

ARTIFICIAL INTELLIGENCE AS A STRATEGIC TOOL FOR SME GROWTH: FROM PROCESS AUTOMATION TO KNOWLEDGE INTELLIGENCE

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Abstract: The foundation of the majority of national economies, small and medium-sized businesses (SMEs), is severely lacking in knowledge of strategic management and digitization. The strategic and social role of artificial intelligence (AI) in supporting the expansion of SMEs is examined in this article, which moves away from routine process automation and toward higher-order “knowledge intelligence.” This paper proposes a conceptual and empirical model for how AI adoption affects organizational capacities, decision-making process efficiency, and customer value creation. It is based on strategic management and innovation diffusion theories. The study used a mixed-methods approach, and observations from 20 SMEs operating in various technology-intensive industries were complemented by reports analyzed by operations managers and founders. The results show that whereas complementing AI practices are more focused on strategic learning, capability building, and data-driven innovation, early applications of AI are focused on operational efficiency (e.g., predictive analytics, automated workflow, and customer interfaces). The results show that the main factors facilitating AI's disruptive effects are management readiness, data maturity, and entrepreneurial attitude. To help SMEs transition from automation-based efficiencies to lasting competitive advantage through knowledge-intelligent systems, the paper concludes with a strategic roadmap.

Keywords: *strategic management and learning, knowledge intelligence, various technology-intensive industries, operational efficiency, small and medium-sized businesses.*

Field: Social sciences

1. INTRODUCTION

Small and medium-sized enterprises (SMEs) emerged as major sources of innovation, job creation, and economic development, especially for technology-intensive practices (Gunasekaran et al., 2011; Kraus et al., 2021). Furthermore, they were inherently structurally constrained compared to large firms, including limited financial and human capital, a lack of skills, and diminished bargaining power in the global value chain (Li, 2011). Digital technologies, and, increasingly, AI, were seen in this light—as both an opportunity and a risk (Haiderzai et al., 2025; Dakić et al., 2024, June). AI brought cost savings, enhanced decision-making, and value creation potential for SMEs, but small businesses still found difficulties in converting this opportunity into scalable and deployable solutions (Davenport & Ronanki, 2018; Vial, 2019).

Artificial intelligence (AI) is a mix of technologies that allow machines to perform some cognitive capabilities, including perception, prediction, pattern recognition, and decision-making, required by human intelligence (Iansiti & Lakhani, 2020). In reality, SME AI solutions included everything from simple predictive systems (demand forecasting, churn prediction, anomaly detection) to sophisticated diagnostic, recommendation, and generative services in various industries, such as autonomous vehicles (Ali et al., 2024; Dakic et al., 2024, October), and yet uptake remained essentially aligned with goals that focused on efficiency (Davenport & Ronanki, 2018; Ransbotham et al., 2021). From the strategic perspective, that begs the question of when AI transitioned itself from being an operational tool to a source of knowledge-based competitive advantage. In the context of the digital economy, the roles played by data, algorithms, and digital tools could be realized, as long as they are integrated into the organizational way of working, as well as leadership, culture, and learning habits (McAfee & Brynjolfsson, 2012; Felin et al., 2023). These AI-related capabilities posed particularly challenging challenges on the part of SMEs, as they had few IT frameworks and resources available to manage all aspects (Khin & Ho, 2019; Kraus et al., 2021).

Previous literature on digital transformation and AI adoption indicated that technology alone could not determine outcomes; for example, management readiness, employees' skills and beliefs, and a culture that was amenable to experimentation also mattered (Sousa & Rocha, 2019; Vial, 2019). Earlier studies indicated that SMEs generally took this stepwise path, beginning with low-level, efficiency-centric-style pilots, and then moving, in some cases, to more advanced, digital, or AI-driven initiatives in products, services, and business processes (European Commission, 2020; Sjödin et al., 2018). This trajectory can be expressed as an S-curve of maturity in digital and AI, with gradual gains early, accelerated

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enhancements as data and capabilities are acquired, and saturation at a point (Sjodin et al., 2018). In this environment, the current research explored three enablers of AI adoption in SMEs: management readiness, data maturity, and entrepreneurial attitude (Maksimović, Vlašković, & Damjanović, 2025).

