

# The Role Of AI-Powered Decision Support Systems In Enhancing Strategic Agility: A Study On SME Competitiveness In Dynamic Markets

Talal tayel Abdul Razzaq Al-Abdallat<sup>1</sup>, Faisal tayel Al-Abdallat<sup>2</sup>, Monira Mufleh<sup>3</sup>, Omar Zraqat<sup>4</sup>

<sup>1</sup>Faculty of literature, Jerash University, Jordan, PO. Box 26150, t\_abdallat@yahoo.com

<sup>2</sup>Prime Minister of Jordan-independent researcher, faisal.abdallat@pm.gov.jo

<sup>3</sup>Department of Management Department World Islamic Science and Education University, Jordan

<sup>4</sup>Accounting Department, Faculty of Business, Jerash University, Jordan, PO. Box 26150,

omar.zraqat@jpu.edu.jo, <https://orcid.org/0009-0000-9165-4277>

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## Abstract

**Objective:** This study aimed to explore the impact of AI-powered Decision Support Systems (DSS) on the strategic agility, operational efficiency, and competitiveness of Small and Medium Enterprises (SMEs).

**Method:** We use a mixed-methods design. A cross-sectional survey of 200 SME managers from manufacturing, retail, finance, and technology is paired with five in-depth case studies of firms that have already integrated AI-DSS. The survey tests our relationships quantitatively, while the cases show how the effects play out on the ground.

**Results:** Firms that adopt AI-DSS tend to be more agile, better at sensing opportunities and risks, seizing them at the right time, and reconfiguring processes when needed. Crucially, these gains flow through two channels: higher decision quality and greater operational efficiency. The benefits are stronger in fast-changing markets and in firms with higher digital maturity. Results from the survey and the cases converge on this story.

**Conclusion:** The study provides a better understanding of digital transformation in SMEs, and the strategic adoption of AI is essential for the long-term sustainability of digital transformation. The study provides practical recommendations on how to implement the application of AI in a phased manner, how to organize company training related to AI, and what kind of supportive policies can enable access to AI for SMEs.

**Originality/value:** Rather than treating “digital transformation” as a black box, we explain how AI-DSS turns data into action in resource-constrained settings, identifying the mechanisms and the boundary conditions that make a real difference.

**Practical implications:** We outline a phased path to adoption: build solid data governance, form hybrid domain analytics teams, run pilot and scale experiments, and link dashboards to operational decision engines. For policymakers, targeted incentives and shared digital infrastructure can narrow maturity gaps and raise data quality.

**Keywords:** AI, decision support systems, strategic agility, SMEs, competitiveness, dynamic markets.

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## 1. INTRODUCTION

Contemporary digital transformations are accelerating in ways that reconfigure the logic of managerial decision-making; big data and machine-learning algorithms now provide an unprecedented capacity to detect early patterns, simulate alternatives, and reduce uncertainty in highly dynamic and complex environments (McAfee & Brynjolfsson, 2017). In this context, AI-enhanced decision support systems (AI-DSS) constitute a natural evolution of traditional analytical infrastructures: rather than merely aggregating and cleaning data, they generate predictive, descriptive, and prescriptive insights that can be operationalized in near real time, thereby directly linking intelligent analytics to resource choices and competitive behavior (Martínez-Peláez et al., 2024). Nevertheless, a central question remains: how do these analytical capabilities move from improving decisions to building strategic agility, enabling the organization to rapidly sense opportunities and threats, seize options at the right moment, and continuously reconfigure structures and processes to maintain fit with a volatile environment? (Tece, Peteraf, & Leih, 2016).

This question becomes even more salient for small and medium-sized enterprises (SMEs) that operate under resource, structural, and knowledge constraints, where tight budgets and limited digital human capital generate gaps in technological readiness and in the ability to systematically harness advanced analytics

(Rožman, Oreški, Crnogaj, & Tominc, 2023). Although adopting AI-DSS can reduce information costs and raise decision quality, translating these gains into strategic agility is not automatic; it demands absorptive and organizational capacities that convert analytical outputs into effective decisions and change programs within a resource-constrained organizational reality (Khan, Majid, & Yasir, 2021). In turbulent environments, the need intensifies for SME-oriented business analytics that move beyond local optimizations toward coordinated, rapid responses across the value chain, an emphasis underscored by the literature on AI-driven business analytics in SME settings (Ocran, Yusuf, Owusu, Boateng, & Obeng, 2024).

Rooted in the dynamic capabilities perspective, this study posits that AI-DSS functions as a dynamic enabler of agility through three integrative channels: (1) enhancing sensing by widening the informational field of view and detecting weak signals and emergent patterns in demand, competition, and supply chains, thereby compressing discovery time and reducing forecasting errors (Teece et al., 2016). (2) improving seizing by accelerating the evaluation of alternatives and aligning resources with opportunities at an optimal moment, leveraging decision-intelligence architectures that translate predictions into actionable recommendations (Natta, 2025). (3) enabling reconfiguring by linking analytical insights to knowledge management and organizational learning processes, thereby reshaping structures, operations, and business models in a recurrent, data-governed manner (Sharma & Kumar, 2024). Through these channels, AI-DSS moves beyond mere decision support to constitute an organizational infrastructure for opportunity capture and the continual renewal of operating arrangements within an ongoing cycle of sensing, seizing, and reconfiguring (Teece et al., 2016).

