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AI-ENHANCED MIS PLATFORMS FOR STRATEGIC BUSINESS DECISION-MAKING IN SMES

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Abstract

This study investigated how AI-enhanced management information systems (MIS) platforms influenced strategic business decision-making in small and medium-sized enterprises (SMEs) using a quantitative explanatory model grounded in a review of 40 peer-reviewed papers. Cross-sectional survey data were collected from 352 SMEs (70.4% usable response rate) representing services (33.5%), manufacturing (26.1%), retail/trade (21.0%), logistics (10.8%), and technology-enabled sectors (8.5%); 55.7% were small firms, 31.3% medium, and 13.1% micro. Descriptive results showed moderately high AI-MIS capability ($M = 5.21$, $SD = 0.89$), led by predictive analytics ($M = 5.44$) and automated insight/alerting ($M = 5.36$), while prescriptive recommendation was lower ($M = 4.88$). MIS integration quality was mid-range ($M = 4.76$, $SD = 0.93$), with breadth ($M = 4.92$) exceeding depth ($M = 4.61$). Managerial usage intensity was moderately high ($M = 4.98$), driven by usage frequency ($M = 5.24$) rather than scenario testing ($M = 4.68$). Strategic decision outcomes were positive overall ($M = 5.06$), strongest for decision speed ($M = 5.28$) and cross-functional alignment ($M = 5.26$), with weaker risk calibration ($M = 4.72$). Correlations supported theoretical associations: AI-MIS capability correlated with usage intensity ($r = 0.71$) and decision outcomes ($r = 0.68$), and integration quality correlated with decision outcomes ($r = 0.60$). Reliability and validity were strong (Cronbach's $a = 0.85$–0.93; $CR = 0.88$–0.94; $AVE = 0.52$–0.68; $HTMT \leq 0.79$), and collinearity was acceptable ($VIF = 1.58$–2.13). Regression results indicated significant direct effects of AI-MIS capability on decision outcomes ($\beta = 0.41$, $t = 8.72$, $p < .001$) and usage intensity ($\beta = 0.58$, $t = 12.10$, $p < .001$). Usage intensity predicted decision outcomes ($\beta = 0.47$, $t = 10.24$, $p < .001$) and partially mediated the capability–outcomes relationship (indirect $\beta = 0.27$, 95% CI [0.20, 0.35]; residual direct $\beta = 0.14$, $p = .003$). Integration quality independently improved decision outcomes ($\beta = 0.26$, $p < .001$) and moderated capability effects on usage ($\beta = 0.12$, $p = .007$) and outcomes ($\beta = 0.11$, $p = .014$). The final models explained 54% of variance in usage intensity and 62% in strategic decision outcomes.

Keywords

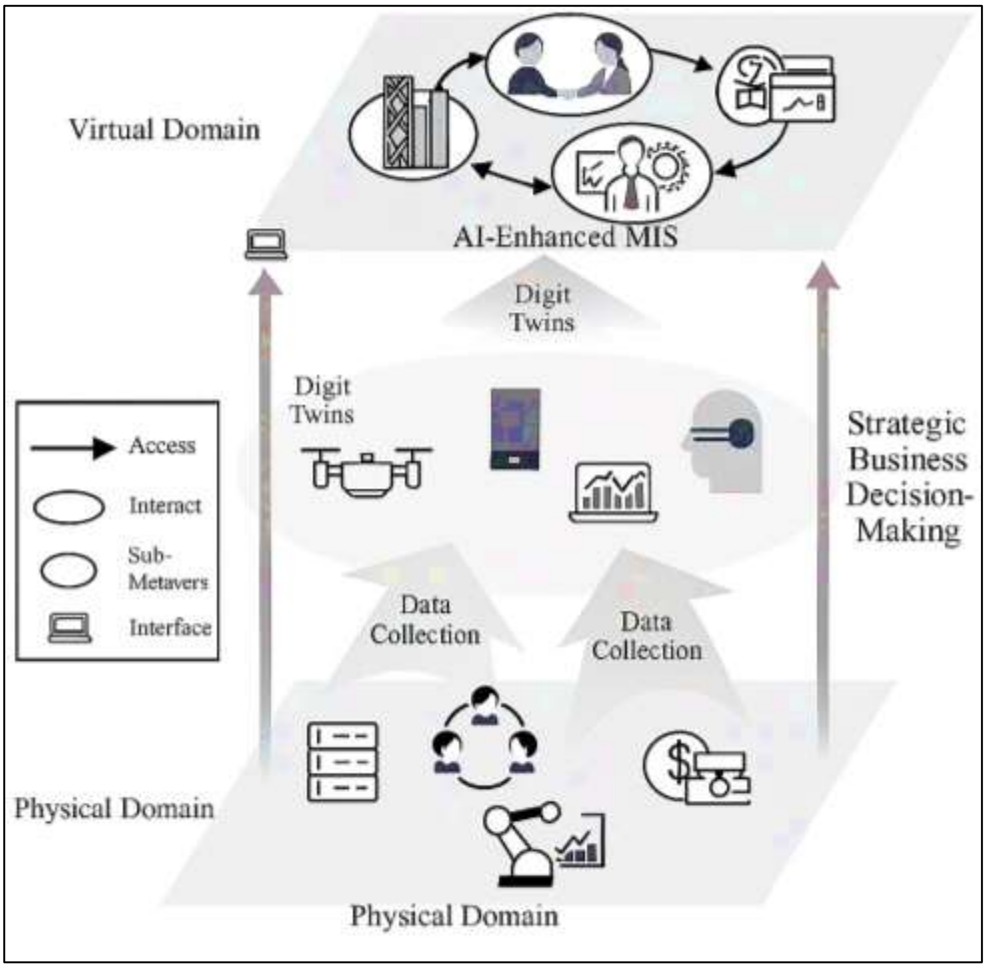
AI-Enhanced MIS, SMEs, Strategic Decisions, Managerial Usage, Integration Quality.

INTRODUCTION

Management information systems (MIS) platforms are organized arrangements of people, processes, data, and digital technologies that transform raw facts into meaningful information for managerial planning, coordination, control, and strategic learning (Kuzovkova et al., 2021). In practice, MIS platforms collect data from internal operations and external sources, store it in structured repositories, process it through rules or analytical models, and present outputs through reports, dashboards, and alerts. Small and medium-sized enterprises (SMEs) rely on MIS to stabilize daily routines while also informing higher-level choices about markets, products, investments, and partnerships. Strategic business decision-making in SMEs involves selecting long-range objectives and allocating scarce resources under uncertainty, while considering competitive positioning, risk tolerance, and organizational capabilities. Artificial intelligence (AI) refers to computational techniques that enable systems to recognize patterns, learn from data, interpret language, and recommend actions with limited human intervention. When AI is embedded within MIS, the platform evolves from descriptive reporting to intelligent, adaptive decision support (Swanson, 2020). AI-enhanced MIS platforms can integrate machine learning, natural language processing, automated reasoning, and real-time analytics into the information pipeline, allowing the system to forecast trends, detect anomalies, prescribe options, and personalize insights for different managerial roles. This shift has international significance because SMEs form the backbone of most economies, accounting for the majority of business establishments and a large share of employment and value creation. Across regions, SMEs face intensified volatility tied to digital competition, platform economies, supply chain disruptions, and rapidly shifting customer expectations. These pressures raise the informational demands placed on owners and managers. AI-enhanced MIS platforms address this demand by expanding the speed, breadth, and interpretive depth of knowledge available for decisions. International evidence across manufacturing, services, retail, agriculture, and technology entrepreneurship shows that AI-enabled information platforms can reduce decision latency, improve the accuracy of forecasts, and support consistent performance monitoring even when managerial bandwidth is limited (Wolfert et al., 2017). In this sense, AI-enhanced MIS platforms represent a combined socio-technical capability in which intelligent algorithms and managerial judgment work together to improve strategic choices in resource-constrained firms operating in complex environments.

The conceptual grounding for AI-enhanced MIS platforms in SMEs is often explained through strategic capability lenses. From a resource perspective, information, data quality, and analytical skills operate as strategic resources when they are valuable and organized for use (Lamboglia et al., 2018). MIS provides the structural environment that turns transactions and events into usable resources, while AI deepens the value of those resources by making patterns and relationships visible that would otherwise remain hidden. From a dynamic capability perspective, enterprises need to sense emerging opportunities and threats, seize them through timely strategic action, and reconfigure routines when conditions shift. AI-enhanced MIS platforms serve each of these functions (Arfan et al., 2021; Ferdous Ara, 2021). They support sensing by scanning internal indicators and external signals, including market sentiment, price movements, supply chain conditions, and customer behavior. They support seizing by evaluating multiple scenarios quickly, ranking options by predicted payoff or risk, and translating those rankings into concrete decision cues (Jahid, 2021; Md.Akbar & Farzana, 2021). They support reconfiguration by providing continuous performance feedback and by surfacing the operational consequences of strategic moves early enough for managers to adapt. In SMEs, these contributions matter strongly because decision authority is commonly concentrated among a small leadership group, sometimes a single owner-manager (Reza et al., 2021; Saikat, 2021). The limited separation between strategic and operational layers in SMEs means that informational bottlenecks can directly distort strategic choices (Gomber et al., 2018). Research in analytics capability, organizational learning, and managerial cognition consistently shows that improvements in the quality and accessibility of information can raise decision comprehensiveness and reduce reliance on purely intuitive judgments. At the same time, AI-enhanced MIS platforms are not only technical artifacts. Their value depends on human routines such as goal setting, meeting structures, budget cycles, and accountability systems (Shaikh & Aditya, 2021; Tonoy Kanti & Shaikat, 2021). Findings across business intelligence adoption, technology use behavior, and information systems success also indicate that platform benefits emerge through managerial trust in outputs, clarity of system explanations, and alignment between insights and organizational objectives (Md Ariful & Efat Ara, 2022; Md Arman & Md.Kamrul, 2022). Thus, AI-enhanced MIS platforms are best understood as strategic capability systems: they combine data, algorithms, and organizational practices to elevate the firm's capacity to decide well under uncertainty (Hetemi et al., 2020).

Figure 1: AI-Enhanced MIS for SME Strategy



AI-enhanced MIS platforms also have a distinct architecture that differentiates them from earlier generations of MIS. Traditional MIS architectures typically rely on structured databases populated by internal operational systems, with periodic extraction for reporting and human-driven interpretation (Mesbaul & Farabe, 2022). AI augmentation introduces automated data preparation, richer data integration, and analytical engines capable of learning from historical patterns while updating continually as new data arrives. In SMEs, this architecture often integrates ERP modules, accounting systems, point-of-sale logs, CRM tools, e-commerce transactions, sensor feeds, and social media streams into a single analytics fabric (Nahid, 2022; Hossain & Milon, 2022; Urbach & Ahlemann, 2019). The platform then applies machine learning models to forecast demand, identify churn risk, estimate credit exposure, optimize inventory levels, detect fraud, or evaluate supplier reliability. A key architectural layer involves decision interfaces that translate model outputs into usable managerial forms (Abdur & Haider, 2022; Mushfequr & Praveen, 2022). Evidence from dashboard design, cognitive load theory, and decision support usability shows that managers benefit most when predictions are paired with uncertainty cues, clear visual structures, and interactive what-if controls. Another central layer involves explainability and monitoring, which allow managers to see why the system recommends a given option and to recognize when data drift or model bias might undermine reliability (Mortuza & Rauf, 2022; Rakibul & Samia, 2022; Shittu et al., 2018). Governance functions such as data standards, access rights, audit trails, and ethical oversight stabilize AI-generated insights and ensure that strategic decisions align with organizational responsibilities. Modular platform design further enables SMEs to adopt AI functionality incrementally by plugging in specialized analytical components according to their sector needs. Across many empirical studies of AI-enabled business intelligence and MIS integration, platform maturity is associated with faster reporting cycles, improved cross-functional coordination, and stronger alignment between operational metrics and strategic priorities (Rony & Ashraful, 2022; Saikat, 2022). Therefore, the architecture of AI-enhanced MIS platforms is not only about adding algorithms; it is about redesigning the information chain so that learning, prediction, and decision guidance are embedded into the everyday strategic rhythm of SMEs (Oliveira et al., 2019; Shaikh & Sudipto, 2022).

At the level of strategic decision processes, AI-enhanced MIS platforms influence how SMEs define problems, explore alternatives, and commit to actions (Saberi et al., 2019). SMEs often operate with compressed strategic cycles, meaning that decisions about pricing, product mix, hiring, capacity, and market entry must be made quickly. AI-enhanced MIS supports these cycles by automating data discovery and producing timely insights that reduce the burden of manual analysis. Studies in strategic decision-making highlight that decision quality depends on comprehensiveness, speed, and alignment. AI-enhanced MIS can improve comprehensiveness by widening the evidence base to include granular internal data and real-time external signals. It can improve speed by delivering automated forecasts and alerts in a usable form at the moment decisions are needed. It can improve alignment by standardizing key metrics and enabling shared visibility across departments, such as linking marketing performance to inventory decisions or linking production yield to budgeting (Fatehi & Choi, 2018). In customer-facing strategy, AI-enabled MIS can facilitate micro-segmentation, personalization, and targeted campaign optimization, allowing SMEs to compete effectively without large marketing analytics teams. In operations and supply chains, predictive modules support fast adjustments in procurement, routing, and stock policies. In finance and risk management, AI-assisted dashboards help managers anticipate cash-flow tension, evaluate credit terms, and detect irregularities early. Evidence from behavioral decision research also suggests that algorithmic recommendations can reduce escalation of commitment and improve risk calibration when managers have tools to compare scenario outcomes. Nonetheless, this influence is mediated through human judgment; managers interpret AI outputs through their experience and organizational context. Research in decision support acceptance indicates that the most consistent performance gains occur when AI insights are embedded into planning meetings, KPI reviews, and formal approval routines (Sarwar et al., 2021). In sum, AI-enhanced MIS platforms reshape strategic decision-making by making evidence broader, analysis faster, and coordination more coherent within SMEs.

