

Factors influencing the use of AI in SMEs: the importance of digital infrastructure

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Abstract

Purpose – This study investigates the factors influencing the use of artificial intelligence (AI) in small- and medium-sized enterprises (SMEs), with a particular focus on a firm's digital infrastructure. It examines the interaction between these factors and the effects of digital infrastructure and AI use on perceived firm performance.

Design/methodology/approach – Data were obtained from a survey of a representative sample of 804 SMEs in Bulgaria. The study is based on the technology-organization-environment (TOE) framework and the resource-based view (RBV). It tests a structural model that posits the mediating role of digital infrastructure between two external and three organizational antecedents and the outcomes of AI use and perceived firm performance.

Findings – The results show that environmental factors and government policies affect top management support, which in turn influences digital strategy and employees' skills. External and organizational factors directly and indirectly contribute to digital infrastructure, which enhances AI use. Digital infrastructure and AI positively influence perceived firm performance. Moderation analysis reveals significant differences between AI users and non-users.

Research limitations/implications – The sample consists of SMEs from only one country and does not differentiate between high-tech and low-tech sectors.

Practical implications – SME managers need to realize that a robust digital infrastructure is a prerequisite for AI use. This requires increased attention to environmental signals, adequate governance policies, management support and employees with digital skills.

Originality/value – This study reveals the potential of combining TOE contextual factors with key company resources – such as digital infrastructure from the RBV – to explain AI use in SMEs.

Keywords SMEs, Use of AI, Digital infrastructure, TOE framework, RBV

Paper type Research article

1. Introduction

The new digital economy is accelerating the adoption of advanced technologies, such as artificial intelligence (AI), the Internet of Things (IoT), and blockchain. In particular, AI technologies have become a key driver of competitive advantage for companies of all sizes (Schwaake *et al.*, 2024; Ayinaddis, 2025). A commonly accepted definition of AI is still lacking (Choudrie *et al.*, 2023; Grashof and Kopka, 2023). Most researchers conceptualize it as the simulation of human intelligence by machines, enabled by technologies such as machine learning, deep learning, data mining, natural language processing, and image recognition (Chowdhury *et al.*, 2023; Badghish and Soomro, 2024).

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The use of AI can lead to significant benefits for firms, including forecasting market trends, supporting decision-making, mitigating risk, and researching customer satisfaction (Sánchez *et al.*, 2025; Gabelaia and Hendieh, 2025). AI and machine learning algorithms are also transforming HR decision-making functions (Mosquera and Soares, 2024; Naoum *et al.*, 2026). However, these algorithms often fail to deliver optimal solutions, mainly due to inherent algorithmic biases (Bandara *et al.*, 2025). Consequently, Úbeda-García *et al.* (2025) emphasize the need for a balanced approach that integrates technological innovation with strict ethical principles.

To strategically deploy AI and achieve long-term success, small- and medium-sized enterprises (SMEs) must first understand its benefits, challenges, and future prospects (Climent *et al.*, 2024). However, compared with large firms, the application of AI in SMEs remains low (Proietti and Magnani, 2025; Mustafa *et al.*, 2025). The adoption rate of AI in large firms (40%) is more than three times higher than in small firms (11.9%) (OECD, 2025). SMEs face difficulties owing to insufficient budgets, constrained human resources, and limited awareness of technological changes (Schönberger, 2023). Mikalef and Gupta (2021) argue that most SME leaders lack the necessary knowledge for AI adoption, while other authors highlight additional barriers, such as employee skill gaps (Choudrie *et al.*, 2023) and a lack of data (Ulrich and Frank, 2021).

One of the most widely used frameworks for examining technology adoption in firms is the Technology-Organization-Environment (TOE) framework (Tornatzky and Fleischer, 1990). This allows researchers to examine how technological, internal organizational, and environmental factors impact technology adoption decisions (Mikalef and Gupta, 2021; Nguyen *et al.*, 2022). Technological factors refer to the available internal and external technologies relevant to an organization. Environmental factors include external conditions, such as competitors, customers, suppliers, and government policies. Organizational context relates to characteristics such as management support, strategy, and human resources (Schwaeke *et al.*, 2024; Faiz *et al.*, 2024).

Despite its utility, the TOE framework does not sufficiently emphasize the specific technological adaptations required for using AI (Sánchez *et al.*, 2025). While the TOE framework is useful for understanding adoption contexts, it lacks a specific focus on the internal technological resources required for implementation, a concept central to the Resource-Based View (RBV; Barney, 1991). To deploy AI effectively, SMEs require substantial data, which necessitates a robust digital infrastructure (Ulrich and Frank, 2021; Oldemeyer *et al.*, 2024). It consists of both tangible assets, including servers, cables, and data centres, and intangible assets such as software, data, networks, and digital capabilities (Schneider and Anderie, 2025). This infrastructure can be considered a strategic firm resource (RBV) that serves as the foundation for all digital transformations, including AI adoption (Omran *et al.*, 2024). Therefore, integrating the TOE framework with the RBV connects a firm's contextual factors with its internal resources in a unified analytical approach (Yilmaz and Hanisch-Blicharski, 2025).

Most studies have investigated AI implementation and use in large organizations, while few have examined AI adoption in the context of SMEs (Schwaeke *et al.*, 2024; Sánchez *et al.*, 2025). Empirical evidence regarding the use of AI in SMEs remains insufficient (Dey *et al.*, 2024; Aljarboa, 2024). Given the significant economic role of SMEs, investigating the factors that influence AI use in this sector is critically important (Schönberger, 2023; Badghish and Soomro, 2024). Understanding these factors is crucial for developing policies to support AI adoption in SMEs, particularly in countries where SMEs lag behind in this regard.

This study responds to these calls by investigating the influence of selected TOE factors on digital infrastructure, AI use, and perceived firm performance in a sample of Bulgarian SMEs. It also examines the interactions between these factors. Specifically, we test a structural model that positions digital infrastructure as a mediator between five antecedents - two external (environmental factors and government policies) and three organizational (top management

support, digital strategy, and employees' skills) – and the outcomes of AI use and perceived firm performance. The main research questions are as follows:

- RQ1. What are the significant TOE factors influencing AI use in SMEs?
- RQ2. How do these factors interact in terms of their impact on AI use in SMEs?
- RQ3. How does digital infrastructure mediate the effects of these factors on AI use and perceived firm performance?
- RQ4. What are the effects of AI use on perceived SME performance?

Regarding firm performance, we were interested in the extent to which the “use of AI” can contribute to various aspects of performance. This approach allowed us to compare the opinions of both AI users and non-users regarding AI's contribution to firm performance. Therefore, within this context, firm performance refers to AI-enabled “perceived firm performance” rather than technology-neutral organizational performance [1].

The results indicate that environmental factors and government policies positively impact top management support, which in turn has a positive influence on both digital strategy and employees' skills. Environmental factors, government policies, digital strategy, and employee skills contribute to a higher level of digital infrastructure, although to varying degrees. In turn, digital infrastructure positively influences both AI use and perceived firm performance, while AI use also has a beneficial effect on perceived firm performance.

2. Literature review

2.1 TOE framework and RBV

The TOE model comprises three key dimensions – technology, organization, and environment - which provide a comprehensive perspective for analyzing new technology implementation at the organizational level (Ayinaddis, 2025). It has been successfully tested in previous studies on AI adoption and use (Baabdullah et al., 2021; Badghish and Soomro, 2024). As the three dimensions of the TOE model interact, there is a need to investigate their relative importance in relation to each other within the context of AI adoption by SMEs (Merhi and Harfouche, 2024).