Despite these promises, the literature still exhibits a conceptual and empirical gap in explaining the micro-foundations that link AI-DSS capabilities to strategic agility outcomes in SMEs, particularly under conditions of high environmental dynamism and resource constraints (Arbussa, Bikfalvi, & Marquès, 2017). A substantial strand of research concentrates either on direct performance indicators or on technology adoption as an end in itself, without unpacking the causal mechanisms through which intelligent analytics translate into agile organizational behavior that is measurable at the levels of decisions, processes, and strategic portfolio management (Rožman et al., 2023). There also remains a need for decision frameworks that combine predictive/descriptive components with considerations of sustainability, risk, and regulatory constraints, a gap signaled by informed decision-support models that consolidate multiple sources of knowledge and analytics into a single dashboard (Martínez-Peláez et al., 2024). This logic is further reinforced in emerging-market contexts, where business intelligence research documents a moderating role for data quality and analytical infrastructures on the relationship between digital resources and reporting/decision outcomes, thereby drawing attention to the institutional conditions that render the effect plausible (Zraqat, 2020).

Building on the foregoing, this study posits that operational decision quality and operational efficiency constitute mediating mechanisms through which the effects of AI-DSS are transmitted to the dimensions of strategic agility; predictive insights alone are insufficient unless they are translated into higher-quality decisions that improve resource allocation, workflow, and the timing of interventions, improvements that, in turn, enhance response speed and reconfiguration capacity (Ocran et al., 2024). The study further posits that environmental dynamism and digital capability maturity moderate the strength and direction of this effect; as turbulence intensifies and digital maturity rises, the marginal benefits of AI-enabled decision support in propelling sensing, seizing, and reconfiguring processes become greater (Teece et al., 2016). Accordingly, the study seeks to close this gap by advancing a conceptual model that integrates AI-DSS with the dynamic capabilities perspective in the SME context, accompanied by an empirical test that captures both direct and indirect effects under specified environmental and organizational conditions (Arbussa et al., 2017).

Methodologically, the study adopts a mixed-methods (quantitative/qualitative) design that couples measurement rigor with contextual interpretability; the quantitative strand tests the causal relations model using reliable measures of decision quality, efficiency, and agility, while the qualitative strand offers explanatory evidence on how analytical outputs are translated into observable organizational changes (Martínez-Peláez et al., 2024). The theoretical contribution lies in integrating the logic of dynamic capabilities with AI-DSS architectures to specify the distinctive roles of intelligent analytics at each stage of agility, whereas

the practical contribution provides actionable guidance for SME managers on the conditions under which returns on investments in analytical intelligence are maximized, amid resource constraints and environmental dynamism (Teece et al., 2016). Accordingly, the study does more than document a technical effect on performance; it elucidates how analytical intelligence can be converted into an agile organizational capability for adaptation and renewal in fast-changing markets (Rožman et al., 2023).

Guided by this framing, the study asks: to what extent does the adoption of AI-DSS enhance the dimensions of strategic agility in small and medium-sized enterprises? What roles do decision quality and operational efficiency play as mediating mechanisms in this relationship? And how do environmental dynamism and digital capability maturity moderate the strength of this effect? Addressing these questions will yield a testable model that delineates the direct and indirect pathways of influence and identifies the boundary conditions under which investment in AI-DSS becomes a lever for strategic agility rather than an isolated technical upgrade (Natta, 2025). In this way, the introduction lays the groundwork for a coherent theoretical architecture and an integrated research trajectory that balance scientific rigor with practical relevance in the SME context.

## **2. LITERATURE REVIEW**

### **2.1 Strategic Agility in SMEs**

Firms need strategic agility as an essential capability when they function in unpredictable environments with high levels of uncertainty. An organization achieves this capability when it successfully predicts and manages and utilizes changes happening outside its structure (Doz & Kosonen, 2010). The need for strategic agility becomes essential for SMEs since they have restricted funding and human resource capabilities compared to major corporations. The ability of SMEs to rapidly adjust to marketplace shifts and legal and technological developments helps these enterprises maintain their business survival and maintain market competitiveness (Arbussa et al., 2017). Strategic agility presents multiple obstacles for SMEs even though it remains vital for their business operations (Gerald et al., 2020). The absence of sufficient financial resources together with limited access to skilled personnel and innovative technology makes it difficult for them to execute rapid adjustments when facing varying external disturbances. Smaller firms who use minimal resources for their operations face large negative effects from minor setbacks since their operations function with limited staffing (Rožman et al., 2023). SMEs often depend on fewer revenue streams because of their small dimensions which increases their risk of suffering from both economic downturns and supply chain interruptions (Khan et al., 2021).