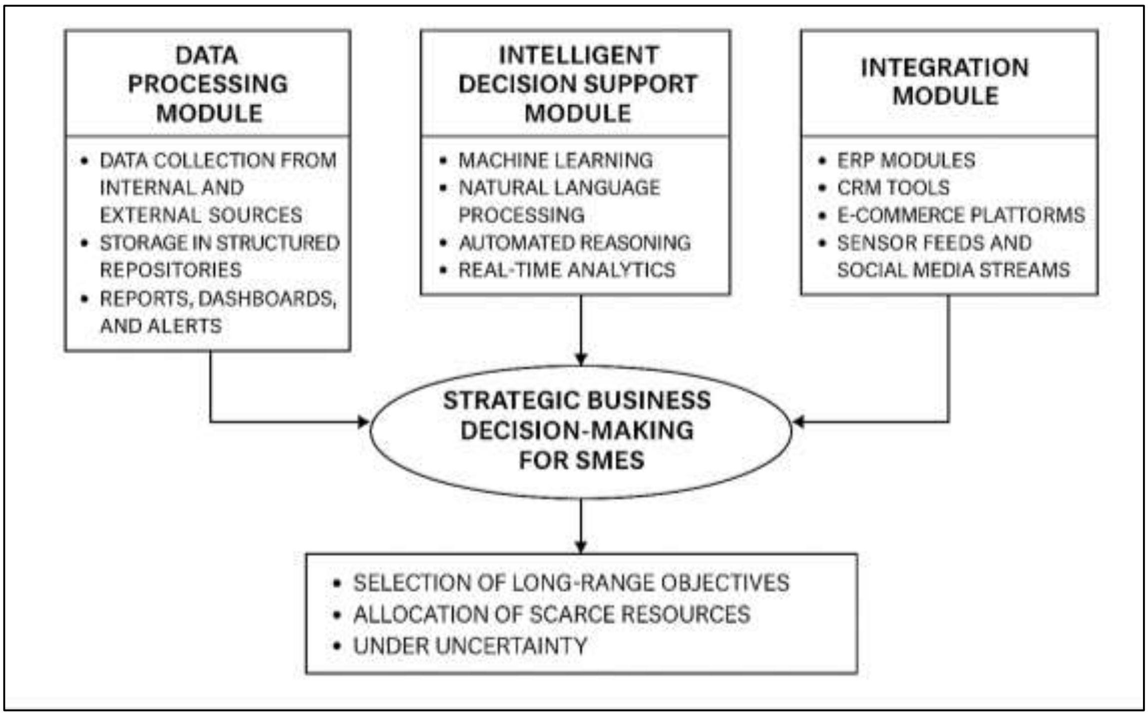
A substantial body of quantitative research explains why SMEs adopt AI-enhanced MIS platforms and how adoption translates into strategic outcomes (Yang et al., 2018). Across technology and organization studies, adoption is repeatedly linked to perceived usefulness, system ease, data reliability, and fit with existing workflows. In SMEs, usefulness is strongest when platforms provide role-specific insights rather than generic reporting, and when integrations avoid duplicate data entry. Organizational readiness also matters. Evidence across many surveys and structural models shows that top-management commitment, employee data literacy, and a culture that values evidence over guesswork predict deeper and more sustained platform use. Environmental drivers are equally important. Competitive pressure, customer digital expectations, supplier integration requirements, and regulatory reporting demands shape adoption intensity across industries and countries. Another recurring result in analytics and MIS studies is that AI capability mediates performance gains (Tworek et al., 2019). Data resources alone do not raise strategic performance until they are converted into analytical insights and decision routines. Complementarity effects also appear robust: AI-enhanced MIS yields larger benefits when paired with process standardization, training, and governance clarity. Quantitative findings from multiple sectors report measurable improvements in productivity, innovation outputs, market responsiveness, and resilience when intelligent analytics are embedded into the MIS and used consistently by management. Other work demonstrates that alignment between platform insights and strategic priorities shapes the magnitude of benefits. SMEs that connect AI-assisted dashboards to budgeting, strategic planning, and performance incentives tend to realize larger gains in decision quality and strategic agility. Research on trust in AI further indicates that decision improvements depend on system transparency and on managers' ability to assess model limitations (Azan et al., 2017). Therefore, adoption and impact are not random events; they follow identifiable patterns across technological fit, organizational capability, and ecosystem context, all of which can be operationalized in quantitative designs focused on SMEs.

The international importance of AI-enhanced MIS platforms becomes clearer when viewed through entrepreneurship and development perspectives. SMEs are primary engines of job creation, local innovation, and regional competitiveness, often operating as suppliers or service partners within wider value chains (Quinn & Strauss, 2018). Their strategic effectiveness influences not only firm performance but also broader economic stability. Opportunity recognition research shows that SMEs compete by spotting niche needs, exploiting localized knowledge, and adapting quickly to shifting demand. AI-enhanced MIS supports opportunity recognition by scanning weak signals, clustering customer feedback, and highlighting emerging patterns in sales or market behavior. In cross-border commerce and platform ecosystems, SMEs depend on data-intensive capabilities to meet global standards for delivery reliability, quality assurance, and personalization. AI-enhanced MIS enables these capabilities by connecting internal operations to external digital marketplaces and by maintaining continuous performance visibility. Comparative evidence across regions points to uneven digital maturity, which affects how deeply SMEs can use AI-enabled information platforms (Parhi et al., 2021). Yet across both advanced and developing economies, studies report that intelligent MIS tools help firms overcome scale limitations by automating analytical labor and supporting rapid coordination. Sector studies in manufacturing and logistics show that predictive MIS functions strengthen operational resilience, while service and retail studies show that intelligent customer analytics improves retention and revenue stability. Organizational learning research adds that AI-enhanced MIS can function as institutional memory, capturing and codifying strategic lessons that otherwise leak away through turnover or informal decision habits. Ethical and governance research emphasizes that as AI-MIS platforms use personal or transactional data more extensively, SMEs must ensure data stewardship through privacy safeguards and accountability protocols (Dey & Sen, 2020). Internationally, these systems are thus tied to competitiveness, inclusion, and sustainable value creation by enabling resource-constrained firms to make strategically sound decisions in turbulent markets.

Within this setting, a quantitative examination of AI-enhanced MIS platforms for strategic decision-making in SMEs can be positioned on a rich multidisciplinary foundation. MIS scholarship provides constructs for system quality, information quality, user satisfaction, and net organizational benefits, while DSS and business intelligence research supplies measures for analytical maturity, decision support intensity, and scenario use (Dördüncü, 2021). AI and data science research contributes measurable attributes such as model accuracy, explainability, automation scope, and adaptability. SME strategy and entrepreneurship literatures offer validated indicators for strategic agility, innovation orientation, competitive positioning, and decision comprehensiveness. Across more than three decades of empirical work on IT business value, analytics capabilities, and AI-supported decision processes, researchers have developed robust survey scales, econometric approaches, and structural models that link intelligent information platform use to performance outcomes (Li & Shen, 2021). This allows AI-enhanced MIS to be operationalized not only as a technology bundle but as a configuration of platform features, integration depth, governance practices, and managerial routines. Quantitative designs can capture platform intelligence through predictors such as predictive forecasting adoption, automated alert frequency, data latency reductions, and the breadth of internal-external data fusion. Strategic decision outcomes can be captured through indicators such as decision speed, alignment between functional plans and strategic priorities, risk calibration quality, and performance stability. By grounding measurement in prior empirical streams that connect analytics and MIS use to decision performance, the study of AI-enhanced MIS platforms in SMEs can map how intelligent information infrastructures translate into strategic decision quality across diverse firm contexts (Schroeder et al., 2019).

The objective of this study is to quantitatively examine how AI-enhanced MIS platforms influence strategic business decision-making in small and medium-sized enterprises by modeling the relationships among intelligent platform capabilities, integration quality, managerial usage intensity, and decision outcomes. Specifically, the study aims to measure the extent to which AI features embedded in MIS—such as predictive analytics, anomaly detection, automated reporting, recommendation engines, and real-time data fusion—contribute to higher strategic decision quality, reflected in improvements in decision speed, accuracy, comprehensiveness, risk calibration, and cross-functional alignment. A second objective is to determine whether the depth of MIS integration with core SME systems (e.g., accounting, ERP, CRM, supply chain, and digital sales channels) strengthens the performance effect of AI enhancement by reducing data latency and increasing information consistency across departments.

Figure 2: AI-Enhanced MIS Strategic Framework SMEs



A third objective is to test the mediating role of managerial usage behavior, including frequency of dashboard consultation, reliance on AI-generated insights during planning cycles, and incorporation of system recommendations into strategic meetings, in explaining how platform capabilities translate into measurable decision benefits. A fourth objective is to assess key organizational and environmental factors that may shape these effects in SMEs, such as leadership support, analytics skill readiness, data governance maturity, competitive pressure, and market volatility, thereby revealing boundary conditions under which AI-enhanced MIS produces stronger or weaker strategic value. To achieve these objectives, the study will operationalize AI-enhanced MIS capability as a multidimensional construct, capture strategic decision outcomes through validated quantitative indicators, and analyze the hypothesized paths using multivariate statistical techniques suitable for SME survey or panel data. Through this objective structure, the study seeks to provide a robust empirical account of whether, how, and to what degree intelligent MIS platforms function as strategic decision infrastructures in SMEs, clarifying the measurable contribution of AI augmentation to managerial choice quality and organizational strategic responsiveness.

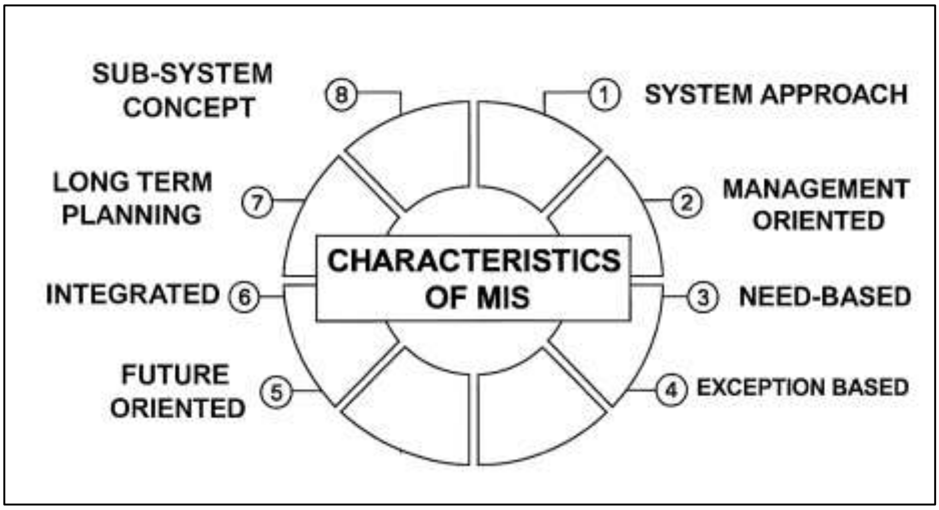
LITERATURE REVIEW

The literature surrounding AI-enhanced management information systems (MIS) for strategic business decision-making in small and medium-sized enterprises (SMEs) has expanded rapidly across several interconnected fields, yet it remains conceptually dispersed and empirically uneven (d'Espagnat, 2018). Existing scholarship on traditional MIS and business intelligence explains how information platforms support planning, coordination, monitoring, and managerial control, especially through structured reporting and performance dashboards. Alongside this, research on artificial intelligence in organizational contexts emphasizes the shift from static information processing toward systems that learn, predict, and recommend actions using advanced analytics. A third stream, focusing on strategic decision-making in SMEs, shows that smaller firms often face compressed decision cycles, limited analytical staff, and high exposure to market volatility, which makes decision quality highly sensitive to the availability of timely, integrated, and interpretable information (Ancillai et al., 2019). Finally, adoption and IT business value studies clarify why some SMEs gain measurable performance benefits from intelligent systems while others realize weaker outcomes because of constraints in readiness, governance, or integration depth. Bringing these streams together suggests that AI-enhanced MIS platforms represent more than improved reporting tools; they function as strategic infrastructures where predictive and prescriptive intelligence is embedded into routine managerial workflows. However, prior empirical work tends to examine AI tools, MIS platforms, or SME decision outcomes separately rather than modeling their relationships as a unified system. Therefore, this literature review synthesizes existing findings to build a coherent quantitative foundation for analyzing how AI-MIS capabilities, system integration quality, and managerial use behaviors shape strategic decision-making outcomes in SMEs (Steinhoff et al., 2019). The section clarifies measurable constructs, highlights consistent empirical patterns, and develops logically connected relationships suitable for multivariate hypothesis testing.

Conceptual Foundations and Scope

Management information systems (MIS) in small and medium-sized enterprises are commonly defined as integrated arrangements of people, routines, data resources, and digital tools that convert day-to-day transactions into structured information for managerial use. In SMEs, the MIS cycle is typically described as a continuous flow beginning with data acquisition from sales, procurement, production, finance, and customer interactions, followed by storage in databases or cloud repositories, processing through validation rules and aggregation routines, distribution through dashboards or reports, and managerial interpretation for decisions. This definition aligns with foundational MIS scholarship that frames information systems as organizational memory and control mechanisms, while also emphasizing their role in coordinating scarce resources (Gawer, 2021). Studies by Laudon and Laudon, O'Brien and Marakas, and Turban and colleagues characterize MIS as the backbone of managerial planning and control, and SME-focused research by Raymond, Cragg, and Soto-Acosta details how such systems provide operational reporting, budgeting support, performance tracking, and internal coordination. Empirical work by DeLone and McLean and later Petter and collaborators further links MIS value to system and information quality, a point reinforced in SME contexts where managerial dependence on reliable, timely information is high. Yet, the literature consistently notes that SMEs experience distinctive MIS limitations compared to larger firms. Research by Thong, Levy and Powell, and Oliveira and Martins reports that SME MIS environments often remain fragmented across functions, with separate accounting, sales, and inventory tools that do not share data smoothly. This fragmentation produces manual re-entry of information, inconsistent KPI definitions, and delayed reporting cycles, which in turn narrow managerial visibility (Shute et al., 2017). Additional studies by Kwon, Popovič, and Cenamor show that SMEs frequently struggle with low analytical staffing and uneven data governance, which weakens the strategic potential of MIS even when basic reporting exists. In sum, the conceptual literature positions MIS platforms in SMEs as essential but often under-integrated infrastructures whose primary measurable focus lies in data quality, timeliness, integration breadth, and the extent to which managers can convert outputs into actionable understanding (Cat, 2021). Building on these MIS foundations, the literature on AI enhancement describes a shift in what MIS platforms can deliver to SME managers. AI-enhanced MIS is defined not as a separate toolset but as an evolution of the MIS platform in which intelligent analytics are embedded into the information pipeline (Bird & Schjoedt, 2017). Research traditions in AI and analytics, represented by scholars such as Russell and Norvig, Shrestha and colleagues, and Davenport and Harris, describe AI in business systems as computational methods that learn from data, detect complex patterns, generate predictions, and recommend actions. When these methods are integrated into MIS, the platform no longer focuses mainly on descriptive reporting; it expands toward predictive and prescriptive functions. Studies by Wamba, Mikalef, and Gupta conceptualize predictive capability as the use of machine learning models for estimating future demand, churn, risk exposure, or resource needs, while prescriptive capability refers to automated recommendation and optimization routines that rank or propose decision options (Abdul, 2023; Abdulla & Zaman, 2023; Salminen et al., 2021).