Management readiness captured leadership perceptions about the strategic possibilities of AI and the drive to connect AI projects to the organizational objectives (Davenport & Ronanki, 2018; Sousa & Rocha, 2019). Data maturity was indicated by the quality, integration, and availability of the data infrastructure needed to train and deploy AI models (McAfee & Brynjolfsson, 2012). Entrepreneurial attitude was described as the willingness to take risks, experiment, innovate, and explore new business models beyond narrow efficiency optimization (Kraus et al., 2021; Zeng et al., 2021). Although growing interest in AI and SMEs is evident, much of the literature still focuses on large organizations or even treats small and medium enterprises as a single group. Thus, it offered little in the way of insights into how different SME profiles—those characterized by management readiness, data maturity, and entrepreneurial attitude—were associated with different phases of AI adoption and when it transitioned from process automation to knowledge-intensive, strategic AI (European Commission, 2020; Ransbotham et al., 2021). This study sought to address that gap by exploring AI adoption in a sample of 20 technology-intensive SMEs that had successfully implemented at least one of these AI solutions (Todosijević, Dakić, Heričko, Kljajić, & Todorović, 2025). It separated into an early stage, when AI was employed primarily for operational activities (e.g., predictive maintenance, demand forecasting, and route optimization), and a complementary stage, when AI supported strategic decision-making, knowledge-intensive service provision, and customer-driven value innovation (e.g., diagnostic decision support, personalized learning, climate optimization, and contract intelligence).

Data maturity, entrepreneurial attitude, and management readiness for each SME were assessed through staged profile analysis. We generated tables and figures summarizing adoption stage distributions, enabler profiles, industry coverage, and a conceptual S-curve of AI maturity across the 20 cases. In doing so, the paper empirically presented a three-phase view of AI maturity for SMEs (Automation, Data Intelligence, and Knowledge Intelligence), which aligns them with the innovation diffusion and digital maturity models but is unique for AI-enabled SMEs (Sjodin et al., 2018). It demonstrated how the management readiness, maturity of data, and entrepreneurial attitude also increased systematically among SMEs that were able to perform the knowledge-rich, complementary use of AI, and that management had a roadmap to go from isolated efficiency pilots to the knowledge-based AI capability in an isolated environment. Apart from technical and data skills, the research underscored the significance of managerial skills in the exploitation of AI value. Earlier works speculated that open innovation might help develop these skills of AI-rooted systems by enabling management learning beyond organizational environments and ecosystems (Papić, Gutić, Pantelić, & Petrović, 2023). The high importance of management readiness of complementary adopters was interpreted as an indication that managerial capabilities had to evolve with the maturity of AI, and open innovation channels—such as collaboration with external AI vendors, startups, universities, and customers—could provide this process with facilitation (Papić et al., 2023). In accordance with the mentioned information, the article is organized in the following way and contains the sections Introduction, Materials and Methods, Results, Discussion, and Conclusion.

2. MATERIALS AND METHODS

This study used a mixed-methods approach, examining secondary quantitative analysis and qualitative case studies that discuss AI adoption in SMEs. The adoption of AI in SMEs and whether and under what circumstances AI helps the transition from automation to knowledge intelligence. The methodology incorporates quantitative examination of the primary organizational enablers to AI adoption and cross-case, qualitative analysis of AI use cases, perceived value, and organizational change. Strategic management, the resource-based view (RBV), innovation diffusion theory, and the three enabling factors—management preparedness, data maturity, and entrepreneurial attitude—form the foundation of this study.

2.1 Sample and Collection of the Data

The empirical material comprises 20 SMEs in technology-intensive sectors (e.g., manufacturing, healthcare, fintech, logistics, creative industries, legal tech, and agtech). The following conditions were applied to all firms: They meet European Commission SME standards (number of employees and turnover). They are set in an area where digital and AI solutions are possible and relevant. They have rolled out at least one AI solution beyond just automation of the office (e.g., predictive analytics, anomaly detection, recommendation systems, generative design, and decision support). Data were collected in two primary manners: fully structured reports and analyses performed by operations managers and/or founders, which included company, industry, and AI use case descriptions. Self-reported scores (1-5 Likert

scale) on management readiness, data maturity, and entrepreneurial attitude. Benefits and challenges in terms of perceived aspects of AI adoption. Evidence was collected in-text and by secondary sources, i.e., internal reports, project descriptions, or publicly available information provided for reference. Combined, this enabled triangulation of data concerning the manner in which AI is put into practice, what is interpreted as its benefits, and how the organizational context underpins or inhibits the application of AI.

