evaluation based on the information support", *Journal of Information Technology Management,* Vol. 13, 2021, pp. 143–158. https://doi.org/10.22059/jitm.2021.80743

[29] D. Kobets, N. Terentieva, N. Shkvyria, N. Lysytsia and I. Siemak, "Digitalization and its impact on the development of contemporary marketing strategies", *Economic Affairs New Delhi,* Vol. 69, No. 2, 2024, pp. 1021–1040. https://doi.org/10.46852/0424-2513.3.2024.26

[30] G. Caiza, V. Sanguña, N. Tusa, V. Masaquiza, A. Ortiz and M. V. Garcia, "Navigating Governmental Choices: A Comprehensive Review of Artificial Intelligence's Impact on Decision-Making", *Informatics,* Vol. 11, No. 3, 2024, p. 64. https://doi.org/10.3390/informatics11030064

[31] E. Filippi, M. Bannò and I. E. Nencini, "Artificial intelligence in business and decision making: Analysis of benefits and challenges for consultancy SMEs", *Piccola Impresa Small Business,* Vol. 2, 2024. https://doi.org/10.14596/pisb.4446

[32] O. Prokopenko, A. Koldovskiy, M. Khalilova, A. Orazbayeva and J. Machado, "Development of Blockchain Technology in Financial Accounting. *Computation,* Vol. 12, No. 12, 2024, p. 250. https://doi.org/10.3390/computation12120250

[33] A. Koldovskiy, "Strategic infrastructure transformation: Revolutionizing financial sector management for enhanced success. Acta Academiae Beregsasiensis", *Economics,* Vol. 5, No. 2024, 2024, pp. 323–332. https://doi.org/10.58423/2786-6742/2024-5-323-332

[34] C. Hu, Q. Mohi Ud Din and A. Tahir, "Artificial Intelligence Symbolic Leadership in Small and Medium-Sized Enterprises: Enhancing Employee Flexibility and Technology Adoption", *Systems,* Vol. 13, No. 4, 2025, p. 216. https://doi.org/10.3390/systems13040216