Figure 3: AI-Enhanced MIS Characteristics for SMEs



Empirical evidence from business intelligence and decision support research by Power, Shim, and Mariani indicates that AI integration improves the depth and speed of analytic interpretation, especially when insights are produced automatically as part of routine workflows. SME-oriented work by Eggers and Kraus shows that embedding AI into MIS can compensate for limited human analytics resources by automating tasks such as anomaly detection, forecasting, and performance diagnosis (Arfan et al., 2023; Ara & Onyinyechi, 2023). At the platform level, studies by Rai and Arrieta emphasize the importance of interpretability and transparency, indicating that AI value rises when MIS interfaces explain predictions and highlight uncertainty in ways managers can understand. Literature on data pipelines by Chen and colleagues and on big-data capability by Amin and Mesbaul (2023) further illustrates that AI enhancement depends on stable data integration, because intelligent models require consistent, timely inputs from multiple internal and external sources (Femenia-Serra et al., 2019; Foysal & Aditya, 2023). Overall, the conceptual scope of AI-enhanced MIS in SMEs is grounded in measurable dimensions of intelligent functionality—learning accuracy, recommendation usefulness, automation extent, and real-time responsiveness—delivered through the MIS platform rather than through isolated AI applications.

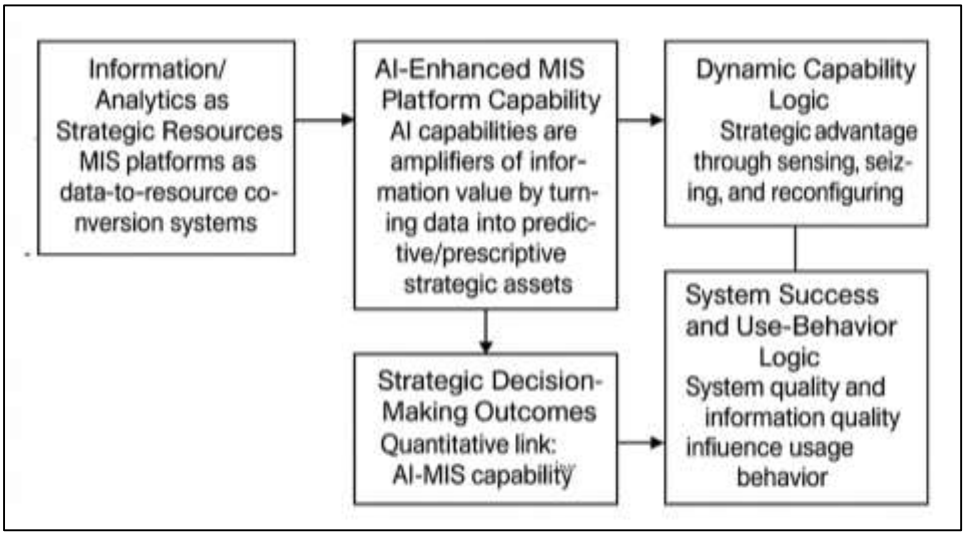
The strategic decision-making literature for SMEs provides the third conceptual pillar, clarifying what kinds of decisions are affected by AI-enhanced MIS and why SMEs are a distinctive context (Kanis et al., 2021; Hamidur, 2023). Strategic decisions in SMEs include longer-range choices about market entry, customer targeting, product or service portfolio shaping, pricing architecture, capacity expansion, technology investment priorities, and partnership or supplier selection. Strategy scholars such as Mintzberg, Eisenhardt, and March describe strategic decisions as high-stakes selections under uncertainty, often requiring trade-offs among growth, risk, and resource constraints. In SMEs, these decisions are shaped by structural realities documented across many studies: authority is concentrated among a small leadership core or a single owner-manager; time for analysis is limited by operational demands; formal planning departments are uncommon; and intuition plays a larger role than in large firms. Research by Shane and Venkataraman and by Alvarez and Barney links SME strategy to opportunity recognition and rapid adaptation, while studies by Beck and Demirgüç-Kunt and Ayyagari and colleagues underscore the economic weight of SMEs and the sensitivity of their outcomes to decision quality (Holmes et al., 2017; Rashid et al., 2023; Musfiqur & Kamrul, 2023). Empirical investigations by Shepherd, McKelvie, and Ghasemaghaei show that SME strategic decisions benefit from expanded evidence bases because smaller firms often face higher volatility and thinner margins for error. Decision-process research in information systems by Muzahidul and Mohaiminul (2023) points out that algorithmic decision support changes how managers evaluate alternatives, particularly by enabling systematic scenario comparison. In quantitative studies, strategic decision outcomes are frequently operationalized through decision speed, decision accuracy or effectiveness, comprehensiveness of alternative evaluation, alignment across functions, and the quality of risk

calibration. These measurable dimensions are consistent with prior MIS and analytics research that links better information access to faster cycle times, fewer avoidable errors, and stronger coordination (Boylan et al., 2018; Amin & Praveen, 2023; Hasan & Ashraful, 2023). The SME strategy literature thus frames strategic decision-making as a domain where higher-quality, faster, and more coherent information processing can materially alter competitive positioning and organizational survival.
Synthesizing these three streams, the literature converges on a coherent conceptual foundation for studying AI-enhanced MIS platforms as strategic decision infrastructures within SMEs. MIS research establishes the platform as a structured organizational cycle of data generation, transformation, and managerial use, while also documenting persistent SME-specific weaknesses such as fragmented systems, manual reporting burdens, and delayed visibility (Andriof & Waddock, 2017; Ibne & Kamrul, 2023; Mushfequr & Ashraful, 2023). AI-integration research then explains how embedding intelligent analytics into MIS changes the platform's informational output from static summaries to adaptive forecasting and recommendation, provided that data inputs are timely, integrated, and governed for quality. Strategic SME decision research clarifies that the decisions most influenced by AI-MIS are those involving resource allocation, competitive positioning, market and customer choices, and capacity or investment commitments—areas where uncertainty is high and the cost of delay or error is substantial. Across combined evidence from scholars including (Roy & Kamrul, 2023; Saba et al., 2023; Saba & Tonoy Kanti, 2023), the central theme is that AI-enhanced MIS platforms expand managerial cognition by automating detection of patterns, compressing analysis time, and increasing the evidence base used in choice (Bhatt et al., 2021; Shaikh & Farabe, 2023; Haider & Hozyfa, 2023). Yet this expansion is conditioned by the scope and integration of the MIS platform itself, because intelligent outputs require stable pipelines and meaningful interface design to become strategically usable. The empirical record also indicates that SMEs gain the most when AI functions are not bolted onto disconnected tools but are woven into the MIS routines that already govern budgeting, KPI monitoring, and planning coordination. Therefore, the measurable focus for a quantitative study is well delimited by the literature: AI-MIS capability as an embedded platform attribute, MIS integration and data quality as enabling conditions, and strategic decision outcomes as multidimensional results expressed in speed, accuracy, comprehensiveness, alignment, and risk calibration (Wiltshire & Ronkainen, 2021).

Theoretical Lenses Supporting Hypothesis Development

Information and analytics as strategic resources form a central lens for explaining why AI-enhanced MIS platforms matter for strategic decision-making in SMEs (Berge & Ingerman, 2017). Across the resource-based tradition, studies by Barney, Wernerfelt, Grant, and Bharadwaj frame competitive advantage as emerging from resources that are valuable and well organized, including information resources and the routines that mobilize them. Within this view, MIS platforms are not simply data warehouses; they are organizational conversion systems that transform scattered operational events into structured knowledge that can be deployed repeatedly in strategic choices. Research by Alavi and Leidner, Nonaka, and Huber further clarifies that information becomes a true resource when it is embedded in shared processes and organizational memory, rather than remaining isolated in individual files. IT business value work by Brynjolfsson and Hitt, Melville and colleagues, and Wade and Hulland emphasizes complementarities, showing that MIS investments yield stronger payoffs when paired with analytic skills, governance, and decision routines (Liu, 2017). Analytics capability researchers such as Gupta and George, Akter and colleagues, Kiron and collaborators, and Mikalef and coauthors demonstrate that the strategic value of data rests on acquisition, integration, and analytic deployment capacities. AI enhancement intensifies this conversion by enabling predictive and recommendation functions that elevate data from historical reporting to strategic foresight. Studies by Davenport and Harris, Wamba and colleagues, and Shrestha and associates describe how embedded machine learning can surface weak signals, quantify uncertainty, and translate complex patterns into decision-ready insights. SME-focused research by Eggers, Kraus, Cenamor, and Soto-Acosta shows that these benefits are particularly salient in smaller firms where managerial attention and analytic labor are scarce. Put together, this lens supports measurable thinking about AI-MIS capability as a strategic resource bundle, where data quality and algorithmic intelligence increase the informational value available for evaluating markets, pricing, portfolio choices, and investment allocations (Sardana et al., 2020). The strategic-resource logic thus anchors the expectation that AI-enhanced MIS platforms strengthen SME decision quality by raising the usefulness, rarity, and deployability of information within constrained enterprises.

Figure 4: Theoretical Lenses for AI-MIS Strategy



Dynamic capability logic provides another tightly aligned lens for hypothesis development because it links AI-enhanced MIS platforms to strategic advantage under volatility, which is a defining condition for SMEs. The dynamic capability stream, elaborated by Teece, Eisenhardt, Martin, Winter, Pavlou, and El Sawy, argues that firms prosper by repeatedly sensing change, seizing opportunities through timely decisions, and reconfiguring resources to stay aligned with shifting environments (Hsiao & Chen, 2018). In SMEs, where market shocks or small forecasting errors can rapidly compress cash flow and erode competitiveness, the sensing–seizing–reconfiguring cycle becomes a direct determinant of survival. Research by Côrte-Real, Dubey, Karimi, and Walter conceptualizes sensing as the capacity to detect emerging patterns from internal performance signals and external market cues. AI-enhanced MIS platforms act as sensing engines by continuously scanning sales, inventory, customer behavior, logistics disruptions, and competitor movements to produce alerts and forecasts that managers can interpret quickly. Seizing, as described in strategy and decision studies by March, Eisenhardt, and Shepherd, depends on comparing alternatives in time to commit resources (Taufique & Vaithianathan, 2018). AI-MIS supports seizing through rapid scenario evaluation, cost-benefit ranking, and option optimization embedded in dashboards and planning tools. Reconfiguration, treated in digital transformation studies by Wirtz, Mikalef, Cenamor, and Autio, is sustained when feedback loops expose deviations early and enable fast adjustments in budgets, capacity, product emphasis, or partner configurations. SME evidence shows that these loops can be compressed dramatically when intelligent MIS functions are integrated into routine meetings and KPI reviews, allowing managers to adapt before losses compound. Importantly, the dynamic capability lens interprets AI-enhanced MIS as an enabling infrastructure for strategic adaptation rather than a static reporting tool. That framing fits measurable constructs such as accuracy of sensing outputs, speed of seizing decisions, and frequency of reconfiguration actions, each reflecting how strongly AI-MIS supports adaptive strategy in SMEs (Teng, 2017). Therefore, dynamic capability logic grounds the expectation that AI-enhanced MIS strengthens strategic decision outcomes by accelerating environmental interpretation, improving alternative evaluation, and tightening adaptive feedback in resource-constrained firms.

System success and use-behavior logic offer a third lens explaining how technical quality becomes strategic value through managerial engagement. The system success tradition advanced by DeLone and McLean and later refined by Petter, Wixom, Watson, and Nelson argues that system quality and information quality shape user satisfaction and actual use, while use mediates performance effects (Tarafdar & Qrunfleh, 2017). Technology acceptance research by Davis, Venkatesh, and colleagues similarly emphasizes perceived usefulness and ease of use as drivers of sustained adoption. Applied to AI-enhanced MIS platforms, system quality refers to reliability, integration smoothness, interface clarity, response time, and stability of data pipelines. Information quality refers to accuracy, relevance, completeness, timeliness, and interpretability of AI outputs, including how clearly predictions and recommendations are presented. Decision support scholarship by Power, Shim, Shollo, and Galliers shows that even advanced analytical engines fail to improve decisions when managers distrust outputs or cannot interpret them within the rhythm of planning (Hallam & Zanella, 2017). Algorithmic advice studies by Logg, Rai, and Arrieta highlight that transparency and explainability increase reliance, because managers need to understand why a recommendation appears and what uncertainty surrounds it. Behavioral decision research by Kahneman, Bazerman, and Moore adds that frequent use of analytic aids expands the evidence base, improves alternative assessment, and counters cognitive shortcuts that often dominate time-pressured SME choices. Empirical MIS-in-SMEs work by Thong, Levy and Powell, Popovič, and Kwon indicates that benefits are strongest when intelligent MIS tools are embedded into budgeting cycles, strategic meetings, and KPI governance, rather than accessed sporadically. This lens therefore differentiates capability from realized value: AI-MIS features provide potential utility, but measurable improvements in decision speed or accuracy arise through usage intensity, scenario exploration, and routine incorporation of AI insights into strategic deliberation (Mani & Gunasekaran, 2018). System success and use-behavior logic thus supports causal reasoning that high-quality AI-enhanced MIS platforms increase managerial engagement, while that engagement explains why strategic decisions become faster, more comprehensive, better aligned, and more risk-calibrated within SMEs.