Studies show that the TOE model alone is insufficient to explain AI use in SMEs and is often combined with other theories, such as the Diffusion of Innovation (DOI) theory, Technology Acceptance Model (TAM), Resource-Based View (RBV), and others (Chatterjee et al., 2021; ul Haq et al., 2025). For example, Yilmaz and Hanisch-Blicharski (2025) combine the TOE model with the RBV to analyze the complex interrelationships between technology, organization, and resources when implementing new technologies. While the TOE framework provides the context (external and internal drivers), the RBV requires that SMEs possess valuable, rare, and inimitable resources (e.g. digital infrastructure, unique data, and skilled employees) (ul Haq et al., 2025). Specifically, the RBV views digital infrastructure and data quality as key tangible and intangible resources that form the backbone for AI adoption and use (Mikalef and Gupta, 2021; Grashof and Kopka, 2023; Chowdhury et al., 2023). This way, the TOE-RBV framework suggests that AI adoption in SMEs depends on linking external capabilities with internal resources and capabilities. The combination of both approaches helps to explain differences between SMEs in terms of intensity, speed, and success in implementing AI (Sánchez et al., 2025; Yilmaz and Hanisch-Blicharski, 2025).

2.2 Environmental factors and government policies

Environmental factors and government policies are critical drivers for AI adoption in SMEs by creating a competitive and regulatory environment in which new technologies are implemented. For example, intense competition exerts pressure on SMEs to adopt AI to increase their efficiency (Schwaake et al., 2024). High consumer and market demand also

stimulate SMEs to adopt AI to improve their competitive positioning (Badghish and Soomro, 2024). Governments may create supportive regulatory frameworks that encourage SMEs to adopt and use AI (Sánchez et al., 2025). According to Holland (2026), key enabling factors for AI adoption and use in SMEs include supportive government policies, innovation ecosystems, financial access, and external market pressures.

2.2.1 Environmental factors, government policies and top management support. Environmental factors influence internal organizational factors, either directly or indirectly, such as top management support, digital strategy, and employee skills (Merhi and Harfouche, 2024). External pressure from competitors, consumers, suppliers, and government regulations can increase SME managers' awareness of the necessity to use AI (Lemos et al., 2022; Badghish and Soomro, 2024). The greater the number of competitors that use AI, the higher the probability that SME managers will increase their support for its adoption.

Researchers have also underlined the importance of government regulations and policies for AI adoption in SMEs (Merhi and Harfouche, 2024; Ayinaddis, 2025). Regulatory compliance requires AI adoption to correspond to principles such as fairness, transparency, accountability, and inclusion (Oldemeyer et al., 2024; Úbeda-García et al., 2025). Government policies can assist SME managers in using AI through specific programs such as subsidies, tax credits, and grants. These policies can lead to greater top management commitment to AI (Dey et al., 2024). This leads to the first two hypotheses:

H1. Environmental factors positively impact top management support for AI use in SMEs.

H2. Government policies positively impact top management support for AI use in SMEs.

2.2.2 Environmental factors, government policies and SMEs' digital infrastructure. Digital infrastructure refers to the hardware and software components that support AI solutions (Arroyabe et al., 2024). Therefore, to deploy AI, SMEs must invest in a higher level of digital infrastructure (Mikalef and Gupta, 2021; Faiz et al., 2024). Shao et al. (2025) argue that external factors, such as market competition, technological advancements, government policies, and changing consumer demands, significantly impact a business's IT infrastructure. According to Wang et al. (2023), market competition can force businesses to upgrade their infrastructure to remain competitive, while supportive government policies provide the means to do so. These considerations support the following two hypotheses:

H3. Environmental factors positively impact SMEs' digital infrastructure.

H4. Government policies positively impact SMEs' digital infrastructure.

2.3 Organizational factors

2.3.1 Top management support and digital strategy. Previous research has found that top management support is essential for SMEs to use new technologies (Lemos et al., 2022; Faiz et al., 2024; Sánchez et al., 2025). Top management support, particularly in terms of awareness and strategic vision, significantly influences the adoption and use of AI (Soomro et al., 2025; Oldemeyer et al., 2024). This vision leads to the creation of a digital strategy for AI adoption and use in SMEs (ul Haq et al., 2025). Researchers show that AI use in SMEs succeeds only when it aligns with a strong and long-term strategy (Schwaeye et al., 2024; Sánchez et al., 2025). Therefore, top management support is crucial for implementing a digital strategy and allocating resources to AI (Ayinaddis, 2025), which leads to the following hypothesis.

H5. Top management support positively influences the digital strategy for using AI.

2.3.2 Top management support and employees' digital skills. SMEs often lack the necessary employee skills and expertise, which hinders their ability to implement AI solutions (Peretz-Andersson et al., 2024). Research has found that managers who invest in continuous

learning tend to have more skilled employees who can effectively use AI in SMEs (Ayinaddis, 2025). Consequently, top managers should be committed to workforce training to ensure that employees are prepared to work with AI (Arroyabe *et al.*, 2024). Other studies also demonstrate that supportive top management significantly influences employees' acceptance of new technologies (Bouncken *et al.*, 2025). This forms the basis of the following hypothesis:

H6. Top management support positively influences employees' skills.

2.3.3 Digital strategy and digital infrastructure. Digital strategy and infrastructure are interdependent. Digital strategies rely on data analytics, which require a digital infrastructure capable of collecting, processing, and storing large amounts of data (Ononiwu *et al.*, 2024). Simultaneously, strategy implementation significantly impacts digital infrastructure by fostering investment in new technologies and supporting new business models. Yang and Shen (2025) found that a digital strategy influences firm innovation by augmenting investments in both human capital and digital infrastructure. Therefore, a digital strategy leads to more investment in new technologies, which justifies the next hypothesis:

H7. Digital strategy enhances the digital infrastructure of SMEs.

2.3.4 Employees' skills and digital infrastructure. Studies find that employees with computer literacy facilitate AI adoption and use (Grashof and Kopka, 2023; Choudrie *et al.*, 2023; Mathagu, 2024), although many SMEs lack such employees (Proietti and Magnani, 2025). Employees' skills are important as they impact the use of appropriate digital infrastructure. This infrastructure alone is insufficient if employees do not possess the skills necessary to fully leverage its tools (OECD, 2025). Therefore, strategic investments in digital infrastructure, along with the development of employees' digital skills, are essential for AI adoption (Aleca and Mihai, 2025). The following hypothesis is proposed:

H8. Employees' skills enhance the digital infrastructure of SMEs.

2.4 Technological factors

2.4.1 Digital infrastructure and the use of AI. Digital infrastructure reflects the readiness of SMEs to adopt AI, and the lack of such infrastructure is one of the main barriers to its use (Mikalef and Gupta, 2021; Ayinaddis, 2025). Many studies have confirmed that digital infrastructure serves as a key enabler for the successful integration of AI technologies in SMEs (Mustapha, 2025; Oldemeyer *et al.*, 2024; Molete *et al.*, 2025). Digital infrastructure comprises hardware, software, and network capabilities that allow for seamless AI deployment and usage (Mathagu, 2024; ul Haq *et al.*, 2025). Therefore, a strong digital infrastructure is a critical determinant of the adoption and effective use of AI in SMEs.

H9. Robust digital infrastructure facilitates AI use in SMEs.

