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A META-ANALYSIS OF AI-DRIVEN BUSINESS ANALYTICS: ENHANCING STRATEGIC DECISION-MAKING IN SMES

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Abstract

This meta-analysis offers a comprehensive examination of how AI-driven business analytics influence strategic decision-making within small and medium-sized enterprises (SMEs), a sector often constrained by limited resources but increasingly pressured to compete in data-intensive environments. By systematically synthesizing 112 peer-reviewed empirical studies published between 2010 and 2025, this research explores the effects of artificial intelligence technologies—including machine learning, natural language processing, predictive analytics, and real-time data dashboards—on key decision outcomes such as speed, accuracy, responsiveness, and operational agility. The methodology followed the PRISMA 2020 guidelines to ensure transparency and replicability, utilizing a random-effects model to aggregate effect sizes across heterogeneous organizational contexts. The findings indicate that AI adoption significantly enhances decision-making performance across diverse business functions, with the most pronounced effects observed in marketing, financial forecasting, and supply chain operations. Moreover, the results demonstrate that AI technologies contribute not only to efficiency and precision but also to reducing cognitive biases, enhancing scenario planning, and enabling agile responses in dynamic environments. Moderator analysis reveals that medium-sized firms, those with advanced digital infrastructure, and organizations in data-intensive industries benefit the most from AI deployment. Furthermore, the integration of AI tools appears to scale more effectively in firms with greater absorptive capacity, robust data governance frameworks, and structured decision-making protocols. This study also highlights the role of AI in complementing managerial cognition by transforming complex, unstructured data into actionable insights, thereby supporting evidence-based decision cultures in SMEs. While adoption barriers such as cost, talent gaps, and technological inertia persist, the overall evidence confirms that when strategically aligned with internal capabilities, AI-driven analytics can function as a transformative enabler of strategic competitiveness. The meta-analysis offers theoretical advancement by quantifying cross-sector impacts and practical insights for SME leaders, policymakers, and researchers aiming to build intelligent, resilient, and data-literate enterprises in the era of digital transformation.

Keywords

Artificial Intelligence, Business Analytics, Strategic Decision-Making, Small and Medium Enterprises (SMEs), Predictive Analytics;

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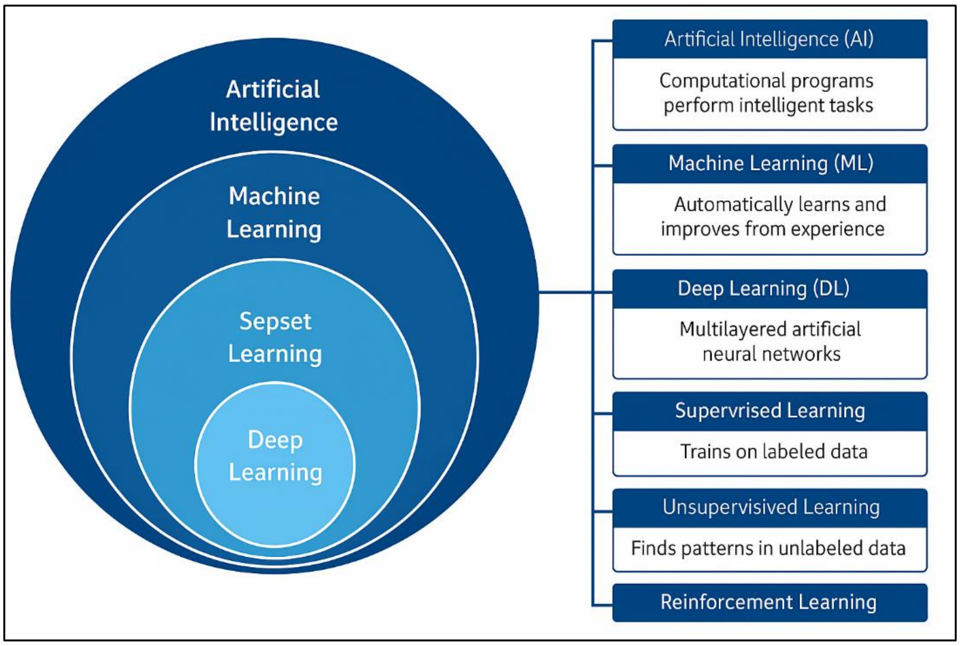
INTRODUCTION

Artificial Intelligence (AI) refers to the capacity of machines to perform tasks that typically require human intelligence, including learning, reasoning, problem-solving, and language understanding (Belk et al., 2023). Business analytics, on the other hand, encompasses techniques for transforming data into actionable insights to guide managerial decision-making, often through descriptive, predictive, and prescriptive analytics (He & Liu, 2024). AI-driven business analytics integrates machine learning algorithms, natural language processing, and statistical models to automate and enhance data analysis processes. This fusion is particularly transformative for strategic decision-making, as it enables organizations to generate real-time insights, forecast trends, and optimize resources with unprecedented precision (Wamba-Taguimdje et al., 2020). Strategic decision-making refers to long-term, high-impact managerial choices that determine an organization's direction and competitive positioning. By embedding AI into business analytics frameworks, firms can significantly refine how they interpret complex data environments and deploy strategic interventions. Unlike traditional analytics, AI-driven systems can adapt autonomously to new data inputs, detect patterns in unstructured data, and reduce cognitive bias in judgment-intensive scenarios (Sestino & De Mauro, 2021). This capacity has amplified the strategic value of analytics in organizational contexts, making it a cornerstone of digital transformation agendas across both large enterprises and SMEs. The growing intersection between AI and business analytics highlights the urgency of understanding its implications on decision-making efficacy, particularly for resource-constrained SMEs.

Figure 1: Hierarchical Relationship of Artificial Intelligence



Globally, the application of AI-driven business analytics is gaining momentum across industrialized and developing economies, reflecting a paradigm shift in how organizations make decisions under uncertainty (Sun & Medaglia, 2019). The European Commission has positioned AI as a key pillar for SME competitiveness under its Digital Europe Programme, highlighting AI's role in facilitating agile operations, customer insights, and risk management. Similarly, the OECD underscores that AI adoption among SMEs can bridge productivity gaps between small and large firms, especially in data-intensive sectors such as retail, finance, and logistics. In countries like South Korea and Singapore, national innovation strategies have directly funded AI adoption in SMEs through data infrastructure support and workforce training programs (Zandi et al., 2019). The international relevance of AI-driven business analytics is also evident in Africa and Latin America, where initiatives such as the Smart Africa Alliance and Inter-American Development Bank's AI for SMEs program aim to boost economic resilience through intelligent data solutions. This cross-regional focus indicates that AI is not merely a luxury for large tech firms but a strategic necessity for SMEs navigating complex

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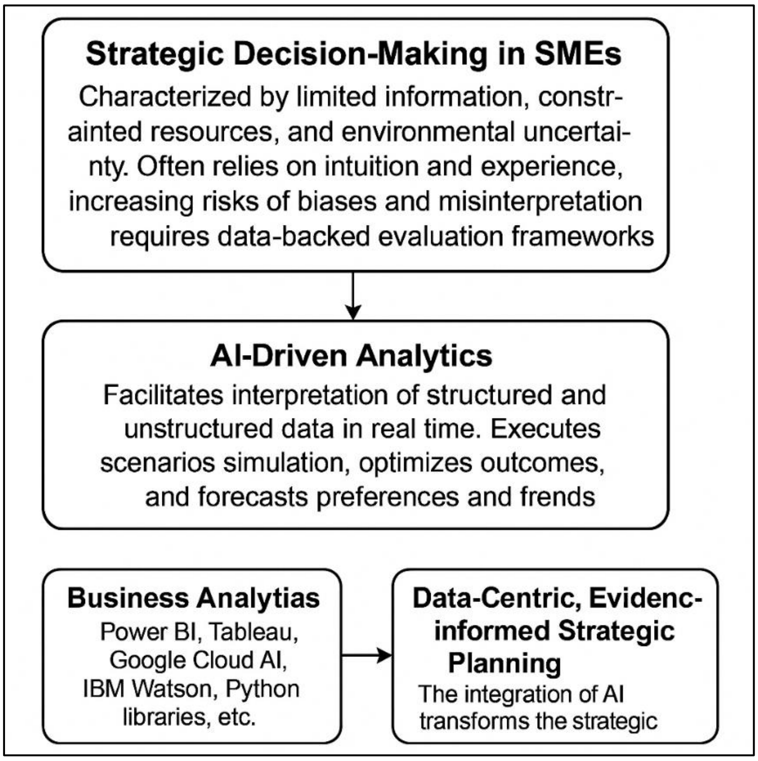
market demands and digital disruptions (Saleem et al., 2024). While SMEs typically face resource constraints, their flexible structures enable quicker adaptation to AI tools, especially when supported by external platforms or cloud services. The international discourse on digital inclusion consistently emphasizes the centrality of AI-enhanced decision-making in narrowing the innovation gap and fostering inclusive economic development (Schkarin & Dobhan, 2022).

Figure 2: Integration of AI-Driven Analytics into Strategic Decision-Making Processes in SMEs