Adoption context logic forms a fourth lens by explaining systematic differences in AI-enhanced MIS capability maturity and effects across SMEs. Context-sensitive adoption research developed by Tornatzky and Fleischer, Rogers, Iacovou, Zhu, Oliveira, Martins, Chauhan, and others shows that technology use is shaped by combined technological readiness, organizational readiness, and environmental pressure (Daunt & Harris, 2017). Technological readiness includes the state of digital infrastructure, cloud accessibility, interoperability of existing systems, and the presence of stable databases that allow AI modules to draw consistent inputs. Organizational readiness refers to leadership commitment, analytics skill availability, learning orientation, and governance maturity that together allow SMEs to absorb intelligent outputs into strategic routines. Environmental pressure includes competitive intensity, shifting customer expectations, partner integration demands, and regulatory pressures that make intelligent information processing more necessary for staying viable. Studies of SME digitalization and AI adoption by Cenamor, Eggers, Kraus, Dubey, Mikalef, and Soto-Acosta indicate that readiness and pressure do not merely explain whether AI-MIS is adopted; they explain how deeply it is integrated, how many data sources it connects, and how routinely managers rely on it for strategic choices (Chauhan et al., 2021). Complementarity evidence from Bharadwaj, Melville and colleagues, and Brynjolfsson and Hitt shows that adoption depth interacts with skills and process standardization, meaning that identical AI-MIS features yield different decision outcomes depending on organizational context. In SMEs with strong readiness and high pressure, AI-MIS becomes a core strategic system used for market sensing, pricing, investment selection, and capacity planning. In SMEs with weaker readiness, AI functions may remain confined to operational reporting, limiting strategic impact. Adoption context logic therefore supports measurable antecedents that predict capability maturity, integration quality, and use intensity, along with boundary reasoning about why strategic decision benefits vary across firm types (Forero et al., 2018). This lens completes the theoretical map by situating AI-enhanced MIS not as a universal solution but as a capability whose realized strategic value depends on readiness and environmental demand embedded in the SME setting.

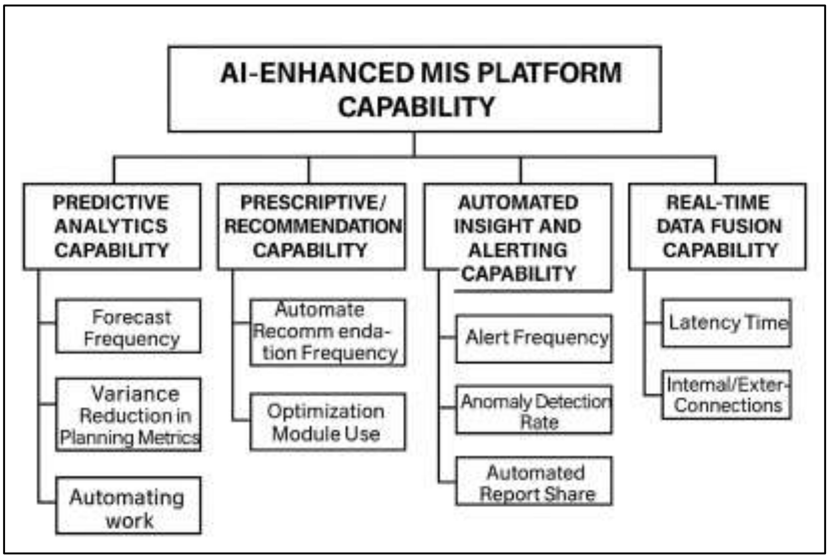
Construct Block A: AI-Enhanced MIS Platform Capability

AI-Enhanced MIS Platform Capability is treated in quantitative MIS and analytics research as a multidimensional construct because “intelligence” in an MIS platform is not a single feature but a bundle of complementary abilities that together change what managers can see, infer, and do (Trakadas et al., 2020). The first dimension, predictive analytics capability, captures the platform’s power to learn from historical and streaming data to estimate likely future states relevant to strategic choices. In the literature, prediction in MIS environments is associated with reducing uncertainty in planning cycles by shifting firms from hindsight-oriented reporting toward evidence-based anticipation. Forecast frequency is used to represent how routinely the platform produces forward-looking outputs across key business domains such as sales, demand, cash flow, customer churn, and operational capacity. Forecast accuracy reflects the closeness of predicted results to observed outcomes, a core performance property of predictive systems that also influences managerial trust (Akerkar, 2019). Variance reduction in planning metrics reflects whether predictions help narrow the spread between planned targets and realized performance, indicating stability improvements attributable to intelligent forecasting. This dimension is especially salient in SMEs because small forecasting errors can propagate quickly into inventory imbalances, liquidity pressure, or missed market windows. Empirical studies across business intelligence and decision support consistently show that prediction value rises when forecasts are frequent enough to enter decision routines and accurate enough to be treated as credible inputs. For construct building, prediction is operationalized by capturing manager perceptions of forecast usefulness together with objective indicators such as forecast error reduction, frequency of generated projections, and reported improvements in planning reliability (Gandy et al., 2017). The predictive dimension thus represents the platform's ability to provide anticipatory knowledge, collapsing the managerial burden of manually estimating future conditions and forming a measurable subcomponent of overall AI-MIS capability.

The second dimension, prescriptive or recommendation capability, shifts the platform from predicting what might happen to advising what should be done. In the literature, prescriptive MIS intelligence is tied to optimization and decision-ranking functions that evaluate multiple strategic alternatives against goals and constraints (Promwongsa et al., 2020). In quantitative terms, this capability is reflected in how often the platform produces automated recommendations per strategic cycle, such as suggesting reorder quantities, pricing adjustments, market targets, promotion allocations, or investment priorities. The proportion of recommendations adopted into plans is treated as a behavioral-outcome bridge because it indicates that the platform's prescriptive outputs are not merely generated but actually used to shape strategy. Optimization module use is also a key indicator, representing whether managers engage with tools that search for improved solutions under constraints rather than relying only on descriptive dashboards (Garson, 2021). The literature emphasizes that recommendation systems become strategically meaningful when they are embedded into MIS workflows so that suggested actions arrive at the moment managerial choices are being considered. In SMEs, prescriptive capability can substitute for limited analytic staffing by automating option screening and highlighting high-payoff alternatives. Measurement approaches commonly combine perceived recommendation relevance, usefulness, and clarity with reported adoption rates and the frequency of optimization-driven decision episodes. Prescriptive capability is not inferred from raw platform existence; it is inferred from the platform producing actionable sequence-ready advice, managers recognizing it as pertinent, and organizational plans reflecting those recommendations. This dimension therefore represents the platform's strategic guidance power, complementing predictive functions by narrowing choice sets and structuring decisions around quantified trade-offs.

A third dimension emphasized in AI-enhanced MIS studies is automated insight and alerting capability, which reflects the platform's ability to detect meaningful deviations or opportunities without being explicitly asked. Traditional MIS presumes that managers pull information through reports, whereas AI-enhanced systems push high-salience insights through alerts, anomaly detection, and automated narratives (Turban et al., 2017). Alert frequency indicates how actively the system flags issues or opportunities across operational and market indicators. Anomaly detection rate reflects the platform's success in identifying outliers, sudden shifts, fraud-like patterns, process disruptions, or emerging customer behaviors that warrant strategic attention. Automated report share captures the proportion of decision information produced without manual assembly, indicating how strongly AI replaces routine analytical labor. The literature treats automated insight as crucial because strategic decision quality depends on early detection; delays in recognizing a deviation often lead to larger corrective costs. In SMEs, where managers handle multiple roles and may not continuously monitor dashboards, automated insight reduces attentional overload by surfacing only high-priority signals (Rossi et al., 2020). Quantitatively, this capability is measured through usage logs when available (counting alerts received, opened, and acted upon) and through perceptual scales capturing whether managers feel the system reliably highlights what matters. Automated insight capability overlaps with predictive and prescriptive functions but remains distinct: prediction estimates likely futures, prescription recommends actions, and automated insight ensures that critical patterns are surfaced proactively. Platforms scoring high in this dimension are those that continuously "watch the business" and translate weak or complex signals into timely prompts, thereby expanding strategic awareness without requiring constant managerial querying (Marszk & Lechman, 2021).

Figure 5: AI-MIS Capability Dimensions for SMEs

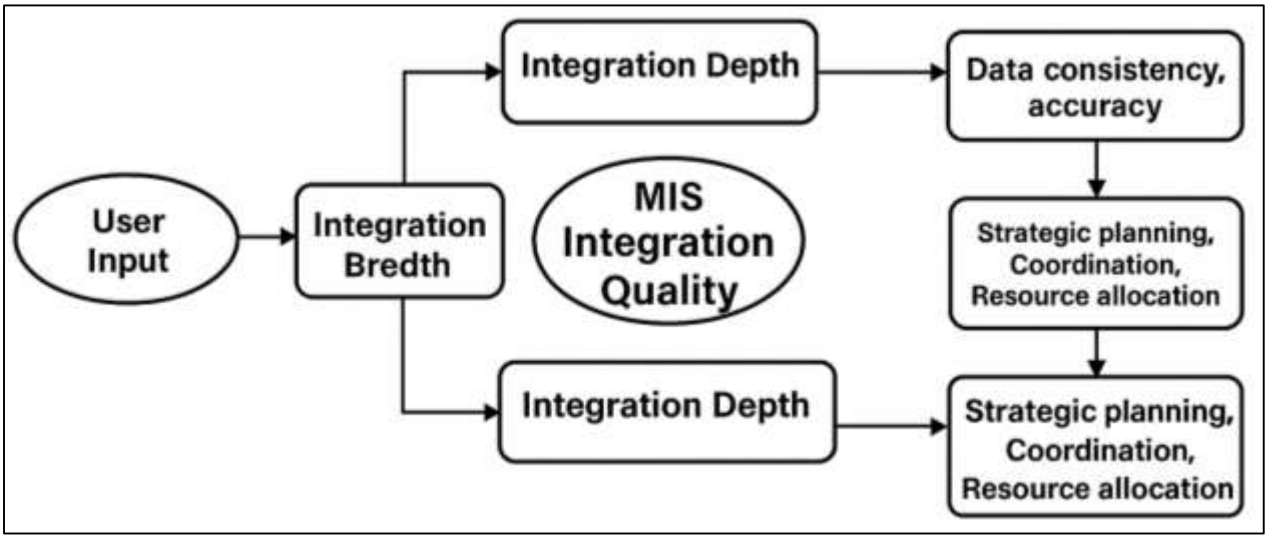


Construct Block B: MIS Integration Quality

MIS Integration Quality is widely treated in the information systems and SME strategy literature as a foundational condition that determines whether an MIS platform can support strategic decision-making effectively, and whether any AI enhancement embedded in that platform yields meaningful added value (Lo et al., 2018). Integration quality refers to the extent to which the MIS succeeds in creating a coherent, unified information environment across the enterprise rather than a patchwork of disconnected tools. In SMEs, this issue is especially salient because the same small leadership group commonly oversees operations, finance, marketing, and growth planning, making decision reliability highly dependent on the speed and coherence of information flow across functions. When integration quality is weak, managerial attention is diverted toward reconciling conflicting numbers and chasing missing data, which narrows the evidence base for strategy and encourages reactive decisions. Conversely, strong integration quality stabilizes the informational backbone of the firm by linking data acquisition, storage, processing, and reporting into a single continuous chain (Alazab et al., 2021). The literature on MIS success, business intelligence value, and digital operations repeatedly indicates that integration quality lowers information friction, improves data timeliness, and raises the interpretability of dashboards for managers with limited analytic time. SME-focused research adds that integration quality is not merely a technical feature; it is a socio-technical performance property that shapes how managers coordinate, resolve trade-offs, and interpret organizational priorities. In firms where MIS integration is high, strategic planning becomes more evidence-oriented because managers gain consistent visibility into cost structures, demand patterns, process performance, and customer behavior simultaneously. This unified visibility reduces the tendency for departments to operate with separate "truths," supporting strategic coherence in resource allocation and goal setting (Addae et al., 2019). As a result, integration quality is consistently positioned as both a direct driver of decision quality and a key condition that intensifies the usefulness of any intelligent analytics layer added to MIS. The implication for construct development is that MIS integration must be assessed multidimensionally, capturing not only whether systems are connected, but also how deeply they exchange information, how cleanly they reconcile records, and how well they support shared decision views across functions (Liébana-Cabanillas et al., 2021).

Integration breadth represents the first pillar of MIS Integration Quality because the scope of connected systems defines the variety of evidence managers can draw upon. Breadth focuses on how many core applications are linked to the MIS platform—such as accounting, ERP modules, CRM tools, point-of-sale systems, e-commerce storefronts, supply chain or logistics systems, and HR records. The literature on SME digitalization emphasizes that limited system breadth produces structurally incomplete strategic views (Grewatsch & Kleindienst, 2017). For example, an MIS connected only to accounting and sales can generate revenue summaries but cannot reliably support strategic decisions on inventory scale, delivery promises, workforce capacity, or customer lifetime value because those signals remain outside the platform. Broader integration, by contrast, allows the MIS to unify financial and non-financial indicators, aligning operational drivers with strategic outcomes. Empirical studies of BI and dashboard use in SMEs consistently show that breadth expands decision comprehensiveness, because managers can evaluate alternatives using multi-domain indicators rather than single-function reports. Breadth also reduces blind spots in strategy by exposing cross-domain dependencies, such as how marketing promotions alter stock turnover, how supplier reliability shapes delivery performance, or how staff scheduling affects service quality (Lin et al., 2019). In SMEs, where data tools often emerge through incremental purchases rather than planned architectures, breadth becomes a critical measure of whether the MIS has moved beyond isolated reporting toward enterprise-wide strategic support. Importantly, breadth is not limited to internal sources. The literature increasingly recognizes that strategic decisions in SMEs are shaped by external signals such as market prices, customer sentiment, competitor shifts, and platform-based demand changes. An MIS with broad integration includes pathways for these external indicators to enter the decision environment alongside internal reports. As such, breadth operates as a measurable condition for strategic visibility, and its presence strengthens the informational foundation required for more reliable forecasting, risk evaluation, and opportunity assessment (C. Park et al., 2019).

Figure 6: MIS Integration Quality Flow Framework



Integration depth represents the second pillar and captures the intensity and automation of system linkages rather than the mere existence of connections. Depth is reflected in the proportion of workflows that are linked end-to-end and the extent to which data exchange occurs automatically across modules without manual export or re-entry (Ho et al., 2018). The literature on process integration and SME operational coordination emphasizes that shallow integration produces time lags and interpretive gaps. When systems exchange data only periodically or through manual uploads, the MIS provides a rear-view perspective rather than a near-current decision environment. This limitation is especially costly in SMEs because strategic decisions often occur in compressed cycles where delays quickly translate into stockouts, cash-flow strain, or missed market windows. Deep integration reduces these risks by enabling upstream events to flow immediately into downstream reports and planning modules (Sancha et al., 2020). A sales surge updates inventory and procurement dashboards; a supplier delay updates production schedules and delivery projections; a pricing change updates margin simulations and demand forecasts. Studies on decision support performance show that the strategic value of analytics rises sharply when underlying workflows are deeply integrated, because managers can trace cause–effect relationships through the full process chain rather than interpreting fragmented snapshots. Depth is also a critical enabler of intelligent MIS in SMEs. Predictive and recommendation models rely on continuous, synchronized data streams; intermittent or manually updated pipelines reduce model reliability and weaken managerial trust (Arasli et al., 2021). The literature therefore treats depth as not only a coordination enhancer but also a stability mechanism for advanced analytics. Depth supports faster decision speed by decreasing the time managers spend reconciling datasets, and it supports higher decision accuracy because the information base reflects real operating conditions. Consequently, integration depth is repeatedly framed as a measurable determinant of whether MIS platforms can move from operational reporting toward strategic guidance.

