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Digitalization, Artificial Intelligence and Strategic Decision-Making for Sustainable Performance in Manufacturing Firms

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ABSTRACT:
Recent research has emphasized the importance of sustainable performance management as organizations face economic uncertainty, digital transformation, and growing pressure to strengthen long-term resilience. In manufacturing sectors, data-supported strategic decision-making has become a key factor of economic sustainability.
This study examines how manufacturing firms manage strategic performance in the context of digitalization and artificial intelligence (AI), and how these practices support sustainable decision-making in real organizational settings.
The research adopts a sequential mixed-methods approach. It builds on an exploratory survey conducted among firms operating in the Czech Republic and is complemented by a qualitative phase based on semi-structured interviews with managers from engineering and manufacturing companies. The qualitative inquiry avoids predefined managerial frameworks in order to capture how strategic performance and decision-making practices are enacted in practice.
Initial findings indicate a gap between formal managerial structures and actual decision-making processes. While firms increasingly rely on performance indicators and digital tools, strategic decisions remain shaped by managerial judgment and organizational context.
The study contributes to sustainability research by showing how AI-supported decision-making can strengthen economic resilience in manufacturing firms.

Keywords: Artificial Intelligence; Strategic Decision-Making; Manufacturing SMEs; Barriers; Digitalization; Economic Sustainability

1. Introduction

The rapid development of digital technologies and artificial intelligence (AI) is significantly transforming how organizations process information, manage performance, and make strategic decisions. AI technologies increasingly enable firms to analyze large volumes of data, improve forecasting accuracy, automate analytical processes, and support managerial decision-making in dynamic and uncertain environments (Dwivedi et al., 2021; Jorzik et al., 2024). As a result, AI is becoming an important component of organizational competitiveness and digital transformation, particularly in industries exposed to strong efficiency and performance pressures.
These developments are especially relevant in manufacturing SMEs, where strategic decision-making depends on the ability to coordinate operational efficiency, long-term planning, and organizational adaptability. AI technologies offer substantial potential for supporting data-driven decision-making, improving performance monitoring, and

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strengthening organizational responsiveness (Hong et al., 2026; Huang et al., 2025). At the same time, manufacturing SMEs often operate with limited analytical capacity, constrained resources, and less formalized management systems, which may complicate the effective integration of AI into strategic decision-making processes (OECD, 2021; Tawil et al., 2024).

Although AI adoption has increased considerably in recent years, existing research suggests that the implementation of AI technologies does not automatically lead to their meaningful integration into strategic management. Empirical studies indicate that firms frequently use AI in fragmented and function-specific ways, particularly in administration, marketing, financial forecasting, or operational optimization, while systematic integration into broader strategic decision-making processes remains limited (Aiudi et al., 2025; Pujari et al., 2024). This distinction between AI adoption and AI integration appears particularly important in SMEs, where decision-making processes are often embedded in everyday managerial practice rather than structured through formalized systems and procedures (Tawil et al., 2024).

Current literature further suggests that this gap between technological adoption and strategic integration is shaped by organizational and managerial factors rather than technology alone. Research highlights barriers such as limited digital maturity, lack of expertise, implementation complexity, insufficient data quality, and uncertainty regarding the strategic value of AI (Badghish & Soomro, 2024; Kittipanya-ngam et al., 2025; Solaimani & Swaak, 2023). At the same time, several studies emphasize that AI should be understood primarily as a tool augmenting managerial judgment rather than replacing human decision-making (Boy Barreto et al., 2024; Štrukelj & Dankova, 2025). Consequently, the effectiveness of AI-supported decision-making depends not only on technological capabilities, but also on how managers interpret, trust, and incorporate AI-generated insights into strategic practice.

Against this background, the present study focuses on the integration of AI into strategic decision-making in manufacturing SMEs, with particular attention to the barriers that hinder this integration. The paper examines how AI is utilized in managerial practice and explores the relationship between formal digital systems and actual decision-making processes within organizations. By focusing on real organizational contexts, the study contributes to the growing discussion on AI-enabled strategic management and provides empirical insight into why AI integration in manufacturing SMEs often remains partial, fragmented, and highly dependent on managerial and organizational conditions.

