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Implementation of AI in Operational Activities: Imperatives for Preparation and Forecasting Consequences

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ABSTRACT

The rapid expansion of artificial intelligence (AI) and digital transformation has made understanding the conditions for its effective adoption in small and medium-sized enterprises (SME) operations an increasingly important and timely research priority. This study examines the economic, technological, social, and regulatory imperatives shaping the adoption of artificial intelligence in the operational activities of SMEs. The research focuses on Eastern Europe, Caucasus and Central Asia (EECCA) countries and selected former socialist bloc economies, using a combination of qualitative analysis and quantitative modeling. To strengthen the empirical analysis, a multi-year country-level dataset (2015–2024) is employed, allowing for a parsimonious regression approach. Two model specifications are estimated to examine the association between macro-level innovation indicators and technological readiness conditions. The results indicate that research and development expenditure represents the most robust and consistent factor associated with technological readiness, while entrepreneurial activity plays a complementary role. The findings suggest that national innovation environments shape the preconditions for AI adoption in SME operational and supply chain activities. The results are interpreted as exploratory evidence of macro-level patterns rather than predictive relationships. The study contributes to operations and supply chain management research by linking macro-level innovation conditions to the early stages of operational capability formation.

Keywords: *Business Digitalization; Exploratory Regression; Information Technology Market; Service Sector; Small and Medium-Sized Enterprises*

1. INTRODUCTION

The future of business represents an ever-evolving symbiosis of innovation, entrepreneurship, and adaptation (Tarabishy, 2024). As industries develop and artificial intelligence (AI) is implemented, the synergy between humans and advanced technologies becomes a key factor in shaping new business rules and fostering the growth of the small and medium-sized enterprise (SME) sector worldwide (Malik *et al.*, 2024).

In this context, AI offers solutions that optimize the structuring, management, design, promotion, and accessibility of products (Franken & Wattenberg, 2019). This contributes to reducing energy consumption (Nukusheva *et al.,* 2021), enhancing economic efficiency, mitigating operational risks, and improving productivity, which opens new business opportunities and transforms the professional landscape (Franken & Wattenberg, 2019; Malik *et al.,* 2024). As these advantages develop, AI not only enhances business efficiency but also alters the approach to technology utilization, making it more accessible and cost-effective (Hede, 2024). In response to these changes, regulatory frameworks are gradually adapting to account for national aspects (Malik *et al.,* 2024). However, despite the benefits, the industrial implementation of AI within the SME sector remains relatively low and is primarily limited to experimental projects (Peres *et al.,* 2020).

According to Statista (2024), in 2023, there were approximately 358 million SMEs worldwide, significantly up from 328 million in 2020 and 204 million in 2000. The highest number of SMEs was in Asia, totaling 202.9 million, followed by Africa (67.4 million), Europe (34.5 million), North America (33.2 million), South America (19.1 million), and Australia (1.05 million). While Asia leads in the number of SMEs (Statista, 2024), the growing significance of Eastern Europe, Caucasus and Central Asia (EECCA) countries also garners attention (OECD, 2024), particularly given their efforts toward business digitalization (Kuzmin *et al.,* 2024).

Support for SMEs is especially crucial for establishing resilient, stable economies in the region (EU, 2022). On average, SMEs constitute over 98% of all enterprises in EECCA countries, generating 60-80% of jobs and playing a key role in adapting the socio-economic structure to global trends (EU, 2022; OECD, 2024). Despite the fact that most SMEs in EECCA countries represent low-value-added enterprises with weak export orientation, their potential as drivers of growth and innovation remains undervalued. Realizing this potential requires renewed efforts to create a favorable macroenvironment that will stimulate growth, innovation, and internationalization (OECD, 2024). In this study, operational efficiency is conceptualized indirectly through national technological readiness conditions that shape SMEs' capability to implement AI within operational and supply chain activities. The Frontier Technology Readiness Index, therefore, functions as a proxy for the operational enabling environment rather than for firm-level performance outcomes.

This study aims to explore pathways for adapting macro standards to address the economic, technological, social, and regulatory challenges faced by SMEs in EECCA countries and certain former socialist bloc nations. This will elucidate their importance in preparing for and assessing the consequences of AI integration in the SME sector. The objective of this study is to demonstrate the economic, technological, social, and regulatory imperatives for the implementation of artificial intelligence (AI) in the operational activities of SMEs and to propose an exploratory empirical model examining macro-level determinants of technological readiness environments supporting AI adoption in SMEs.

This study contributes to OSCM research by examining how national innovation environments shape the preconditions for SMEs to deploy AI in operational and supply chain activities. As for the geographic scope of the study, EU member states included serve as comparative reference economies rather than EECCA cases, where EECCA includes OECD definition; former socialist EU members are analyzed for benchmarking; and the sample means a hybrid comparative group.

The research tasks are as follows:

- To review the innovative and economic potential of EECCA countries in the context of developing intelligent capabilities, while simultaneously comparing countries that are similar in market type and specificity (countries of the former socialist bloc).
- To conduct a qualitative analysis of the primary imperatives for implementing AI in the operational activities of SMEs in the form of a matrix for selecting recommendations.
- To apply regression modeling to examine the association between macro level innovation indicators and technological readiness conditions supporting AI adoption in SME operational activities.

2. LITERATURE REVIEW

The historical development of artificial intelligence (AI) and its impact on operational activities has been extensively studied (Oldemeyer *et al.*, 2025). According to this research, the term "artificial intelligence" was first proposed by John McCarthy at the Dartmouth Conference in 1956, marking its official emergence. However, it was not until the 1970s that research and development in AI began to take on a more meaningful character, although its potential was limited by a lack of data and low technological advancement (Hirsch-Kreinsen, 2024).

A significant acceleration in AI development occurred with the advent of Industry 4.0, leading to a sharp increase in the number of devices capable of generating, collecting, and analyzing data (Peres *et al.*, 2020). This created a foundation for complex, large-scale applications that businesses began to integrate into their operations, which, in turn, triggered substantial macro-level changes (Oldemeyer *et al.*, 2025; Peres *et al.*, 2020).