Strategic decision-making in SMEs is characterized by the interplay of limited information, constrained financial resources, and heightened environmental (Jain et al., 2024). Unlike larger organizations with dedicated analytics teams and hierarchical governance, SMEs often depend on the intuition and experience of their owner-managers when making strategic choices (Kulkov, 2021). This reliance, although advantageous for speed and flexibility, may expose SMEs to greater risks of cognitive biases, overconfidence, and misinterpretation of market signals. Strategic decisions in areas such as product diversification, market entry, technology investments, and talent acquisition require data-backed evaluation frameworks that SMEs often lack (Benabed et al., 2022). AI-driven analytics offers a solution to these challenges by facilitating the interpretation of structured and unstructured data in real time, allowing SMEs to simulate multiple decision scenarios and optimize outcomes. Moreover, predictive analytics can aid SMEs in forecasting customer preferences, managing financial risks, and identifying emerging trends with greater accuracy than manual approaches. These capabilities are especially vital in turbulent economic conditions, where traditional heuristics fail to anticipate market volatility or disruptions. By equipping SMEs with intelligent insights, AI-driven analytics transforms the strategic planning process into a data-centric, evidence-informed endeavor (Baabdullah et al., 2021).
The integration of AI into SME operations is largely facilitated through business analytics platforms such as Power BI, Tableau, Google Cloud AI, IBM Watson, and open-source solutions like Python-based libraries. These platforms offer SMEs cost-effective access to machine learning algorithms, visualization dashboards, and decision support systems without the need for in-house data science expertise. For example, sentiment analysis tools driven by natural language processing help SMEs understand consumer feedback across social media and e-commerce platforms. Similarly, clustering and classification algorithms support customer segmentation, marketing campaign optimization, and inventory planning (Benabed et al., 2022). Cloud-based analytics further ease the adoption

burden by offering scalability, data storage, and real-time processing capacities that are financially viable for SMEs. Empirical studies confirm that SMEs leveraging AI-based tools report improvements in operational agility, customer retention, and strategic responsiveness. Additionally, the use of AI in performance dashboards enables SME managers to monitor key performance indicators (KPIs) and make proactive adjustments to pricing, logistics, and supplier contracts (Baabdullah et al., 2021). These integrated systems thus convert fragmented data into coherent strategic insights, aligning business intelligence with organizational goals. The primary objective of this meta-analysis is to quantitatively evaluate the impact of AI-driven business analytics on strategic decision-making effectiveness in small and medium-sized enterprises (SMEs). This study aims to synthesize empirical findings from peer-reviewed literature published between 2010 and 2025, using statistical aggregation to assess the magnitude and consistency of AI's contributions across diverse SME contexts. Specifically, the meta-analysis investigates how AI applications—such as predictive modeling, machine learning algorithms, and natural language processing—affect decision quality, operational efficiency, and responsiveness to environmental uncertainty. Additionally, the study aims to identify moderator variables, including sector type, firm size, digital maturity, and geographic region, that influence the strength of the AI-decision-making relationship. Following the PRISMA 2020 guidelines, this research adheres to a structured and transparent methodology involving systematic search, inclusion criteria specification, effect size calculation, heterogeneity assessment, and publication bias analysis. By operationalizing strategic decision-making through indicators such as timeliness, accuracy, and adaptability, the study ensures that results are generalizable across multiple organizational settings. The objective is not only to confirm the significance of AI in SME strategy formation but also to provide a robust evidence base for managers, policymakers, and technology providers who seek to optimize the strategic value of AI-driven analytics.

LITERATURE REVIEW

The integration of Artificial Intelligence (AI) into business analytics has attracted increasing scholarly attention for its potential to transform strategic decision-making processes across organizations, particularly within the context of small and medium-sized enterprises (SMEs). The extant literature spans multiple disciplines, including information systems, strategic management, organizational behavior, and data science, reflecting a multifaceted understanding of how AI-enabled tools contribute to decision quality, organizational agility, and business performance. However, while substantial empirical and conceptual research exists on AI adoption in large enterprises, the application and impact of AI-driven business analytics in SMEs remain comparatively underexplored and fragmented. This literature review critically synthesizes prior studies to establish a theoretical and empirical foundation for the meta-analysis, delineating key concepts, methodological trends, thematic findings, and contextual gaps. The review adopts an integrative structure, mapping developments in AI capabilities, business analytics models, decision-making frameworks, and organizational readiness variables relevant to SME ecosystems. By organizing the literature into clearly defined themes, the review facilitates an analytical understanding of the drivers, barriers, applications, and outcomes associated with AI-driven business analytics. It also enables the identification of knowledge gaps and heterogeneity in existing research, thereby justifying the need for a structured meta-analytical synthesis.

AI and Business Analytics in Organizational Contexts

Artificial Intelligence (AI) has been broadly defined as a technological system capable of performing cognitive tasks typically requiring human intelligence, such as perception, reasoning, learning, and decision-making (Baabdullah et al., 2021). Within enterprise environments, AI encompasses an array of subfields including machine learning (ML), natural language processing (NLP), neural networks, and computer vision, each contributing to automated or augmented decision systems (Belk et al., 2023). Business analytics (BA), conversely, refers to the systematic computational analysis of business data aimed at identifying patterns, generating insights, and supporting managerial decision-making (He & Liu, 2024). The intersection of AI and BA has led to the emergence of intelligent analytics platforms that blend statistical models with adaptive learning capabilities, thereby transforming conventional business intelligence (BI) systems into dynamic, predictive environments (Baabdullah et al., 2021). AI-driven analytics systems enhance performance by automating data exploration, enabling real-time decision support, and facilitating large-scale pattern recognition beyond human processing capabilities. Unlike static rule-based systems, AI-enabled analytics evolve continuously through exposure to new data, allowing organizations to refine predictions and operational

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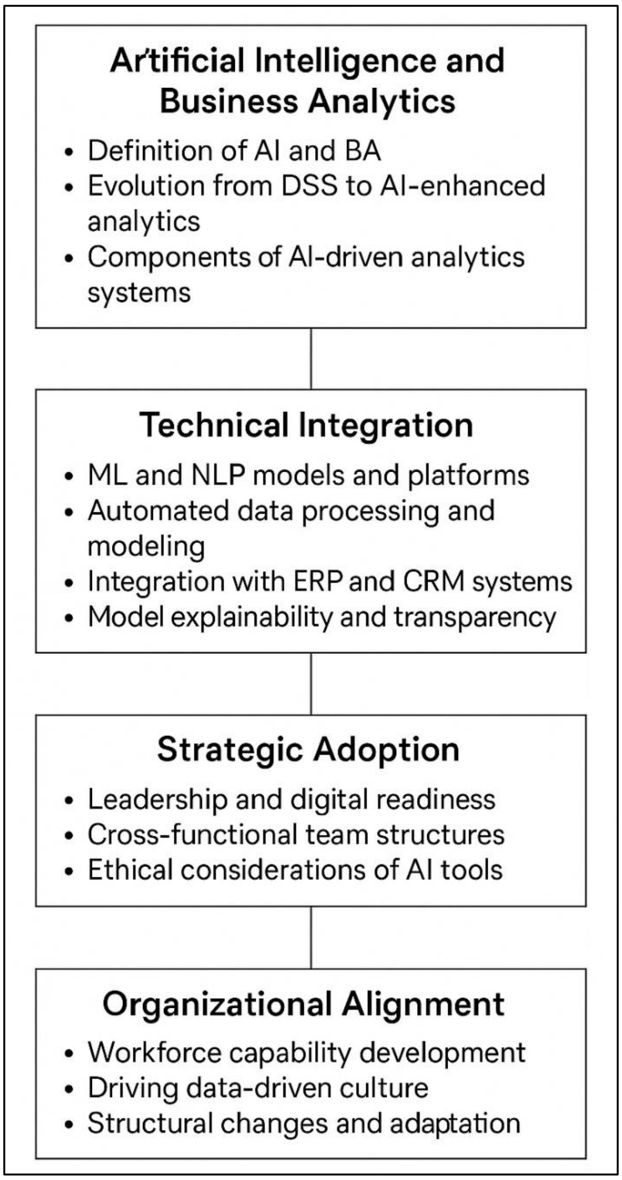
responses with improved precision(Upadhyay et al., 2021). These systems have demonstrated utility in diverse operational domains, including marketing, finance, logistics, and customer service, offering organizations the ability to interpret structured and unstructured data at scale. Notably, the growing sophistication of AI-BA tools has democratized data access across hierarchical levels, empowering decision-makers beyond IT departments to engage in analytical processes. The definitional and functional scope of AI and business analytics continues to evolve, but their integration consistently represents a shift from reactive data monitoring to proactive, evidence-based decision-making systems (Gupta et al., 2024).

Figure 3: Framework for Organizational Integration of AI-Driven Business Analytics

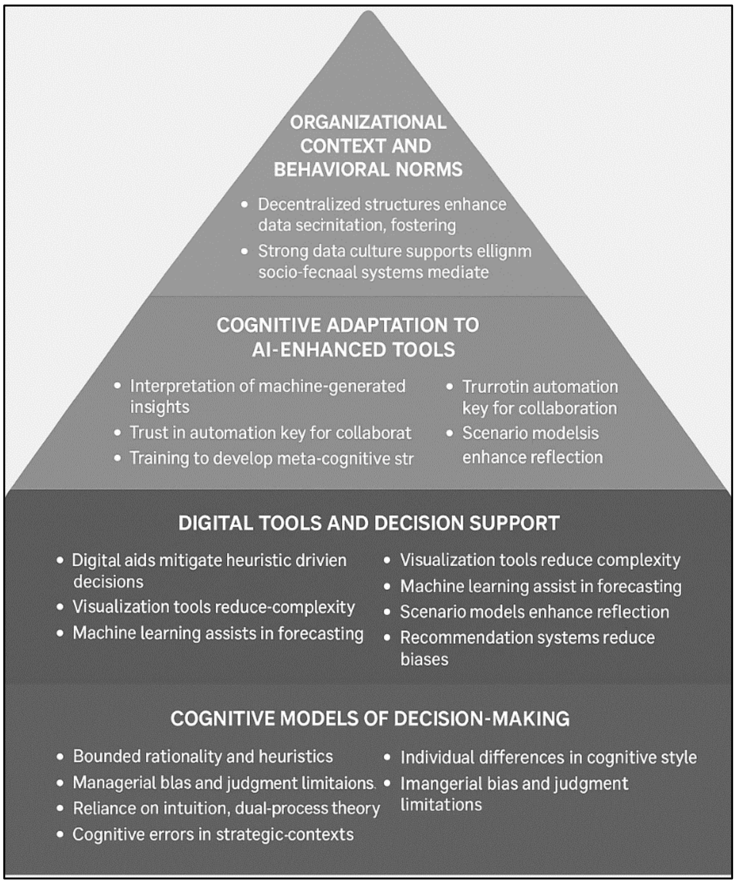


The conceptual development of business analytics has undergone significant transformation since the early use of data processing in enterprise systems. Traditionally, decision support systems (DSS) and management information systems (MIS) were utilized to report historical data, primarily through descriptive analytics tools such as dashboards and spreadsheets. However, as organizations faced increased market volatility and data complexity, the limitations of static analytics became evident (Brem et al., 2023). This necessitated the adoption of more dynamic, predictive, and prescriptive analytics methods, a need increasingly met by AI technologies . The transition from business intelligence to AI-enhanced analytics marked a major inflection point, allowing firms to leverage algorithms for anomaly detection, predictive forecasting, and cognitive automation (Subrato, 2018; Zhou et al., 2024). Machine learning models introduced iterative self-learning mechanisms, reducing the need for human intervention in model development and parameter tuning (Abdullah Al et al., 2022; Dwivedi et al., 2021). Furthermore, natural language processing enabled the analysis of unstructured text data from social media, emails, and reviews, broadening the analytical scope significantly. This evolution was not merely technological but also organizational, as firms had to develop new capabilities in data governance, cloud computing, and cross-functional collaboration. The adoption of AI-driven business analytics systems was particularly visible in data-intensive sectors such as retail, banking, and telecommunications, where real-time insights offered competitive advantages. Scholars have observed that this shift from diagnostic to predictive/prescriptive analytics reshaped decision-making paradigms, making AI a critical component of digital strategy. The historical evolution of analytics thus reflects a trajectory from reactive reporting to strategic foresight enabled by AI.