Based on this objective, the study addresses the following research question:

How is artificial intelligence integrated into strategic decision-making in manufacturing SMEs, and what barriers hinder this integration?

2. Theoretical Background

Research on AI integration in organizations has evolved from technology-centric perspectives toward frameworks that recognize the interdependence of technological, organizational, and contextual factors. The Technology-Organization-Environment (TOE) framework offers a comprehensive lens for understanding AI adoption by identifying three critical dimensions: technological readiness (infrastructure, compatibility,

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complexity), organizational factors (managerial support, resources, culture), and environmental pressures (competitive dynamics, regulatory context) (Badghish & Soomro, 2024; Jackson & Allen, 2024). Empirical studies applying the TOE framework demonstrate that AI adoption in SMEs depends less on technological availability and more on organizational capabilities and managerial commitment (Almashawreh et al., 2024).

Complementing the TOE perspective, the capability-based view emphasizes that AI technologies alone do not generate competitive advantage; rather, value emerges from organizations' ability to combine AI with complementary resources, competencies, and routines (Mikalef & Gupta, 2021). This distinction between AI adoption—implementing specific technologies—and AI integration—embedding AI into strategic processes and organizational decision-making—has become central to understanding why technological implementation often fails to produce strategic transformation (Aiudi et al., 2025).

Despite anticipated benefits such as improved forecasting, performance monitoring, and organizational responsiveness (Hong et al., 2026; Huang et al., 2025), empirical evidence suggests that AI integration into strategic management remains fragmented in practice. Firms frequently adopt AI selectively for operational tasks—administration, marketing, financial forecasting—without systematically embedding it into strategic decision-making processes (Aiudi et al., 2025; Pujari et al., 2024). Research further indicates that integration barriers are primarily organizational rather than technological, including limited digital maturity, insufficient expertise, data quality problems, and uncertainty regarding AI's strategic value (Kittipanya-ngam et al., 2025; Solaimani & Swaak, 2023).

These challenges appear particularly pronounced in manufacturing SMEs, which typically operate with centralized decision-making structures, limited formalization, and constrained resources (OECD, 2021; Tawil et al., 2024). Although manufacturing firms may benefit substantially from AI-supported decision-making, empirical understanding of how AI is actually integrated into strategic management in real organizational settings remains limited, particularly regarding the gap between technological implementation and strategic utilization.

3. Methods

This study forms part of a broader sequential mixed-methods project examining AI integration in manufacturing SMEs. The present paper reports findings from the qualitative phase, which followed an earlier exploratory survey focused on AI adoption and performance management practices in Czech firms. The qualitative phase was designed to provide deeper insight into how AI is incorporated into strategic decision-making processes in real organizational settings.

3.1 Research design and sample

The study adopts an interpretive qualitative multiple-case design. Respondents were selected using purposive sampling based on their direct involvement in strategic decision-making processes and managerial activities related to digitalization, performance management, or AI utilization.

Prior to data collection, mandatory inclusion criteria were established: firms had to qualify as SMEs, operate in the engineering sector or related manufacturing industries in the

Czech Republic, and be represented by a respondent holding a decision-making role — an owner, managing director, or senior manager with direct responsibility for strategic management, finance, or digitalization. Within these boundaries, sampling proceeded emergently to maximize variability in firm size, digitalization level, and formalization of management systems. Respondents were recruited through three parallel channels — an external research agency, the researcher's personal professional network, and snowball referrals from earlier participants — with the same inclusion criteria applied consistently across all three channels.

The final sample consisted of 19 managers and owner-managers from Czech manufacturing SMEs. In all cases, one key informant per firm was interviewed to ensure a comprehensive overview of organizational processes, managerial routines, and decision-making practices. Given the qualitative, interpretive nature of the study, researcher reflexivity was treated as integral to the analytical process. The lead researcher's professional background in management and digitalization facilitated rapport with respondents but also required active reflection on its potential influence on data collection and interpretation. Where respondents were recruited through the researcher's personal network, this may have increased openness in some cases while also reducing the likelihood of probing or critical follow-up questions in others. Analytic memos documenting interpretive decisions and their rationale were maintained throughout coding to make these influences traceable rather than implicit. The sample included firms with different levels of digitalization, data maturity, and formalization of management systems, allowing comparison across varying organizational contexts.