2.2 Measures and Operationalization

Three fundamental enablers were operationalized as follows: Management Readiness—perceived strategic understanding of AI, leadership focus, sponsorship support for AI initiatives, and willingness to embrace changes in ways of working. On a scale ranging from 1 to 5 in terms of readiness (1 is very low, 5 is very high). Data Maturity—quality, integration, and availability of data, implementation of basic data governance practices, and availability of data infrastructure that may support AI. Approximated on a 1–5 scale (1 = very low data maturity, 5 = very high data maturity). Entrepreneurial Attitude—openness to experimentation, taking chances and risks, and seeking out new business opportunities in AI-enabled business models or services. Assessed on a one-to-five scale (1 = very low entrepreneurial attitude, 5 = very high). The main AI application was classified into two main categories for each SME: Operational Efficiency (for example, predictive maintenance, demand forecasting, route optimization, automated workflow, and churn prediction) or Strategic Knowledge Intelligence (e.g., diagnostic decision support, personalized learning, anomaly detection for cyber risk, generative design, contract analysis, and climate optimization). Depending on the character of the use case, as well as the use of AI in the organization, each SME had been categorized into one of the two AI adoption stages: early—AI that is mainly used for operational efficiency and small increments in processes. Complementary—AI in strategic learning, decision-making, capabilities improvement, and customer value innovation.

Data analysis involved three stages: Step 1: Descriptive and comparative analysis. The descriptive statistics were calculated for the three enablers (management readiness, data maturity, and entrepreneurial attitude). The SMEs were ranked by AI adoption stage: early vs. complementary, with the mean score for each enabler computed. This enabled an intuitive exploration of how enabler profiles cluster within stages and across stages and therefore across different functionalities. Step 2: Conceptual and cross-case synthesis. Qualitative descriptions of the AI use cases, perceived benefits, and organizational changes were presented using a cross-case comparison design. Main categories of AI benefits were then coded as follows: cost reduction and efficiency, operational speed and reliability, decision accuracy and risk reduction, innovation capability, and customer value creation. We then mapped these codes onto a three-phase conceptual model of AI maturity in SMEs: Step 3: Automation—AI powers basic efficiency and process automation. Data Intelligence—AI and analytics help with data-informed decision-making. Knowledge Intelligence—AI is entrenched in core organizational knowledge and learning activities. To indicate these stages, a conceptual S-curve of AI maturity (Figure 4) was sketched to elucidate these phases and to link the empirical patterns to emerging theories of innovation diffusion and digital maturity.

2.3 Ethical Implications

Due to the exploratory and practical approach, all participating SMEs were treated with strict confidentiality. Company names referred to in the tables and figures are pseudonyms (for example, AlphaTech Manufacturing, MedInsight, and SecureSight) to safeguard privacy but also to convey the context of the particular sector. No sensitive financial data were collected, and all assessments are provided in an aggregated form or are anonymized.

2.4 Limitations of the Methodology

The selected design is exploratory and illustrative instead of being statistically representative. The sample of 20 SMEs is small, which makes it biased in favor of technology-intensive sectors and businesses that have employed one or more AI solutions already. Accordingly, the results are not intended for general statistical interpretation on a large scale but rather to provide theoretical clarity and the design of a strategic roadmap for further empirical research to be undertaken about AI maturity in SMEs.

3. RESULTS

The empirical analysis of 20 technology-intensive SMEs contributes new insight into the practices through which AI is currently adopted, with some of the organizational profiles defining varied stages of AI adoption. We have found the following companies: AlphaTech, NeuroRetail, MedInsight, AgroVision, CleanEnergySolutions, FinWise, EduLearn, LogiFlow, SecureSight, AutoSense, SmartBuild, FoodChainAI, FashionFit, HotelEase, GreenGrow, LegalAide, ArtVision, HealthTrack, MarketPulse, and OceanWatch. Major enablers are driving the change from efficiency-oriented to knowledge-intelligent AI deployment. The findings are provided in the sequence that corresponds to the succeeding figure and tables.