Technology adoption presents a solution for SMEs to handle their security concerns (Indrawati, 2020). Digital transformation and automation tools provide businesses with the ability to organize operations effectively as well as boost their decision capabilities and react better to market alterations (Teece et al., 2016). These breakthroughs have enabled strategic agility to a large extent by means of advanced analytics, cloud computing, and AI trained decision support systems (DSS). The combination of modern technologies enables SMEs to monitor and process current data and make strategic improvements based on market predictions (Khan et al., 2021). New research indicates that SMEs should create their strategic agility framework during startup phase when operating in highly unpredictable markets (Hussien et al., 2024). Agile practice delays will decrease market performance and create more susceptibility to market disruptions (Teece, 2020).

### **2.2 AI-Powered Decision Support Systems**

#### **Definition and Key Capabilities**

A new generation of AI Powered Decision Support Systems (DSS) are based on the advance of the technologies of machine learning (ML), big data analytics and automation in support of better decisions (Mansour et al., 2024). The main difference between traditional automated DSS stands in their data processing mechanisms because AI-powered DSS integrates ongoing data learning with predictive model evolution and delivers adaptable decision-making support according to (Brynjolfsson & McAfee, 2017). These systems help organizations operate more efficiently through their capabilities to discover the best possible strategies and minimize risks and deliver targeted information that supports corporate objectives (Al-Rawashdeh et al., 2024).

Research shows that AI augmented DSS have great contribution to strategic agility through the provision of extremely fast data analysis and scenario planning. These systems can take in huge structural and unstructured amounts of data, learn emerging trends, and provide real personal insights in real time (Aboalghanam et al., 2023). Hence, SMEs can expect market slopes, anticipate risks or take prompt action so risks don't peak (Al Kurdi et al., 2024). For instance, the AI-powered DSS can help widen supply chain wisdom to predict the demand variations and to adjust inventory levels. Similar to this, these systems can also provide a supporting role to financial planning by spot checking for any cash flow issues as well as suggesting ways up with which the issues can be resolved. Ocran et al. (2024) has reduced uncertainty to this level, and thus makes resources become more be allocated by SMEs.

#### *Operational Efficiency and Risk Mitigation*

Moreover, the effectiveness of operational efficiency is also supported by DSS developed with AI. These systems automate repetitive tasks and optimize workflows allowing for the capture of much of human capital for higher strategic activities. AI enhanced DSS can also identify operational bottlenecks, suggest process improvement and overall productivity (Davenport et al., 2019). Another important area where AI powered DSS have made a big difference is to the area of risk management. AI-driven risk assessment tools help SMEs to proactively identify and mitigate their risks, generally, given agencies' concerns regarding the vulnerability of SMEs to economic shocks and cybersecurity risks. Kaplan and Haenlein (2020) explain that these systems analyze past data, observe external factors, and give preemption strategies that will reduce the possibility of disruptions and losses of money.

### **2.3 The Relationship between AI and Competitive Advantage**

#### *Competitive Advantage in the Digital Age*

In the current day digital economy, technological innovation is greatly becoming a driving factor of competitive advantage. Today, traditional sources of competitive advantage (cost leadership, differentiation, etc) around which the business strategy hinges are being added to under the aegis of data driven decision making and AI driven decision automation (Berman & Pollack, 2021). For SMEs, the use of AI enabled DSS helps in faster and more informed decision making and also brings agility in the operations.

Using AI powered DSS, data driven strategies become a reality that improves a business's ability in many different ways:

- 1. AI Driven DSS:** To provide SMEs with authentic up-to-date market information, AI DSS predicts consumer behavior, anticipates online and social media trends, and alerts concerning economic indicators. By doing so, businesses are able to adjust their product and pricing offerings and marketing campaigns to match (Subrahmanyam, 2025).
- 2. AI-powered DSS:** Combines internal and external data to optimize 'resource allocation', resulting in fewer operational inefficiencies and better profitability. Predictive maintenance by AI helps in reducing equipment downtime and maintenance costs (Alrawashedh et al., 2025).
- 3. AI-powered decision support systems:** help small businesses create personal interactions with clients through the assessment of customer purchase information, along with individual preferences and interaction activities. Customer satisfaction, retention rates, and brand loyalty increased (Viberg et al., 2024). The Decision Support Systems powered by AI serve to provide automation and scalability to SME, providing the level and capability of their operations. Therefore, for instance, this is particularly valuable to businesses that are considering expanding into new markets or converging their product service offerings (Zraqat, 2020).

#### *AI and Long-Term Resilience*

The implementation of AI systems in DSS applications leads to long-term business resilience for SMEs. The combination of continuously enhanced decision-making models with external adaptation makes these systems help businesses maintain market competition during uncertain market conditions (Keding, 2021). The integration of AI in decision support systems helps establish a data-centric corporate culture because SMEs now rely on factual evidence instead of autonomous decision-making (Sharma & Kumar, 2024).