2.4.2 Digital infrastructure and perceived firm performance. Studies reveal that effective digital infrastructure is crucial for SMEs to remain competitive in today's digital and globalized markets (Molete *et al.*, 2025; Almeida and Okon, 2025). Digital infrastructure positively impacts SME performance by improving operational efficiency, boosting innovation, and increasing competitiveness (OECD, 2025). Schwaeke *et al.* (2024) show that digital infrastructure can significantly improve SME performance through faster decision-making, efficient operations, and new avenues for innovation. Aleca and Mihai (2025) also demonstrate how digital infrastructure, digital skills, and the use of cloud technologies influence labor productivity in European Union countries. This provides the background for the tenth hypothesis:

H10. Robust digital infrastructure has a positive effect on perceived firm performance.

2.4.3 *AI use and perceived firm performance.* Several researchers have demonstrated that AI adoption contributes significantly to SME performance (Aljarboa, 2024; Mustapha, 2025; Soomro *et al.*, 2025). AI can improve SME performance by enabling data-driven decisions, enhancing predictive modelling, and accelerating product development (ul Haq *et al.*, 2025). As Baabdullah *et al.* (2021) assert, AI practices positively influence both the financial and non-financial performance of SMEs. Other studies also find a significant influence of AI adoption on SMEs’ operational and economic performance (Badghish and Soomro, 2024; Ayinaddis, 2025), leading to the eleventh hypothesis:

H11. AI use positively impacts perceived SME performance.

Based on the literature review, this study tests a structural model with digital infrastructure posited as a mediator between two external and three internal factors, as well as the impact of these factors on AI use and perceived firm performance (see Figure 1). The model contains eight constructs and 11 main hypotheses. Additionally, we examine the moderation effects of a dummy variable (users and non-users of AI) on the relationship between digital infrastructure and use of AI, and between use of AI and perceived firm performance.

3. Methodology

3.1 Sample and data collection

This study is based on a population of 250,153 non-financial enterprises in Bulgaria that met the criteria of having a minimum revenue of €15,000 in the previous year. From this population, a representative sample of 804 enterprises was obtained. The sample size was calculated for a 95% confidence level, a population proportion of 50%, and a margin of error of ±3.46%. Data were collected between January and March 2025 through computer-assisted personal interviews using a standardized questionnaire by the research agency Noema (noema.bg).

Regarding size, 48.1% of the surveyed enterprises were microenterprises (0–9 employees), followed by small (25.5%; 10–49 employees), medium (17.8%; 50–249 employees), and large enterprises (8.6%; over 250 employees). Large companies were included for descriptive comparisons, but were excluded from the structural model estimation. By sector, 29.5% of the firms are in services (excluding ICT services), followed by trade (25.9%), manufacturing (24.1%), and construction (20.5%). Most respondents were owners (48.5%) or high-level managers (43.8%), suggesting competent responses to the questions. The sex distribution was relatively even: 50.7% of men and 49.3% of women. Respondents aged 40–49 years comprised the largest group (33.8%), followed by those aged 56–65 (21.6%), 39 years (20.3%), and 50–55 years (21.8%). Most respondents had a higher education (69.3%), followed by those with a secondary education (30.5%).

As only one manager was interviewed per SME, we addressed the potential problem of common method variance (CMV) using Harman’s one-factor test (Podsakoff *et al.*, 2003). All

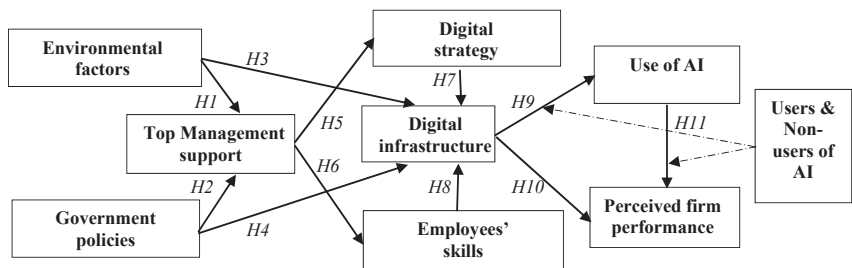


Figure 1. Conceptual model

the construct indicators were included in the exploratory principal component factor analysis. The total variance extracted by a single factor was 36.206%, indicating that CMV was not a significant concern for this sample (see [Supplementary Material, Appendix A, Table A1](#), available online [2]). We also assured respondent anonymity to reduce social desirability bias. Furthermore, all VIFs in PLS-SEM for both the external and internal models were below 3, indicating low bias (see [Supplementary Material, Appendix B, Tables B10 and B11](#), available online [3]).

3.2 Variable measurement

This study uses part of a larger questionnaire on AI applications in Bulgarian SMEs. Eight constructs were measured using 40 items. All items were measured on a 5-point Likert scale, ranging from 1 (completely disagree/not at all important) to 5 (completely agree/very important). The items for each construct were adapted from established scales: environmental factors ([Merhi and Harfouche, 2024](#); [Ayinaddis, 2025](#)); government policies ([Nguyen et al., 2022](#); [Badghish and Soomro, 2024](#)); top management support ([Mikalef and Gupta, 2021](#); [Chatterjee et al., 2021](#)); digital strategy ([Baabdullah et al., 2021](#); [Mikalef and Gupta, 2021](#)); employee skills ([Badghish and Soomro, 2024](#); [Grashof and Kopka, 2023](#)); digital infrastructure ([Baabdullah et al., 2021](#); [Badghish and Soomro, 2024](#)); AI usage ([Boston Consulting Group \(BCG\), 2024](#)); and perceived firm performance ([Badghish and Soomro, 2024](#)) (see [Supplementary Material, Appendix A, Table A2 - Questionnaire](#)). The questionnaire was piloted with managers from ten firms, and slight modifications were made based on their feedback.

4. Analysis of results

4.1 Descriptive statistics

According to the data, 128 companies (15.9%) are using AI and planning additional investments; 68.9% are not using AI and have no plans to do so or are unsure, while 15.2% are not currently using AI but plan to implement it in the near future. These figures are higher than the official statistics, which report that only 8.5% of Bulgarian companies use AI ([NSI, 2025](#)). This discrepancy is due to the more stringent criteria used to define the study population.

AI is primarily applied to the following business functions: marketing and customer relations (12.2%), supply chain and sales (11.8%), financial management (10.4%), human resource management (10.3%), and manufacturing processes (8.4%) (multiple responses allowed). Among the specific AI technologies in use, the largest share of SMEs used text analytics (7.6%) and chatbots for inquiries, customer support, and reservations (7%). Slightly over 4% used text mining/natural language generation (4.6%), personalized AI-driven recommendations (4.4%), computer vision for quality control (4.1%), and AI-powered scheduling and workforce management (4.0%). Less than 4% of the surveyed SMEs used other AI technologies.

With minor exceptions, there were no significant differences in the use of these technologies based on firm size, sector, foreign capital participation, export activity, or the demographic characteristics of managers.

4.2 Evaluation of the measurement model

Data were analyzed using SmartPLS 4 software. The model was assessed for indicator reliability, internal consistency, convergent validity (AVE), discriminant validity (Heterotrait-monotrait ratio, HTMT), and collinearity ([Hair et al., 2022](#)). Nine indicators with low loadings (<0.7) were excluded from the analysis. The outer loadings of the remaining 31 indicators were all above 0.7, indicating sufficient indicator reliability (see [Supplementary Material, Appendix B, Table B1](#)).