A qualitative approach was considered appropriate because the study aimed to explore how AI integration is understood and enacted within everyday managerial practice. Given the exploratory nature of the topic and the relatively limited empirical understanding of AI integration in manufacturing SMEs, semi-structured interviews enabled deeper insight into organizational routines, managerial perceptions, and contextual barriers shaping strategic decision-making.

3.2 Data collection and analysis

Data were collected through semi-structured online interviews conducted between January and April 2026 via Microsoft Teams. Interviews lasted approximately 35–60 minutes and focused on strategic decision-making, performance management practices, work with data, digitalization, and AI utilization in managerial activities.

Sixteen interviews were recorded with participant consent and transcribed verbatim; the remaining three (R4, R7, R11) could not be recorded for technical and organizational reasons and were instead documented through field notes taken during and immediately after the interview. All interviews were anonymized using respondent codes (R1–R19).

Saturation was identified at approximately the 15th interview, when subsequent interviews no longer yielded new analytical categories or patterns; the remaining four interviews were conducted to confirm this assessment. Variation in the volume of codes generated per interview reflected differences in interview length, recording format, and respondent reflexivity on the topic, rather than methodological inconsistency across the sample.

The data were analyzed using inductive thematic analysis following Braun and Clarke (2022). Interview transcripts were coded iteratively and grouped into higher-order

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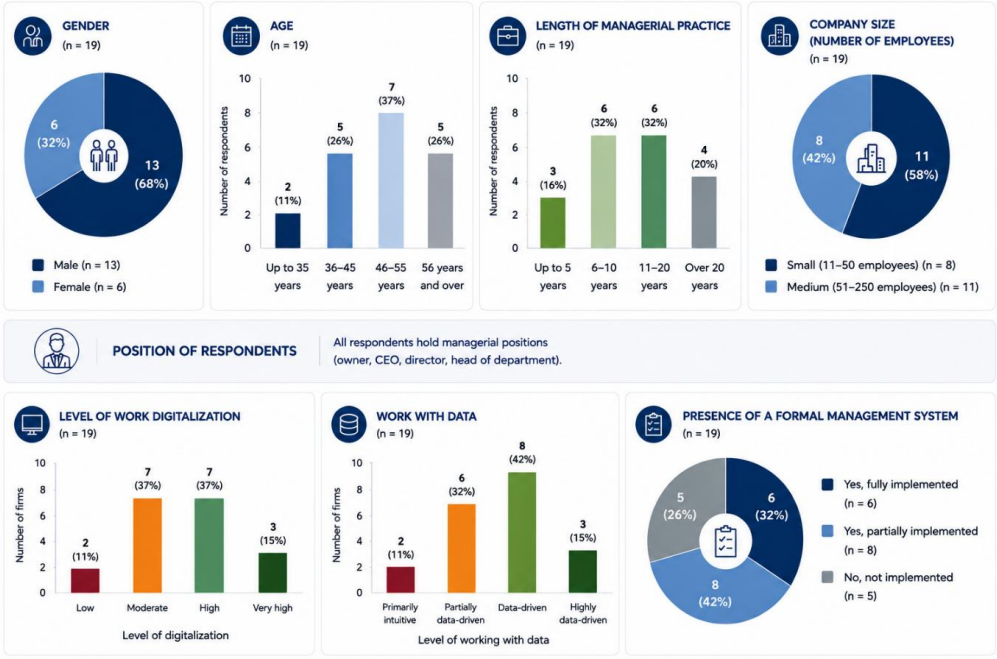
categories related to AI use, strategic decision-making, organizational barriers, and data maturity. Cross-case comparison was subsequently used to identify recurring patterns and differences across firms. The analysis was supported by ATLAS.ti. All participants agreed to participate in the interview and to the anonymized processing of the data in accordance with institutional ethical standards.