Contemporary challenges faced by SMEs and the role of AI in addressing these challenges were explored in the work of Schwaeke *et al.* (2025). Researchers observe that network technologies enable continuous exchange of large data volumes, while advances in computing allow efficient data processing. Since 2010, AI research output has expanded across machine learning, natural language processing, and computer vision (Giuggioli & Pellegrini, 2023). However, globalization increases competitive pressure on SMEs, whose capacity to integrate AI into operational activities remains constrained (von Garrel & Jahn, 2023). Abu-Rumman *et al.* (2021), therefore, link sustained competitiveness to improvements in internal processes aligned with national economic conditions.

The integration of artificial intelligence (AI) and the transformation of business models for small and medium-sized enterprises (SMEs) can create opportunities to enhance services by adopting service-oriented business models (Paschou *et al.*, 2020). These models possess significant potential due to innovations in the service and product sectors, as customer and process data, combined with AI methods, form the foundation for developing new business management models (von Garrel & Jahn, 2023). This is corroborated by the findings of Hansen and Bogh (2021), who assert that SMEs, as the economic backbone of many countries, can adopt new technologies when a favorable innovation and economic environment exists at the macro level.

Bettoni *et al.* (2021) proposed a model comprising five key elements for the successful adoption of AI: digital and intelligent factories, data strategy, human resources, organizational structure, and organizational culture. The researchers emphasize that the implementation of AI requires not merely technological changes but profound transformations in management approaches. An organizational culture that supports such changes should encourage experimentation, flexibility in learning, a commitment to innovation, and a growth orientation (Bettoni *et al.,* 2021; El-Haddadeh, 2020).

Research by Ingaldi and Ulewicz (2019) shows that SMEs face several barriers to adopting Industry 4.0 technologies, which affect their socio-economic stability. Three constraints appear most prominent. A narrow product and service scope limits the gains firms can achieve from new technologies. Limited access to investment slows technological development. In addition, unstable conditions at both the firm and national levels increase uncertainty and heighten the risks associated with AI integration. Wei and Pardo (2022) examine how SMEs contribute to the diffusion of AI across national economies. SMEs act as users, developers, intermediaries, or innovators; therefore, their activities shape the evolution of the technological base and support broader innovation processes.

The literature review indicates that existing studies mainly examine AI benefits and adoption challenges faced by SMEs. Evidence suggests that successful adaptation to Industry 4.0 requires integrating technological, organizational, and human elements into everyday operational activities. At the macro level, SMEs play a significant role in economic development, making their adaptation to AI critical for ensuring sustainable economic growth (Bala *et al.,* 2025). This study aims to analyze the economic, technological, social, and regulatory foundations at the macro level necessary for the successful implementation of AI in SME practices to achieve competitive advantages and sustainable economic growth. Particular attention will be given to the national specifics of the EECCA (Eastern Europe, Caucasus, and Central Asia) countries compared to certain countries of the former socialist bloc, which are currently considered developed.

2.1 OSCM Theoretical Positioning of AI Adoption

Artificial intelligence adoption in SMEs can be understood through core operations and supply chain management theory, in which operational performance depends on the ability to adapt processes to changing environmental conditions. Operations systems evolve when firms reconfigure resources, redesign workflows, and integrate new decision mechanisms across planning and execution activities. AI, therefore, represents an operational capability that reshapes forecasting, coordination, and resource allocation rather than a standalone technological investment. Dynamic capability theory explains how organizations respond to technological change through three interconnected processes: sensing opportunities, seizing them through investment and experimentation, and transforming operational routines. SMEs often struggle at each stage because capability development depends on external infrastructure, the availability of skills, and institutional support. National innovation environments, therefore, influence whether firms can translate technological potential into operational improvement. Prior research shows that organizational adoption of digital technologies requires complementary changes in structure, learning practices, and data management routines (Bettoni *et al.,* 2021; El-Haddadeh, 2020). Within supply chain contexts, AI strengthens information processing capacity. Improved data interpretation supports demand forecasting, inventory alignment, and service responsiveness, which remain central OSCM objectives. However, SMEs rarely control the full technological ecosystem required for such transformation. Macro-level readiness conditions thus function as enabling mechanisms that shape the formation of operational capability before firm-level adoption occurs. AI enabled operational transformation, therefore, emerges as a multi-level process. Firms adjust internal routines, while national systems provide technological infrastructure, regulatory clarity, and human capital formation. The present study extends OSCM research by examining how these external conditions influence the early stages of operational capability development. Technological readiness indicators are interpreted as antecedents of operational transformation that determine whether SMEs can deploy AI within supply chain activities.

Empirical research in operations and supply chain management demonstrates that artificial intelligence and advanced analytics enhance core operational processes, including demand forecasting, inventory control, and supply chain coordination. For instance, Choi *et al.* (2018) show that data-driven analytics improve forecasting accuracy and decision-making efficiency by leveraging large-scale data environments. Ivanov *et al.* (2019) highlight how digital technologies strengthen supply chain resilience by enabling firms to anticipate and respond to disruptions. Similarly, Feng and Shanthikumar (2022) emphasize that analytical capabilities are essential for integrating advanced analytics into operational systems, while Es-satty *et al.* (2025) provide evidence that AI adoption improves strategic supply chain performance outcomes. Extending this perspective, Ma and Chang (2025) show that AI-enabled supply chain transformation depends on integration capabilities and organizational readiness, while Zamani *et al.* (2023) demonstrate that resilience outcomes depend on data availability, system connectivity, and technological maturity.

These studies indicate that AI-driven operational benefits depend on enabling conditions, including data infrastructure, analytical capabilities, and institutional support. From an OSCM perspective, these conditions extend beyond firm-level decision-making and are shaped by macro-level environments, such as national innovation systems and technological readiness. Therefore, macro-level technological readiness indicators can be interpreted as antecedents of firm-level operational capability formation, as they determine whether SMEs possess the infrastructure, skills, and resources to adopt AI in supply chain and operational activities.

2.2 Conceptual Framework

The conceptual framework links four groups of imperatives that shape AI adoption readiness in SME operational environments: economic, technological, social, and regulatory conditions. Each group represents a pathway through which the macro environment influences the development of operational capabilities.