3.1 The Stages of AI Adoption and the Sample Overview

The sample included 20 SMEs from various industries that had implemented at least one AI solution. From 20 SMEs, 13 (65%) were placed in the early stage, and 7 (35%) in the complementary stage. Early adopters used AI primarily to improve operational efficiency in areas such as predictive maintenance, dynamic pricing, route optimization, inventory optimization, and churn prediction. Complementary adopters used AI in roles that required more knowledge (for example, support for diagnostic decision-making, personalized learning, cybersecurity anomaly detection, generative design, contract intelligence, and climate optimization). The SMEs were situated across 20 technology-intensive industries such as manufacturing, healthcare, fintech, logistics, education, cybersecurity, fashion, hospitality, agtech, legal tech, creative industries, marketing, and maritime. The distribution of industries illustrates this cross-sector impact for AI; each industry was represented by at least one case (Figure 1).

3.2 Enablement profiling of stage of adoption

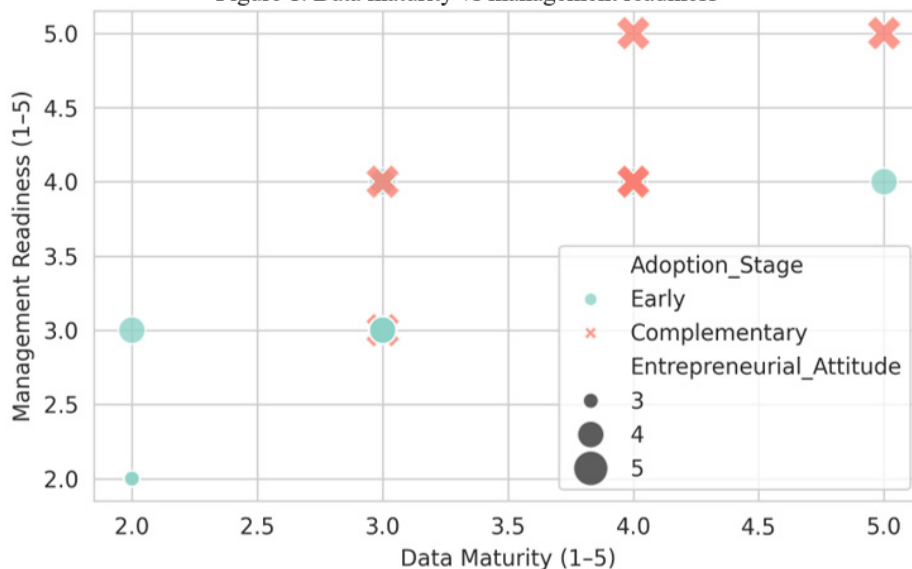
Three enablers were rated on a 5-point scale for each SME: management readiness, data maturity, and entrepreneurial attitude. Our findings show the mean value of each of these enablers by stage of adoption, where complementary adopters scored significantly higher on all three enablers compared to early adopters on average: Management readiness shows that early: mean score ≈ 3.08 . Complementary: mean score ≈ 4.14 . Data maturity. Early: mean score ≈ 3.00 . Complementary: mean score ≈ 3.86 . Entrepreneurial attitude. Early: mean score ≈ 3.85 . Complementary: mean score ≈ 4.86 . Differences between stages were positive and meaningful for each enabler. The gaps in management readiness and entrepreneurial attitude were most obvious and also more significant with the transition to the Complementary stage in that data maturity increased significantly.

3.3 Data maturity and management preparation

The data maturity and management readiness relationship was analyzed with the help of a scatter plot (Figure 1). On the x-axis, maturity of the data was plotted, and on the y-axis, management readiness; marker size was the level of entrepreneurial attitude, and colors and shapes indicated the stage of AI adoption. A positive relationship between maturity of data and management readiness was indicated with a scatter plot. SMEs with higher data maturity were also to report more management readiness. Complementary adopter firms were predominantly in the upper-right of the plot, being high in data maturity coupled with high management adoption readiness and usually larger marker sizes (higher entrepreneurial attitude). Early adopters were clustering relatively near the center and lower left side, suggesting a relatively low degree of both enabler presences.

Figure 1. Data maturity vs management readiness

Figure 1. Data maturity vs management readiness



Source: author's contribution.