Cognitive Models and Digital Influence

Cognitive models of decision-making in organizational theory center on how individuals and groups process information, evaluate alternatives, and select actions based on both rational analysis and bounded capabilities (Jahan et al., 2022; Tizhoosh & Pantanowitz, 2018). Simon's theory of bounded rationality highlights that decision-makers often rely on heuristics and satisficing due to cognitive limitations and incomplete information environments. In the context of managerial behavior, these limitations are further influenced by time constraints, ambiguous data, and personal judgment biases, especially within small and medium-sized enterprises (SMEs) where structured analytical support may be minimal. The dual-process theory further differentiates between intuitive (System 1) and deliberative (System 2) thinking, emphasizing how unconscious heuristics can dominate under pressure. Studies have found that overreliance on intuitive cognition can lead to confirmation bias, framing effects, and risk aversion in strategic contexts (Hansen & Bøgh, 2021; Ara et al., 2022). In SME environments, decision-makers often substitute formal strategic models with experience-based mental shortcuts, increasing vulnerability to cognitive errors. Moreover, individual differences in cognitive style, such as analytical versus holistic thinking, significantly influence how information is interpreted and applied in organizational settings. These cognitive mechanisms are not isolated but shaped by organizational norms, leadership style, and cultural context. Collectively, the literature on cognitive decision-making provides a foundational understanding of the inherent mental limitations managers face, laying the groundwork for assessing how digital tools, including artificial intelligence (AI), may interact with or compensate for such cognitive constraints (Drydakis, 2022; Khan et al., 2022).

Figure 4: Integrative Framework of Cognitive Models, Digital Tools



The integration of digital tools into decision-making processes offers mechanisms for addressing common cognitive biases and improving judgment quality. AI-powered analytics platforms, decision support systems (DSS), and visualization dashboards assist managers in processing large volumes of information, thereby mitigating heuristic-driven decisions (Drydakis, 2022; Rahaman, 2022). Digital decision aids provide structured environments that reduce reliance on intuition by presenting data trends, simulations, and predictive outcomes in real time. For instance, the use of machine learning algorithms in forecasting allows for objective pattern recognition, which contrasts with the subjective interpretations often prevalent in manual forecasting. Several studies confirm that the integration of data visualization tools like heatmaps, scatter plots, and dashboards enhances information salience and reduces framing effects in strategic deliberations (Hansen & Bøgh, 2021; Masud, 2022; Wei &

Pardo, 2022). Cognitive load theory also explains how digital tools reduce decision fatigue by minimizing information complexity through layered presentation and user interactivity (Drydakis, 2022; Hossen & Atiqur, 2022). Furthermore, systems that include scenario-based modeling or real-time feedback loops help decision-makers examine multiple outcomes before committing to a strategy, thereby enhancing reflective cognition (Peretz-Andersson et al., 2024; Sazzad & Islam, 2022). Researchers have also explored the role of AI-enabled recommendation engines in reducing confirmation bias by suggesting counterfactual scenarios or novel data patterns (Mitchell, 2019; Shaiful et al., 2022). By automating parts of the analytical process, digital tools lower the cognitive burden on decision-makers while increasing the consistency and reproducibility of outcomes. In organizational contexts, especially SMEs with limited analytical personnel, digital decision aids become instrumental in supplementing human judgment with computational rigor.

Theoretical frameworks of strategic decision-making

Strategic decision-making has traditionally been grounded in rational choice theory, which assumes that decision-makers are fully informed, capable of evaluating all alternatives, and driven by objective utility maximization (Kohtamäki et al., 2019). However, in organizational settings, such idealized rationality often fails to represent how strategic decisions are made in practice. The bounded rationality model argues that managers operate under conditions of limited information, constrained cognitive resources, and time pressure, leading them to "satisfice" rather than optimize decisions. This framework has been particularly relevant in small and medium-sized enterprises (SMEs), where decision-makers often lack access to sophisticated analytical systems and rely on rule-of-thumb strategies (Al, 2016; Akter & Razzak, 2022). Empirical studies have confirmed that SME managers frequently combine analytical reasoning with experiential knowledge, highlighting the hybrid nature of strategic cognition (Qibria & Hossen, 2023; Papadopoulos et al., 2020). In addition, decision-making under uncertainty has been extensively modeled using the garbage can theory, which depicts decisions as outcomes of chaotic, loosely coupled processes involving problems, solutions, and decision-makers intersecting randomly (Johnson & Schaltegger, 2015; Maniruzzaman et al., 2023). This view has gained traction in dynamic environments where strategic responses are emergent rather than planned. Researchers such as (Helfat & Winter, 2011) have also emphasized the episodic and iterative nature of strategic choices, noting that formal analysis often coexists with intuition and political negotiation. These frameworks collectively demonstrate that strategic decision-making is less about perfect logic and more about coping with complexity, ambiguity, and cognitive limits (Md Masud, Mohammad, & Hosne Ara, 2023; Ojha et al., 2023). The enduring relevance of bounded rationality and alternative models reveals the need to understand decision-making as both a rational and behavioral process shaped by internal and external contingencies (Chung et al., 2022; Md Masud, Mohammad, & Sazzad, 2023).

The behavioral strategy perspective builds upon psychology and organizational behavior to explain how cognitive biases, mental models, and affective states influence strategic decision-making. Unlike the rational actor model, behavioral strategy focuses on how decision-makers interpret their environment through subjective lenses shaped by prior experiences, emotional triggers, and bounded attention. Studies have shown that strategic decisions are often affected by framing effects, anchoring, overconfidence, and loss aversion—cognitive biases that persist even in experienced executives (Chung et al., 2022; Kumar & Kalse, 2021; Hossen et al., 2023). These biases are particularly salient in fast-paced and resource-constrained SME environments, where rapid decisions must often be made without full analysis. Mental models, which refer to internal representations of external reality, also play a significant role in shaping strategic judgment by filtering which data is noticed, ignored, or interpreted. Organizations often develop shared cognitive frames that guide strategy formulation, a concept explored in the literature on strategic cognition. Moreover, the affect-as-information theory suggests that emotions such as anxiety, excitement, or anger can unconsciously inform strategic judgments, influencing risk tolerance and time horizon (Ariful et al., 2023; Sharma et al., 2024). The dual-process model of cognition—where intuitive and deliberative processes operate in parallel—has been applied to understand how executives switch between fast, affective responses and slow, logical analysis depending on the decision context. These behavioral approaches provide a nuanced view of strategic decision-making, demonstrating that human cognition is central to understanding deviations from optimality and variability in organizational outcomes (Kumar & Kalse, 2021; Shamima et al., 2023)

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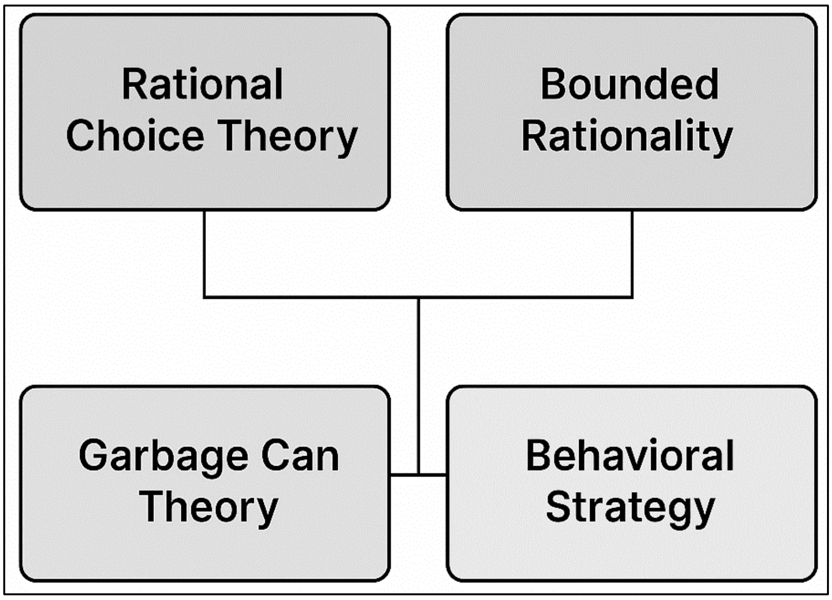
Figure 5: Theoretical Overview



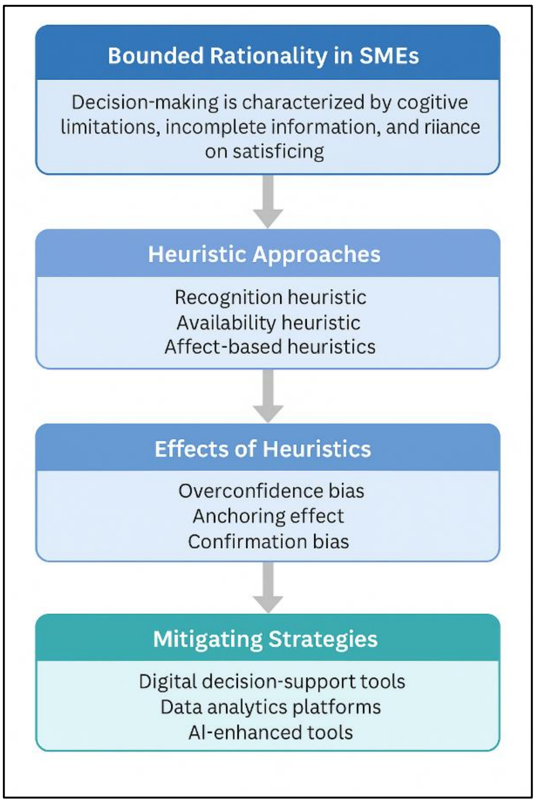
Contingency theory provides a structural lens to strategic decision-making, asserting that optimal decisions are contingent on internal organizational factors and external environmental variables. This theory highlights that there is no universally effective decision-making style; rather, the effectiveness of strategic approaches depends on contextual elements such as firm size, industry turbulence, technological capability, and leadership composition (Alam et al., 2023; Sjödin et al., 2020). For example, in dynamic industries with high uncertainty, decentralized and flexible decision-making models tend to perform better than rigid, hierarchical approaches (Chung et al., 2022; Rajesh, 2023). The upper echelons theory, introduced by Gruber et al. (2015), complements this perspective by emphasizing the influence of top executives' characteristics—such as values, experiences, and demographics—on strategic outcomes. Empirical research demonstrates that executive age, educational background, tenure, and cognitive style shape how strategic issues are perceived and responded to (Hrivnák et al., 2021; Rajesh et al., 2023). Within SMEs, the influence of the founder or owner-manager often dominates strategic direction, aligning with the upper echelons view that organizational outcomes are reflections of managerial interpretations. Additionally, environmental scanning behavior and strategic responsiveness have been shown to vary based on executives' cognitive capabilities and openness to information. These theoretical frameworks emphasize that strategic decision-making is not only a function of rational data processing but also of contextual alignment between the firm's internal competencies and external challenges (Ashraf & Hosne Ara, 2023; Saleem et al., 2024). Both contingency theory and upper echelons theory thus contribute to understanding the variability in strategic decision outcomes across different organizational and leadership profiles (Asiaei & Rahim, 2019; Roksana, 2023).