4. Results

The qualitative analysis revealed several recurring patterns related to AI adoption, managerial decision-making, organizational barriers, and data maturity. Although firms differed in their levels of digitalization and technological infrastructure, similar limitations in strategic AI integration emerged across the cases. The following sections summarize the main themes identified through the cross-case analysis.

Before presenting the qualitative findings, Figure 1 summarizes the main characteristics of the respondents and participating firms included in the study.

Figure 1: Characteristics of respondents and participating firms



Note. Author's own elaboration based on interview data.

4.1 AI adoption remains fragmented and primarily operational

The findings indicate that AI technologies are already present in most participating manufacturing SMEs; however, their use remains largely fragmented and concentrated in operational or administrative activities rather than systematically integrated into strategic management processes. Respondents most frequently described the use of AI tools such

as ChatGPT, Copilot, or similar applications for text generation, translations, information retrieval, reporting, documentation, and administrative support.

Firms primarily associated AI with administrative efficiency, productivity, and routine knowledge-processing tasks. At the same time, AI utilization was typically described as individual and decentralized rather than formally embedded within organizational structures or strategic management systems.

"We mainly use AI for routine tasks, text preparation, translations, and searching for information, but not really for strategic decisions." (R3)

"AI helps us save time in administrative work, but it is not something we systematically use in company management." (R11)

Even firms with relatively advanced digital infrastructures, including ERP systems, dashboards, KPI reporting, or MES implementation, reported only limited integration of AI into strategic decision-making. In most cases, AI functioned as a supplementary productivity tool rather than as a formal component of strategic management or performance management systems.

The findings further suggest that AI adoption in manufacturing SMEs often develops incrementally and experimentally. Rather than implementing comprehensive AI strategies, firms tend to adopt isolated AI applications responding to immediate operational needs. AI integration therefore appears evolutionary and situational rather than strategically coordinated. Despite increasing AI adoption, strategic decision-making across the firms remained strongly human-centered and reliant on managerial interpretation and experience.

4.2 Strategic decision-making remains strongly human-centered

A dominant pattern across the interviews was the continued reliance on human judgment, managerial intuition, and experience-based reasoning in strategic decision-making. Regardless of firms' technological maturity or level of digitalization, respondents consistently emphasized that final strategic decisions remain the responsibility of managers and owners.

AI was predominantly perceived as a supporting technology rather than an autonomous decision-making system. Respondents described AI as a "helper," "assistant," or "support tool" used to prepare information, structure ideas, accelerate analytical work, or provide additional perspectives. Managers simultaneously stressed the importance of contextual interpretation and personal responsibility for final decisions.

"AI can support us with information, but the final decision must remain with people who know the business and understand the context." (R12)

"We still make strategic decisions mainly based on experience and intuition." (R5)

"AI is a tool, not a replacement for management." (R15)

This pattern was particularly visible in owner-managed SMEs, where strategic decision-making remained highly centralized and strongly embedded in managerial experience and tacit organizational knowledge. Several respondents explicitly rejected the possibility of delegating strategic decisions to AI systems, arguing that strategic management requires contextual understanding and practical judgment that cannot be fully replaced by technology.

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The findings therefore suggest that AI currently supports mainly the pre-decision phase of managerial work, particularly information processing, analytical preparation, and administrative simplification, while the core strategic decision-making process remains deeply human-centered. At the same time, the findings suggest that the persistence of human-centered decision-making is closely connected to organizational and managerial barriers constraining deeper AI integration.

4.3 Organizational barriers outweigh technological barriers

The findings indicate that the main barriers preventing deeper AI integration are not primarily technological, but organizational and managerial in nature. Respondents rarely described technological unavailability as the key problem. Instead, firms reported difficulties associated with organizational readiness, data quality, limited internal capacities, implementation complexity, and uncertainty regarding the practical use of AI in strategic management.

One of the most frequently mentioned barriers was insufficient data quality and fragmented data infrastructures. Several firms acknowledged that they lacked reliable or sufficiently structured data required for more advanced analytical or AI-supported decision-making.