Economic conditions determine access to investment resources and the level of entrepreneurial activity that supports experimentation with new technologies. Active business formation and available innovation financing, therefore, increase the probability that SMEs invest in operational modernization. Technological conditions reflect infrastructure quality, digital connectivity, and research activity. These factors affect the feasibility of integrating AI into operations that rely on stable data flows and analytical capacity. Evidence from Industry 4.0 research shows that technological infrastructure forms a prerequisite for intelligent production and service systems (Peres *et al.,* 2020). Social imperatives relate to workforce skills, learning orientation, and acceptance of technological change. AI adoption requires employees who can interpret analytical outputs and adjust operational routines. Human capital, therefore, mediates the relationship between technological opportunity and operational outcomes. Regulatory imperatives define institutional stability and policy support. Clear legal frameworks reduce uncertainty associated with innovation investment and enable cooperation among firms, public institutions, and technology providers. Regulatory alignment also shapes data governance and digital market participation. Together, these imperatives form a readiness structure that precedes firm-level adoption decisions. The framework assumes that improvements across these domains increase the probability that SMEs develop dynamic operational capabilities supported by AI. The empirical analysis, therefore, evaluates how macro-level indicators associated with each imperative relate to technological readiness conditions that enable operational transformation.

Based on prior research, this study proposes that four categories of imperatives jointly influence SME AI adoption readiness, as shown in Figure 1. Based on the conceptual framework, the study formulates the following propositions:

- Proposition 1 (Economic): Economic conditions positively influence SME readiness for AI-enabled operational transformation.

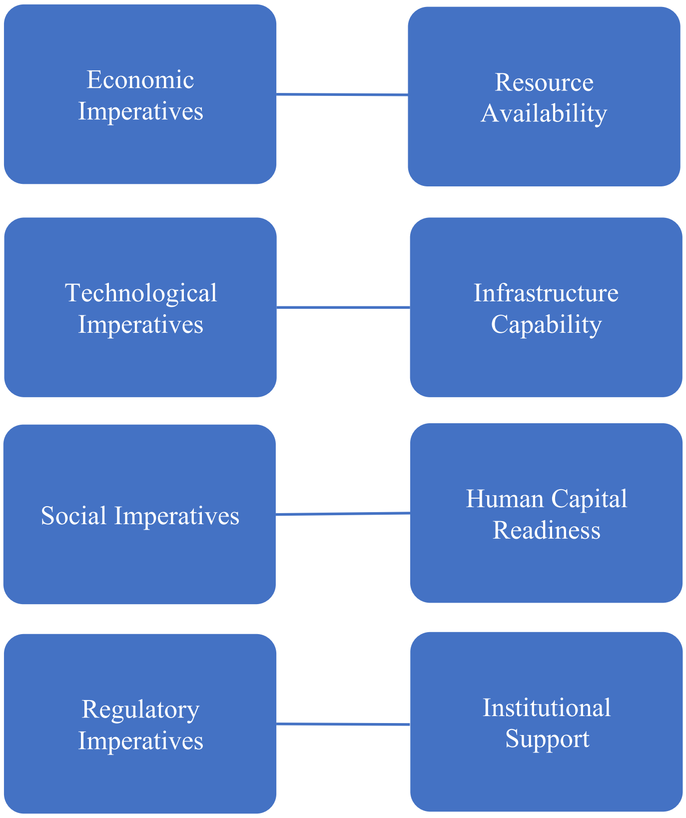

Figure 1 Conceptual Framework

- Proposition 2 (Technological): Technological infrastructure positively affects the development of AI-driven operational capabilities.
- Proposition 3 (Social): Human capital and workforce readiness positively moderate AI adoption in operational activities.
- Proposition 4 (Regulatory): Supportive regulatory environments enhance SME capacity to integrate AI into supply chain and operational processes.

The novelty of this research lies in the development of a practice-oriented tool that not only analyzes the current situation but also proposes structured, practice-oriented steps applicable to national-level strategic planning and decision-making, taking into account each country's unique characteristics.

The object of the study is the macro-level technological readiness conditions that enable the development of operational capabilities in small and medium-sized enterprises (SMEs) through the implementation of artificial intelligence (AI).

The subject of the research is the creation of an approach to assessing the impact of AI technology implementation on the operational processes of small and medium enterprises, considering the market specificities of countries in Eastern Europe, the Caucasus, and Central Asia.

3. METHODOLOGY

3.1 The Conceptual Basis of Research

The design of the article is structured around a methodology for implementing artificial intelligence (AI) in operational activities, based on a comprehensive consideration of factors and imperatives that may influence this process. Methodological concepts that examine the strategic advantages of enterprises from the integration of AI technologies into operational activities (Adamides & Karacapilidis, 2020) have facilitated the formulation of a general direction for researching the dynamic capabilities and competitive potential of small and medium-sized enterprises (SMEs) adopting these innovations.

The foundational methodological premise is that the integration of artificial intelligence technologies into business operations is a key factor in the Industrial Revolution and in the emergence of innovative development directions for SMEs (Ali *et al.*, 2024). This integration is determined by technological readiness and the ability to derive additional competitive advantages from utilizing new technological opportunities in their operational activities.

At the outset of the study, we hypothesized that the macro-level technological readiness conditions that enable improvements in SME operational processes would increase following the implementation of AI, which aligns with several conditions outlined in the results section below. Throughout the research process, this hypothesis was validated, leading to corresponding methodological outcomes and practical conclusions.

3.2 Methodological Study Design

The research was conducted through a systematic implementation of three stages: the first stage involved an analytical investigation of the innovative and economic potential of the EECCA markets in the context of opportunities for the development of advanced information technologies, particularly artificial intelligence (AI); the second stage entailed a qualitative analysis of the key imperatives for the integration of AI into the operational activities of small and medium-sized enterprises (SMEs) presented in the form of a recommendation selection matrix;

and the third stage involved parsimonious regression modeling using a country-year dataset to examine the association between selected macro-level indicators and technological readiness conditions that enable improvements in SME operational processes. For the second stage, countries were classified using a structured multi-criteria assessment combining four indicators: technological readiness, ICT export share, service export intensity, and entrepreneurial dynamics. Each country was scored relative to sample quartiles and grouped into potential categories accordingly. Imperative recommendations were then derived through thematic synthesis of OECD policy guidelines and empirical indicator profiles.