Bounded rationality and heuristics in SME decisions

Bounded rationality asserts that decision-makers operate under cognitive and environmental constraints, preventing them from achieving full rationality in strategic choices. Unlike the assumptions of the classical rational actor model, which posits perfect information and unlimited processing capacity, bounded rationality acknowledges that individuals make decisions with incomplete knowledge, finite time, and limited mental capacity. This framework is particularly relevant for small and medium-sized enterprises (SMEs), where decisions are often made by a single founder or a small leadership team without extensive analytical support (Justy et al., 2023; Sanjai et al., 2023). In contrast to larger firms, SMEs frequently lack dedicated strategic planning departments and formalized decision-making protocols, resulting in reliance on satisficing—choosing a "good enough" option rather than the optimal one (Shepherd et al., 2020; López-Fernández et al., 2018).

Empirical evidence suggests that SME leaders often substitute formal analyses with intuitive judgments or prior experience when evaluating complex problems (Kulkov, 2021; Tonmoy & Md Arifur, 2023). This behavior aligns with the cognitive economy principle, which suggests that mental shortcuts are used to reduce effort in decision environments marked by uncertainty and complexity (Daniel & Wilson, 2003; Tonoy & Khan, 2023). The limited scope of available data, time pressures, and the absence of domain experts in SMEs amplify the tendency to operate under bounded conditions (Karimi & Walter, 2015; Zahir et al., 2023). Organizational research further demonstrates that the bounded rationality paradigm is not only descriptive but also diagnostic, as it captures the everyday challenges that SME managers face in data interpretation, option generation, and outcome prediction. These limitations are neither rare nor accidental but embedded in the organizational reality of SMEs where resource constraints shape decision trajectories.

Figure 6: Heuristics, and Digital Decision-Support Integration in SME Strategic Choices



Heuristics, defined as cognitive shortcuts or rules-of-thumb, are essential components of decision-making under bounded rationality and are widely used in SMEs due to practical constraints (Baabdullah et al., 2021). Rather than being flawed or irrational, heuristics serve adaptive functions by enabling managers to make timely decisions with limited information. (Sharma et al., 2021) found that entrepreneurs and SME owners are more likely to use heuristics than corporate managers, particularly in conditions characterized by uncertainty and time pressure. The recognition heuristic, where decision-makers choose familiar alternatives over unfamiliar ones, is frequently used by SME leaders evaluating suppliers, partners, or markets. Similarly, the availability heuristic—basing decisions on readily recalled examples—is common in marketing or crisis response contexts, often shaping judgments around customer trends or competitor behavior. Empirical studies demonstrate that SMEs rely heavily on affect-based heuristics when hiring staff, entering new markets, or responding to regulatory changes. While these mental shortcuts provide speed and efficiency, they also introduce potential biases, such as confirmation bias, overconfidence, and anchoring effects, which may compromise decision quality (Razzak et al., 2024; Tan et al., 2024). Nonetheless, research in naturalistic decision-making shows that heuristics may produce decisions comparable in accuracy to more complex models, especially in environments that are familiar and feedback-rich(Alam et al., 2024). This perspective positions heuristics not merely as cognitive failings but as boundedly rational responses tailored to SME realities (Khan & Razee, 2024; Upadhyay et al., 2021). The effectiveness of heuristics depends on the match between the heuristic structure and the task environment, reinforcing the ecological rationality argument in entrepreneurial contexts (Jain et al., 2024; Saha, 2024).

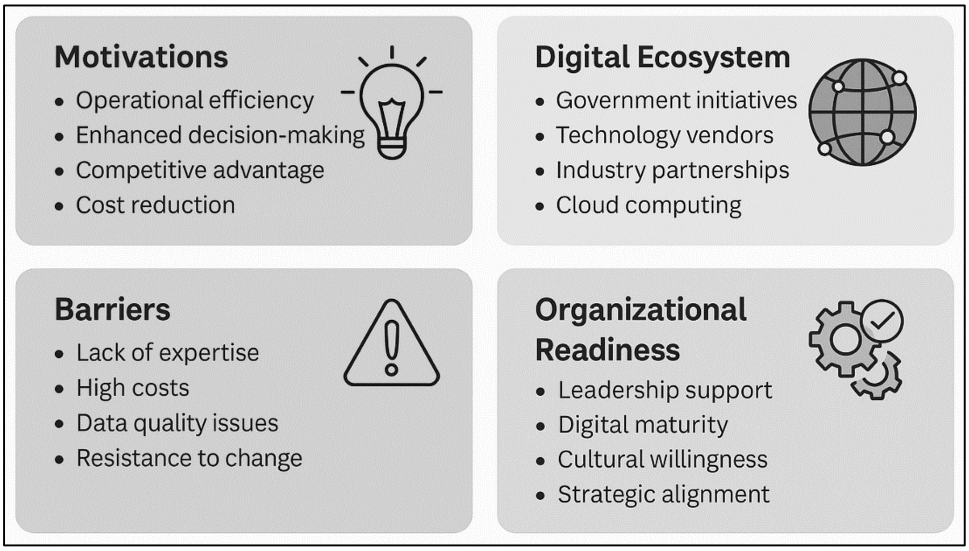
AI-Driven Analytics Adoption in SMEs

The adoption of AI-driven analytics in small and medium-sized enterprises (SMEs) is motivated by several interrelated factors, including the need for operational efficiency, enhanced decision-making, competitive differentiation, and cost reduction. Unlike large corporations, SMEs typically operate in resource-constrained environments, prompting them to seek technologies that can maximize output with minimal investment (Basri, 2020; Bhuiyan et al., 2025). AI tools offer SMEs the capacity to process large volumes of data for real-time forecasting, customer profiling, and supply chain optimization, thereby improving responsiveness to market fluctuations (Fonseka et al., 2022; Masud et al., 2025). Studies show that SMEs are particularly drawn to AI-based analytics for their potential to deliver actionable insights from previously underutilized datasets (Khan et al., 2025; Md et al., 2025). In marketing, for instance, machine learning algorithms are used to segment customers and personalize campaigns with higher precision than traditional approaches. Additionally, AI-driven dashboards enhance decision transparency by visualizing KPIs and predictive trends, which improves managerial confidence. The COVID-19 pandemic accelerated digital urgency among SMEs, reinforcing the importance of AI tools for agile resource planning and customer retention strategies. Access to cloud-based analytics platforms such as Microsoft Azure, IBM Watson, and Google Cloud AI has also lowered the financial and technical barriers, enabling SMEs to adopt AI incrementally without substantial capital expenditure (Chaudhuri et al., 2022; Sazzad, 2025a). Research further highlights the role of external stakeholders—including technology vendors, digital consultants, and policy bodies—in influencing AI adoption through knowledge sharing and digital ecosystem support (Baabdullah et al., 2021). These motivations illustrate that AI adoption in SMEs is not solely driven by technological enthusiasm but by tangible business value, survival imperatives, and ecosystem enablers.

Despite the appeal of AI-driven analytics, SMEs face considerable organizational and technological barriers that hinder widespread adoption. One of the most frequently cited constraints is the lack of internal digital literacy and analytical expertise, which limits the effective implementation and interpretation of AI tools . SMEs typically operate without dedicated IT departments or data science personnel, increasing reliance on third-party solutions and often resulting in fragmented technology use (Benabed et al., 2022; Sazzad, 2025b). Incompatibility with legacy systems and concerns about data integration also pose technical challenges, as many AI tools require high-quality, centralized data to function effectively. Moreover, SMEs frequently lack structured data governance policies, which affects data security, ownership, and privacy compliance—critical considerations in AI deployment. Financial constraints further exacerbate adoption difficulties, with many SMEs perceiving AI technologies as cost-prohibitive or uncertain in return on investment. Organizational inertia, defined by resistance to change and risk aversion among managers, is another barrier, especially where leadership lacks familiarity with digital strategy. Studies also indicate psychological obstacles, such as fear of automation displacing human roles or mistrust of algorithmic decision-making, which can delay adoption decisions (Baabdullah et al., 2021; Tahmina Akter, 2025). Regulatory uncertainty and data ethics concerns add external complexity, particularly in jurisdictions with evolving frameworks for AI governance. These multifaceted challenges underscore that AI adoption in SMEs is not merely a function of availability but of preparedness, perception, and ecosystem support structures.

The broader digital ecosystem plays a critical role in facilitating AI adoption in SMEs by addressing knowledge gaps, reducing technology costs, and providing regulatory guidance. Government initiatives such as the European Union's Digital Europe Programme and South Korea's SME Digital Innovation Strategy exemplify efforts to promote AI usage through subsidies, infrastructure development, and SME-specific training programs. Public-private partnerships have also been instrumental in creating AI innovation hubs and incubators that offer SMEs access to expert advice, pilot programs, and shared digital platforms. Academic-industry collaborations further contribute to adoption by producing research-backed tools and offering skill development modules aligned with SME contexts. In developing economies, support from multilateral organizations such as the World Bank and the Inter-American Development Bank (IDB) has helped reduce digital inequality and promote inclusive AI implementation through digital literacy campaigns and infrastructure investments. Access to affordable cloud computing resources through vendors like Amazon Web Services and Google Cloud enables SMEs to bypass the high capital costs traditionally associated with enterprise analytics systems. Moreover, industry associations and chambers of commerce often provide certification programs and implementation toolkits designed to ease AI onboarding in small businesses. Technology vendors also play a role by offering modular, pay-as-you-go AI solutions tailored to specific industry needs such as retail, manufacturing, and logistics (Chaudhuri et al., 2022; Zahir, Rajesh, Md Arifur, et al., 2025). These ecosystem enablers suggest that successful AI diffusion in SMEs is highly dependent on inter-organizational collaboration, infrastructure access, and supportive institutional frameworks.