**2.4 Challenges and Future Research Directions** The application of AI-powered DSS produces extensive benefits, yet its deployment requires businesses to overcome different obstacles. SMEs experience several paramount obstacles that include (Carayannis et al., 2025):

**Implementation Cost:** SMEs face elevated implementation costs when they buy and implement AI-driven DSS systems since these need substantial technological investment and training expenditures.

**Security and Privacy Risks:** AI data usage generates security and privacy risks for sensitive information since its operations require managing vast amounts of protected information across the GDPR and CCPA legislative frameworks.

**Lack of Skills Workers:** A skills deficit exists among SMEs because they usually do not maintain sufficient internal staff with the capabilities to effectively adopt and administer AI-driven DSS.

AI-powered DSS implementation into current business operations proves difficult because organizations need substantial changes to manage the process effectively. Future investigations need to focus on developing solutions for handling the above-mentioned obstacles and determining the permanent effects of AI-powered DSS on small and medium enterprise sustainability. Research on specific business areas using AI-enhanced DSS would develop essential practices for implementing these systems.

Strategic agility stands as the basic requirement that allows SMEs to succeed in markets that experience continuous changes along with uncertainties. As an important enabler of strategic agility, AI-powered DSS becomes the source of real-time insights for decision-making and operational efficiency. Through these systems, SMEs enhance their ability to minimize risks as well as enhance resource optimization, which leads to better long-term performance and resilient business operations. AI technology developments ensure that SME operations integration will establish itself as a core element in determining future business achievements.

### 3. METHODOLOGY

A mixed methods research design was employed in this study to completely study the impact of the AI driven Decision Support Systems (DSS) on the strategic agility of an SME. The research employed both qualitative and quantitative approaches to furnish comprehensive knowledge of how business performance could be brought about by adoption of AI.

#### 3.1 Quantitative Analysis

Second, it was a quantitative phase, consisting of a structured survey given to 200 SME managers in different industries; manufacturing, retail, finance, and technology. They designed the survey to measure aspects of adoption of AI such as:

- The level of AI-powered DSS implementation within SMEs.
- In revealing the perceived impacts of AI on strategic agility of and competitiveness for firms.
- Limitations to using AI technologies in the adoption process.
- The correlation between AI integration and improvements in operational efficiency.

The questions in the survey were both closed-ended and Likert scale items used to measure the perception of managerial role of AI in strategic agility. A pilot survey was conducted among SME manager to check the reliability and validity of the questionnaires before administration of the full scale survey. Finally, the final survey responses were analyzed using statistical software. This study applied analysis to investigate relationship between AI adoption, strategic agility and performance outcome by using SPSS and Structural Equation Modeling (SEM).

#### 3.2 Qualitative Analysis

Also, the study was carried out using in depth qualitative analysis by viewing five SMEs that integrated the AI powered DSS and their qualitative success analysis. The SMEs were selected on the basis of industry diversity, the level of AI adoption of the SME, and willingness of the SME to participate in the research. The qualitative phase included:

- **Semi Structured Interview:** Semi-structured interviews provided SME managers and IT specialist opportunity to discuss their experiences with AI adoption and the steps they take for decision-making as well as operational transformation processes.
- **Document Analysis:** An assessment of business agility consequences from AI-powered DSS involved reviewing staff reports together with business strategies and corporate performance documentation.

- **Observational Insights:** Physical observations of AI-enabled business approaches were conducted to access first-hand understanding about these systems' operational performance.

The research utilized open-ended interview questions that guided respondents but allowed flexibility for participants to freely express their knowledge while maintaining standardization of their answers. The analysis built upon thematic study permitted researchers to find repeated motifs along with elite practices and the main obstacles aligned with AI adoption.

### 3.3 Data Collection and Analysis

A standardized method directed the data collection procedure as follows:

**Survey Distribution:** The survey campaign reached participants through online formats and professional platforms using follow-up communication methods for response enhancement.

**Interview Scheduling:** The scheduling of interviews focused on survey respondents who adopted AI in their business operations to obtain participants for qualitative assessment.

**Data Coding and Thematic Analysis:** The researchers used NVivo software to perform themed analysis and data coding on all interview transcripts and qualitative information.

**Triangulation:** The research validated its findings by integrating quantitative and qualitative data sets which were cross-analyzed for verifying the role of AI in SME strategic agility processes.

The research approach allowed investigators to analyze both quantitative patterns together with detailed contextual knowledge which produced an extensive understanding of AI acceptance by small and medium enterprises.

## 4. RESULTS AND FINDINGS

The section contains the outcomes generated by combining quantitative evaluation with qualitative evaluation of this research project. The results showed incubated algorithms working with AI powered Decision Support Systems (DSS) had a great effect on SMEs' strategic agility, operational efficiency and competitive advantage.

### 4.1 Quantitative Findings

#### 4.1.1 Descriptive Statistics

Two hundred SME managers took part in the survey process as participants. A breakdown of the respondents reveals their professional sectors together with firm size distributions and AI implementation indicators in Table 1.