4. DISCUSSION

Results of the 20 SME case studies revealed new perspectives with respect to the degree to which AI has been adopted in technology-intensive SMEs and when it has moved on to a knowledge-based competitive advantage as a way of transforming from an operational efficiency tool. This section introduces the major empirical trends while considering the theoretical background based on strategic management, the resource-based view (RBV), and innovation diffusion theory. We managed to cover that most SMEs are in the early stage, deploying AI primarily on operational tasks like predictive maintenance, pricing, routing, inventory optimization, and churn prediction. Which aligns with the existing literature indicating that AI adoption starts with routine, structured processes (Davenport & Ronanki, 2018; Ransbotham et al., 2021).

A smaller number of Complementary Adopters used AI in knowledge-intensive domains—diagnostic support, personalized learning, anomaly detection, generative design, contract analysis, and climate optimization—resulting in improved decision accuracy, service innovation, and customer value. This is consistent with RBV arguments that AI becomes strategic when embedded within organizational capabilities (Felin et al., 2023). Perceived benefits emerged in a phased manner. Automation—efficiency, data intelligence—accuracy and customer value, and knowledge intelligence—innovation and strategic learning, enabling the incremental processes of digital transformation (Vial, 2019; Sjödin et al., 2018). AI maturity was closely related with three enablers (management readiness, data maturity, and entrepreneurial attitude). Complementary adopters ranked higher in all three dimensions consistently. They had leaders who cared about strategic AI, were better equipped to work with data systems to better leverage them, and had more entrepreneurial cultures in place—supporting the influence of leadership, data infrastructure, and digital entrepreneurialism on successful transformation (Sousa & Rocha, 2019; McAfee & Brynjolfsson, 2012; Kraus et al., 2021). Clustering showed that these enablers intersected to create a mutually reinforcing capability bundle facilitating strategic, knowledge-intensive AI applications (Corres, 2017), consistent with RBV and dynamic capabilities theory.

4.1 Limitations and Further Research

The small tech-focused cohort (n = 20) restricts generalization, and managers' self-assessments may be bias-inducing. Bigger and more representative samples, long-term studies of AI maturity development, objective measures of performance, and an analysis of regulatory and ecosystem factors driving the transition from automation to knowledge intelligence will all be welcome in future research.

5. CONCLUSION

In conclusion, the results demonstrated that AI's contributions to SMEs went from a purely operational efficiency-driven path to a knowledge-intelligent, strategic resource role, but only for enterprises that built managerial readiness, data maturity, and an entrepreneurial mindset. This paper examined the strategic role of AI in SMEs, ranging from automation to advanced knowledge intelligence in terms of capabilities, decision support, and customer value. Using 20 technology-oriented SMEs, we discovered two adoption stages (early and complementary) influenced by managerial preparation, data maturity, and entrepreneurial mentality. The majority of SMEs continue to employ AI as an efficiency tool, but more advanced businesses are deploying AI as a knowledge enabler for learning, competence development, and innovation.

We can conclude that complementary adopters were consistently more leader-ready and/or had better data systems and/or were more entrepreneurial—explaining why some SMEs advance beyond automation and others continue to seek efficiency. Here, we suggest a three-phase AI maturity model for SMEs. Phase 1 – Automation: Limited-scope, siloed projects; rudimentary data; AI is understood to be the efficiency instrument. Phase 2 – Data Intelligence: Improved data quality and integration; AI to drive decisions, customer value, and service innovation. Phase 3 – Knowledge Intelligence: AI embedded in learning and strategy; firms build capabilities for continuous data-driven improvement, innovative activities, and unique value creation.

Future research should have a more strategic roadmap for SMEs that covers setting up reliable data platforms, improving data quality, basic governance, and setting up AI use cases to help the business grow. Building AI-ready leadership and culture—educating managers, getting projects working with KPIs, and supporting experimentation. With the end goal to scale AI—embed successful pilots, develop internal or hybrid abilities, and have AI used toward decision support and innovation.