"The biggest problem is not the technology itself, but the quality and availability of data." (R7)

"We are still not digitally mature enough to integrate AI into broader company processes." (R14)

Respondents also emphasized organizational and cultural barriers, including employee resistance, lack of AI-related competencies, insufficient training, and limited managerial capacity to systematically address AI implementation. In smaller firms, management teams were often described as overloaded with operational responsibilities, leaving limited time and resources for experimentation and digital transformation initiatives.

Security concerns and uncertainty regarding data governance emerged repeatedly across the interviews. Respondents expressed concerns about sensitive information, data leakage, cybersecurity risks, and loss of control over organizational knowledge.

"People are afraid of sharing sensitive company information with AI systems." (R9)

Interestingly, these concerns appeared particularly strong among more digitally mature firms, suggesting that higher levels of digitalization may increase awareness of governance and security-related risks associated with AI implementation.

Overall, the findings suggest that AI integration is constrained less by the availability of AI technologies themselves and more by firms' ability to embed these technologies into existing organizational structures, managerial routines, and decision-making processes. Importantly, the findings suggest that higher levels of digitalization alone do not eliminate the organizational barriers constraining deeper AI integration.

4.4 Data maturity does not automatically lead to AI integration

An important finding emerging from the analysis is that higher levels of digitalization and data maturity do not necessarily result in deeper AI integration into strategic decision-making. Several firms demonstrated relatively advanced approaches to

data management, including ERP systems, MES implementation, KPI reporting, business intelligence platforms, and extensive operational data collection.

Despite these capabilities, AI remained largely disconnected from strategic decision-making processes even in technologically advanced firms. In many cases, firms used sophisticated reporting systems and performance monitoring tools while simultaneously relying on human judgment and managerial interpretation when making strategic decisions.

"We have ERP, reporting, dashboards, and a lot of data, but strategic decisions are still made by management discussions and experience." (R16)

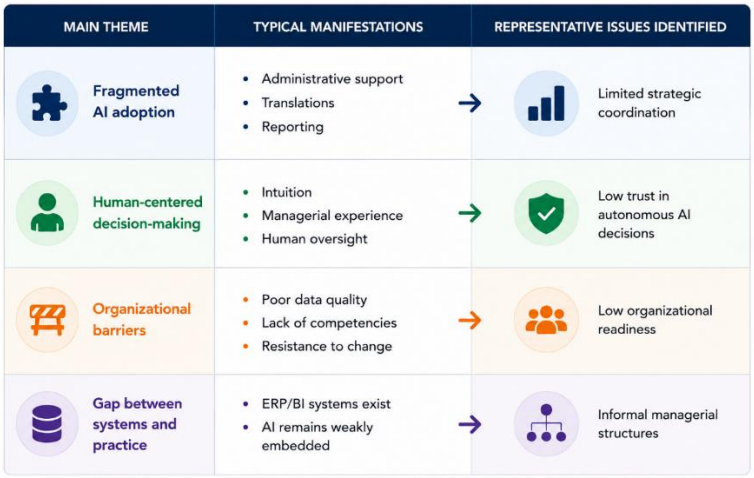
"Even though we collect a lot of production data, AI is still not directly connected to our strategic decision-making." (R18)

The findings suggest that the transition from digitalization to AI-enabled strategic management is not automatic. Data infrastructure alone does not guarantee organizational readiness for AI integration. Instead, AI integration appears to depend on broader organizational factors, including managerial trust, governance structures, perceived relevance of AI for specific business processes, and alignment between technology and organizational routines.

The findings also highlight the specificity of manufacturing SMEs, particularly those operating in project-based or low-standardization production environments. Several respondents argued that the complexity and uniqueness of their production processes limited the applicability of standardized AI solutions.

Overall, the findings indicate that AI use in manufacturing SMEs remains predominantly operational and only partially embedded within broader strategic decision-making processes. Figure 2 summarizes the main themes and recurring patterns identified across the interviews, and Table 1 reports the corresponding coding frequencies and representative quotations for each theme.

Figure 2: Overview of main themes and recurring patterns



Note. Author's own elaboration based on interview data.