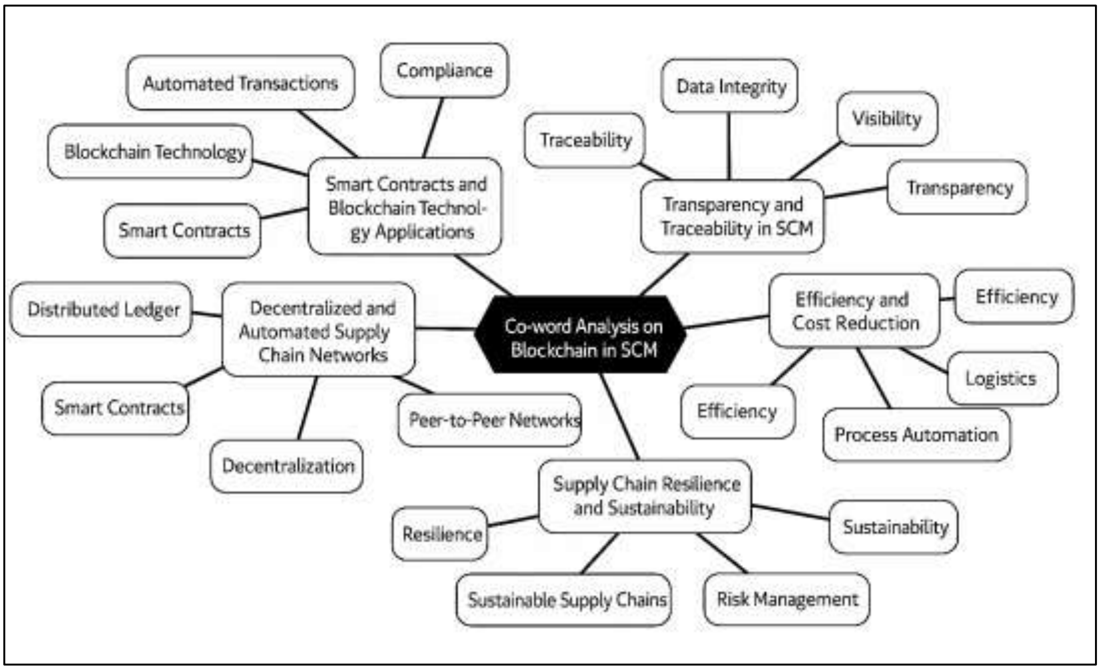
Data consistency and accuracy, together with cross-functional visibility, complete MIS Integration Quality by ensuring that integrated information becomes strategically usable rather than merely centralized. Data consistency and accuracy refer to whether different modules agree on shared facts, whether duplicate records are minimized, and whether missing data is reduced enough to support stable analysis (Mohtaramzadeh et al., 2018). The literature on data governance and SME analytics repeatedly shows that inconsistent data undermines confidence and can produce systematic strategic error. A platform that integrates many sources but fails to reconcile them creates a sophisticated-looking dashboard built on unstable inputs. Such inconsistency inflates reconciliation costs, encourages managerial skepticism, and weakens the adoption of analytics in strategy discussions. Strong consistency and accuracy, by contrast, indicate that the MIS provides a reliable "single version of truth," which is essential for evidence-based choices on investment, pricing architecture, market entry, or capacity scaling. Cross-functional visibility quality extends this logic into the managerial sphere by capturing whether integration produces shared access to the same KPIs and aligned performance definitions across departments (Siyal et al., 2021). The literature on strategic alignment stresses that SMEs benefit from common dashboards and symmetrical access because coordination depends on shared interpretation rather than layered bureaucracy. When marketing, operations, and finance view the same core indicators and interpret them through aligned definitions, strategic decisions become more coherent and less conflicted at implementation. This shared visibility reduces interdepartmental friction, improves prioritization clarity, and supports consistent execution of strategic plans. Together, consistency/accuracy and cross-functional visibility do two things in quantitative models: they directly raise strategic decision outcomes by improving the reliability and interpretability of information, and they strengthen the contribution of AI-enhanced MIS by providing clean, coherent inputs and trusted output environments (Makhloufi et al., 2021). In this synthesized view, MIS Integration Quality functions as a platform-level capability that both elevates decision quality on its own and amplifies the strategic impact of embedded AI by reducing informational friction and increasing shared managerial confidence.

Construct Block C: Managerial Usage Intensity (Mediating Variable)

Managerial usage intensity is treated in the literature as the behavioral bridge that converts platform capability into realized strategic value, particularly in SMEs where technology adoption does not automatically translate into decision improvement (Tuu et al., 2021). Even when an AI-enhanced MIS platform offers advanced prediction, recommendation, and alerting, the system's strategic contribution remains latent until managers engage with it frequently and purposefully. Usage intensity therefore represents not a general attitude toward technology but a concrete pattern of interaction between decision makers and the platform's analytical outputs. Research across management information systems, decision support, and analytics adoption consistently shows that information quality and analytical sophistication improve outcomes only when managers integrate them into regular work routines. In SME contexts, this mediation logic is stronger because a small leadership core typically performs multiple roles and tends to rely on habitual decision shortcuts unless analytical tools become part of the everyday decision rhythm (Santoro et al., 2019). Usage intensity captures how often managers consult dashboards, how routinely they open automated reports, and how consistently they return to the platform for strategic monitoring rather than treating it as a peripheral reporting tool.

Studies of BI and MIS practice show that frequent engagement gradually increases managerial familiarity with data patterns and raises confidence in interpreting analytical signals, which promotes wider evidence use in strategy formation. Usage intensity also interacts with cognitive and behavioral factors documented in decision research: repeated exposure to structured analytics enables managers to recognize variance, question intuition-based assumptions, and refine mental models of business drivers. In practical terms, this means that platform capability influences strategic decision outcomes through the extent to which managers make the system a repeated input into planning, control, and strategic discussions. Because SMEs often lack dedicated analytics teams, the manager's own engagement substitutes for specialized analytical labor; high usage intensity indicates that the platform has become an internal "analytical partner." The literature therefore positions managerial usage intensity as a mediating construct that explains why similar AI-MIS investments produce different strategic results across SMEs (Linuesa-Langreo et al., 2018). Firms with high capability but low managerial engagement show limited improvements, while firms with high engagement show measurable gains in decision speed, comprehensiveness, alignment, and accuracy. This view frames usage intensity as a behavioral capability in its own right, reflecting not only what the platform can do but what managers actually allow it to do within the strategic life of the enterprise (Su & Chan, 2017).

Figure 7: MIS Integration Quality Concept Map



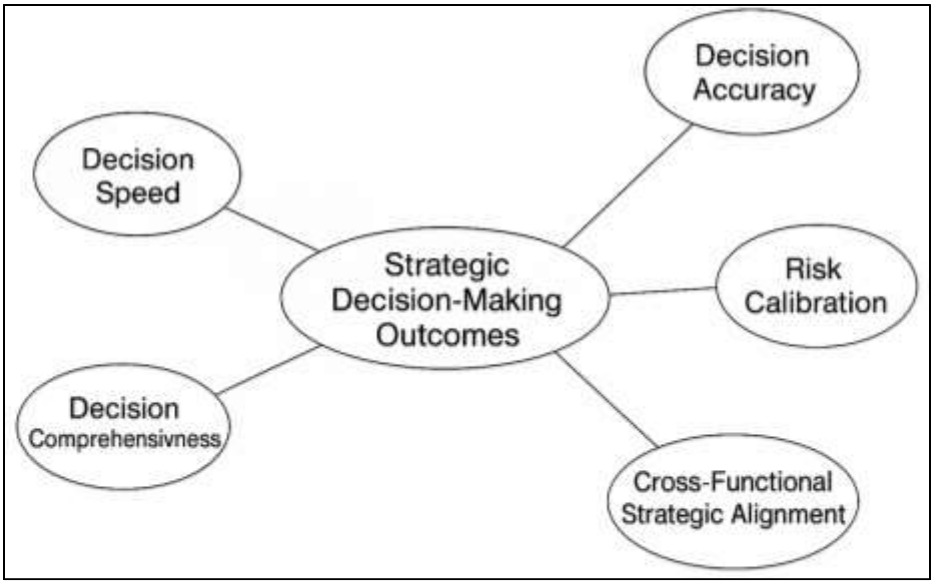
Platform usage frequency forms the first dimension of managerial usage intensity because it captures the basic level of managerial exposure to AI-MIS insights. Frequency refers to how often managers log into the system, view dashboards, interact with high-level reports, and open automated analytical summaries. In the literature, frequency is consistently linked to learning effects: the more often decision makers consult the MIS, the more likely they are to notice evolving patterns, understand business drivers, and detect anomalies early (Huang & Liu, 2017). For SMEs, this dimension is critical because decisions must often be made quickly, and infrequent MIS consultation leaves managers exposed to noisy impressions and incomplete situational awareness. Frequent usage also indicates whether the platform has been embedded into routine managerial cycles such as weekly sales reviews, monthly budgeting, or daily operations monitoring. Evidence from quantitative studies on MIS and BI usage shows that when dashboards are accessed regularly, managers rely less on static historical reports and more on dynamic indicators that reflect current performance and emerging risks. Opening automated reports is particularly relevant to AI-enhanced platforms because these reports represent a push-based flow of intelligence; if managers ignore them, the system's proactive value collapses (Verma, 2021). Usage frequency therefore operates as a measurable signal that managers are maintaining continuous contact with strategic indicators, rather than limiting system interaction to compliance-driven reporting (Grewatsch & Kleindienst, 2017). In SMEs, this contact tends to shape both decision speed and decision confidence. When managers consult the platform frequently, they reduce the time required to gather evidence, shorten deliberation cycles, and increase readiness to act because the informational groundwork has already been updated in their minds. Frequency also supports cross-functional coherence because shared dashboards create common reference points for different decision participants. Thus, the literature treats usage frequency not as a trivial count of logins but as an indicator that AI-MIS intelligence is being absorbed into managerial cognition and organizational routines (Leenders et al., 2019). This establishes the foundation for higher-order strategic reliance and scenario activity, meaning that frequency is the entry-level behavioral requirement for the platform's capabilities to have any realistic pathway toward strategic payoff.

Construct Block D: Strategic Decision-Making Outcomes

Strategic decision-making outcomes are treated in the literature as the ultimate dependent domain through which the value of information systems, analytics, and AI-enhanced platforms is empirically verified, especially in SMEs where strategic choices immediately shape survival and growth (Elbanna, 2018). Across classical strategy and decision scholarship, strategic decision quality is not a single event but a patterned outcome reflected in how quickly managers move from recognizing an issue to committing resources, how accurately those commitments match environmental realities, and how coherently the organization executes them across functions. Early work by Simon, Cyert and March, and Mintzberg describes strategic decisions as bounded-rational processes where time pressure and imperfect information create trade-offs between speed and accuracy. Later studies by Eisenhardt, Dean and Sharfman, and Papadakis emphasize that decision outcomes become measurable when researchers examine the process–performance link: decisions are better when they are timely, evidence-based, risk-aware, and institutionally aligned (Killen et al., 2020). In SME-specific contexts, research by Shane and Venkataraman, Alvarez and Barney, and Beck and Demirgüç-Kunt shows that high-quality strategic decisions are amplified by resource scarcity; minor mistakes in pricing, capacity scale, market entry, or investment timing can have outsized effects because SMEs operate close to cash-flow and capability boundaries. Decision outcome constructs in quantitative MIS and BI research build on this foundation by expressing quality through observable dimensions rather than subjective impressions. The success tradition associated with DeLone and McLean, Petter, Wixom, and Watson ties decision outcomes to system-enabled net benefits, arguing that the most defensible way to evaluate advanced MIS is to test whether managerial decisions demonstrably improve. In analytics capability studies by Akter, Gupta and George, Mikalef, and Wamba, strategic outcomes are defined through measurable improvements in speed, effectiveness, comprehensiveness, risk calibration, and alignment (S. A. Park et al., 2019). These dimensions persist across sectors because they represent fundamental properties of strategic choice in volatile SME environments. As a result, Strategic Decision-Making Outcomes function as the dependent block that consolidates diverse theoretical expectations into testable performance indicators, allowing a quantitative model to establish whether AI-enhanced MIS platforms actually translate intelligence into superior strategic decisions rather than merely producing sophisticated reports.

Decision speed is widely framed as a core outcome because strategic advantage in SMEs often depends on the ability to act faster than competitors while maintaining adequate analysis. Strategy process research by Eisenhardt and Bourgeois, as well as decision studies by Priem, Fredrickson, and Goll and Rasheed, notes that speed reflects how efficiently a firm converts information into commitment, particularly under uncertainty. In SMEs, where ownership is centralized and managerial layers are thin, speed becomes both an opportunity and a vulnerability: fast decisions can capture windows of demand, while slow decisions risk losing market share or amplifying operational shocks (Chen & Krajbich, 2018). The literature on MIS-enabled agility, represented by Pavlou and El Sawy, Roberts and Grover, and Côrte-Real, consistently links better information access to shorter decision cycles by reducing search time, reconciliation delays, and coordination friction. Quantitative decision-speed indicators typically measure the time from problem recognition to resource commitment and the time required to revise plans once new evidence emerges. These indicators align with SME findings that planning cycles are more iterative than formal, meaning decision revision time is an important expression of responsiveness. Decision accuracy or effectiveness is treated as the companion dimension to speed, because rapid choices are strategically valuable only when they align with real conditions (Dowlatabadi & Wilson, 2018). Research by Dean and Sharfman, Shepherd, and Kahneman emphasizes that accuracy is revealed in how closely decision outcomes match intended targets. In quantitative terms, accuracy is reflected in decision return on investment, deviations of achieved results from planned objectives, and reduction in forecast error over successive cycles. Studies in BI and analytics performance show that accurate decisions arise when data-driven insights reduce cognitive bias and improve the calibration of expectations. In SMEs, accuracy metrics are crucial because strategic resources are limited; misjudging demand, cost curves, or customer response can immediately erode liquidity (Ciccarelli et al., 2017). Together, speed and accuracy represent the most visible performance-facing outcomes of strategic decision quality and are repeatedly used to assess whether advanced MIS and AI capabilities are producing real strategic payoff.