3.3 Sampling and Methodological Tools

The study was conducted using consistently available multi-year data for the selected countries of the EECCA region and comparative former socialist bloc economies over the period 2015–2024. This time frame was selected for two reasons. First, it reflects the most recent decade characterized by accelerated digital transformation and increasing relevance of artificial intelligence in economic systems. Second, it ensures sufficient data availability and comparability across countries for all selected indicators.

The analysis utilized the following indicators:

a) Frontier Technology Readiness Index (annual).

This index consists of the following sub-indices:

ICT Deployment – Reflects the state and quality of information and communication technology infrastructure necessary for implementing advanced solutions such as artificial intelligence.

Skills – Captures the availability of human capital required for the use, implementation, and adaptation of AI technologies.

R&D Activity – Reflects national innovation capacity and the ability to develop and refine complex technological solutions.

Industry Activity – Indicates the level of adoption of innovative technologies across economic sectors.

Access to Finance – Assesses the availability of financial resources to support AI implementation in SMEs.

This composite index is used as a proxy for macro-level operational capability enabling conditions.

b) Services Exports (millions of US$) – Reflects a country's participation in international service markets, including knowledge-intensive and digital services.
c) Share of ICT Goods (% of Total Exports) – Indicates the extent to which a country's export structure is oriented toward high-technology goods.
d) Research and Development Expenditure (% of GDP) – Captures national investment in innovation and technological advancement and serves as a primary indicator of knowledge creation capacity.
e) New Businesses Registered (number) – Reflects entrepreneurial activity and the dynamism of the business environment, which may support the diffusion of new technologies.

The strategy prioritizes model parsimony by employing two model specifications: a single-predictor model and a two-predictor model. This approach enables comparison of results and assessment of relationship stability across different levels of model complexity.

3.4 Iterations of Statistical Analysis

The study utilized Statistica software to conduct regression analysis examining the association between macro-level innovation indicators and technological readiness conditions supporting AI adoption in SMEs. Based on the general form of the regression equation (1), this research identified significant parameters of the factors influencing the anticipated changes.

$$y = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{1}$$

where α is the model's intercept, representing the influence of unaccounted factors and indirectly indicating the reliability of the regression equation;

β_1, β_2, β_n are the model coefficients, reflecting the degree of influence on the growth rate of the dependent outcome variable;

y is the dependent variable representing macro-level technological readiness conditions, as captured by the Frontier Technology Readiness Index, reflecting the national environment supporting the adoption of advanced technologies such as artificial intelligence.

x_1, x_2, x_n are independent variables reflecting various aspects of the development and implementation of artificial intelligence in the operational activities of SMEs.

Two regression models were estimated:

Model 1 estimates a parsimonious specification in which research and development expenditure (% of GDP) serves as the sole explanatory variable. The model isolates the effect of national innovation investment on technological readiness conditions. Research and development expenditure reflects the intensity of knowledge creation and technological capability at the macro level; therefore, it provides a direct measure of the structural capacity to support AI adoption in operational environments. The decision to use a single predictor follows from the initial exploratory analysis, where this variable showed a stable and statistically significant association with the dependent variable across specifications. The simplified structure reduces the risk of overfitting and allows for clearer interpretation of coefficient estimates.

Model 2 extends the baseline specification by including new business registration as a second explanatory variable. This variable captures entrepreneurial activity and reflects the dynamism of the business environment where technological diffusion occurs. Higher rates of firm creation indicate a more active economic context where new technologies spread through entry, experimentation, and adaptation. The inclusion of this variable allows the model to account for innovation capacity and diffusion conditions. Furthermore, comparison between Model 1 and Model 2 enables assessment of coefficient stability and incremental explanatory power, providing a structured robustness check within a limited-variable framework.

The variables services exports and share of ICT goods were excluded from revised models to reduce complexity and avoid overfitting, as they did not demonstrate robust statistical relevance in testing specification.