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Table 1: Coding frequencies and representative quotations by theme

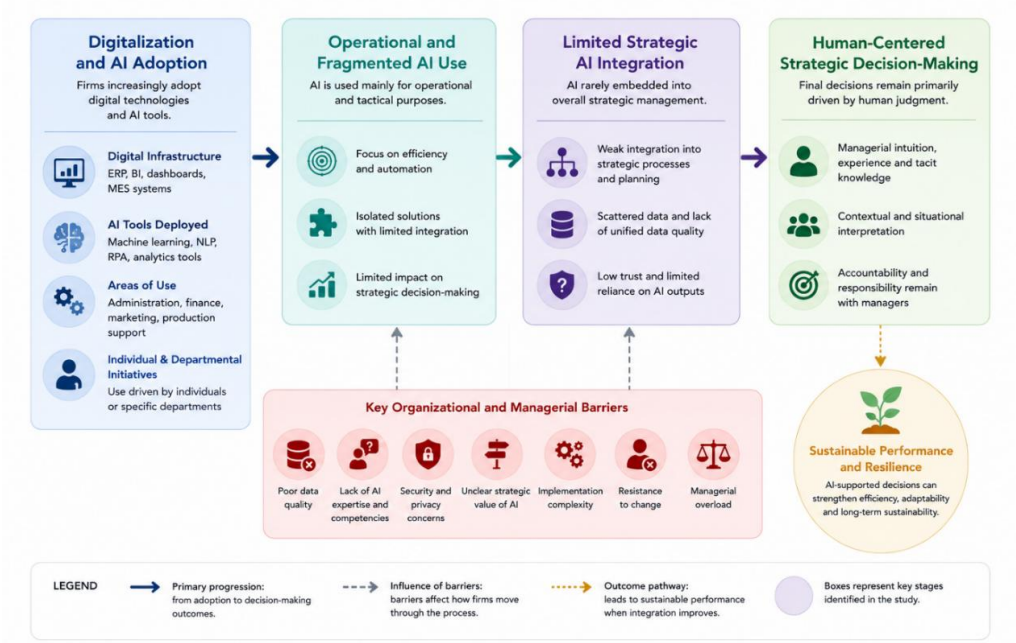
Theme (Section)	Coding frequency (n)	Representative quotation
4.1 Fragmented AI adoption	38	*"We mainly use AI for routine tasks, text preparation, translations, and searching for information, but not really for strategic decisions."* (R3)
4.2 Human-centered decision-making	25	*"AI can support us with information, but the final decision must remain with people who know the business and understand the context."* (R12)
4.3 Organizational barriers	30	*"The biggest problem is not the technology itself, but the quality and availability of data."* (R7)
4.4 Data maturity paradox	29 (Data) + 19 (Digitalization)	*"We have ERP, reporting, dashboards, and a lot of data, but strategic decisions are still made by management discussions and experience."* (R16)

Note. Coding frequencies reflect the number of codes assigned within each thematic category during inductive-deductive coding in ATLAS.ti (270 codes across 19 interviews, 13 thematic groups). For Theme 4.4, frequencies are reported separately for the two related code groups ("Data" and "Digitalization") that jointly informed this theme. Author's own elaboration based on interview data.

5. Discussion

This study contributes to AI adoption literature by demonstrating that the primary challenge for manufacturing SMEs lies not in technological access but in the organizational integration of AI into strategic routines. These findings challenge the technological determinism implicit in earlier AI adoption research, which often assumes that implementing advanced technologies automatically translates into strategic transformation. The data reveal a more complex reality: although firms increasingly adopt AI-based applications, these technologies remain confined to operational and administrative tasks rather than embedded within strategic management processes. Figure 3 summarizes the main relationships identified across the cases.

Figure 3: Relationship between AI adoption, organizational barriers, and limited strategic integration in manufacturing SMEs



Note. Author's own elaboration based on interview data.