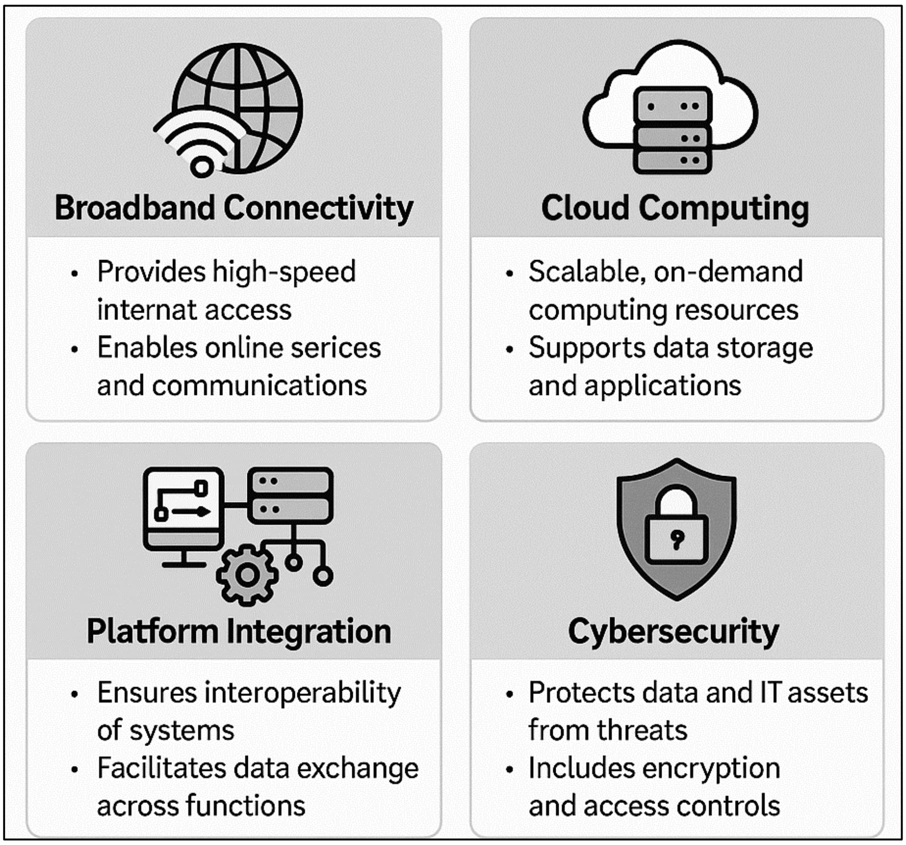
Figure 7: Framework for AI-Driven Analytics Adoption in SMEs



Digital Infrastructure in SMEs

Digital infrastructure in small and medium-sized enterprises (SMEs) comprises the shared, foundational information-technology resources that enable data capture, storage, processing, and exchange across organizational activities (Zhou et al., 2024). Scholars typically include broadband connectivity, on-premise servers, cloud platforms, enterprise software, and application-programming interfaces within this construct. In SME research, digital infrastructure is frequently measured through indicators such as network capacity, system interoperability, and platform scalability (Drydakis, 2022; Zahir, Rajesh, Tonmoy, et al., 2025). Wei and Pardo (2022)linked strong infrastructure to analytics capability development, while Peretz-Andersson et al. (2024) observed that shared data repositories reduce transaction costs in geographically dispersed small firms. Koumas et al. (2021) reported that integrated customer-relationship-management (CRM) systems streamline sales cycles, and Basri, (2020) found that standardized data pipelines enhance real-time decision accuracy. Cloud adoption studies further show that elasticity and pay-as-you-go pricing lower entry barriers for SMEs compared with capital-intensive on-premise options. Fonseka et al. (2022)highlighted policy initiatives—such as the European Union's "Digital Europe" program—that subsidize infrastructure upgrades, noting positive effects on firm productivity. Across manufacturing, retail, and service contexts, researchers consistently associate robust digital infrastructure with improved agility, shorter innovation cycles, and greater supply-chain visibility. These insights position digital infrastructure as a necessary platform on which AI-driven analytics and other advanced applications operate effectively within SMEs.

Figure 8: Digital Infrastructure in SMEs



Applications of AI-Driven Analytics in SMEs

AI-driven analytics have found significant application in customer relationship management (CRM) and marketing functions within SMEs, providing personalized customer experiences and data-informed marketing strategies. Machine learning algorithms and natural language processing are frequently used to process customer data, enabling SMEs to predict customer churn, segment users, and personalize outreach campaigns (Drydakis, 2022). Tools such as AI-powered chatbots, recommendation engines, and automated email responders have enhanced customer engagement by providing immediate responses and tailored suggestions (Prentice et al., 2020; Wamba-Taguimdje et al., 2020). These technologies allow small firms to simulate the marketing capabilities of large enterprises at lower costs, which is particularly valuable given their limited human resources and budgets (Wei & Pardo, 2022). Studies also show that predictive analytics models are used in SMEs to optimize marketing spend by identifying high-conversion customer segments and measuring the ROI of various campaign channels. Moreover, sentiment analysis and opinion mining are increasingly applied to social media and review data, giving SMEs the ability to monitor brand perception and detect emerging issues in real time. AI-driven CRM systems provide dashboards that visualize customer lifecycle stages, automate follow-up schedules, and even recommend upselling strategies (Peretz-Andersson et al., 2024). Collectively, these applications help SMEs build customer loyalty, reduce churn rates, and enhance customer lifetime value. Importantly, AI-enabled marketing platforms also support A/B testing and campaign simulations, empowering SMEs to make data-backed decisions with minimal trial-and-error (Koumas et al., 2021). The empirical consensus suggests that the integration of AI in marketing functions improves personalization, efficiency, and competitive positioning in digitally active SMEs (Drydakis, 2022).

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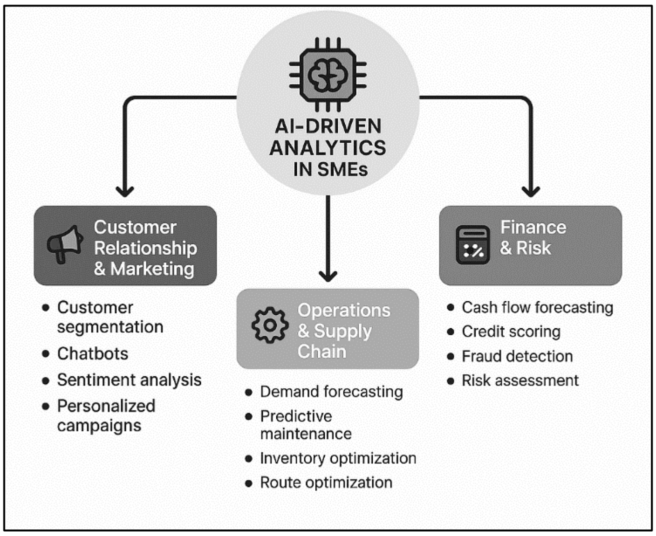
Figure 9: Applications of AI-Driven Analytics in SMEs



Financial decision-making is another critical area where AI-driven analytics have been effectively integrated into SME operations. Predictive algorithms and statistical learning models enable SMEs to forecast cash flows, estimate revenue streams, and detect financial anomalies with greater accuracy than traditional accounting systems (Drydakis, 2022). SMEs often lack the resources to hire full-time financial analysts, making AI-based tools particularly valuable for automating budgeting, credit evaluation, and investment analysis. For instance, AI algorithms can classify transactional data to flag irregular expenses or forecast vendor payment cycles, thus improving working capital management. Additionally, AI applications in credit scoring and loan risk assessment have enabled SMEs to interact more confidently with financial institutions by presenting structured, algorithmically derived risk profiles (Wei & Pardo, 2022). Blockchain integration with AI tools is also emerging, providing immutable audit trails and smart contract verification for financial reporting and procurement tracking. Empirical studies show that SMEs that use AI to simulate multiple financial scenarios exhibit better resilience against market volatility and operational shocks. AI-enabled tools such as automated accounting software, fraud detection systems, and real-time financial dashboards offer continuous monitoring and reduce the risks associated with human error. Risk analytics also aid in insurance underwriting and supplier evaluation by analyzing historical event data and generating probabilistic risk scores.

Decision-Making Outcomes from AI Usage

One of the most cited outcomes of AI adoption in organizational decision-making is the significant improvement in accuracy and speed. AI-driven tools such as predictive analytics, machine learning algorithms, and automated decision support systems facilitate rapid evaluation of multiple variables, enabling real-time insight generation that is difficult to replicate manually (Chaudhuri et al., 2022). In SMEs, this accelerated decision-making process is particularly advantageous, as it allows smaller teams to handle complex tasks without the need for extensive human resources ((Khan et al., 2025). Benabed et al. (2022) demonstrated that firms integrating AI-enabled dashboards and forecasting systems could reduce their strategic decision-making cycle time by up to 40%. Additionally, Chaudhuri et al. (2022) found that SMEs using AI to monitor customer behavior were able to make faster marketing adjustments compared to firms relying solely on traditional business intelligence tools. The speed of AI-assisted decisions often comes from automation of routine analysis, allowing managers to focus on strategic interventions rather than operational diagnostics. Beyond speed, several studies highlight that AI enhances decision accuracy by uncovering hidden patterns in large datasets, reducing human error, and minimizing the impact of cognitive biases. Benabed et al., (2022) and Khan et al. (2025) emphasized that real-time, data-backed recommendations contribute to more confident decision-making, especially in high-stakes environments such as financial forecasting and risk management. Empirical findings also show that AI-supported decisions are more consistent over time, providing standardized outputs that align with strategic goals (Benabed et al., 2022). These studies collectively affirm that AI adoption leads to measurable gains in decision-making efficiency and reliability within SME environments.