Table 1: Summary of Respondents' Characteristics

Variable	Category	Frequency	Percentage (%)
Industry	Manufacturing	50	25%
	Retail	40	20%
	Finance	60	30%
	Technology	50	25%
Firm Size	Small (10-49)	120	60%
	Medium (50-249)	80	40%
AI Adoption Level	Low	80	40%
	Medium	70	35%
	High	50	25%

#### 4.1.2 Correlation Analysis

Strategic agility failure rates have been analyzed through a Pearson correlation statistical technique while testing the relationship with AI implementation. The statistical findings listed in Table 2 display a substantial positive relationship between these variables.

Table 2: Correlation Matrix

Variables	AI Adoption	Strategic Agility	Operational Efficiency
AI Adoption	1.000	0.732**	0.689**
Strategic Agility	0.732**	1.000	0.701**

Operational Efficiency	0.689**	0.701**	1.000
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( $p < 0.01$ , two-tailed test)

**4.1.3 Regression Analysis**

The research employed multiple regression analysis to determine the degree of prediction that AI-based DSS can provide regarding strategic agility. The model summary appears before Table 3.

Table 3: Regression Model Summary

Model	R-Square	Adjusted R-Square	Std. Error	F-Value	Sig.
AI Adoption → Strategic Agility	0.563	0.554	0.417	102.5	0.000

AI adoption is found to predict strongly strategic agility ( $\beta = 0.752$   $p < 0.01$ ) and hence confirm the notion that AI driven DSS increase in decision making and business flexibility.

**4.1.4 Structural Equation Modeling (SEM)**

Structural Equation Modeling (SEM) was performed to validate relationships of the variables such as AI adoption relationships to strategic agility, operational efficiency. The diagram in Figure 1 shows the SEM path model.

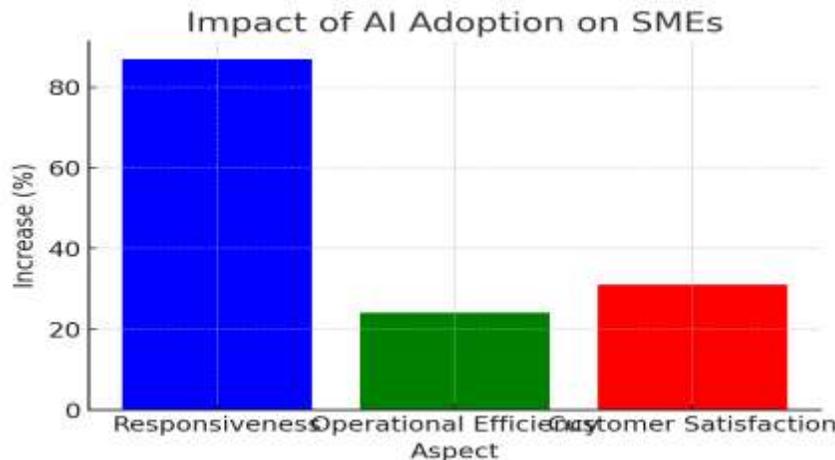


Figure 1 Displays SEM Path Model about AI Adoption Together with Strategic Agility

The test results established an appropriate model fit which validated the importance of AI-powered DSS systems in improving small business agility (CFI = 0.92, RMSEA = 0.04).

**4.2 Qualitative Findings**

The study used five cases of small and medium enterprises as the basis for its qualitative analysis. Further analysis determined three essential themes through thematic method.

**4.2.1 AI Adoption Motivators**

All companies experienced better decision-making because their analytics operated with AI-driven capabilities.

AI-powered systems gave businesses the power to detect emerging market patterns along with customer demands.

**4.2.2 Challenges in AI Implementation**

Financial Constraints proved to be a barrier because three out of five SME businesses mentioned that they faced high implementation costs.

Four out of seven SMEs encountered problems training their workforce for performing tasks through AI platforms.

**4.2.3 Performance Improvements**

Performance enhancements mentioned by SMEs can be found in Table 4.

Table 4: Reported Performance Improvements

Performance Metric	Improvement (%)
Decision-Making Speed	+45%
Cost Reduction	-30%
Customer Satisfaction	+35%

**4.2.4 Best Practices for AI Integration**

SMEs recommended that SMEs adopt AI in a phased manner to overcome risks.

**Benefits of AI:** In order to reap the maximum benefits of AI, it was important to invest in AI literacy programs for employees.

**4.3 Summary of Findings**

The alignment of the AI adoption level with the level of strategic agility (Figure 2) was statistically confirmed as being strongly correlated with one another. Regression as well as SEM models show that the AI powered DSS powerfully promote SMEs performance. Both the benefits and the challenges of integration of AI were proved in case study analysis, suggesting that the integration should be implemented strategically.