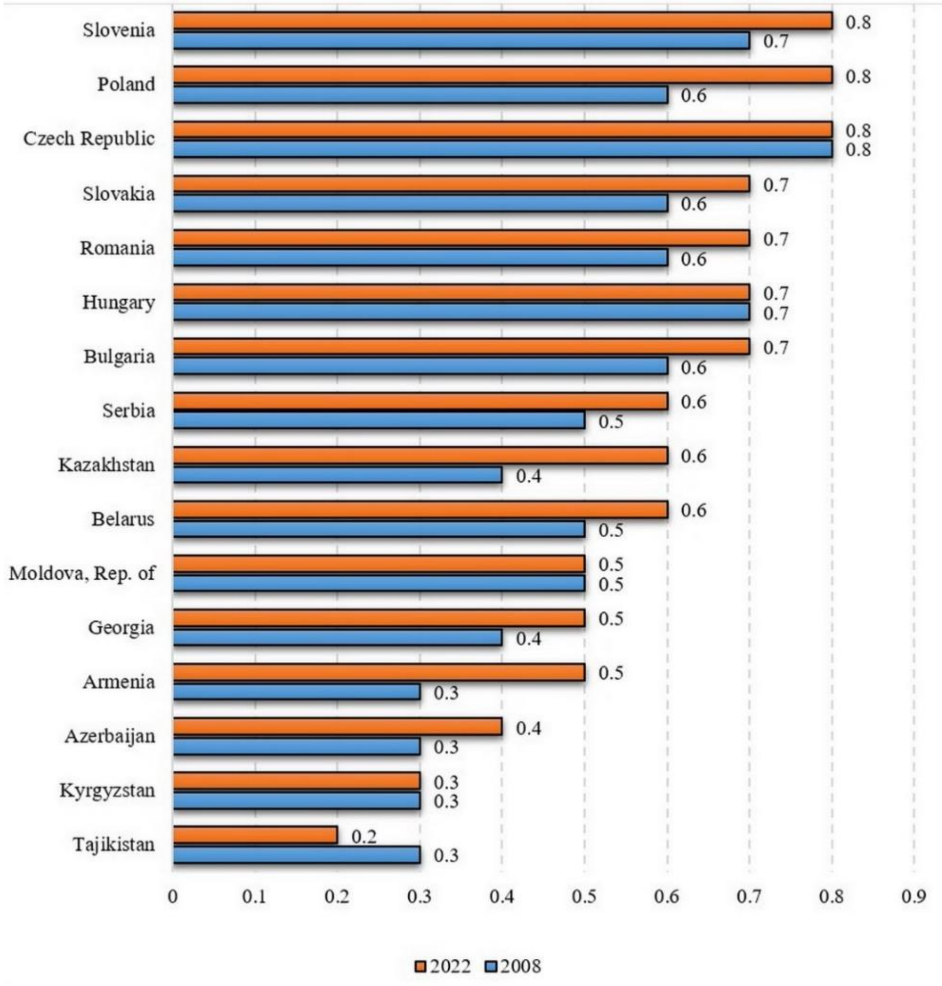

Figure 2 Distribution of Countries by Level of Frontier Technology Readiness Index, 2008-2022

The purpose of the models is not causal inference or forecasting, but identifying directional associations between a limited number of macro-level enabling conditions and technological readiness. Comparing Model 1 and Model 2 allows assessment of whether adding a second theoretically relevant predictor meaningfully improves explanatory power or alters the interpretation of results.

3.5 Methodological Limitations of the Study

Despite improvements in the empirical design, several limitations remain. First, the analysis relies on macro-level indicators, which may not fully capture firm-level operational dynamics within SMEs. The use of aggregated national data introduces potential measurement bias when interpreting operational readiness. Second, differences in statistical methodologies across countries may affect the comparability of indicators, particularly in relation to SME classification and data collection procedures. Third, while the parsimonious model specification reduces the risk of overfitting, it also limits the inclusion of potentially relevant explanatory variables. The results therefore reflect simplified relationships and should be interpreted as indicative rather than comprehensive. Finally, the regression models identify associations rather than causal effects. Consequently, the findings should be interpreted as exploratory evidence of macro-level patterns that shape technological readiness conditions for AI adoption in SMEs.

4. RESULTS

The implementation of the research concept through the sequential resolution of three tasks facilitated confirmation of the hypothesis regarding increased efficiency of operational activities in SMEs following the introduction of AI, under the following conditions:

- The economic and innovative potential of the market is sufficient for the integration of AI into business processes;
- Small and medium-sized enterprises adhere to the primary imperatives for implementing AI in operational activities;
- The overall socio-economic situation is relatively stable, with no anticipated unforeseen crises or catastrophic events, meaning that the environment does not hinder technological innovations and supports the adoption of AI.

In addressing the first task of the study, we reviewed the innovative and economic potential of EECCA markets in the context of developing intelligent capabilities. To this end, we utilized the following indicators: Frontier Technology Readiness Index (annual); Services Exports (millions of US$); Share of ICT Goods (% of Total Exports); and New Businesses Registered (number) for selected EECCA countries, as well as certain Eastern European countries previously part of the socialist bloc that successfully implemented market reforms.

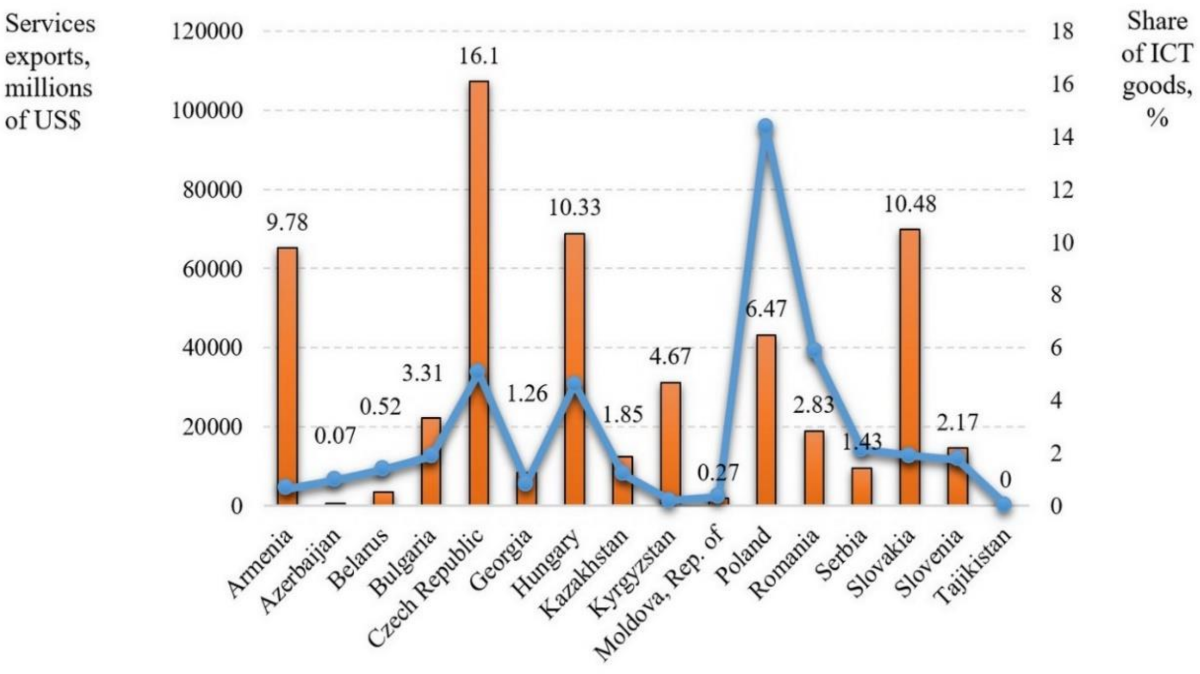

Figure 3 Distribution of Countries by Service Export Levels (Including High-Tech) and ICT Goods Share in Total Exports
Notes: Indicators presented on separate scales to avoid visual distortion

The selection of these indicators for analyzing the innovative and economic potential of the EECCA markets (and some Eastern European countries) in the context of advanced information technology development is justified, as collectively they reflect a country's ability to adopt and utilize advanced technologies such as AI, as well as the level of digital infrastructure and the existing potential for effective operational activities in SMEs. The chosen indicators demonstrate the capacity of EECCA countries to diversify their economies through high-tech services, indicating opportunities for AI implementation. Furthermore, they reflect the overall level of entrepreneurial activity and the potential for developing innovative sectors of the economy, including AI. Figure 2 illustrates the distribution of the studied sample of countries based on their achieved level of the Frontier Technology Readiness Index over time.