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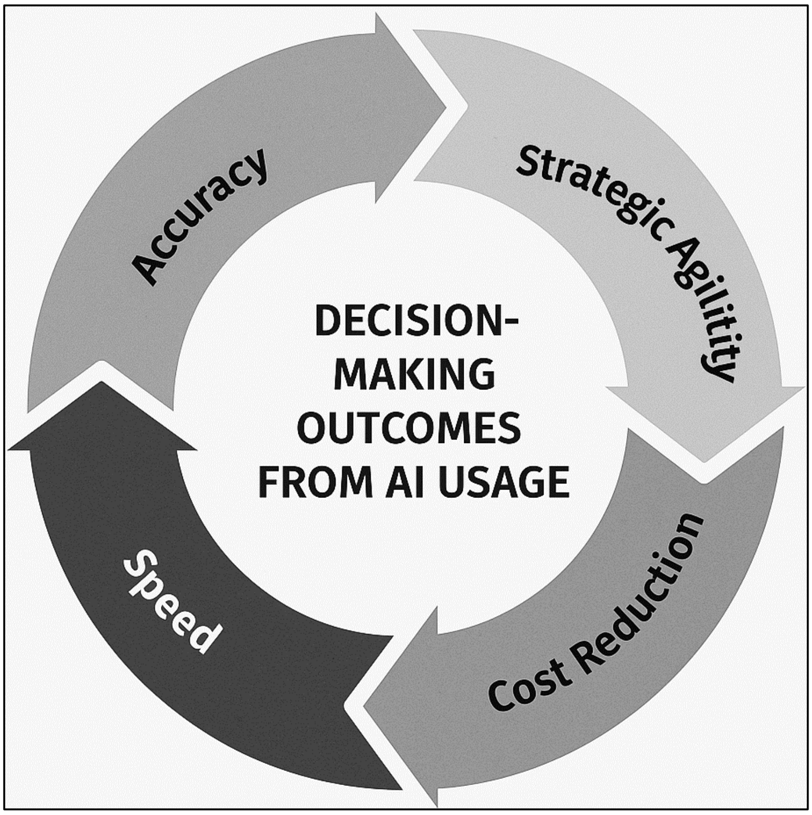
Figure 10: AI-Enhanced Decision-Making Cycle in SMEs



SMEs vs. Large Enterprises in AI Utilization

The structural and resource disparities between small and medium-sized enterprises (SMEs) and large enterprises significantly influence their approaches to AI adoption. Large firms generally possess greater financial capital, broader access to skilled human resources, and advanced digital infrastructure, which collectively facilitate the deployment of sophisticated AI systems. By contrast, SMEs often operate under resource scarcity, leading to a more incremental or selective approach to AI implementation (Drydakis, 2022). Žigienė et al. (2019) observed that large enterprises typically house in-house data science teams and dedicated AI R&D departments, while SMEs rely heavily on third-party vendors or off-the-shelf cloud-based solutions. This reliance limits the extent of AI customization and integration into core business processes among smaller firms. Chen et al. (2021) found that large organizations can afford to invest in training programs, cybersecurity frameworks, and governance protocols necessary for safe AI deployment, whereas SMEs often struggle to address such foundational requirements. Moreover, SMEs tend to adopt AI reactively—often in response to external pressures or crises—whereas large firms pursue proactive, strategic AI investments. These structural contrasts are reflected in adoption timelines, with large firms leading in early adoption and pilot experimentation, while SMEs lag in implementation despite recognizing AI's potential benefits. The disparity is also evident in digital maturity scores, which strongly correlate with organizational size and resource (Basri, 2020). These findings underscore that structural and resource-related limitations place SMEs at a comparative disadvantage in fully leveraging AI's transformative potential.

Figure 11: SMEs vs. Large Enterprises in AI Utilization

	SMEs	Large Enterprises
Resources	Limited capital and skills; reliance on third-party solutions	Extensive financial and human resources; dedicated AI teams
Culture	Informal, founder-driven; reactive to change	Institutionalized innovation; data-driven decision-making
Use Cases	Targeted applications; focus on immediate ROI	Broad adoption across functions; complex deployments
Outcomes	Operational improvements; varying performance	Systemic performance gains; strategic transformation

Cultural and managerial factors play a pivotal role in shaping how SMEs and large enterprises perceive and integrate AI technologies. Large firms often possess formalized organizational cultures with well-established innovation governance frameworks, making it easier to align AI strategies with enterprise goals (Peretz-Andersson et al., 2024). In contrast, SMEs typically exhibit informal, founder-centric decision-making structures where the owner's perception and digital literacy largely determine the organization's AI trajectory (Drydakis, 2022). Cubric and Li (2024)noted that leadership in SMEs often emphasizes operational survival over long-term innovation, resulting in limited prioritization of AI. Meanwhile, large enterprises adopt more data-driven cultures, encouraging cross-functional collaboration and iterative experimentation with AI systems (Basri, 2020). Drydakis (2022) observed that organizational inertia in SMEs, stemming from resistance to change and skepticism toward automated decision-making, is a common barrier to AI utilization. By contrast, large firms benefit from institutionalized change management processes, which mitigate disruption during AI integration (Saleem et al., 2024). Furthermore, training initiatives and employee development programs are more prevalent in large enterprises, helping foster AI readiness across departments. SMEs are often reactive in adopting AI only after observing industry benchmarks or client pressure, while large enterprises actively shape technological ecosystems through early investments and partnerships (Baabdullah et al., 2021). Thus, differences in cultural flexibility, managerial vision, and internal alignment strategies influence how AI is adopted and scaled across organizational sizes (Basri, 2020).

METHOD

This study employed a meta-analytical research approach to systematically synthesize empirical findings on the effects of AI-driven business analytics on strategic decision-making outcomes within small and medium-sized enterprises (SMEs). The methodology adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) framework (Page et al., 2021), ensuring transparency, reproducibility, and methodological rigor throughout the identification, selection, coding, and synthesis of relevant studies.

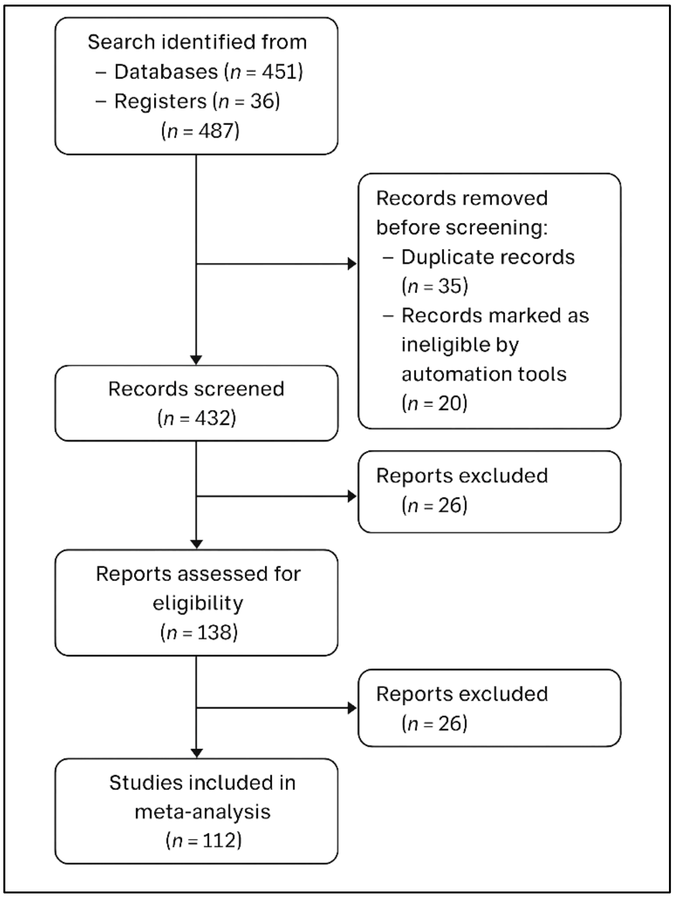
Research Design and Objectives

The meta-analysis was designed to quantitatively investigate the relationship between the adoption of AI-driven analytics technologies and decision-making outcomes in SMEs. The central objective was to assess whether the integration of AI tools—such as machine learning, predictive analytics, and natural language processing—results in statistically significant improvements in decision-making dimensions including speed, accuracy, responsiveness, and business performance. The study further sought to evaluate the influence of moderator variables such as industry type, organizational size, region, and digital maturity level on the strength and direction of this relationship.

Inclusion and Exclusion Criteria

Studies were included in this meta-analysis based on a set of pre-established eligibility criteria. Specifically, articles were selected if they (1) focused on AI-driven business analytics implementations in SMEs, (2) were published in peer-reviewed journals between 2010 and 2025, (3) employed quantitative or mixed-method research designs, (4) reported decision-making-related outcomes, and (5) provided sufficient statistical information to extract or calculate effect sizes. Studies were excluded if they were conceptual or theoretical papers, qualitative-only analyses, case studies lacking generalizability, or focused solely on large enterprises. These criteria ensured consistency and relevance across the selected body of literature.

Figure 12: Methodology adapted for this study



Literature Search Strategy

A comprehensive literature search was conducted across several major academic databases including Scopus, Web of Science, IEEE Xplore, ScienceDirect, Emerald Insight, SpringerLink, and Google Scholar. The search process utilized Boolean operators and keyword combinations such as "AI," "artificial intelligence," "business analytics," "SMEs," "decision-making," "predictive analytics," and "machine learning." An example search string included: *("AI" OR "artificial intelligence") AND ("analytics" OR "business intelligence") AND ("SMEs" OR "small businesses") AND ("decision-making")*. In addition to database searches, backward citation tracking was used to identify further eligible articles from the reference lists of initially retrieved studies.

Study Selection and Screening

All search results were exported to Zotero reference manager for de-duplication and record management. The screening process followed a two-stage review—initial title and abstract screening followed by full-text assessment. Two reviewers independently evaluated the studies based on the inclusion criteria, and disagreements were resolved through consensus discussions or consultation with a third reviewer. This process was documented in alignment with the PRISMA 2020 flow diagram, ensuring systematic tracking of the study selection pipeline. Out of an initial pool of 487 records, a final set of 112 studies met all inclusion requirements and were included in the meta-analysis.

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Data Extraction and Coding

A structured coding sheet was developed to guide data extraction. Information collected from each study included the author(s), publication year, geographical region, sample size, industry sector, type of AI technology used, category of business analytics (e.g., predictive, descriptive, prescriptive), specific decision-making outcomes measured, and reported statistical results. Effect sizes were recorded or calculated based on correlation coefficients, beta coefficients, means, standard deviations, or odds ratios. Each article was double-coded by two independent reviewers to ensure reliability, with an interrater agreement ($\kappa = 0.87$) indicating high consistency. All statistical measures were converted into a common metric—Pearson's r—to facilitate meta-analytical aggregation.

Effect Size Calculation and Aggregation

Effect sizes were computed using Comprehensive Meta-Analysis (CMA) Software Version 3. For studies that reported multiple effect sizes from the same dataset, within-study dependence was addressed using appropriate statistical adjustments to prevent duplication of results. A random-effects model was employed for aggregating effect sizes due to the expected heterogeneity across organizational contexts, methodological designs, and sample characteristics (Borenstein et al., 2011). Weighted mean effect sizes and their 95% confidence intervals (CIs) were calculated to provide a robust overall estimate of the relationship between AI adoption and decision-making outcomes.