Cronbach’s alpha for all constructs ranged from 0.839 to 0.906, composite reliability (rho_c) from 0.892 to 0.932, Dijkstra-Henseler’s reliability coefficient (rho_a) from 0.842 to 0.907, and the AVE for all constructs was above 0.50 (see [Supplementary Material, Appendix B, Table B2](#)). All bootstrap confidence intervals for AVE, rho_c, rho_a, and Cronbach’s alpha are significant ([Appendix B, Tables B3 - B6](#)). These results demonstrate good internal consistency and convergent validity.

The Fornell-Larcker criterion showed that the square root of the AVE for each construct was higher than its highest correlation with any other construct ([Appendix B, Table B7](#)). For all construct pairs, the HTMT values were below the threshold of 0.85 ([Hair et al., 2022](#)) ([Appendix B, Tables B8-B9](#)). Thus, the model meets the established criteria for reliability and validity.

4.3 Evaluation of the structural model

The variance inflation factor (VIF) values for all predictor constructs were below 3, indicating that collinearity was not a significant issue in the structural model ([Appendix B, Tables B10-B11](#)). The direct effects of environmental factors and government policies on top management support explained 4% of the variance. The explained variances for the other endogenous constructs were as follows: digital strategy (36%), employee skills (31%), digital infrastructure (42%), AI use (25%), and perceived firm performance (44%) ([Appendix A, Table A3](#)). These results indicate that the model has good explanatory power.

All Q^2 prediction values were positive. For the key endogenous constructs (digital infrastructure and AI use), the mean absolute error values of the PLS model (PLS_SEM_MAE) were lower than those of the linear regression model (LM_MAE), except for two items of digital infrastructure ([Appendix A, Table A4](#)). The majority of the indicators in the PLS analysis had smaller prediction errors than those in the linear model, indicating medium predictive power ([Hair et al., 2022](#)).

4.4 Main results

[Table 1](#) presents the results of structural model testing, including the standardized regression coefficients (path coefficients) and their 95% bias-corrected confidence intervals.

The data reveal that the two external factors (environmental pressures and government policies) both have a positive and significant, though relatively weak, impact on top management support ($\beta = 0.109$ and $\beta = 0.140$, respectively), supporting [H1](#) and [H2](#). The

Table 1. Path coefficients – Confidence intervals

	Original sample (O)	Sample mean (M)	2.5%	97.5%
Digital strategy → Digital infrastructure	0.099	0.098	0.002	0.197
Employees’ skills → Digital infrastructure	0.109	0.109	0.017	0.200
Environmental factors → Digital infrastructure	0.313	0.313	0.255	0.371
Environmental factors → Top management support	0.109	0.110	0.027	0.192
Government policies → Digital infrastructure	0.397	0.397	0.333	0.460
Government policies → Top management support	0.140	0.141	0.062	0.218
Digital infrastructure → Perceived firm performance	0.330	0.330	0.264	0.397
Digital infrastructure → Use of AI	0.506	0.507	0.448	0.561
Top management support → Digital strategy	0.599	0.603	0.490	0.705
Top management support → Employees’ skills	0.562	0.570	0.455	0.678
Use of AI → Perceived firm performance	0.432	0.432	0.368	0.494

Note(s): All confidence intervals exclude zero, indicating statistical significance at $p < 0.05$

impact of these external factors on digital infrastructure was stronger ($\beta = 0.313$ and $\beta = 0.397$, respectively), supporting H3 and H4. Top management support has a strong, significant, and positive impact on both digital strategy ($\beta = 0.599$) and employee skills ($\beta = 0.562$), confirming H5 and H6. Digital strategy and employees' skills influence digital infrastructure, although comparatively weak ($\beta = 0.099$ and $\beta = 0.109$), supporting H7 and H8. Digital infrastructure has a strong positive impact on AI use ($\beta = 0.506$) and a moderate impact on perceived firm performance ($\beta = 0.330$), providing support for H9 and H10. Finally, AI use significantly and positively influences perceived firm performance ($\beta = 0.432$), supporting H11.

All specific indirect effects except for four (Appendix B, Table B12), total effects (Appendix B, Table B13), and total indirect effects (Appendix B, Table B14) are also significant. This confirms the significant mediating role of digital infrastructure and underscores the combined influence of environmental and internal organizational factors on building robust digital capabilities, increasing AI usage, and enhancing firm performance.

5. Discussion

Figure 2 shows all constructs, paths with coefficients, and R^2 values for the endogenous variables (see also Appendix A, Figure A2).

Businesses cannot control external factors and they must instead adapt to them. Competitive pressure is one of the most frequently cited environmental motivators for managers to adopt new technologies (Sánchez *et al.*, 2025; Merhi and Harfouche, 2024). Changing consumer preferences also force SME managers to implement AI solutions - from chatbots to predictive tools. SME managers also rely on external government support programs to receive the guidance and resources necessary to implement AI (Dey *et al.*, 2024; Ayinaddis, 2025). For example, financial support can enable SMEs to acquire AI software and hardware and hire skilled professionals, thus overcoming barriers to developing digital infrastructure (Arroyabe *et al.*, 2024). Government fiscal policies also play a direct role in how companies can invest in their AI infrastructure (Mathagu, 2024).

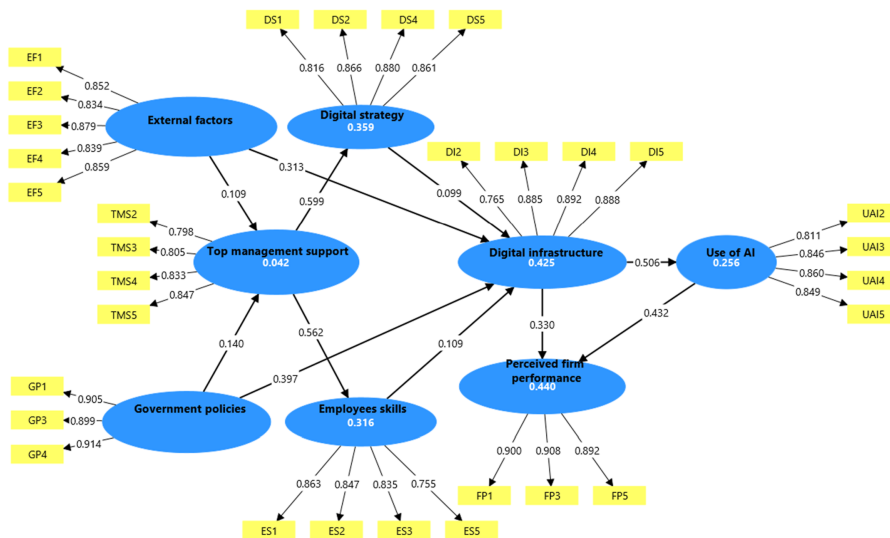


Figure 2. Structural model with standardized path coefficients and R^2 values

However, the present data show that external factors and government policies explain very little of the variance in top management support ($R^2 = 4\%$). This suggests that many managers are either insensitive to external signals about AI or, more likely, that government programs are not well-targeted at raising managerial awareness. [Sánchez et al. \(2025\)](#) argue that weak government practices can discourage SME managers from implementing AI. [Idemudia et al. \(2023\)](#) support this argument by showing that many SMEs in Nigeria have been overlooked in national digital transformation plans.

The availability of new digital technologies, such as big data analytics, cloud computing, machine learning and AI, creates an environment that influences SMEs' decisions regarding their digital infrastructure. These technologies require SMEs to move from traditional IT infrastructure to a more robust digital infrastructure capable of supporting machine learning and AI workloads ([Arroyabe et al., 2024](#)). Therefore, environmental technological factors exert pressure on SMEs to update their infrastructure, which in turn enables the adoption of new digital technologies ([Shao et al., 2025](#)).