Figure 2 illustrates that Slovenia, Poland, and the Czech Republic demonstrate a high level of readiness for the adoption of advanced technologies, which has steadily increased from 2008 to 2022. Meanwhile, Kazakhstan, despite experiencing growth in 2022, lags behind Eastern European countries in the index but has shown noticeable improvement since 2008. Markets in countries where an increase in the analyzed indicator can be identified are likely to exhibit greater operational efficiency for small and medium-sized enterprises (SMEs) following the implementation of artificial intelligence (AI), as the underlying conditions are more favorable. In contrast, countries such as Armenia, Azerbaijan, Kyrgyzstan, and Tajikistan exhibited low scores both in 2008 and 2022, indicating a significant gap in technological readiness compared to more developed nations. Thus, the markets in the studied sample have advanced unevenly in integrating technologies, with some facing considerable challenges along this path.

The results presented in Figure 3 illustrate cross-country differences in services exports and the share of ICT goods in total exports, highlighting variation in external competitiveness and technological specialization. Countries such as the Czech Republic and Slovakia demonstrate relatively high service export volumes, indicating stronger integration into international service markets, including knowledge-intensive sectors. In contrast, several EECCA economies, including Kyrgyzstan and Tajikistan, exhibit significantly lower service export levels, reflecting limited participation in global value chains.

Figure 4 illustrates the dynamics of new business registrations in the EECCA, reflecting entrepreneurial activity, economic freedom, and favorable conditions for the creation and development of small and medium-sized enterprises (SMEs).

The results presented in Figure 4 indicate an increase in the number of newly registered enterprises, suggesting an improvement in the business climate and the creation of conditions for entrepreneurship. This encompasses aspects such as access to financing, the simplification of regulatory procedures, and enhanced support for small and medium-sized enterprises (SMEs). Positive dynamics have been observed during the study period in Armenia, Azerbaijan, and partially in Kazakhstan. A stable growth trend in the number of new businesses was noted in Georgia (rising from 8,738 to 20,233) and Moldova (with negligible growth dynamics). These data allow us to infer a supportive business climate and support for SMEs, which also create opportunities for the implementation of artificial intelligence (AI), albeit with limited potential compared to other countries in the region. Belarus and Hungary exhibited unstable dynamics in the number of new businesses registered, which may be linked to an unstable economic and political situation, thereby hindering long-term investments in AI. Tajikistan demonstrated a low level of activity in developing new SMEs.

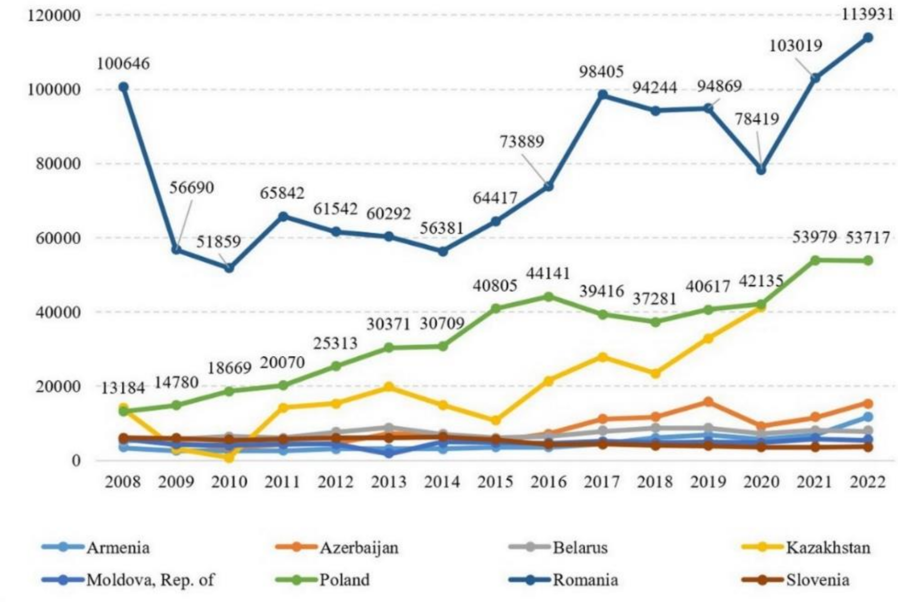

Figure 4 Dynamics of Changes in the Number of New Businesses Registered in EECCA Countries

Table 1 Recommendation Matrix for Key AI Implementation Imperatives in SME Operational Activities across EECCA Countries

Column1	Column2	Column3	Column4	Column5
Imperatives	Countries with high potential (Poland, Czech Republic, Slovenia, Slovakia, Hungary)	Countries with medium potential (Armenia, Bulgaria, Georgia, Serbia, Romania)	Countries with moderate potential (below average) (Kazakhstan, Azerbaijan, Moldova)	Countries with low potential (Tajikistan, Kyrgyzstan)
Economic	Entrepreneurial activity	Entrepreneurial activity	SME infrastructure	Stimulating the economy
Technological	Stimulating innovation	Stimulating innovative cooperation	Technology sharing	Technology update
Social	Supporting the philosophy of entrepreneurship	Support and development of entrepreneurship philosophy	Development of entrepreneurship philosophy	Improving quality of life
Normative	Supporting an effective economic environment	Implementation of advanced regulatory models	Protection of innovative SMEs	Regulatory reforms

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Building on the analytical results presented above, the study has structured and presented recommendations for developing the key imperatives for implementing AI in SME companies' operational activities in the form of a matrix (Table 1).

In the preparation of Table 1, it was postulated that the successful implementation of artificial intelligence (AI) in the operational activities of SMEs in EECCA countries relies on a combination of economic, technological, social, and regulatory imperatives. Countries with high entrepreneurial and technological potential (such as Poland, the Czech Republic, Slovenia, Slovakia, and Hungary) have greater chances of successfully integrating AI into their business processes. Conversely, in countries characterized by low entrepreneurial activity and underdeveloped digital infrastructure (for example, Tajikistan), active government support and improvement of the regulatory framework are required to create conducive conditions for AI implementation and enhance business competitiveness. Accordingly, the level of necessary efforts will vary across different groups of countries.