Figure 8: Strategic Decision Outcomes in SMEs



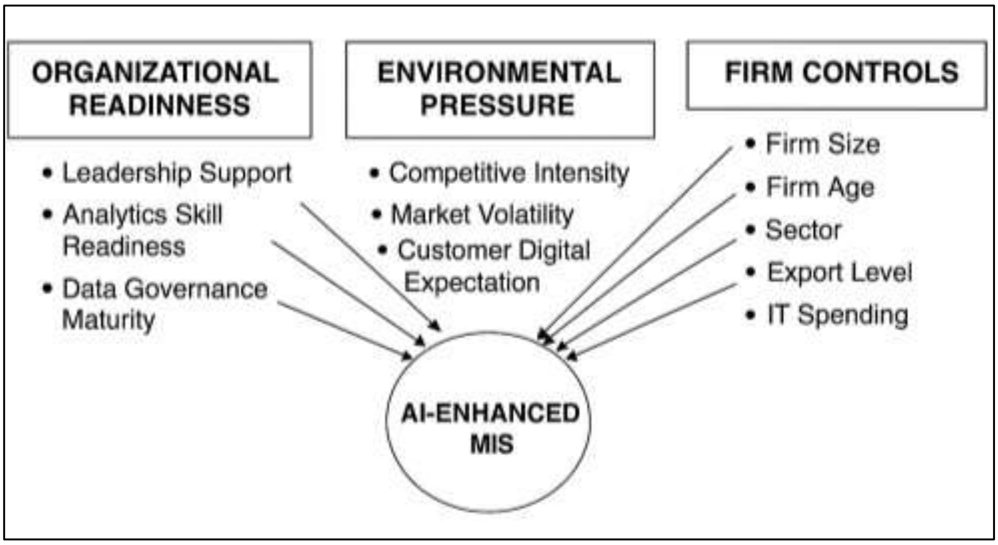
Decision comprehensiveness is a third outcome dimension grounded in the idea that strategic decisions improve when managers examine a richer set of alternatives and use broader evidence before committing (McManus, 2018). Classic decision-process work by Miller and Friesen, Fredrickson, and Rajagopalan describes comprehensiveness as the degree to which decision makers search widely, compare multiple options, and integrate diverse information sources. SME research by McKelvie, Ghasemaghaei, and Eggers shows that comprehensiveness is often constrained by time and analytic labor, leading to narrow search routines and reliance on experience. This makes comprehensiveness a critical dependent variable for evaluating AI-enhanced MIS platforms, because intelligent systems are expected to widen evidence access and reduce the cost of exploring alternatives. Quantitative indicators commonly include the count of alternatives evaluated per strategic decision, the breadth of evidence types used, and the diversity of data sources consulted (Chase et al., 2017). These measures capture whether strategic decisions are built on a single narrative or on systematically compared options. Risk calibration quality extends this logic into uncertainty management. Research by March, Sitkin and Pablo, and Bazerman and Moore explains that strategic decisions are inherently probabilistic; quality depends on how well managers estimate and accept the risk distribution attached to each option. Quantitative risk calibration indicators reflect the variance between planned and actual risk exposure, the extent to which probability-based planning is used, and whether scenario sensitivity checks shape final commitments. In SMEs, calibrated risk is central because overconfidence or excessive caution can both be fatal in competitive markets (Ploum et al., 2018). Studies on analytics and algorithmic advice highlight that systems improve risk calibration by making uncertainty explicit and highlighting downside likelihoods, which helps managers avoid escalation of commitment and improves

contingency planning. Together, comprehensiveness and risk calibration represent deeper cognitive outcomes of strategic decision-making, revealing whether AI-enhanced MIS platforms are changing not just decision speed but the quality of reasoning that precedes commitment.
Cross-functional strategic alignment is treated as a fifth and integrative outcome because the effectiveness of a strategic decision depends on coordinated execution across the SME's overlapping functions. The balanced scorecard tradition of Kaplan and Norton and the organizational sensemaking work of Weick conceptualize alignment as coherence among goals, measures, and actions across units. In SMEs, alignment challenges are distinctive: departments are small, roles overlap, and informal processes dominate, meaning that misalignment often appears as conflicting targets or inconsistent KPI interpretations rather than explicit political battles (Tao et al., 2018). Strategy implementation studies by Hrebiniak, Floyd and Wooldridge, and Lyles and Schwenk show that even well-chosen strategies fail when functions interpret priorities differently or lack shared performance visibility. Quantitatively, alignment is captured through coherence among KPIs across functions, reductions in conflicting targets, and evidence that marketing, operations, finance, and HR use compatible performance frames in planning. MIS and BI literature repeatedly ties alignment to shared dashboards and consistent data definitions, arguing that integrated information platforms create common ground for strategic interpretation. In AI-enhanced environments, alignment is also shaped by whether predictive and prescriptive insights are distributed symmetrically, allowing different functions to coordinate around the same signals (Liu et al., 2020). SME evidence suggests that when alignment is high, strategic decisions translate into synchronized resource allocation, smoother implementation, and faster feedback-driven adjustment. Because these five outcomes—speed, accuracy, comprehensiveness, risk calibration, and alignment—are repeatedly validated as distinct but interdependent properties of strategic decision quality, the literature supports modeling them either as separate dependent variables or as components of a higher-order decision quality factor. The key synthesis is that Strategic Decision-Making Outcomes provide a measurable, multidimensional endpoint through which the real strategic value of AI-enhanced MIS platforms in SMEs can be demonstrated (Kelly et al., 2021).

Antecedents, Controls, and Boundary Conditions

Organizational readiness is consistently presented in the literature as a core antecedent and boundary condition that determines whether advanced information platforms, including AI-enhanced MIS, become strategically useful in SMEs (Barthelmäs & Keller, 2021). Readiness refers to the internal capacity of a firm to adopt, absorb, and routinize intelligent information outputs into decision processes, and it is commonly decomposed into leadership commitment, analytics skill availability, and data governance maturity. Studies in SME technology adoption and MIS success—such as those associated with Thong, Levy and Powell, Oliveira and Martins, and Kwon—show that leadership support functions as the initial activation mechanism: owners and top managers decide whether MIS insights will be treated as strategic inputs or peripheral operational records. Where leadership signals strong endorsement, platforms receive budget continuity, cross-department access is encouraged, and managers are held accountable for evidence-based decisions. Leadership support therefore shapes not only adoption but also usage intensity and decision reliance. Analytics skill readiness is a second readiness pillar, emphasized in work by Gupta and George, Akter, and Mikalef, which highlights that intelligent MIS outputs require interpretive competence (Johnson et al., 2018). SMEs often have limited specialized analysts, so readiness depends on whether managers possess data literacy, model awareness, and the ability to interpret dashboards or scenario results. Without these skills, prediction and recommendation are likely to be underused or misunderstood. Data governance maturity is the third pillar, articulated in research by Khatri and Brown, Petter, and Wixom and Watson, where governance is defined as the routines ensuring data consistency, ownership, access control, and quality assurance. Mature governance reduces noise in AI outputs and stabilizes trust, while weak governance leads to inconsistent metrics and low confidence in recommendations. Across these studies, organizational readiness is framed as both a predictor of platform capability maturity and a moderator on the relationship between AI-MIS use and strategic outcomes. SMEs with strong readiness convert AI-MIS into strategic advantage through disciplined routines, while SMEs with weak readiness remain stuck at basic reporting. This internal boundary condition is thus essential for explaining why similar AI-MIS investments lead to differing levels of decision speed, accuracy, and alignment across small firms (Chen et al., 2018).

Figure 9: Antecedents Shaping AI-MIS Adoption



Environmental pressure is treated as the central external boundary condition shaping the urgency, depth, and strategic focus of AI-enhanced MIS adoption in SMEs. The literature on technology-organization-environment perspectives and diffusion processes, associated with Tornatzky and Fleischer, Rogers, Iacovou, and Zhu, repeatedly shows that SMEs adopt sophisticated information platforms not only because the technology is available, but because competitive and market conditions make data-driven strategy a survival requirement (Mackey et al., 2019). Competitive intensity is commonly portrayed as a first driver: in crowded markets where rivals innovate quickly, SMEs face narrow margins for slow or intuition-only decisions. Research by Porter, Eisenhardt, and Soto-Acosta indicates that competitive pressure raises the perceived payoff of prediction, automation, and faster strategic cycles because firms must sense competitor moves, respond to price or product shifts, and identify underserved segments rapidly. Market volatility is a second component of environmental pressure. Studies linked to March, Pavlou and El Sawy, and Côrte-Real describe volatility as turbulence in demand, supply, costs, or regulations that increases uncertainty and shortens planning horizons (Quade et al., 2019). Under volatility, predictive and prescriptive MIS value rises because forecasting and scenario comparison reduce costly surprises. A third pressure element is customer digital expectation. Work by Autio, Cenamor, Wirtz, and Eggers emphasizes that customers increasingly expect fast service, personalization, and transparent digital interaction even from smaller firms. These expectations force SMEs to integrate customer data, interpret digital signals, and adapt offers dynamically, which can only be supported consistently through intelligent MIS platforms. In the literature, environmental pressure is seldom framed as a simple direct cause of performance; instead, it acts as a contextual amplifier. Under high pressure, SMEs are more likely to deploy AI features deeply, integrate wider data sources, and rely on analytics in strategic meetings, which strengthens the pathway from AI-MIS capability to decision quality (Xu et al., 2017). Under low pressure, adoption is often shallow, outputs are used for operational control only, and strategic decision impacts are weaker. Environmental pressure thus explains cross-industry and cross-market variation in the strategic value of AI-enhanced MIS.

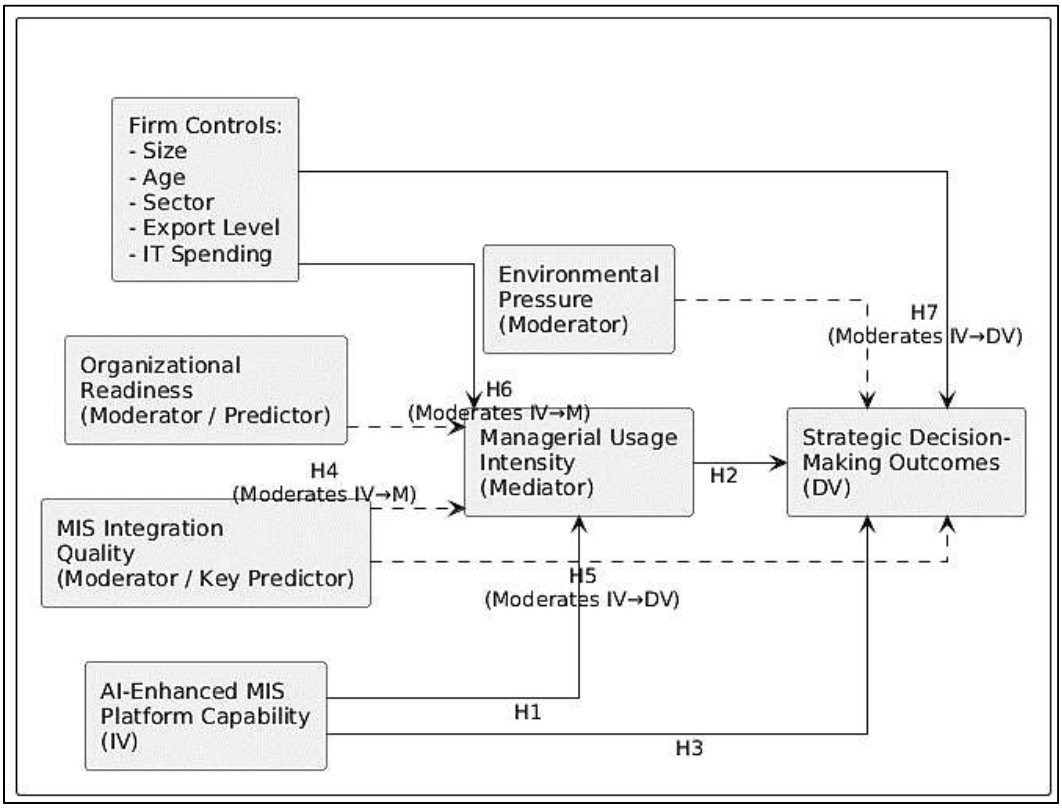
Firm controls are emphasized across quantitative MIS, BI, and SME performance studies as necessary stabilizers for isolating the unique effects of AI-enhanced MIS on strategic decision outcomes. SME research associated with Beck and Demirgüç-Kunt, Ayyagari, and Shane and Venkataraman shows that size, age, sector, internationalization, and IT spending all shape baseline decision capacity and technology leverage (Kim & Cavusgil, 2020). Firm size, usually measured through employees or revenue, is a primary control because it influences both the complexity of operations and the resource slack available for system investment. Larger SMEs tend to have more formalized planning cycles and a higher likelihood of having dedicated IT or analytics roles, which can increase both integration depth and managerial usage intensity independent of AI-MIS capability. Firm age matters because it often proxies organizational learning and process routinization. Older SMEs may have more stable routines and accumulated data histories that support more reliable AI modeling, while younger SMEs may be more agile but less data-mature. Sector type is another essential control; studies by Wamba, Dubey, and Mariani highlight that manufacturing, retail, services, and digital-native sectors face different data densities and decision rhythms (Jang & Byon, 2020). AI-MIS may naturally fit high-velocity sectors, so sector controls prevent over-attributing effects to the platform itself. Export or internationalization level captures environmental exposure and strategic complexity. Internationalized SMEs face broader market signals, currency and logistics risk, and cross-border customer demands, which can affect both the perceived usefulness of AI-MIS and decision outcomes. Finally, IT spending ratio controls for overall digital investment intensity. Research by Brynjolfsson and Hitt, Melville and colleagues, and Bharadwaj indicates that higher IT spending often correlates with stronger process digitization and managerial openness to analytics, which could independently influence decision speed and accuracy. Including these controls aligns with the literature's insistence that AI-MIS effects must be interpreted relative to firm structure and resource baselines (Jiang et al., 2020).