The results of this study align with those of other researchers ([Sánchez et al., 2025](#); [Schwaeke et al., 2024](#)) regarding the effects of technology-related environmental pressures and government initiatives on the development of SMEs' digital infrastructure for AI adoption and use ($\beta = 0.313$ and $\beta = 0.397$, respectively).

The awareness and knowledge of SME managers are crucial for new technology adoption, as they are responsible for strategic decisions and resource allocation ([Chatterjee et al., 2021](#)). According to [Lemos et al. \(2022\)](#), new technologies can be successfully introduced only with top management support. Other studies also highlight the importance of top managers in creating a digital strategy and mobilizing organizational resources for AI use ([Baabdullah et al., 2021](#); [Merhi and Harfouche, 2024](#); [Faiz et al., 2024](#)). In turn, digital strategy enhances a firm's capacity to adapt to environmental changes ([Yang and Shen, 2025](#)).

In the digital era, SMEs require digital leaders who can motivate and inspire employees to acquire digital skills ([Arroyabe et al., 2024](#)). Top management support can reduce technophobia and make employees more confident and capable of using new digital tools ([Bouncken et al., 2025](#)). For example, [Wang et al. \(2024\)](#) show a significant positive relationship between digital leadership, digital employee capabilities, and organizational performance. The present results support [Ayinaddis' \(2025\)](#) argument that top management commitment directly impacts the formulation of business strategy ($\beta = 0.599$) and the provision of training to increase employees' skills regarding AI ($\beta = 0.562$). In turn, enterprises with digitally skilled employees achieve greater productivity gains than those lacking such capabilities ([Aleca and Mihai, 2025](#)).

[Schönberger \(2023\)](#) argued that SMEs must integrate AI technologies into their business strategies to remain competitive in the digital marketplace. Researchers agree that the implementation of a digital strategy presupposes the allocation of more resources to the digital infrastructure ([Yang and Shen, 2025](#)). Digital strategies influence digital infrastructure by transforming traditional IT infrastructure into a foundation for innovation and growth ([Gao et al., 2022](#)). The results of this study also show a positive impact of digital strategy on digital infrastructure, although not very strong ($\beta = 0.099$). This may be due to financing constraints such as high investment costs and insufficient financial resources. The descriptive statistics support this, showing that 56% of respondents cited high implementation costs as the main reason for not using AI.

The current digital economy requires employees to operate and collaborate with AI to achieve beneficial outcomes ([Faiz et al., 2024](#)). Employees possessing the necessary digital skills can effectively use AI and drive productivity growth ([Sánchez et al., 2025](#); [Aleca and Mihai, 2025](#)). In this way, employees' skills directly influence the digital infrastructure by allowing its effective utilization. However, many studies have found that the delayed adoption of AI in SMEs is due to a lack of a skilled workforce ([Badghish and Soomro, 2024](#); [Oldemeyer et al., 2024](#)). The present results reveal a positive, but weak influence of employees' skills on digital infrastructure ($\beta = 0.109$). This suggests that employees in the surveyed SMEs are not

sufficiently prepared to make the best use of digital infrastructure, a point also indicated by 55% of the respondents.

Several studies have shown the positive influence of technological infrastructure on the adoption of AI by SMEs (Mathagu, 2024; Oldemeyer *et al.*, 2024). The maturity of digital infrastructure influences a company's ability to connect with AI from providers and partners, which can support AI adoption and use (Badghish and Soomro, 2024). Other researchers have emphasized the importance of advanced digital infrastructure to enable adoption of AI across various sectors (Sánchez *et al.*, 2025; Ayinaddis, 2025). Merhi and Harfouche (2024) found that a well-established IT infrastructure is an essential prerequisite for using AI, while an inadequate IT infrastructure is among the key technological barriers for SMEs to implement AI (Oldemeyer *et al.*, 2024; Proietti and Magnani, 2025). The strongest direct impact of digital infrastructure on AI use in this study ($\beta = 0.506$) confirms the important role of RBV strategic resources in new technology adoption.

Researchers agree that the integrated use of IT technologies enables companies to succeed by optimizing resource utilization, reducing costs, increasing employee productivity, and enhancing customer loyalty and satisfaction (Molete *et al.*, 2025; OECD, 2025). According to Almeida and Okon (2025), digital infrastructure not only ensures operational reliability but also helps manage costs and enhance overall productivity. In line with these findings, the present results also demonstrate a significant and positive impact of digital infrastructure on perceived firm performance ($\beta = 0.330$).

Literature has shown that the use of AI can improve SME performance by increasing efficiency, enabling data-driven decisions, and accelerating product development (Mikalef and Gupta, 2021; Aljarboa, 2024; Ayinaddis, 2025). For example, Hwang and Kim (2022) find that adopting emerging technologies enhances the productivity of SMEs. The use of AI technologies contributes significantly to the economic, social, and environmental performance of SMEs (Soomro *et al.*, 2025). The results of this study support the significant and positive contribution of AI use to perceived firm performance ($\beta = 0.432$).

We also assess the moderating effects of a dummy variable (non-users - 0 and users - 1) on the relationships between digital infrastructure and use of AI, and between use of AI and perceived firm performance. This variable positively moderates the impact of digital infrastructure on use of AI and negatively moderates the impact of AI on perceived firm performance. This means that users of AI are more convinced of the positive effects of digital infrastructure on AI use, while non-users of AI are more optimistic about the positive effects of AI on firm performance (Appendix B, Tables B15, B16, and Figure B1). The more cautious position of AI users can be explained by the fact that the use of AI may not result in immediate performance benefits (Grashof and Kopka, 2023; Oldemeyer *et al.*, 2024). The report of McKinsey (2026) shows that while 88% of companies embraced AI, only 8% are scaling it effectively. Other research illustrates even the negative impacts of AI, such as employment displacement, bias and discrimination (Kassa and Worku, 2025). Therefore, improving firm performance requires more than adoption of AI. Úbeda-García *et al.* (2025) suggest using HRM practices that can mitigate the negative effects of digitalization, such as: promoting work-life balance; empowering employees; and training in new skills.

The total effects show that government policies (regulations, incentives) and environmental factors (market competition, customer demands, new technology development) have the strongest impact on digital infrastructure (0.413 and 0.326 respectively), followed by top management support (0.121) (Appendix B, Table B13). This suggests that rapidly advancing external technology and governmental programs play a more decisive role in its development compared to internal factors. Regarding the use of AI, digital infrastructure has the greatest impact on it (0.506), followed by government policies (0.209), and environmental factors (0.165). As indicated above, the weaker influence of digital strategy and employees' skills on both digital infrastructure and use of AI might be due to insufficient financial and other resources as well as employees not being sufficiently trained to use it effectively. Digital infrastructure and the use of AI also have the strongest total impact on

perceived firm performance (0.548 and 0.432 respectively), followed by government policies (0.227), and environmental factors (0.179) ([Appendix B, Table B13](#)). These data suggest that the use of AI in SMEs is determined mostly by government policies, environmental pressures, and firm digital infrastructure. Top management support, digital strategy, and employees' skills also contribute positively to AI use, although to a lesser degree.

6. Conclusions

The goal of this study was to investigate the factors influencing AI use in SMEs, with a particular emphasis on digital infrastructure as a key strategic firm resource. Based on the TOE framework and the RBV, we tested a structural model positing the mediating role of digital infrastructure between two external and three organizational factors and the outcomes of AI use and perceived firm performance. The results showed that environmental factors and government policies positively impact top management support and digital infrastructure. Top management support positively influences digital strategy and employee skills. Digital strategy and employee skills positively impact digital infrastructure, which, in turn, influences both AI use and perceived firm performance. Finally, AI use contributes to perceived firm performance.