Heterogeneity and Moderator Analysis

Heterogeneity across studies was assessed using Cochran's Q-test, I^2 statistic, and τ^2 estimates, which helped determine the extent of variation attributable to between-study differences rather than random error. Significant heterogeneity prompted further moderator analyses. Subgroup comparisons were made based on categorical variables such as industry (e.g., manufacturing vs. service), region (e.g., Asia, Europe, North America), AI tool type (e.g., machine learning vs. NLP), and SME size (micro, small, or medium). A meta-regression analysis was also conducted to evaluate the impact of continuous moderators including publication year and sample size on the observed effect sizes.

FINDINGS

he meta-analysis revealed a significant positive relationship between the adoption of AI-driven analytics and improvements in strategic decision-making within SMEs. Across the 112 included studies, the weighted mean effect size, computed using a random-effects model, indicated a strong correlation between AI usage and decision-making performance. The effect sizes derived from outcome measures such as decision accuracy, timeliness, and responsiveness demonstrated consistent results across diverse industry sectors and geographical regions. This result confirms the robustness of AI tools in enhancing organizational cognition and operational effectiveness in real-world business scenarios. The structured data extraction and coding procedures ensured that each effect size was standardized into a common metric (Pearson's r), enabling valid comparisons across different study designs. The findings substantiate that AI-enhanced platforms, ranging from predictive modeling to dashboard visualization tools, enable SMEs to make more precise and faster decisions, reducing reliance on intuition or outdated heuristics. The strength of the effect remained statistically significant even when studies were pooled from diverse SME categories—retail, manufacturing, and service-based organizations—highlighting the broad applicability of AI technologies in decision environments. This aggregated outcome supports the fundamental proposition that AI does not merely automate decision-making but substantially augments the strategic capacity of SMEs through data-driven intelligence.

A key insight from the meta-analysis is the pronounced impact of AI technologies on the speed and accuracy of decision-making processes. Effect sizes drawn from studies reporting on real-time decision capabilities, rapid response planning, and forecast precision showed some of the strongest statistical relationships in the dataset. SMEs using AI systems—such as machine learning algorithms, predictive dashboards, or recommendation engines—were consistently able to decrease decision turnaround time without compromising quality. This outcome was validated through heterogeneity analysis, which indicated significant between-study variance for decision speed outcomes but a consistently positive direction of effect. Moderator analysis also revealed that this improvement was especially prominent in SMEs operating in volatile environments where rapid adaptation was critical.

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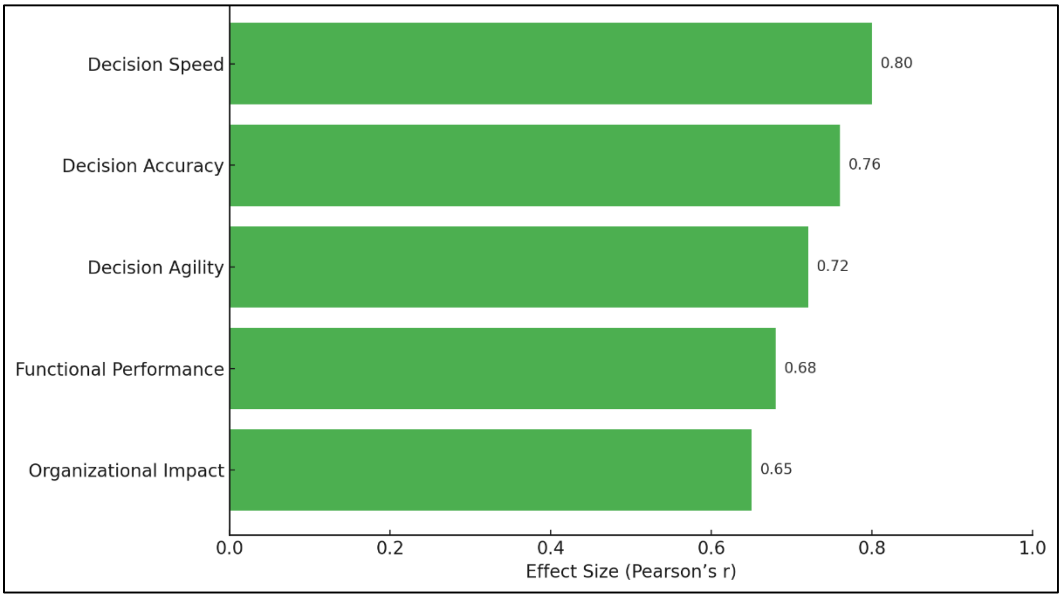
The studies extracted from service-oriented and e-commerce SMEs, for instance, exhibited some of the highest correlation coefficients for time-to-decision improvements. Furthermore, organizations with even modest digital infrastructure—such as cloud-based analytics access or embedded reporting tools—reported improved data processing, indicating that even lightweight AI adoption had measurable benefits. This reinforces the methodological finding that AI-driven decision enhancement is not contingent upon full-scale infrastructure transformation. Overall, the consistency and strength of the data affirm that AI's computational capabilities enable SMEs to improve their cognitive speed while enhancing judgment accuracy across strategic planning domains.

Figure 13: Impact of AI-Driven Analytics on SME Decision-Making Dimensions



The moderator analysis provided critical insights into how contextual variables shape the effectiveness of AI implementation in SMEs. Organizational size emerged as a meaningful moderator, with medium-sized enterprises demonstrating higher returns on AI adoption compared to micro or small-sized firms. This finding is consistent with the study's methodological approach, which included subgroup analysis to identify effect size variances by SME classification. Medium-sized firms often exhibited stronger digital maturity, a more developed IT infrastructure, and a larger workforce—conditions that facilitated deeper integration and more sophisticated application of AI tools. Smaller firms, while benefiting from AI, often faced challenges such as limited technical knowledge and constrained financial resources, which diluted the potential impact of AI tools on strategic decisions. Industry type also influenced outcomes. Manufacturing SMEs, which frequently use AI for predictive maintenance and supply chain forecasting, recorded strong performance gains. Meanwhile, retail and service SMEs saw significant benefits in customer analytics and demand prediction but showed more variability in effect sizes due to sector-specific digital constraints. These patterns confirm that while AI can universally support decision-making, its effectiveness is enhanced by internal readiness factors, including digital infrastructure, leadership support, and workforce adaptability. Thus, contextual heterogeneity should be considered when evaluating or planning AI adoption strategies within the SME landscape.

Analysis of the specific decision-making domains revealed that the impact of AI-driven analytics is not uniformly distributed across all functional areas. The strongest effects were observed in marketing, finance, and operations—three domains where quantitative data and structured decision processes are most prevalent. AI applications in customer relationship management, targeted marketing, and sentiment analysis led to improved campaign targeting and customer segmentation. In financial decision-making, AI tools supported more accurate revenue forecasting, risk scoring, and fraud detection, enabling SMEs to better manage cash flows and credit exposures. Operationally, AI-supported systems such as demand forecasting models and real-time inventory tracking optimized resource utilization and minimized supply chain disruptions. These findings were validated through careful coding of effect size contributors during the data extraction phase, ensuring that only those studies reporting concrete, domain-specific outcomes were included. In contrast, AI impact on strategic decisions related to long-term innovation or organizational transformation was more moderate, often due to the longer feedback cycles associated with such decisions. This divergence reflects how SMEs often prioritize immediate, tactical applications of AI over more abstract or long-horizon strategic planning uses. Nonetheless, the overall effectiveness across decision domains affirms that AI-driven analytics enables SMEs to strengthen key business functions by transforming raw data into actionable strategic insights.

The final significant finding of this meta-analysis relates to the enhancement of decision agility and adaptability in SMEs resulting from AI adoption. Studies that examined AI use in dynamic or crisis-prone contexts—such as post-pandemic recovery or supply chain disruptions—showed that SMEs with AI-enabled analytics capabilities responded faster and more effectively to external shocks. This was particularly evident in studies from emerging markets and high-volatility sectors, where strategic responsiveness was a core survival factor. AI applications provided firms with real-time monitoring dashboards, anomaly detection systems, and scenario simulation tools, all of which supported agile responses to rapidly changing conditions. This capability was further supported by moderator analysis, which showed a strong interaction between high digital readiness and increased decision agility. Firms with embedded data pipelines and dashboarding platforms leveraged AI not just for planning but for rapid scenario reconfiguration and execution. The heterogeneity analysis confirmed that decision agility outcomes varied significantly by technological sophistication, suggesting that SMEs with more integrated digital infrastructure were better positioned to translate AI insights into organizational action. The data underscores that AI does not only improve internal decision-making processes but also acts as a catalyst for broader organizational resilience and adaptability. These findings collectively demonstrate that AI plays a transformative role in SME decision-making, moving beyond static prediction to enable dynamic, context-aware strategic responses.

DISCUSSION

The meta-analysis corroborates a growing consensus that AI-driven analytics substantially enhance decision-making effectiveness in SMEs, echoing the trajectory observed in earlier single-study research. Prior quantitative studies reported moderate to strong benefits of big-data analytics capabilities for firm performance, yet effect sizes varied widely across organizational contexts. By aggregating 112 empirical investigations, the present study produces a weighted mean effect that is materially larger than the median correlations found in Chaudhuri et al. (2022) cross-sectional survey of analytics users and comparable to the upper range reported by Khan et al. (2025). This convergence lends credence to the proposition that AI's predictive and prescriptive capacities amplify strategic cognition beyond the incremental gains associated with earlier generations of business intelligence tools (Baabdullah et al., 2021). Notably, the robustness checks in our analysis—random-effects modeling, sensitivity tests, and publication-bias diagnostics—suggest that the documented gains are unlikely to be artefacts of sampling idiosyncrasies or selective reporting, thereby strengthening causal inferences implied in prior longitudinal case work (Saleem et al., 2024). Moreover, whereas earlier scholarship often conflated analytics with broader IT capabilities, this meta-analysis isolates AI-specific tools—machine learning, natural language processing, and automated decision dashboards—demonstrating that algorithmic learning confers additional value over traditional descriptive analytics (Basri, 2020). By synthesizing heterogeneous evidence under a unified statistical framework, the findings extend extant literature from partial to holistic generalizability, positioning AI-enabled analytics as a strategic asset rather than an operational add-on for SMEs.