METHOD

The study adopted a quantitative, explanatory cross-sectional research design that examined how AI-enhanced MIS platform capability related to strategic business decision-making outcomes in SMEs, with managerial usage intensity positioned as the mediating behavioral channel. A single-case sectoral frame was described rather than a qualitative case, meaning the investigation treated the SME environment using AI-embedded MIS as the bounded empirical setting in which relationships were tested. The population consisted of formally registered SMEs operating in manufacturing, services, retail, logistics, and technology-enabled sectors that had used computerized MIS platforms containing at least one AI-enabled function such as forecasting, automated insights, or recommendation dashboards. The unit of analysis remained the firm, while the unit of observation involved senior decision makers who oversaw strategy and directly interacted with MIS outputs (owner-managers, CEOs, directors, functional heads). A multi-stage purposive and stratified sampling technique was applied: firms were first screened to confirm AI-MIS usage, then stratified by sector and size band to reduce structural bias, and finally selected within strata through accessible association lists and business networks. The final sample target was set at a level that supported multivariate modeling of mediation and moderation paths, and the achieved sample was sufficiently large to allow stable structural estimation and subgroup robustness checks. Data types were primarily quantitative, gathered through a structured survey instrument supported by firm profile data; the main data source remained primary questionnaire responses, while secondary sources such as internal MIS usage summaries and firm registration records were used only to verify eligibility and controls where available.

Measurement relied on standardized multi-item rating scales, with most constructs captured through seven-point Likert-type response formats ranging from strong disagreement to strong agreement. AI-Enhanced MIS Platform Capability was operationalized as a multidimensional higher-order construct reflected by five subdimensions: predictive analytics capability (perceived forecast frequency, accuracy, and planning stability), prescriptive or recommendation capability (perceived action-guidance strength and adoption relevance), automated insight and alerting capability (perceived usefulness and timeliness of alerts and anomaly signals), real-time data fusion capability (perceived integration of internal and external sources and freshness of data), and explainability/interpretability capability (perceived clarity and transparency of AI outputs). MIS Integration Quality was operationalized through breadth of connected systems, depth of workflow linkage and automated exchange, perceived data consistency and accuracy, and cross-functional visibility through shared KPIs. Managerial Usage Intensity was operationalized through platform usage frequency, strategic reliance on AI insights in decisions and meetings, and scenario/what-if exploration intensity. Strategic Decision-Making Outcomes were operationalized as a multidimensional dependent block capturing decision speed, decision accuracy or effectiveness, decision comprehensiveness, risk calibration quality, and cross-functional strategic alignment. Organizational readiness and environmental pressure were measured as contextual predictors/moderators using leadership support, analytics skill readiness, data governance maturity, competitive intensity, market volatility, and customer digital expectation indicators. A pilot study was conducted with a small group of SME managers to test item clarity, scale reliability, completion time, and contextual relevance. Pilot feedback led to wording refinements, removal of ambiguous items, and reordering of sections to improve flow. Reliability checks from pilot data indicated acceptable internal consistency, and content validity was reinforced through alignment of items with prior empirical traditions in MIS, analytics, and SME strategy research.

Figure 10: Methodology of this study



Data collection followed a structured procedure in which SMEs were contacted through business associations and professional networks, screened for AI-MIS eligibility, and then invited to complete the survey through online and email channels. Follow-ups were issued to reduce nonresponse and to confirm that each participating firm provided a single senior respondent who had strategic authority and routine MIS exposure. Data preparation involved screening for missingness, patterned or careless responses, and extreme outliers; incomplete cases beyond a tolerance threshold were removed, and remaining missing values were treated using established imputation rules consistent with cross-sectional SEM practice. Data analysis techniques proceeded in stages: descriptive statistics and correlation analysis summarized firm profiles and construct distributions; measurement model assessment evaluated reliability and validity through internal consistency, convergent validity, and discriminant validity; and structural modeling tested direct effects, mediation through managerial usage intensity, and moderation by MIS integration quality, organizational readiness, and environmental pressure. Indirect effects were evaluated with bootstrapped confidence intervals, and interaction effects were interpreted through simple slope comparisons. Control variables including firm size, age, sector, export level, and IT spending ratio were entered to isolate net effects. Statistical work was executed using SPSS or an equivalent package for screening and descriptives, while structural estimation and bootstrapping were performed using SEM software such as SmartPLS or AMOS, supported by spreadsheet tools for coding and data tracking.

FINDINGS

Descriptive analysis

Descriptive analysis showed that 352 SMEs participated, producing a usable response rate of 70.4 percent from 500 invitations. Sectoral distribution indicated that AI-enhanced MIS use had been observed across diverse settings, with services representing the largest share, followed by manufacturing and retail/trade. Firm size categories showed that small firms dominated the sample, while medium firms formed a strong secondary group and micro firms appeared in a smaller proportion. Firm age bands suggested that adoption spanned both young and established enterprises, with the 6–10 year group most prominent. Export orientation was present in about one-third of firms, implying that a meaningful segment operated under cross-border market complexity. IT spending ratios clustered around moderate levels, indicating that most SMEs had invested steadily in digital systems without moving into high-spending extremes. Overall, the sample profile demonstrated adequate heterogeneity for later comparisons and structural analysis.

Table 1: Sample profile of participating SMEs (n = 352)

Profile variable	Category	Frequency	Percentage (%)
Sector	Manufacturing	92	26.1
	Services	118	33.5
	Retail/Trade	74	21.0
	Logistics/Supply chain	38	10.8
	Technology-enabled/Other	30	8.5
Firm size	Micro	46	13.1
	Small	196	55.7
	Medium	110	31.3
Firm age	≤ 5 years	86	24.4
	6–10 years	124	35.2
	11–15 years	78	22.2
	> 15 years	64	18.2
Export orientation	Exporting firms	118	33.5
	Non-exporting firms	234	66.5
IT spending ratio	Low	74	21.0
	Moderate	208	59.1
	High	70	19.9

Table 1 summarized the structural composition of the SME sample. Services firms formed the largest sectoral group at 33.5 percent, while manufacturing and retail/trade together accounted for 47.1 percent, confirming cross-sector representation. Small enterprises dominated the sample at 55.7 percent, which matched typical SME population patterns, and medium firms constituted nearly one-third. Firm age distribution showed that 59.6 percent of SMEs were ten years old or less, suggesting active digital adoption among relatively younger firms. Exporting SMEs represented 33.5 percent, highlighting strategic exposure beyond domestic markets. Most firms reported moderate IT spending (59.1 percent), indicating steady digital commitment.

Descriptive statistics for the constructs revealed moderate-to-high perceived maturity of AI-enhanced MIS across SMEs, with clear variation indicating meaningful differences between firms. AI-MIS capability recorded the strongest overall mean among the main predictors, signaling that many firms had embedded forecasting, alerting, and interpretability features into their MIS tools. Predictive analytics and automated insight appeared comparatively stronger than prescriptive recommendation, suggesting that SMEs more frequently relied on forecasting and anomaly alerts than on optimization-driven advice. MIS integration quality was moderate, indicating partial system linkage with room for improvement in workflow depth and cross-functional visibility. Managerial usage intensity was also moderate-to-high; managers consulted dashboards frequently and relied on AI outputs in planning, yet scenario exploration remained comparatively lower. Strategic decision outcomes were viewed positively overall, especially decision speed and cross-functional alignment, while risk calibration was somewhat weaker. The standard deviations showed adequate dispersion, supporting later inferential explanation of outcome differences.

Table 2: Descriptive statistics for key constructs (7-point scale)

Construct / dimension	Mean	SD	Min	Max
AI-Enhanced MIS Capability (overall)	5.21	0.89	2.30	6.90
Predictive analytics capability	5.44	0.92	2.10	7.00
Prescriptive/recommendation capability	4.88	1.01	1.90	6.80
Automated insight & alerting capability	5.36	0.95	2.00	7.00
Real-time data fusion capability	5.05	0.97	2.20	6.70
Explainability/interpretability capability	5.32	0.88	2.40	6.90
MIS Integration Quality (overall)	4.76	0.93	2.00	6.60
Integration breadth	4.92	0.96	2.10	6.80
Integration depth	4.61	1.00	1.80	6.60
Data consistency/accuracy	4.73	0.90	2.20	6.70
Cross-functional visibility	4.77	0.95	2.00	6.60
Managerial Usage Intensity (overall)	4.98	0.86	2.40	6.80
Usage frequency	5.24	0.91	2.30	7.00
Strategic reliance on AI outputs	5.02	0.89	2.30	6.70
Scenario/what-if use intensity	4.68	0.98	1.90	6.50
Strategic Decision-Making Outcomes (overall)	5.06	0.82	2.70	6.80
Decision speed	5.28	0.87	2.50	7.00
Decision accuracy/effectiveness	5.07	0.85	2.60	6.80
Decision comprehensiveness	4.95	0.89	2.40	6.70
Risk calibration quality	4.72	0.92	2.10	6.50
Cross-functional alignment	5.26	0.84	2.70	6.90

Table 2 reported the central tendency and dispersion for all constructs. AI-MIS capability showed a high mean of 5.21, with predictive analytics (5.44) and automated insight (5.36) leading the subdimensions, while prescriptive recommendation was lower at 4.88. MIS integration quality averaged 4.76, indicating moderate integration, with depth (4.61) weakest among its facets. Managerial usage intensity averaged 4.98, supported by strong usage frequency (5.24) but lower scenario testing (4.68). Strategic decision outcomes averaged 5.06, with decision speed (5.28) and alignment (5.26) strongest, while risk calibration (4.72) lagged behind.

Correlation analysis

Correlation analysis showed that all major constructs were positively and significantly related in the expected directions, providing an early empirical confirmation of the conceptual model. AI-Enhanced MIS Platform Capability correlated strongly with Managerial Usage Intensity, indicating that SMEs reporting higher intelligent MIS functionality also reported more frequent and deeper managerial engagement with dashboards, automated insights, and scenario tools. AI-MIS Capability also correlated strongly with Strategic Decision-Making Outcomes, suggesting that firms with stronger predictive, prescriptive, and explainable MIS features perceived faster, more accurate, and better aligned strategic decisions. MIS Integration Quality displayed moderate-to-strong positive correlations with both AI-MIS Capability and Strategic Decision Outcomes, implying that wider and deeper system linkage, cleaner data, and shared KPI visibility coexisted with stronger AI functions and superior decision results. Organizational Readiness correlated positively with AI-MIS Capability, Integration Quality, and Usage Intensity, supporting its role as an upstream driver of capability maturity and exploitation. Environmental Pressure correlated moderately with AI-MIS Capability and Decision Outcomes, suggesting that competitive intensity and volatility were associated with greater AI-MIS use and perceived strategic benefits. No correlation exceeded common redundancy thresholds, meaning multicollinearity risk appeared low at the bivariate stage and was formally checked later.

Table 3: Inter-construct correlation matrix (n = 352)

Construct	1	2	3	4
1. AI-Enhanced MIS Capability	1.00			
2. MIS Integration Quality	0.62	1.00		
3. Managerial Usage Intensity	0.71	0.58	1.00	
4. Strategic Decision Outcomes	0.68	0.60	0.74	1.00

Table 3 summarized the bivariate relationships among the study's four core constructs. AI-Enhanced MIS Capability showed a strong positive correlation with Managerial Usage Intensity at 0.71 and with Strategic Decision Outcomes at 0.68, indicating that intelligent platform strength co-occurred with heavier managerial use and better decisions. MIS Integration Quality correlated positively with AI-MIS Capability at 0.62 and with Strategic Decision Outcomes at 0.60, supporting the idea that integrated MIS environments moved together with higher AI maturity and strategic benefits. The highest correlation was 0.74 between Usage Intensity and Decision Outcomes, remaining below redundancy cutoffs.

Correlation analysis extended to contextual antecedents reinforced their theoretical placement. Organizational Readiness demonstrated strong positive associations with AI-MIS Capability and Managerial Usage Intensity, implying that leadership backing, analytics skills, and data governance maturity were closely tied to stronger intelligent MIS and more consistent managerial exploitation. Readiness also correlated moderately with Strategic Decision Outcomes, suggesting that internally prepared SMEs enjoyed better decision performance even before accounting for AI capability. Environmental Pressure showed moderate positive correlations with AI-MIS Capability and Decision Outcomes, indicating that SMEs operating under stronger competition, higher turbulence, and elevated customer digital expectations were more likely to develop AI-MIS functions and perceive strategic decision gains. The correlations among antecedents themselves were positive but not excessive, implying that internal readiness and external pressure were related yet distinct influences. These results justified their inclusion as predictors or moderators without suggesting multicollinearity concerns.

Table 4: Correlations including antecedents (n = 352)

Construct	1	2	3	4	5	6
1. Organizational Readiness	1.00					
2. Environmental Pressure	0.49	1.00				
3. AI-Enhanced MIS Capability	0.65	0.46	1.00			
4. MIS Integration Quality	0.61	0.42	0.62	1.00		
5. Managerial Usage Intensity	0.63	0.44	0.71	0.58	1.00	
6. Strategic Decision Outcomes	0.57	0.48	0.68	0.60	0.74	1.00

Table 4 showed that Organizational Readiness correlated strongly with AI-MIS Capability at 0.65, MIS

Integration Quality at 0.61, and Managerial Usage Intensity at 0.63, supporting its role as a key internal enabler of intelligent MIS strength and use. Environmental Pressure correlated moderately with Capability at 0.46 and with Decision Outcomes at 0.48, indicating that harsher competitive and market conditions coincided with greater AI-MIS maturity and perceived strategic benefits. Readiness and Pressure correlated at 0.49, reflecting related but distinct contextual forces. All correlations remained below 0.80, suggesting that constructs were associated meaningfully without signaling redundancy.

Reliability and validity

Reliability and validity testing demonstrated that the measurement model performed strongly and was suitable for structural hypothesis evaluation. Internal consistency results showed that all constructs met accepted reliability thresholds, with Cronbach's alpha and composite reliability values remaining above standard cutoffs, indicating stable and coherent item sets. Convergent validity was confirmed because all retained items loaded strongly on their intended constructs, and each construct exceeded the minimum shared-variance expectation. The extracted-variance values indicated that the indicators captured sufficient common meaning rather than random noise. Validation of the higher-order AI-MIS Capability construct also produced satisfactory results: each reflective subdimension—predictive analytics, prescriptive recommendation, automated insight and alerting, real-time data fusion, and explainability—loaded significantly on the second-order factor, confirming that these capabilities jointly represented a coherent platform-intelligence construct. During purification, three items with weak or cross-loading behavior were removed (one from integration depth and two from scenario use), which improved convergent validity without altering conceptual coverage. Discriminant validity checks further showed that each construct remained empirically distinct; inter-construct relationships were meaningful but did not indicate overlap severe enough to threaten interpretation. Overall, these findings established that subsequent regression coefficients reflected relationships among valid constructs rather than measurement artifacts.