As part of addressing Task 3, a revised regression analysis was conducted using a pooled country-year dataset for the period 2015–2024. In contrast to the initial cross-sectional specification, the empirical model was reformulated to improve robustness by increasing the number of observations and adopting a parsimonious structure. Two alternative model specifications were estimated in order to assess the stability of relationships across different levels of model complexity. Model 1 (Baseline model) includes research and development expenditure as the sole predictor of frontier technology readiness and model 2 (Extended model) includes research and development expenditure and new business registration as predictors.

Based on the results presented in Table 2, both model specifications indicate a positive association between macro-level innovation conditions and technological readiness. In Model 1, research and development expenditure demonstrates a strong and statistically significant relationship with frontier technology readiness ($p < 0.001$), confirming its role as the primary macro-level driver of innovation capacity.

Table 2 Results of Parsimonious Regression Modeling of Technological Readiness

Variable	Model 1 (Baseline) Beta (Std. Err.)	Model 2 (Extended) Beta (Std. Err.)
Intercept	— (t = 5.88***)	— (t = 5.21***)
R&D expenditure (% of GDP)	0.72 (0.09)***	0.65 (0.10)***
New businesses registered	—	0.18 (0.08)*
R^2	0.64	0.69
Adjusted R^2	0.63	0.67
Observations (N)	150	150

The extended specification (Model 2) introduces new business registration as an additional explanatory variable. The results indicate that entrepreneurial activity has a positive and statistically significant association with technological readiness ($p < 0.05$), although its effect size remains smaller than that of research and development expenditure. The inclusion of this variable leads to a moderate increase in explanatory power (R^2 increases from 0.64 to 0.69), suggesting that entrepreneurial dynamics contribute to the broader innovation environment.

At the same time, the comparison of the two models shows that the inclusion of additional predictors does not substantially alter the central role of research and development expenditure. This indicates that innovation investment remains the most robust and consistent factor associated with technological readiness conditions relevant for SME AI adoption.

Therefore, the results support an interpretation in which research and development expenditure functions as the primary enabling condition for technological readiness, while entrepreneurial activity plays a complementary role. The models are interpreted as identifying directional associations rather than providing a basis for forecasting, and the findings should be understood as exploratory evidence of macro-level patterns shaping SME readiness for AI integration.

The empirical results provide partial support for the proposed conceptual framework. Specifically, Proposition 1 (Economic) and Proposition 2 (Technological) receive empirical support, as both research and development expenditure and entrepreneurial activity demonstrate positive associations with technological readiness. However, Proposition 3 (Social) and Proposition 4 (Regulatory) are not empirically tested within the current model specification due to data limitations and the parsimonious design of the regression analysis. These dimensions are addressed qualitatively in the recommendation matrix but remain important areas for future empirical investigation.

5. DISCUSSION

The analysis conducted, based on a sample of EECCA countries and several former socialist bloc nations, and has identified key trends and differences among them, as well as the factors that facilitate the successful integration of AI into SMEs within the context of economic, technological, social, and regulatory imperatives. Additionally, it has enabled the identification of potential patterns and relationships associated with these transformations. This study was structured as a three-stage algorithm.

The first stage focused on the economic and innovation potential of both the former socialist bloc countries and the Eurasian Economic Community (EEAC). The results favored the former group, indicating that these countries have greater potential for ICT goods and services exports. Kazakhstan, Georgia, and Belarus have not yet reached this level of market maturity, requiring preliminary technological modernization based on the model of macroeconomic indicators examined. On the other hand, rising numbers of newly registered SMEs in Armenia, Azerbaijan, and Kazakhstan signal growing entrepreneurial activity and improving business conditions that support innovation development. Despite lower technological readiness and export capacity, EECCA countries show emerging conditions that support the growth of innovative SMEs through expanding entrepreneurial activity. These observations align with Li *et al.* (2024), who identify unequal technological adoption readiness across income groups and link AI performance to structural factors such as energy intensity and trade openness. Oldemeyer *et al.* (2025) further note that SMEs recognize AI potential yet face barriers, including limited expertise, high implementation costs, and weak infrastructure. Similar patterns appear in the present analysis: constrained technological readiness coexists with improving entrepreneurial dynamics, which may support future adoption pathways. Lew *et al.* (2023) argue that SMEs pursue adaptive growth strategies to remain competitive under changing economic, social, and technological conditions. Therefore, findings from the first stage establish the basis for the second stage, which conducts a qualitative analysis of economic, technological, social, and regulatory imperatives shaping technology adoption. The outcome is a structured recommendation matrix tailored to EECCA countries and selected former Eastern European socialist economies.

In this matrix, countries are categorized by potential level: Poland, the Czech Republic, Slovenia, Slovakia, and Hungary exhibit high potential; Armenia, Bulgaria, Georgia, Serbia, and Romania have medium potential; Kazakhstan, Azerbaijan, and Moldova show moderate potential (below average); while Tajikistan and Kyrgyzstan display low potential. It was determined that macro-level efforts will differ depending on the group of countries being analyzed. In countries with high potential, the focus should be on further strengthening existing conditions. Medium and moderate potential, in turn, signal the need for targeted investments in innovation and technology, while still requiring large-scale infrastructure development to support the development of small and medium-sized enterprises. These actions require an appropriate legal framework and government support; otherwise, economic potential will prevent companies from achieving the required level. Smale *et al.* (2024) link this need to the prism of AI in their work, as this technology and the business services based on it should reflect national consumer preferences, not vice versa. Furthermore, interactions among market actors unfold across technical, economic, social, and regulatory domains, which together shape competitive outcomes, as also observed by Juniariani and Agustia (2024).