6.1 Theoretical and methodological implications

This study confirms the value of integrating the TOE framework with the RBV to analyse technology adoption and use in SMEs. The two theoretical perspectives are interrelated, as several technological and organizational factors from the TOE framework align with a firm's internal resources ([ul Haq et al., 2025](#)). The TOE model highlights the importance of external factors, including the broader technology support infrastructure, while the RBV underscores the significance of strategic internal technological resources, specifically digital infrastructure. Having strong internal resources and capabilities (RBV) allows a firm to better respond to environmental pressures. Therefore, integrating the TOE framework and the RBV provides a more comprehensive understanding of AI adoption in SMEs ([Yilmaz and Hanisch-Blicharski, 2025](#)). From a methodological perspective, this study demonstrates the value of positioning digital infrastructure as a full mediator between TOE factors and AI outcomes. By testing this mediating role, the study reveals how external and organizational factors translate into AI use and improved firm performance, not merely whether they are associated. Future research should consider similar mediation designs when examining technology adoption in resource-constrained contexts, as direct-effect models may obscure important indirect pathways.

6.2 Managerial implications

The ability of SMEs to adopt and use new digital technologies is crucial for their survival and development in the digital age. Therefore, managers must actively implement these technologies, particularly AI, to harness their potential benefits ([Lemos et al., 2022](#)). The results of this study demonstrate to SME managers that robust digital infrastructure is a prerequisite for deploying AI technologies. Developing such infrastructure, however, requires managers who are sensitive to environmental signals, committed to creating and implementing a digital strategy, and dedicated to providing training to their employees. As AI automates routine tasks, businesses need to invest in upskilling employees to work alongside AI technologies ([Climent et al., 2024](#)). According to [McKinsey report \(2026\)](#) the race for talent has been transformed into the race for training. Government policies can facilitate these processes through targeted programs aimed at reducing the financial and human resource constraints that SMEs face regarding AI adoption and use.

Additionally, managers of SMEs that have not yet adopted AI should be more cautious in their expectations regarding AI's contribution to firm performance. Besides the use of AI,

increasing firm performance requires other important changes such as creating a work environment that encourages productivity (Kassa and Worku, 2025), and enhancing employees' skills to ensure continued employability in the AI era (Ubeda-García *et al.*, 2025).

6.3 Limitations and future research

This study had several limitations. First, it uses cross-sectional data, which does not allow tracking changes in AI use among the surveyed SMEs over time. Second, while the structural model is robust, it does not capture all potential external and internal factors that influence AI use. Third, the investigated SMEs are from different sectors but are not differentiated between high-tech and low-tech industries, despite sector likely playing an important moderating role in AI adoption. Fourth, the study is based on data from SMEs in only one European country, which is not at the forefront of AI adoption. Therefore, these findings cannot be directly generalized to SMEs in more technologically advanced nations. Future research using longitudinal and multi-source data is needed to understand the specific conditions and requirements under which SMEs can leverage AI more effectively to realize its full benefits.

Notes

1. We would like to thanks the anonymous reviewer for suggesting this term.
2. <https://cloud.nasledstvo.bg/s/5rjor7exqRAQepq>
3. <https://cloud.nasledstvo.bg/s/5rjor7exqRAQepq>

Supplementary material

The supplementary material for this article can be found online.

References

- Aleca, O.E. and Mihai, F. (2025), "The role of digital infrastructure and skills in enhancing labor productivity: insights from industry 4.0 in the European union", *Systems*, Vol. 13 No. 2, p. 113, doi: [10.3390/systems13020113](https://doi.org/10.3390/systems13020113).
- Aljarboa, S. (2024), "Factors influencing the adoption of artificial intelligence in e-commerce by small and medium-sized enterprises", *International Journal of Information Management Data Insights*, Vol. 4 No. 2, 100285, doi: [10.1016/j.jjime.2024.100285](https://doi.org/10.1016/j.jjime.2024.100285).
- Almeida, F. and Okon, E. (2025), "Impact of digitalization on SMEs performance: the mediating role of IoT", *Digital Transformation and Society*, Vol. 4 No. 4, pp. 407-422, doi: [10.1108/DTS-11-2024-0240](https://doi.org/10.1108/DTS-11-2024-0240).
- Arroyabe, M.F., Arranz, C.F.A., De Arroyabe, I.F. and de Arroyabe, J.C.F. (2024), "Analyzing AI adoption in European SMEs: a study of digital capabilities, innovation and external environment", *Technology in Society*, Vol. 79, 102733, doi: [10.1016/j.techsoc.2024.102733](https://doi.org/10.1016/j.techsoc.2024.102733).
- Ayinaddis, S.G. (2025), "Artificial intelligence adoption dynamics and knowledge in SMEs and large firms: a systematic review and bibliometric analysis", *Journal of Innovation and Knowledge*, Vol. 10 No. 3, 100682, doi: [10.1016/j.jik.2025.100682](https://doi.org/10.1016/j.jik.2025.100682).
- Baabdullah, A.M., Alalwan, A.A., Slade, E.L., Raman, R. and Khatatneh, K.F. (2021), "SMEs and artificial intelligence (AI): antecedents and consequences of AI-based B2B practices", *Industrial Marketing Management*, Vol. 98, pp. 255-270, doi: [10.1016/j.indmarman.2021.09.003](https://doi.org/10.1016/j.indmarman.2021.09.003).
- Badghish, S. and Soomro, Y.A. (2024), "Artificial intelligence adoption by SMEs to achieve sustainable business performance: application of technology-organization-environment framework", *Sustainability*, Vol. 16 No. 5, 1864, doi: [10.3390/su16051864](https://doi.org/10.3390/su16051864).