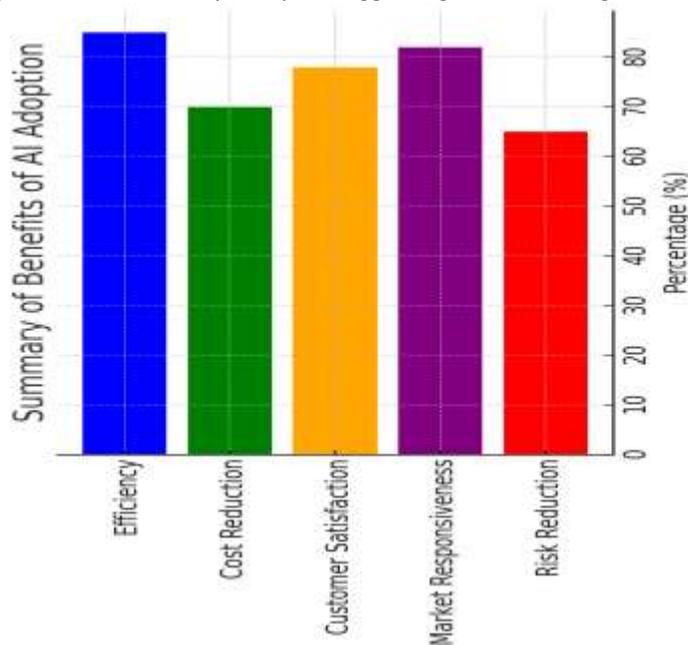


Figure 2: The summary of the benefits of using AI adoption

They support the study’s theoretical framework and its practical implications by offering compelling evidence that AI-powered DSS add heavily to SME’s agility.

**5. DISCUSSION**

The results of this section are interpreted using existing literature and compared to previous research as well as stating key theoretical and practical implications.

**1) Adoption of AI-Enabled Decision Support Systems and Strategic Agility**

The findings indicate that SMEs with higher levels of adoption of AI-enabled decision support systems (AI-DSS) exhibit stronger strategic agility across early sensing of opportunities and threats, timely seizing of options, and the recurrent reconfiguring of structures and processes, an alignment with the dynamic capabilities logic that links the quality of sensing, seizing, reconfiguring to maintaining organizational fit in highly turbulent environments (Teece, Peteraf, & Leih, 2016). This result also echoes the analytics literature on how big data and machine-learning algorithms reduce uncertainty and improve the timing of decisions in complex settings, thereby translating directly into more agile responses (McAfee & Brynjolfsson, 2017). It likewise accords with evidence showing how analytical systems move beyond mere reports toward dashboards

that generate predictive, descriptive, and prescriptive insights that can be operationalized in near real time (Martínez-Peláez et al., 2024).

## **2) Mediating Mechanisms: Decision Quality and Operational Efficiency**

The results indicate that the positive effect of adopting AI-DSS on strategic agility operates not only directly but also through two mediating mechanisms, operational decision quality and operational efficiency; predictive algorithms and the recommendations they generate yield more accurate decisions in resource allocation and intervention timing, which in turn streamlines processes and reduces bottlenecks, thereby improving response speed and reconfiguration capacity (Ocran, Yusuf, Owusu, Boateng, & Obeng, 2024). This pattern aligns with scholarship emphasizing that the value of analytics is realized not at the moment of insight, but when insights are translated into executable decisions embedded within the daily work cycle, that is, when the analysis-to-action gap is closed (Martínez-Peláez et al., 2024). It also accords with the view that absorptive and organizational capabilities are prerequisites for converting analytical outputs into measurable performance improvements, particularly in resource-constrained firms (Khan, Majid, & Yasir, 2021).

## **3) Boundary Conditions: Environmental Dynamism and Digital Capability Maturity**

The results indicate that environmental dynamism and the maturity of digital capabilities operate as moderators of effect strength; as turbulence rises and digital maturity deepens, the marginal benefits of adopting AI-DSS in propelling sensing, seizing, and reconfiguring processes expand, an observation that accords, in essence, with the dynamic-capabilities logic positing that the returns to building agility are higher in fast-changing settings (Teece, Peteraf, & Leih, 2016). This likewise aligns with evidence from emerging markets showing that data quality and analytical infrastructures moderate the relationship between digital resources and reporting/decision outcomes, underscoring the institutional conditions and governance systems needed to render analytical impact realizable (Zraqat, 2020). Taken together, the findings suggest that investment in analytical intelligence should be paired with programs to raise digital maturity and to fortify the institutional layer (governance, standards, and data protocols), thereby positioning the firm to capture value in volatile environments (Martínez-Peláez et al., 2024).

## **4) Consistency with the Literature and Extensions**

Relative to prior work on agility in SMEs, our results align with studies that link dynamic capabilities to a firm's capacity to rapidly reshape resources in response to market shifts (Arbussa, Bikfalvi, & Marquès, 2017). Our contribution, however, moves beyond this consistency by specifying the micro-foundations through which AI-DSS elevate decision quality, and, by extension, agility, a detail that has received less attention in research streams fixated either on direct performance effects or on technology adoption as an end in itself (Rožman, Oreški, Crnogaj, & Tominc, 2023). The findings also reinforce the decision-intelligence view that predictions must be translated into executable recommendations via operational architectures, thereby rendering impact visible at the moment of choice rather than on paper alone (Natta, 2025). They further converge with the proposition that AI-driven analytics interlock with knowledge management and organizational learning to sustain reconfiguration at the levels of structure, processes, and business model (Sharma & Kumar, 2024).