REFERENCES

- Ali, T. E., Ali, F. I., Dakić, P., & Zoltan, A. D. (2024, December). Trends, prospects, challenges, and security in the healthcare internet of things. *Computing*, 107. doi:10.1007/s00607-024-01352-4.
- Davenport, T. H., & Ronanki, R. (2018). Artificial intelligence for the real world. *Harvard Business Review*, 96(1), 108–116.
- Dakić, P., Stupavský, I., & Todorović, V. (2024, June). The Effects of Global Market Changes on Automotive Manufacturing and Embedded Software. *Sustainability*, 16, 4926. doi:10.3390/su16124926
- Dakic, P., Zivkovic, M., Jovanovic, L., Bacanin, N., Antonijevic, M., Kaljevic, J., & Simic, V. (2024, October). Intrusion detection using metaheuristic optimization within IoT/IIoT systems and software of autonomous vehicles. *Scientific Reports*, 14. doi:10.1038/s41598-024-73932-5
- European Commission. (2020). SME strategy for a sustainable and digital Europe. European Commission.
- Felin, T., Zenger, T. R., & Lewin, P. (2023). The theory of the firm and artificial intelligence. *Strategic Management Journal*, 44(S1), 42–68.
- Gunasekaran, A., Rai, B. K., & Griffin, M. (2011). Resilience and competitiveness of small and medium-sized enterprises: An empirical research. *International Journal of Production Research*, 49 (18), 5489–5509.
- Haiderzai, M. D., Dakić, P., Stupavský, I., Aleksić, M., & Todorović, V. (2025, January). Pattern Shared Vision Refinement for Enhancing Collaboration and Decision-Making in Government Software Projects. *Electronics*, 14, 334. doi:10.3390/electronics14020334
- Iansiti, M., & Lakhani, K. R. (2020). *Competing in the age of AI: Strategy and leadership when algorithms and networks run the world*. Harvard Business Review Press.
- Khin, S., & Ho, T. C. (2019). Digital technology, digital capability and organizational performance: A mediating role of digital innovation. *International Journal of Innovation Science*, 11(2), 177–195.
- Kraus, S., Palmer, C., Kailer, N., Kallinger, F. L., & Spitzer, J. (2021). Digital entrepreneurship: A research agenda on new business models for the twenty-first century. *International Journal of Entrepreneurial Behavior & Research*, 27(2), 336–361.
- Li, L. (2011). Assessing the influence of organizational culture on supply chain integration and performance: A SEM approach. *Management Research Review*, 34(5), 325–346.
- McAfee, A., & Brynjolfsson, E. (2012). Big data: The management revolution. *Harvard Business Review*, 90(10), 60–68.
- Maksimović, S., Vlašković, V., & Damjanović, A. (2025, August). LEADERSHIP FRAMEWORKS AMIDST CRISIS-INDUCED EVENTS. *SCIENCE International Journal*, 3, 65–73. doi:10.35120/
- Papić, T., Gutić, B., Pantelić, N., Petrović, N. (2025). The Role of Open Innovation in Enhancing Managerial. Paper presented at Sinteza 2025 - International Scientific Conference on Information Technology, Computer Science, and Data Science. doi:10.15308/Sinteza-2025-396-401
- Ransbotham, S., Khodabandeh, S., Kiron, D., LaFountain, B., & Chung, M. (2021). The cultural benefits of artificial intelligence in the enterprise. MIT Sloan Management Review & Boston Consulting Group.
- Sousa, M. J., & Rocha, Á. (2019). Leadership styles and skills developed through game-based learning. *Journal of Business Research*, 94, 360–366.
- Sjödin, D. R., Parida, V., & Kohtamäki, M. (2018). Digitalization and servitization: A systematic review and research agenda. *Industrial Marketing Management*, 83, 302–317.
- Vial, G. (2019). Understanding digital transformation: A review and a research agenda. *The Journal of Strategic Information Systems*, 28(2), 118–144.
- Todosijević, A., Dakić, P., Heričko, T., Kljajić, Ž., & Todorović, V. (2025, September). Crime Pattern Detection Utilizing Power BI Visualizations on the Microsoft Fabric Data Platform With the Public data.police.uk Dataset. 2025 15th International Conference on Advanced Computer Information Technologies (ACIT) (pp. 593–598). IEEE. doi:10.1109/ait65614.2025.11185634
- Zeng, J., Khan, Z., & De Silva, M. (2021). The emergence of multi-sided platform MNEs: Internalization theory and networks. *International Business Review*, 30(2), 101786.