5.1 Organizational capabilities outweigh technological infrastructure

This finding both confirms and extends this theoretical perspective (Mikalef & Gupta, 2021). The findings directly support the capability-based view of AI integration (Mikalef & Gupta, 2021), demonstrating that organizational and managerial barriers—not technological constraints—determine integration depth. Respondents rarely cited technological unavailability as the primary obstacle. Instead, they emphasized limited internal competencies, fragmented data infrastructures, operational overload, and uncertainty about AI's strategic relevance. This extends Mikalef and Gupta's (2021) AI capability framework. Firms may possess technological access while simultaneously lacking the complementary capabilities (data governance, analytical skills, managerial routines) required to transform AI outputs into strategic insights. The findings thus empirically distinguish between AI availability (technical access) and AI capability (organizational readiness to leverage AI strategically).

5.2 Fragmented adoption versus strategic integration

This finding contradicts linear diffusion models while confirming sociotechnical systems theory (Makarius et al., 2020). The study reveals that AI adoption in manufacturing SMEs follows a pragmatic, needs-driven logic rather than strategic coordination. Firms adopt isolated AI applications (ChatGPT for documentation, dashboards for reporting) in response to immediate operational pressures, resulting in fragmented implementation across departments. This pattern directly contradicts the linear diffusion models that

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assume technologies progressively penetrate organizational layers. Instead, the findings align with sociotechnical systems theory, which emphasizes that technology integration depends on alignment between technical capabilities and organizational structures, processes, and cultures. AI integration therefore appears evolutionary and situational rather than strategically planned—a finding with significant implications for how SMEs approach digital transformation.

5.3 Augmentation, not automation: human-centered decision-making persists

This finding confirms and extends the augmentation–automation paradox (Raisch & Krakowski, 2021). A critical finding is that strategic decision-making remains strongly human-centered despite digitalization advances. Managers perceive AI as supporting pre-decision analytical work while reserving final strategic judgment for themselves. This observation directly supports Raisch and Krakowski's (2021) augmentation-automation paradox, which conceptualizes AI as amplifying managerial cognition rather than replacing it. However, this study extends this framework by revealing that even technologically mature firms with ERP systems, dashboards, and KPI reporting still default to managerial experience and tacit knowledge for strategic decisions. This suggests that the persistence of human-centered decision-making reflects not only technological limitations but also deeply embedded managerial mental models and trust structures that resist delegating strategic interpretation to AI systems.

5.4 Digitalization ≠ AI integration: the maturity paradox

This finding contradicts the implicit assumption in TOE framework applications that digital maturity mechanically drives AI integration (Badghish & Soomro, 2024; Jackson & Allen, 2024). Contrary to expectations, higher levels of digitalization and data maturity do not automatically translate into deeper AI integration. Several firms demonstrated advanced data infrastructures (MES, BI platforms, extensive operational data) yet reported minimal AI involvement in strategic decision-making. This finding challenges the implicit assumption in TOE framework applications that organizational readiness (digitalization) mechanically drives AI adoption. Instead, the data suggest a non-linear relationship: digital maturity creates *necessary conditions* for AI integration but does not guarantee it. The transition from digitalization to AI-enabled strategic management appears contingent on additional factors—managerial trust, perceived AI relevance to specific business processes, and cultural readiness to incorporate algorithmic insights into strategic routines.

5.5 Informal performance management as an integration barrier

This finding extends sociotechnical systems theory into a new empirical context (Makarius et al., 2020). Manufacturing SMEs in the sample rarely employed formal strategic frameworks (e.g., Balanced Scorecard), instead relying on implicit approaches to performance monitoring. This informality creates structural barriers to AI integration. AI-generated insights require standardized processes and formalized KPIs to be systematically incorporated into decision-making. From a sociotechnical perspective, the absence of formalized management systems prevents the organizational scaffolding necessary for translating AI outputs into strategic action. This finding suggests that AI integration in

SMEs may require prior formalization of managerial processes—a pathway that differs fundamentally from larger enterprises with established strategic frameworks.

5.6 Theoretical and practical implications

Theoretically, this study advances AI integration research by empirically validating the distinction between technological adoption and strategic integration through the lens of capability-based and sociotechnical perspectives (Makarius et al., 2020). The findings demonstrate that AI should be conceptualized as part of a broader organizational transformation process requiring complementary investments in skills, governance, and routines—not as a standalone technological solution.