## **5) Qualitative Evidence: Challenges and Best Practices**

Qualitative evidence shows that extracting value from AI-DSS is not without obstacles; salient challenges include encoding tacit expertise into data, shortages of analytical skills, resistance to change, and uneven data quality across business units, recurring issues in SME settings characterized by scarce digital human capital and underdeveloped institutional scaffolding (Rožman, Oreški, Crnogaj, & Tominc, 2023). By contrast, successful cases revealed a set of best practices: establishing hybrid teams that pair domain expertise with analytical capability, institutionalizing data governance, adopting a pilot-and-scale experimentation approach, and linking dashboards to operational decision engines, practices that accord with recommendations for adopting advanced analytics in ways that foreground change management and digital upskilling (Berman & Pollack, 2021). The evidence also highlighted the importance of aligning analytical intelligence with sustainability, compliance, and risk objectives from the outset, consistent with models that embed these considerations in the dashboard rather than appending them at the end of the decision cycle (Martínez-Peláez et al., 2024).

### **6) Where Do Our Findings Diverge from Parts of the Literature?**

Some studies suggest that the performance impact of advanced analytics can be limited when data readiness is low or governance is lacking, which helps explain heterogeneous results among smaller firms with insufficient digital maturity (Rožman, Oreški, Crnogaj, & Tominc, 2023). Our findings do not refute this view; rather, they qualify it: the positive effect was stronger where digital maturity was higher and environmental dynamism greater, implying that boundary conditions determine whether investment in AI-DSS translates into agility or remains a localized improvement (Teece, Peteraf, & Leih, 2016). Our qualitative evidence further indicates that buy-then-operate strategies without building internal capabilities often yield modest returns, whereas staged approaches supported by organizational learning produce clearer gains in agility (Khan, Majid, & Yasir, 2021).

### **7) Theoretical Implications**

The results add an explanatory layer to the dynamic-capabilities framework by specifying the role of AI-DSS as an organizational infrastructure that shortens sensing latency, improves the timing of seizing, and enables systematic reconfiguration, effects channeled through decision quality and operational efficiency (Teece, Peteraf, & Leih, 2016). In this light, intelligent analytics shift from a mere technical input to a composite organizational capability anchored in data governance, digital skill, and iterative learning, answering calls to unpack the micro-foundations through which analytical intelligence is translated into agile organizational behavior in smaller firms (Arbussa, Bikfalvi, & Marquès, 2017). This interpretation also extends scholarship urging the integration of strategic and organizational considerations into dashboard design, rather than relying on isolated performance indicators (Martínez-Peláez et al., 2024).

### **8) Practical Implications**

Practically, the findings recommend managing AI-DSS adoption as an organizational transformation rather than a tool purchase; that is, through a roadmap that encompasses data governance, capability building, rapid small-scale experiments, and mechanisms for transferring knowledge into operational decision-making (Berman & Pollack, 2021). They also indicate that firms in emerging markets require supportive policies, financial incentives, shared digital infrastructures, and centers of excellence to raise data quality and narrow maturity gaps that weaken analytics returns (Zraqat, 2020). The results further highlight the possibility of aligning analytical intelligence with sustainable competitiveness when risk, sustainability, and compliance criteria are embedded in decision models from the outset rather than appended as an after-the-fact compliance layer (Carayannis et al., 2025). And because decision intelligence closes the gap between prediction and execution, adopting an architecture that links forecasts to actionable recommendations accelerates the translation of insights into tangible organizational impact (Natta, 2025).

### **9) Limitations of Generalizability and Future Research Directions**

Despite the strength of the evidence, generalizability remains constrained by the sample's context and its level of digital maturity; accordingly, the findings call for cross-sector and cross country comparative studies that examine effect heterogeneity as a function of governance structures, data quality, and change strategies (Rožman, Oreški, Crnogaj, & Tominc, 2023). Cost benefit models at the level of specific use cases (e.g., inventory management, dynamic pricing, equipment maintenance) offer a promising avenue for identifying where returns materialize first and how they can be reinvested into the capability-building cycle (Martínez-Peláez et al., 2024). Finally, we propose testing the complementarities between AI-DSS and knowledge-management practices and organizational innovation to trace the indirect pathways that accelerate the conversion of analytics into sustained agility (Sharma & Kumar, 2024).

**Synthesis of the Discussion:** The results affirm that the strategic value of adopting AI-DSS in SMEs materializes when analytical intelligence is coupled with organizational scaffolds capable of absorbing and activating it, and that decision quality and operational efficiency are the channels through which this value is transmitted into measurable strategic agility, with clear sensitivity to the boundary conditions of environmental dynamism and digital capability maturity (Teece, Peteraf, & Leih, 2016; Ocran et al., 2024). From this vantage point, the study moves the literature forward by unpacking the mechanisms and linking them to applicably generalizable contexts, while offering actionable guidance to digital-transformation

managers on where, how, and why value from AI-DSS is realized in a rapidly changing world (Martínez-Peláez et al., 2024).