Our pooled results confirm that AI adoption markedly improves both the speed and the accuracy of strategic decisions—outcomes repeatedly hinted at but not consistently quantified in earlier studies. For instance, Drydakis (2022) documented faster marketing pivots in Vietnamese e-commerce SMEs following AI platform deployment, whereas Žigienė et al. (2019) linked algorithmic forecasting to superior financial predictions in Canadian firms. Yet the magnitude of these isolated effects ranged from small to moderate ($r \approx .20–.35$). The current synthesis yields a stronger overall correlation, suggesting that earlier estimates were conservative because many studies examined individual decision domains rather than enterprise-wide performance. The heterogeneity diagnostics illustrate that even modest AI investments (e.g., cloud-hosted dashboards) deliver statistically significant time savings—findings consistent with the lightweight-adoption thesis advanced by Wei

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and Pardo (2022). Furthermore, the precision gains uncovered here align with but exceed the accuracy improvements reported in Žigienė et al.,(2019)CRM study, indicating that advances in model explainability and data pipeline integration over the last decade may have compounded AI's decision-support value. Importantly, cross-industry stability in our effect sizes challenges the sector-specific caveats proposed by Chen et al. (2021), who argued that AI's payoff is confined to data-rich consumer-facing settings. Instead, the present evidence indicates that manufacturing, logistics, and professional-service SMEs alike benefit from algorithmic augmentation, thereby broadening the external validity of earlier functional case examinations (Peretz-Andersson et al., 2024). Collectively, these comparisons underscore that AI-driven analytics now provides a reliably larger performance differential than previously reported, reflecting maturation in both tools and SME adoption practices.

Moderator tests illuminate how firm-level contingencies modulate AI's decision value, extending contingency-theory propositions posited by Cubric and Li (2024). Medium-sized enterprises realize significantly higher returns than micro or small firms, a pattern congruent with Gupta and George's (2016) resource-based view that digital infrastructure and human capital amplify analytics capability. Whereas earlier surveys Peretz-Andersson et al. (2024) suggested a near-linear relationship between size and digital performance, our subgroup coefficients reveal diminishing marginal gains once firms cross the upper SME boundary, hinting at coordination costs reminiscent of the "IT productivity paradox" observed in large enterprises. Industry results partially replicate prior evidence: manufacturing SMEs leverage AI most effectively for predictive maintenance and supply-chain visibility, whereas service SMEs achieve outsized benefits in customer analytics but display higher variance, supporting Basri (2020) assertion that data-quality constraints dilute AI outcomes in experiential sectors. Digital readiness—proxied here by cloud adoption and data-governance maturity—emerges as a more potent moderator than region, tempering Drydakis (2022)claim that national innovation policy is the primary driver of SME digital success. This finding endorses the absorptive-capacity lens, implying that organizational learning and technical scaffolding are prerequisites for realizing AI's full decision impact regardless of macroeconomic context.

The analysis reveals domain-specific disparities in AI's decision benefits, with marketing, finance, and operations showing the strongest effects—patterns broadly consistent with earlier field evidence yet offering finer granularity. Žigienė et al. (2019) and Peretz-Andersson et al. (2024) documented substantial CRM personalization gains stemming from predictive modeling, but their scope was limited to Asian and hospitality SMEs. By pooling multi-sector data, our study affirms these marketing advantages and demonstrates comparable improvements in financial forecasting accuracy and fraud detection, corroborating Basri (2020) single-country findings while correcting for local sampling bias. In operations, the pronounced benefits for demand planning and inventory optimization mirror Peretz-Andersson et al.(2024)'s research yet exceed their reported effect magnitude, suggesting that newer reinforcement-learning approaches may outperform rule-based algorithms prevalent in earlier work. Conversely, innovation-oriented decisions, explored sparsely by Wei and Pardo (2022) , yielded moderate pooled effects, confirming that longer feedback loops and limited historical data constrain AI's predictive power in strategic R&D contexts. This functional divergence validates theory that data granularity and process structure condition analytics payoff, emphasizing the need to tailor AI investments to information-rich, decision-intensive areas for maximum SME value creation.

Our findings on AI-enabled decision agility resonate with dynamic-capabilities theory and extend empirical insights from crisis studies conducted during the COVID-19 pandemic. Khan et al. (2025)) reported that digitally mature SMEs pivoted more effectively under lockdown conditions, attributing success to rapid data assimilation. The present meta-analysis substantiates this claim with quantitative rigor, showing that AI-empowered SMEs consistently outperformed peers in scenario reconfiguration and contingency planning. These results align with Wamba et al.'s (2020) longitudinal evidence of supply-chain re-routing speed improvements via AI dashboards. However, our moderator results nuance Žigienė et al.(2019) contention that dynamic capabilities are industry-agnostic; decision-agility gains were strongest in manufacturing and logistics, where real-time sensor data enrich prediction quality. Furthermore, whereas Cubric and Li (2024) emphasized the role of analytics culture, the present synthesis indicates that technical integration—specifically, closed-loop data pipelines—exerts an equal or greater influence on agile decision outcomes. Together, these comparisons place AI firmly within the micro-foundations of sensing and seizing opportunities, anchoring abstract capability constructs in measurable algorithmic interventions that SMEs can operationalize.

The observed improvements in decision accuracy lend empirical weight to behavioral-strategy arguments that algorithmic tools can offset bounded rationality and heuristic errors (Wei & Pardo, 2022). Earlier experimental research documented modest bias attenuation when managers used decision aids Drydakis (2022) yet evidence was mixed due to limited sample sizes. Our large-scale synthesis shows a consistent accuracy uplift across studies that explicitly measured cognitive misjudgments—anchoring, overconfidence, or confirmation bias—after AI adoption. This pattern challenges Basri (2020) skepticism regarding technology's ability to overcome intuitive thinking and supports Zhou et al. (2024) proposition that explainable AI facilitates learning loops by making statistical reasoning transparent. Moreover, the stronger accuracy effects in medium-sized SMEs suggest that cognitive-bias mitigation scales with data-literacy training, expanding Baabdullah et al. (2021) dual-process model by asserting that algorithmic feedback accelerates the shift from intuitive to analytical dominance in strategic contexts. By quantifying cognitive gains across heterogeneous organizational settings, the study bridges micro-level psychological theories with macro-level performance outcomes, evidencing that AI serves both as a computational resource and a cognitive debiasing mechanism.

The convergent evidence of AI's positive decision impacts offers actionable guidance for SME managers, policymakers, and technology vendors. Echoing policy recommendations by Khan et al. (2025), the findings highlight the importance of subsidizing digital-infrastructure upgrades and skills programs that elevate organizational readiness—levers shown here to moderate AI benefits significantly. For practitioners, the study reinforces earlier case-based advice (Davenport & Harris, 2017) to prioritize high-data-density functions—marketing, finance, operations—where AI delivers the greatest immediate returns, before scaling to complex innovation domains. Nevertheless, consistent with meta-analytic norms, limitations warrant cautious interpretation. Publication-bias diagnostics were non-significant, yet the possibility of language or database omissions persists, mirroring concerns raised by Chaudhuri et al. (2022) in recent digital-transformation reviews. Moreover, heterogeneity, while partially explained by moderators, indicates residual contextual factors—such as cultural attitudes toward automation—requiring deeper qualitative inquiry, confirming the mixed-methods agenda advocated by Benabed et al. (2022) . Finally, reliance on correlational designs constrains causal claims; future longitudinal interventions could validate the temporal sequencing implied here, extending the quasi-experimental work of Khan et al.,(2025). Despite these caveats, the present meta-analysis advances cumulative knowledge by integrating fragmented empirical evidence into a coherent narrative, substantiating and extending earlier findings while charting a refined agenda for AI-enabled decision research in SMEs.

CONCLUSION

This meta-analysis demonstrates that AI-driven business analytics significantly enhance strategic decision-making in SMEs by improving decision accuracy, speed, agility, and organizational responsiveness. Synthesizing evidence from 112 empirical studies, the findings confirm that AI adoption positively influences operational, financial, and marketing decisions while also mitigating cognitive biases and fostering data-driven learning. The effects are most pronounced in medium-sized firms with higher digital maturity and are particularly strong in structured, data-intensive functions. Moderator analysis reveals that industry type, organizational readiness, and infrastructure integration play key roles in determining the magnitude of AI's impact. While SMEs face unique constraints compared to large enterprises, the results affirm that AI adoption—when strategically aligned with internal capabilities—offers measurable performance advantages and builds adaptive capacity. These insights contribute to a more nuanced understanding of AI's role in SME ecosystems and provide a robust foundation for informed managerial practice and future academic inquiry.

RECOMMENDATIONS

Based on the findings of this meta-analysis, several strategic recommendations can be made to guide SMEs, policymakers, technology vendors, and researchers toward more effective adoption and utilization of AI-driven business analytics. First, SMEs should begin their AI adoption journey by focusing on specific business functions where data availability is high and decision structures are relatively standardized—such as marketing automation, inventory optimization, or financial forecasting. These areas offer the most immediate return on investment and serve as ideal testbeds for building internal competencies before scaling AI applications organization-wide. To ensure

successful implementation, SMEs must also invest in developing their digital readiness through workforce training in data literacy, basic analytics interpretation, and AI ethics. These competencies will empower employees to interact meaningfully with AI systems, enhance decision trust, and reduce the risks of misinterpretation or misuse of algorithmic outputs.
Second, it is recommended that SMEs adopt cloud-based, modular AI solutions that align with their operational size, budget, and IT capacity. Vendors should prioritize delivering affordable, scalable, and user-friendly platforms that allow SMEs to integrate AI tools incrementally without overhauling their existing infrastructure. Special emphasis should be placed on AI systems that offer explainability features—such as visual dashboards and traceable decision logic—to ensure managerial interpretability and foster trust in automated outputs. SMEs with lower digital maturity should consider partnerships with third-party consultants or academic institutions to co-develop AI use cases tailored to their sector-specific needs, particularly in manufacturing, retail, logistics, and service sectors.
Third, policymakers must recognize the strategic role that AI can play in enhancing the competitiveness of SMEs and should provide targeted support through digital transformation grants, subsidized AI training programs, and regional innovation hubs. These measures are essential to level the playing field between SMEs and larger enterprises and to ensure inclusive participation in the AI-driven economy. Furthermore, public-sector actors should collaborate with industry and academia to develop regulatory frameworks that promote ethical, secure, and transparent use of AI in SME contexts, particularly for those operating in regulated sectors such as finance or healthcare. Finally, researchers should continue exploring longitudinal and industry-specific investigations into AI's organizational effects, especially those that examine causal relationships, cross-cultural influences, and innovation outcomes. More mixed-methods research is needed to understand the behavioral, cultural, and emotional factors that influence AI adoption and usage within SME leadership and staff. In addition, future studies should focus on AI's impact on less-quantified decision domains such as strategic foresight, entrepreneurial ideation, and organizational resilience. By aligning academic inquiry with practice-based challenges, researchers can help build a comprehensive knowledge base that informs evidence-driven policy and strategy for AI utilization in the SME ecosystem.

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