- Bandara, R.J., Biswas, K., Akter, S., Shafique, S. and Rahman, M. (2025), "Addressing algorithmic bias in AI-driven HRM systems: implications for strategic HRM effectiveness", *Human Resource Management Journal*, Vol. 35 No. 4, pp. 1047-1063, doi: [10.1111/1748-8583.12609](https://doi.org/10.1111/1748-8583.12609).
- Barney, J. (1991), "Firm resources and sustained competitive advantage", *Journal of Management*, Vol. 17 No. 1, pp. 99-120, doi: [10.1177/014920639101700108](https://doi.org/10.1177/014920639101700108).
- Boston Consultancy Group (2024), "AI adoption in 2024: 74% of companies struggle to achieve and scale value", available at: [https://www.bcg.com/press/24october2024-ai-adoption-in-2024-74-of-companies-struggle-to-achieve-and-scale-value#:~:text=%22In%20fact%2C%2062%25%20of,\(19%25%20and%2022%25](https://www.bcg.com/press/24october2024-ai-adoption-in-2024-74-of-companies-struggle-to-achieve-and-scale-value#:~:text=%22In%20fact%2C%2062%25%20of,(19%25%20and%2022%25) (accessed 12 December 2025).
- Bouncken, R., Schmitt, F. and Kraus, S. (2025), "Digital empowerment: top management and employee-driven change", *Management Decision*, Vol. ahead-of-print No. ahead-of-print, pp. 1-24, doi: [10.1108/MD-04-2025-1114](https://doi.org/10.1108/MD-04-2025-1114).
- Chatterjee, S., Rana, N.P., Dwivedi, Y.K. and Baabdullah, A.M. (2021), "Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model", *Technological Forecasting and Social Change*, Vol. 170, 120880, doi: [10.1016/j.techfore.2021.120880](https://doi.org/10.1016/j.techfore.2021.120880).
- Choudrie, J., Manandhar, N., Castro, C. and Obuekwe, C. (2023), "Hey Siri, Google! Can you help me? A qualitative case study of smartphones AI functions in SMEs", *Technological Forecasting and Social Change*, Vol. 189, 122375, doi: [10.1016/j.techfore.2023.122375](https://doi.org/10.1016/j.techfore.2023.122375).
- Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A. and Truong, L. (2023), "Unlocking the value of artificial intelligence in human resource management through AI capability framework", *Human Resource Management Review*, Vol. 33 No. 1, 100899, doi: [10.1016/j.hrmr.2022.100899](https://doi.org/10.1016/j.hrmr.2022.100899).
- Climont, R.C., Haftor, D.M. and Staniewski, W. (2024), "AI-enabled business models for competitive advantage", *Journal of Innovation and Knowledge*, Vol. 9 No. 3, 100532, doi: [10.1016/j.jik.2024.100532](https://doi.org/10.1016/j.jik.2024.100532).
- Dey, P.K., Chowdhury, S., Abadie, A., Vann Yaroson, E. and Sarkar, S. (2024), "Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small- and medium-sized enterprises", *International Journal of Production Research*, Vol. 62 No. 15, pp. 5417-5456, doi: [10.1080/00207543.2023.2179859](https://doi.org/10.1080/00207543.2023.2179859).
- Faiz, F., Le, V. and Masli, E.K. (2024), "Determinants of digital technology adoption in innovative SMEs", *Journal of Innovation and Knowledge*, Vol. 9 No. 4, 100610, doi: [10.1016/j.jik.2024.100610](https://doi.org/10.1016/j.jik.2024.100610).
- Gabelaia, I. and Hendieh, J. (2025), "The transformative power of AI and its impact on business strategy, financial operations, and marketing decision-making: a case study method", *International Journal of Innovation Science*, Vol. ahead-of-print No. ahead-of-print, pp. 1-21, doi: [10.1108/IJIS-02-2025-0051](https://doi.org/10.1108/IJIS-02-2025-0051).
- Gao, F., Lin, C. and Zhai, H. (2022), "Digital transformation, corporate innovation, and international strategy: empirical evidence from listed companies in China", *Sustainability*, Vol. 14 No. 13, p. 8137, doi: [10.3390/su14138137](https://doi.org/10.3390/su14138137).
- Grashof, N. and Kopka, A. (2023), "Artificial intelligence and radical innovation: an opportunity for all companies?", *Small Business Economics*, Vol. 61 No. 2, pp. 771-797, doi: [10.1007/s11187-022-00698-3](https://doi.org/10.1007/s11187-022-00698-3).
- Hair, J.F., Hult, G.T.M., Ringle, C.M. and Sarstedt, M. (2022), *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*, 3rd ed., Sage, Los Angeles, London, Delhi.
- Holland, J. (2026), "Artificial intelligence adoption for sustainable development in SMEs: challenges, strategic pathways and lessons for developing economies", *International Journal of Sustainability in Business and Economics*, Vol. 2 No. 1, doi: [10.51137/wrp.ijbsbe.502](https://doi.org/10.51137/wrp.ijbsbe.502).
- Hwang, W.-S. and Kim, H.-S. (2022), "Does the adoption of emerging technologies improve technical efficiency? Evidence from Korean manufacturing SMEs", *Small Business Economics*, Vol. 59 No. 2, pp. 627-643, doi: [10.1007/s11187-021-00554-w](https://doi.org/10.1007/s11187-021-00554-w).

- Idemudia, S.O., Chima, O.K., Ezeilo, O.J., Ojonugwa, B.M., Ochefu, A. and Adesuyi, M.F. (2023), "Digital infrastructure barriers faced by SMEs in transitioning to smart business models", *International Journal of Scientific Research in Science, Engineering and Technology*, Vol. 10 No. 4, pp. 353-370, available at: <https://ijsrset.com/paper/12356.pdf>
- Kassa, B.Y. and Worku, E.K. (2025), "The impact of artificial intelligence on organizational performance: the mediating role of employee productivity", *Journal of Open Innovation: Technology, Market and Complexity*, Vol. 11 No. 1, 100474, doi: [10.1016/j.joitmc.2025.100474](https://doi.org/10.1016/j.joitmc.2025.100474).
- Lemos, S.I.C., Ferreira, F.A.F., Zopounidis, C., Galariotis, E. and Ferreira, N.C.M.Q.F. (2022), "Artificial intelligence and change management in small and medium-sized enterprises: an analysis of dynamics within adaptation initiatives", *Annals of Operations Research*, Vol. 353 No. 1, pp. 197-223, doi: [10.1007/s10479-022-05159-4](https://doi.org/10.1007/s10479-022-05159-4).
- Mathagu, S.W. (2024), "Artificial intelligence in small and medium enterprises – an empirical analysis of critical factors", *Premier Journal of Science*, Vol. 1, 100009, doi: [10.70389/PJS.100009](https://doi.org/10.70389/PJS.100009).
- McKinsey (2026), "The state of AI in 2025: agents, innovation and transformation", available at: <https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai> (accessed 12 March 2026).
- Merhi, M.I. and Harfouche, A. (2024), "Enablers of artificial intelligence adoption and implementation in production systems", *International Journal of Production Research*, Vol. 62 No. 15, pp. 5457-5471, doi: [10.1080/00207543.2023.2167014](https://doi.org/10.1080/00207543.2023.2167014).
- Mikalef, P. and Gupta, M. (2021), "Artificial intelligence capability: conceptualization, measurement calibration and empirical study on its impact on organizational creativity and firm performance", *Information and Management*, Vol. 58 No. 3, 103434, doi: [10.1016/j.im.2021.103434](https://doi.org/10.1016/j.im.2021.103434).
- Molete, O.B., Mokhele, S.E., Ntombela, S.D. and Thango, B.A. (2025), "The impact of it strategic planning process on SME performance: a systematic review", *Businesses*, Vol. 5 No. 1, p. 2, doi: [10.3390/businesses5010002](https://doi.org/10.3390/businesses5010002).
- Mosquera, P. and Soares, M.E. (2024), "Dealing with work overload in the IT industry", *Management Decision*, Vol. 62 No. 7, pp. 2111-2135, doi: [10.1108/MD-06-2023-0970](https://doi.org/10.1108/MD-06-2023-0970).
- Mustafa, H.N., Ab Ghani, N.I. and Adam, A. (2025), "Enhancing performance in SMEs: a conceptual framework for AI adoption through digital readiness and employee digital skills", *International Journal of Entrepreneurship and Management Practices*, Vol. 8 No. 31, pp. 226-236, doi: [10.35631/IJEMP.831015](https://doi.org/10.35631/IJEMP.831015).
- Mustapha, A. (2025), "Big data as a service in the digital economy: a structural model of adoption, capabilities and performance", *International Journal of Social and Educational Innovation*, Vol. 12 No. 24, pp. 261-280, available at: <https://journals.aseiacademic.org/index.php/ijsei/article/view/557> (accessed 10 December 2025).
- Naoum, R.F., Szakadati, T. and Balogh, G. (2026), "Artificial Intelligence (AI) in human resource management (HRM): a systematic review of its dual impact on diversity, equity and inclusion (DEI)", *Management Review Quarterly*, doi: [10.1007/s11301-025-00580-y](https://doi.org/10.1007/s11301-025-00580-y).
- Nguyen, T.H., Le, X.C. and Vu, T.H.L. (2022), "An extended technology-organization-environment (TOE) framework for online retailing utilization in digital transformation: empirical evidence from Vietnam", *Journal of Open Innovation: Technology, Market and Complexity*, Vol. 8 No. 4, p. 200, doi: [10.3390/joitmc8040200](https://doi.org/10.3390/joitmc8040200).
- NSI (National Statistical Institute (2025), "Enterprises using artificial intelligence technologies", available at: <https://www.nsi.bg/statistical-data/312/895> (accessed 26 December 2025).
- OECD (2025), "AI adoption by small and medium-sized enterprises. OECD discussion paper for the G7", available at: https://www.oecd.org/content/dam/oecd/en/publications/reports/2025/12/ai-adoption-by-small-and-medium-sized-enterprises_9c48eae6/426399c1-en.pdf (accessed 15 December 2025).
- Oldemeyer, L., Jede, A. and Teuteberg, F. (2024), "Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges",