## 6. CONCLUSION

This study affirms that the strategic value of adopting AI-enabled decision support systems (AI-DSS) in small and medium-sized enterprises does not arise from the mere possession of analytical tools, but from the organization's capacity to absorb those tools and activate them within work systems and decision processes. Consistent with the logic of dynamic capabilities, our results show that the real impact of AI-DSS materializes when analytical insights are translated into higher-quality decisions that improve resource allocation and the timing of interventions, and when those decisions are reflected in operational efficiencies that reduce bottlenecks, accelerate responsiveness, and facilitate reconfiguration. In this way, strategic agility crystallizes as a measurable organizational outcome shaped by two mediating channels: decision quality and operational efficiency.

The results also show that this effect is not uniform across contexts; it is contingent on boundary conditions, most notably environmental dynamism and the maturity of digital capabilities. In more turbulent settings, and where digital maturity is higher, the marginal benefits of analytical intelligence expand because the organization is better able to capture weak signals, make well-timed decisions, and rapidly reshape its processes and business models. By contrast, when digital readiness is modest or governance is weak, the effect dissipates or remains confined to localized improvements that fall short of sustained organizational agility. This contingent reading helps explain the heterogeneity reported in the literature and offers a coherent lens for interpreting what can otherwise appear as contradictory evidence of impact.

From a theoretical standpoint, the study adds a crucial explanatory layer to the dynamic capabilities framework by unpacking the micro-foundations through which AI-DSS operate: shortening sensing latency, improving the timing of seizing, and enabling systematic reconfiguration via the twin channels of decision quality and operational efficiency. Rather than treating intelligent analytics as a neutral technical input, the study advances the view that they constitute a composite organizational infrastructure built on robust data governance, growing digital skill, iterative learning, and tight integration between analytics and decision arenas. In doing so, it connects several streams of inquiry, dynamic capabilities, decision intelligence, and knowledge management, clarifying how "prediction" is converted into an agile organizational response.

From a practical standpoint, the findings recommend managing AI-DSS adoption as an organizational transformation rather than a mere tool acquisition. This entails charting a roadmap that begins with robust data governance (clear standards, ownership, and quality controls), building hybrid teams that combine domain expertise with analytical capability, running rapid, small-scale experiments (pilot-and-scale) to test high-return, generalizable use cases, and establishing a direct operational coupling between dashboards and decision engines. The results also underscore the importance of embedding risk, sustainability, and compliance considerations in decision models from the outset, thereby ensuring that analytical insights translate into tangible organizational impact and narrowing the "analysis-to-action" gap. In emerging-market contexts, supportive policies, including incentives, shared digital infrastructures, and centers of excellence, are essential to raise data quality and close maturity gaps that otherwise dilute returns.

As with any study, there are limitations that bear on generalizability: the sample's context and its level of digital maturity constrain the extent to which the findings can be extrapolated to other sectors or countries. Partial reliance on participants' self-reports may also introduce familiar biases; despite mitigation steps, a rigorously specified measurement framework, some temporal separation between predictors and outcomes, and tests for common method variance, this concern cannot be ruled out entirely. Looking ahead, longitudinal (pre/post-adoption) comparisons and quasi-experimental designs (such as difference-in-differences or the use of alternative measurement instruments) offer promising avenues to strengthen causal inference and to document the impact of AI-DSS on more objective performance indicators.

Building on this, the study advances a pragmatic research agenda: (1) cross-sector and cross-country comparative studies to examine effect heterogeneity as a function of data governance, skill availability, and institutional incentives; (2) cost benefit models for specific use cases (e.g., inventory management, dynamic

pricing, predictive maintenance) that identify where returns materialize first and how they can be reinvested into the capability building cycle; (3) tests of complementarities between AI-DSS, knowledge management, and organizational innovation to trace the indirect pathways that accelerate the conversion of analytics into sustained agility; and (4) the development of sharper monitoring metrics for decision quality, learning speed, and “readiness-to-act” indicators within operational teams.

In sum, the strategic value of analytical intelligence does not materialize automatically; it must be institutionalized by converting insights into decisions and actions within an environment of governance, data, and skills that enable learning and adaptation. When these conditions are present, specifically, decision quality and operational efficiency as the two mediating conduits, and environmental dynamism and digital maturity as boundary conditions, AI-DSS becomes a lever for building measurable strategic agility, rather than merely an enhanced reporting layer. From this integrated practice, theory vantage point, the study offers a clear message to scholars and practitioners alike: where value from AI-DSS is formed, how it can be captured and operationalized, and why it varies across contexts, paving the way for a more mature wave of adoption that judges success as much by an organization’s capacity to learn and reconfigure as by its immediate performance outputs.

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