Practically, the findings imply that manufacturing SMEs seeking deeper AI integration must simultaneously develop organizational capabilities alongside technological infrastructure: building data governance frameworks, cultivating analytical competencies, formalizing strategic processes, and fostering managerial trust in algorithmic insights. Technology acquisition alone will not deliver strategic value without these complementary organizational adaptations.

5.7 Limitations and future research directions

The study's single-informant design may not capture divergent perspectives within firms, and the focus on current generative AI tools (ChatGPT, Copilot) may not reflect emerging enterprise-grade AI systems. No documentary evidence or additional informants within the same firm were used to cross-validate individual accounts in this qualitative phase; findings therefore reflect each respondent's own perspective rather than a triangulated organizational account. This limitation is partly addressed in a subsequent phase of the broader research project, in which a small number of contrasting cases were examined through multiple informants, on-site observation, and internal documentation — an approach that could be extended to the present sample in future research. Future research should address three critical gaps. First, longitudinal studies tracking AI integration trajectories over 3–5 years would reveal how organizational capabilities and strategic embedding evolve as firms mature digitally, moving beyond the snapshot perspective captured here. Second, cross-country comparative research examining AI integration in manufacturing SMEs across institutional contexts (e.g., Central Europe vs. Nordic countries vs. Asian economies) would clarify how regulatory environments, digital infrastructure availability, and managerial cultures shape integration pathways. Third, multi-level quantitative studies linking AI integration depth with objective performance outcomes (productivity, innovation rates, competitive positioning) would test whether the organizational capabilities identified here translate into measurable strategic value. Measurable indicators for such studies could include, for example, the extent to which AI-related processes are formalized within strategic routines (as a proxy for integration depth), the maturity of data governance structures and cross-functional AI competencies (as a proxy for organizational capability), and indicators such as productivity growth, resource efficiency, or innovation output (as proxies for sustainable performance). Additionally, research exploring sector-specific AI integration patterns (discrete vs. process manufacturing, B2B vs. B2C orientation) could refine understanding of contextual factors moderating the adoption-integration relationship. Such comparative research could also

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examine whether governance maturity — for instance, the presence of formalized data governance frameworks or dedicated AI oversight structures — moderates the relationship between AI adoption and performance outcomes across manufacturing subsectors.

6. Conclusion

This study examined how AI is integrated into strategic decision-making in manufacturing SMEs and identified the barriers hindering this process. The findings revealed that although AI technologies are increasingly present in manufacturing firms, their use remains fragmented, operationally oriented, and weakly embedded within strategic management processes. The main barriers are organizational rather than technological: limited internal competencies, fragmented data environments, insufficient organizational readiness, and the persistence of experience-based managerial routines constrain strategic AI use. Strategic decision-making remained strongly human-centered, with AI functioning primarily as an augmentation mechanism supporting managerial interpretation rather than replacing judgment.

The study contributes to AI-enabled strategic management literature by empirically distinguishing between AI adoption and strategic integration. The findings demonstrate that digitalization alone does not automatically lead to AI-supported strategic transformation. Instead, meaningful integration depends on organizations' ability to align technological capabilities with managerial practices, organizational routines, and internal competencies.

Practically, the findings point to four theme-specific priorities for manufacturing SMEs seeking deeper AI integration. First, addressing the fragmentation observed in AI use (Section 4.1) suggests a need for formalized routines that embed AI tools into defined organizational processes, rather than leaving their use to individual discretion. Second, the persistence of human-centered decision-making (Section 4.2) suggests that building managerial trust in algorithmic insights may be a precondition for any deeper delegation of analytical work, rather than a by-product of technology adoption alone. Transparent, explainable AI outputs may represent one practical route toward such trust. Third, the organizational barriers identified in this study (Section 4.3), particularly limited competencies and data governance gaps, suggest that targeted competency development and clearer data governance frameworks may help firms move from isolated AI use toward more systematic application. Fourth, the maturity paradox observed in Section 4.4 suggests that formalizing strategic processes may be a necessary condition for translating existing data infrastructure into AI-supported strategic value. These associations are grounded in respondents' own accounts rather than in measured performance outcomes, and should be read as directions warranting further empirical testing rather than established causal effects.

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