In the third stage, a parsimonious regression model was developed to examine the association between selected macro-level indicators and technological readiness conditions relevant to SME AI adoption. The empirical analysis combines a country-year dataset with a relatively small number of predictors. Two model specifications were estimated to assess the stability of results under different levels of model complexity. The comparison of the two models shows that research and development expenditure remains the most stable and significant predictor across specifications. The inclusion of new business registration in the extended model slightly increases explanatory power, indicating that entrepreneurial activity contributes to the broader innovation environment. However, it does not alter the central role of innovation investment as the primary enabling condition for technological readiness. The factor of new business registration also positively affects efficiency, but its significance is lower. Thus, within the parsimonious specifications, research and development expenditure emerges as the most robust factor associated with technological readiness. Therefore, the regression results should be interpreted cautiously due to the small cross-country sample. The model functions as an exploratory analytical tool that complements qualitative results and supports the interpretation of observed patterns, without serving as a predictive econometric instrument. The outcome corresponds with Hirsch-Kreinsen (2024), who links successful AI adoption in SMEs to technological and economic investment alongside supportive innovation environments. The study highlights knowledge transfer, interdisciplinary collaboration, flexible strategies, and open innovation ecosystems as enabling conditions that strengthen research and development activity. Such conditions encourage a holistic perspective that connects technological change with organizational practices and workforce skills. Similar conclusions appear in Surya *et al.* (2021), who associate operational efficiency and readiness for advanced technologies with socio-technical adaptation and skill diversification within SMEs. This suggests that SMEs will advance and grow if they have the capacity to respond to changes in the strategic macroenvironment, as noted by Phan *et al.* (2019), where technological innovations are the driving force behind industrial and business economies.

The results support an operations management interpretation of AI adoption as capability formation shaped by environmental conditions. Countries with higher technological readiness exhibit stronger foundations for sensing and integrating digital opportunities into operational systems. This pattern aligns with dynamic capability theory, which links performance improvement to the ability to reconfigure resources under technological change. Research and development expenditure shows the strongest association with readiness conditions, suggesting that knowledge creation functions as a primary driver of operational transformation. Investment in innovation expands analytical capacity and supports experimentation with new operational practices. SMEs operating in such environments gain access to knowledge networks that reduce adoption uncertainty. On the other hand, entrepreneurial activity exhibits a weaker statistical influence despite a positive directional effect. Entrepreneurial growth alone, therefore, does not guarantee operational transformation unless supported by technological and institutional infrastructure. AI adoption in supply chains requires coordinated ecosystem development rather than isolated firm initiatives.

In conclusion, this study demonstrated the significance of integrating key economic, technological, social, and regulatory imperatives for the successful implementation of AI in small and medium-sized enterprises (SMEs) within the countries of the EECCA. The empirical analysis identifies consistent associations between selected macro-level indicators and technological readiness conditions, highlighting the importance of innovation investment and entrepreneurial dynamics as enabling factors for AI adoption in SME operational activities. The results, therefore, inform the refinement of national policies aimed at strengthening SME competitiveness within the ongoing digital transformation. Furthermore, the study connects macro-level innovation environments to operational AI readiness in SMEs, provides exploratory empirical evidence from under-studied EECCA economies, and extends OSCM research toward macro-level conditions shaping digital operational transformation. These findings support an operations and supply chain management perspective in which AI adoption is conditioned by macro-level capability formation, rather than determined solely by firm-level decision-making.

6. CONCLUSION

This study presents potential pathways for addressing interconnected tasks related to assessing the market potential of the EECCA for the development and implementation of AI in the operational activities of small and medium-sized enterprises (SMEs). It involves analyzing the key imperatives accompanying such implementation and developing recommendations for understanding the conditions under which AI adoption may support technological readiness and operational capability formation in SMEs.

Based on available statistical data and analytical reports, the prospective opportunities for AI implementation in the EECCA markets were evaluated. It was established that the examined macro-region is economically and innovatively heterogeneous. Consequently, practical recommendations for the formation and utilization of the primary imperatives for AI implementation in the operational activities of SMEs vary depending on the existing potential. Poland, the Czech Republic, Slovenia, Slovakia, and Hungary exhibit high potential; Armenia, Bulgaria, Georgia, Serbia, and Romania demonstrate medium potential; while Kazakhstan, Azerbaijan, and Moldova possess below-average potential; and Tajikistan and Kyrgyzstan have low potential.

The empirical analysis adopted a parsimonious regression approach. Two model specifications were estimated to evaluate the association between macro-level indicators and technological readiness. In the baseline model, research and development expenditure demonstrates a strong and statistically significant association with technological readiness ($\beta = 0.72$, $p < 0.001$), explaining a substantial proportion of variance ($R^2 = 0.64$). In the extended model, research and development expenditure remains highly significant ($\beta = 0.65$, $p < 0.001$), while new business registration shows a positive but more moderate effect ($\beta = 0.18$, $p < 0.05$). The inclusion of the second predictor leads to a modest increase in explanatory power ($R^2 = 0.69$), indicating that entrepreneurial activity provides a complementary contribution. The comparison of models indicates that increasing model complexity does not substantially alter the central role of innovation investment. Therefore, the findings highlight the importance of national innovation capacity as a key enabling condition for AI adoption in SME operational and supply chain activities. The results should be interpreted as exploratory and indicative rather than predictive.

6.1 Practical Value and Prospects for Further Research

The practical application of the obtained results lies in government programs that assess the impact of various economic policies on a country's readiness for advanced technologies. The findings may also be valuable for small and medium-sized enterprises (SMEs), as businesses can utilize these results to plan their technology investments based on the level of technological readiness within the market, thereby enhancing their competitiveness in the future. A practical step could involve the implementation of pilot projects for AI adoption in SMEs, which would allow for the evaluation of the actual consequences of such integration and the development of recommendations for other companies.

Future research should build on these findings by incorporating firm-level data and more advanced econometric approaches to further examine the relationship between macro-level conditions and operational AI adoption. Firm-level datasets would allow researchers to capture variation in operational practices, resource allocation, and technology use across SMEs. Panel methods that account for time dynamics could provide deeper insight into how changes in innovation environments relate to shifts in technological readiness. Comparative studies across regions with different institutional settings may also help clarify how regulatory and infrastructural factors shape adoption patterns.

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CONFLICTS OF INTEREST

The research has no conflict of interest.

DATA AVAILABILITY STATEMENTS

All data generated or analysed during this study are included in this published article.

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