- Omrani, N., Rejeb, N., Maalaoui, R., Dabić, M. and Kraus, S. (2024), "Drivers of digital transformation in SMEs", *IEEE Transactions on Engineering Management*, Vol. 71, pp. 5030-5043, doi: [10.1109/TEM.2022.3215727](https://doi.org/10.1109/TEM.2022.3215727).
- Ononiwu, M.I., Onwuzulike, O.C. and Shitu, K. (2024), "The role of digital business transformation in enhancing organizational agility", *World Journal of Advanced Research and Reviews*, Vol. 23 No. 3, pp. 285-308, doi: [10.30574/wjarr.2024.23.3.2670](https://doi.org/10.30574/wjarr.2024.23.3.2670).
- Peretz-Andersson, E., Tabares, S., Mikalef, P. and Parida, V. (2024), "Artificial intelligence implementation in manufacturing SMEs: a resource orchestration approach", *International Journal of Information Management*, Vol. 77, 102781, doi: [10.1016/j.ijinfomgt.2024.102781](https://doi.org/10.1016/j.ijinfomgt.2024.102781).
- Podsakoff, P.M., MacKenzie, S.B., Lee, J.-Y. and Podsakoff, N.P. (2003), "Common method biases in behavioral research: a critical review of the literature and recommended remedies", *Journal of Applied Psychology*, Vol. 88 No. 5, pp. 879-903, doi: [10.1037/0021-9010.88.5.879](https://doi.org/10.1037/0021-9010.88.5.879).
- Proietti, S. and Magnani, R. (2025), "Assessing AI adoption and digitalization in SMEs: a framework for implementation", available at: <https://arxiv.org/pdf/2501.08184> (accessed 10 November 2025).
- Sánchez, E., Calderón, R. and Herrera, F. (2025), "Artificial intelligence adoption in SMEs: survey based on TOE–DOI framework, primary methodology and challenges", *Applied Sciences*, Vol. 15 No. 12, p. 6465, doi: [10.3390/app15126465](https://doi.org/10.3390/app15126465).
- Schönberger, M. (2023), "Artificial intelligence for small and medium-sized enterprises. Identifying key applications and challenges", *Journal of Business Management*, Vol. 21, pp. 89-112, doi: [10.32025/JBM23004](https://doi.org/10.32025/JBM23004).
- Schneider, S. and Anderie, L. (2025), "Digital infrastructure", in Schneider, S. and Anderie (Eds), *Digital Business Management*, Springer, Cham, pp. 37-47, doi: [10.1007/978-3-031-83177-5_4](https://doi.org/10.1007/978-3-031-83177-5_4).
- Schwaake, J., Peters, A., Kanbach, D.K., Kraus, S. and Jones, P. (2024), "The new normal: the status quo of AI adoption in SMEs", *Journal of Small Business Management*, Vol. 63 No. 3, pp. 1297-1331, doi: [10.1080/00472778.2024.2379999](https://doi.org/10.1080/00472778.2024.2379999).
- Shao, Q., Lin, J., Liou, J.J.H., Zhu, D. and Tzeng, G.-H. (2025), "Analysis of key factors affecting the digital transformation of small and medium-sized manufacturing enterprises in China", *Sage Open*, Vol. 15 No. 2, doi: [10.1177/21582440251336077](https://doi.org/10.1177/21582440251336077).
- Soomro, R.B., Al-Rahmi, W.M., Dahri, N.A., Almuqren, L., Al-Mogren, A.S. and Aldaijy, A.A. (2025), "SEM–ANN analysis to examine impact of artificial intelligence technologies on sustainable performance of SMEs", *Scientific Reports*, Vol. 15 No. 1, p. 5438, doi: [10.1038/s41598-025-86464-3](https://doi.org/10.1038/s41598-025-86464-3).
- Tornatzky, L.G. and Fleischer, M. (1990), *The Processes of Technological Innovation*, Lexington Books, Lexington, MA.
- Úbeda-García, M., Marco-Lajara, B., Zaragoza-Sáez, P.C. and Poveda-Pareja, E. (2025), "Artificial intelligence, knowledge and human resource management: a systematic literature review of theoretical tensions and strategic implications", *Journal of Innovation and Knowledge*, Vol. 10 No. 6, 100809, doi: [10.1016/j.jik.2025.100809](https://doi.org/10.1016/j.jik.2025.100809).
- ul Haq, F., Suki, N.M., Zaigham, N., Masood, A. and Rajput, A. (2025), "Exploring AI adoption and SME performance in resource-constrained environments: a TOE–RBV perspective with mediation and moderation effects", *Journal of Digital Economy*, doi: [10.1016/j.jdec.2025.07.002](https://doi.org/10.1016/j.jdec.2025.07.002).
- Ulrich, P. and Frank, V. (2021), "Relevance and adoption of AI technologies in German SMEs - results from survey-based research", *Procedia Computer Science*, Vol. 192, pp. 2152-2159, doi: [10.1016/j.procs.2021.08.228](https://doi.org/10.1016/j.procs.2021.08.228).

- Wang, L., Zhao, W., Wei, Z. and Xiong, Z. (2023), "Government support and business model innovation in new venture: based on knowledge-based theory and socio-cognitive theory", *Management Review*, Vol. 35 No. 2, pp. 171-180, doi: [10.14120/j.cnki.cn11-5057/f.2023.02.006](https://doi.org/10.14120/j.cnki.cn11-5057/f.2023.02.006).
- Wang, G., Mansor, Z.D. and Leong, Y.C. (2024), "Linking digital leadership and employee digital performance in SMEs in China: the chain-mediating role of high-involvement human resource management practice and employee dynamic capability", *Heliyon*, Vol. 10 No. 16, e36026, doi: [10.1016/j.heliyon.2024.e36026](https://doi.org/10.1016/j.heliyon.2024.e36026).
- Yang, D. and Shen, H. (2025), "Research on the impacts and mechanisms of digital strategy on corporate innovation investment", *Journal of Open Innovation: Technology, Market and Complexity*, Vol. 11 No. 1, 100471, doi: [10.1016/j.joitmc.2025.100471](https://doi.org/10.1016/j.joitmc.2025.100471).
- Yilmaz, C. and Hanisch-Blicharski, A. (2025), "Technological and organizational determinants of AI integration in SME Business analytics systems", doi: [10.20944/preprints202512.0567.v1](https://doi.org/10.20944/preprints202512.0567.v1).
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