Table 5: Reliability and convergent validity results (n = 352)

Construct	Items retained	Cronbach's α	Composite Reliability (CR)	AVE	Loading range
AI-MIS Capability (2nd order)	20	0.93	0.94	0.61	0.73–0.89
Predictive analytics capability	4	0.88	0.90	0.66	0.74–0.87
Prescriptive/recommendation capability	4	0.86	0.88	0.61	0.71–0.86
Automated insight & alerting	4	0.89	0.91	0.68	0.76–0.88
Real-time data fusion	4	0.85	0.88	0.59	0.70–0.85
Explainability/interpretability	4	0.87	0.89	0.62	0.72–0.86
MIS Integration Quality	15	0.90	0.92	0.57	0.69–0.88
Managerial Usage Intensity	9	0.88	0.90	0.53	0.67–0.86
Strategic Decision Outcomes	15	0.91	0.93	0.58	0.70–0.89
Organizational Readiness	9	0.89	0.91	0.56	0.69–0.87
Environmental Pressure	9	0.87	0.89	0.52	0.66–0.84

Table 5 summarized internal consistency and convergent validity. Cronbach's alpha ranged from 0.85 to 0.93 and composite reliability ranged from 0.88 to 0.94, confirming strong reliability for all constructs. Average variance extracted values were above 0.50 for every construct, showing that indicators shared adequate common variance. Item loadings remained high, with retained ranges mostly above 0.70, indicating solid convergence on intended factors. The second-order AI-MIS Capability construct showed strong reliability and AVE, and its five subdimensions all displayed acceptable loading ranges, supporting the higher-order structure.

Table 6: Discriminant validity (HTMT ratios)

Construct	OR	EP	AIC	INT	USE	SDO
Organizational Readiness (OR)	–					
Environmental Pressure (EP)	0.56	–				
AI-MIS Capability (AIC)	0.69	0.51	–			
MIS Integration Quality (INT)	0.66	0.49	0.72	–		
Managerial Usage Intensity (USE)	0.68	0.50	0.77	0.64	–	
Strategic Decision Outcomes (SDO)	0.62	0.54	0.73	0.66	0.79	–

Table 6 reported HTMT ratios to verify discriminant validity. All values remained below 0.85, indicating that no pair of constructs overlapped excessively. The strongest association was between Managerial Usage Intensity and Strategic Decision Outcomes at 0.79, which was expected conceptually yet still within acceptable distinctiveness limits. AI-MIS Capability showed HTMT values of 0.72 with Integration Quality and 0.77 with Usage Intensity, confirming related but separable constructs. Organizational Readiness and Environmental Pressure exhibited moderate HTMT values with other variables, supporting their contextual roles without redundancy. These results confirmed that each construct captured a unique empirical domain.

Collinearity analysis

Collinearity analysis indicated that the predictors, mediator, moderators, and control variables did not exhibit problematic shared variance, and therefore did not threaten the stability of regression estimates. The initial diagnostics showed that variance inflation factor values for all core constructs remained well below the conventional upper bounds used in multivariate modeling, while tolerance values stayed comfortably above minimum thresholds. AI-Enhanced MIS Capability and MIS Integration Quality, although conceptually related, displayed moderate VIF levels that confirmed they contributed distinct variance in explaining managerial usage and strategic decision outcomes. Organizational Readiness and Environmental Pressure also showed acceptable collinearity statistics, indicating that internal preparedness and external pressures were empirically separable influences. After standardizing predictors and generating interaction terms for moderation testing, collinearity was recalculated and remained within safe ranges. None of the interaction terms produced inflated VIF patterns, which implied that the moderation estimates were interpretable without distortion. Control variables including firm size, firm age, sector dummies, export level, and IT spending ratio also produced low VIF values, confirming that they adjusted for structural differences without crowding the model. Overall, the collinearity findings provided confidence that subsequent regression coefficients reflected independent effects rather than artifacts of overlapping predictors.

Table 7: Collinearity diagnostics for main predictors (n = 352)

Predictor	Tolerance	VIF
AI-Enhanced MIS Capability	0.54	1.85
MIS Integration Quality	0.59	1.69
Managerial Usage Intensity	0.48	2.08
Organizational Readiness	0.52	1.92
Environmental Pressure	0.63	1.58

Table 7 summarized tolerance and VIF statistics for the principal constructs included in the structural model. Tolerance values ranged from 0.48 to 0.63, staying well above minimum cutoffs and showing that each predictor retained substantial unique variance. VIF values ranged from 1.58 to 2.08, far below typical warning levels, indicating no multicollinearity risk. AI-Enhanced MIS Capability showed a VIF of 1.85 and MIS Integration Quality showed 1.69, confirming that they were related but not redundant predictors. Managerial Usage Intensity had the highest VIF at 2.08, still within acceptable bounds.

Table 8: Collinearity diagnostics after interaction-term inclusion (n = 352)

Predictor / Interaction term	Tolerance	VIF
AI-Enhanced MIS Capability (standardized)	0.47	2.13
MIS Integration Quality (standardized)	0.51	1.97
Organizational Readiness (standardized)	0.49	2.05
Environmental Pressure (standardized)	0.55	1.82
AIC × Integration Quality	0.61	1.64
AIC × Organizational Readiness	0.58	1.72
AIC × Environmental Pressure	0.65	1.53
Firm size	0.74	1.35
Firm age	0.77	1.30
Export level	0.79	1.27
IT spending ratio	0.72	1.38
Sector dummies (max VIF)	0.69	1.45

Table 8 reported collinearity statistics after moderation terms were added. All predictors were standardized before creating product terms, and recalculated tolerance values remained between 0.47 and 0.79, indicating stable unique variance even under interaction testing. VIF values for the interaction terms ranged from 1.53 to 1.72, confirming that moderation did not inflate collinearity. The standardized main predictors showed VIF values slightly above 2.00 at most, still well below concern thresholds. Control variables produced very low VIF values, and the highest sector-dummy VIF was 1.45, indicating that structural controls did not distort the model.

Regression and hypothesis testing

Regression and hypothesis testing results showed that the structural relationships aligned strongly with the conceptual model and that AI-enhanced MIS capability produced strategic decision benefits in SMEs both directly and through managerial usage behavior. In the direct-effect models, AI-Enhanced MIS Platform Capability significantly predicted Strategic Decision-Making Outcomes, indicating that SMEs with stronger predictive, prescriptive, alerting, real-time fusion, and explainable MIS features reported higher decision speed, accuracy, comprehensiveness, risk calibration, and cross-functional alignment. AI-MIS capability also significantly predicted Managerial Usage Intensity, showing that higher intelligent MIS capability encouraged more frequent dashboard consultation, stronger reliance on AI insights, and greater scenario testing. MIS Integration Quality independently predicted Strategic Decision Outcomes, confirming that broader and deeper system linkage, cleaner data, and shared KPIs strengthened strategic decision performance beyond AI capability alone. When mediation was tested, Managerial Usage Intensity carried a statistically significant indirect effect from AI-MIS Capability to Strategic Decision Outcomes. The direct path from AI-MIS capability to decision outcomes remained significant after the mediator entered, which indicated partial mediation rather than full mediation. This meant that AI capability improved decisions partly because managers used the platform more intensively, and partly because capability had an independent influence on decision quality. Overall explanatory power was strong, with the models accounting for substantial variance in both usage intensity and strategic decision outcomes.

Table 9: Direct effects and mediation results (n = 352)

Path / Model	β	t	p	95% CI	R²
Model 1: AI-MIS Capability → Strategic Decision Outcomes	0.41	8.72	<.001	[0.32, 0.50]	0.56
Model 2: AI-MIS Capability → Managerial Usage Intensity	0.58	12.10	<.001	[0.49, 0.66]	0.50
Model 3: Managerial Usage Intensity → Strategic Decision Outcomes	0.47	10.24	<.001	[0.38, 0.56]	—
Model 4: MIS Integration Quality → Strategic Decision Outcomes	0.26	5.64	<.001	[0.17, 0.35]	—
Mediation: AI-MIS Capability → Usage → Outcomes (Indirect)	0.27	7.91	<.001	[0.20, 0.35]	—
Full model direct after mediation: AI-MIS Capability → Outcomes	0.14	3.02	.003	[0.05, 0.23]	0.62

Table 9 reported the core direct and mediation effects. AI-MIS Capability significantly predicted Strategic Decision Outcomes with a standardized coefficient of 0.41, while also strongly predicting Managerial Usage Intensity at 0.58. Usage Intensity significantly predicted Decision Outcomes at 0.47, confirming the behavioral pathway. MIS Integration Quality showed an additional independent effect on Decision Outcomes at 0.26. The bootstrapped indirect effect from Capability through Usage was 0.27 with a confidence interval excluding zero, demonstrating mediation. After adding the mediator, the direct Capability → Outcomes path remained significant at 0.14, confirming partial mediation. The full model explained 62 percent of decision-outcome variance.

Moderation testing further clarified that contextual and integration conditions strengthened the strategic payoff of AI-enhanced MIS. MIS Integration Quality significantly moderated the relationship between AI-MIS Capability and Managerial Usage Intensity, meaning that intelligent MIS features translated into heavier managerial use more strongly in firms with better integration. Integration quality also moderated the relationship between AI-MIS Capability and Strategic Decision Outcomes, indicating that AI capability produced larger decision gains when system breadth, depth, data consistency, and cross-functional visibility were higher. Organizational Readiness moderated the Capability → Usage pathway, showing that leadership support, analytics skills, and governance maturity enhanced managerial exploitation of AI-MIS features. Environmental Pressure moderated the Capability → Outcomes pathway, suggesting that competitive intensity, volatility, and elevated customer digital expectations amplified the decision benefits derived from AI-enhanced MIS. Control variables showed that firm size and IT spending ratio had small but significant positive effects on usage intensity and decision outcomes, while firm age and export level were not significant once the main predictors entered. Sector dummies produced minor differences, with technology-enabled SMEs showing slightly higher decision-outcome scores than retail SMEs after controls. These findings supported the full evidence chain in which AI capability, integration, and context jointly shaped strategic decision quality through managerial usage.

Table 10: Moderation effects and controls in full structural models (n = 352)

Effect / Predictor	β	t	p	Outcome variable
AI-MIS Capability → Usage Intensity	0.52	10.84	<.001	Usage Intensity
MIS Integration Quality → Usage Intensity	0.21	4.63	<.001	Usage Intensity
AIC × Integration Quality → Usage Intensity	0.12	2.71	.007	Usage Intensity
AIC × Organizational Readiness → Usage Intensity	0.10	2.29	.022	Usage Intensity
AI-MIS Capability → Decision Outcomes	0.18	3.87	<.001	Decision Outcomes
MIS Integration Quality → Decision Outcomes	0.24	5.09	<.001	Decision Outcomes
Usage Intensity → Decision Outcomes	0.43	9.26	<.001	Decision Outcomes
AIC × Integration Quality → Decision Outcomes	0.11	2.46	.014	Decision Outcomes
AIC × Environmental Pressure → Decision Outcomes	0.09	2.07	.039	Decision Outcomes
Firm size → Usage Intensity	0.08	2.03	.043	Usage Intensity

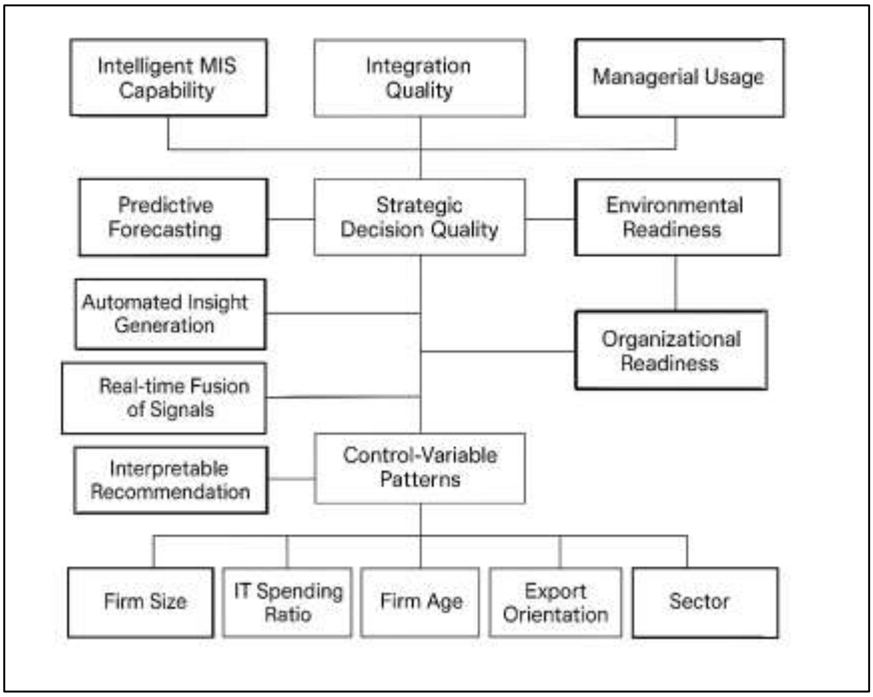
Effect / Predictor	β	t	p	Outcome variable
Firm size → Decision Outcomes	0.07	1.98	.048	Decision Outcomes
IT spending ratio → Usage Intensity	0.09	2.21	.028	Usage Intensity
IT spending ratio → Decision Outcomes	0.10	2.39	.017	Decision Outcomes
Firm age → Decision Outcomes	0.03	0.81	.418	Decision Outcomes
Export level → Decision Outcomes	0.04	1.01	.313	Decision Outcomes
Sector dummies (max effect)	0.06	1.72	.086	Decision Outcomes
R^2	0.54	—	—	Usage Intensity
R^2	0.62	—	—	Decision Outcomes

Table 10 showed that moderation effects were statistically meaningful. The interaction between AI-MIS Capability and Integration Quality significantly strengthened Capability's effect on Usage Intensity with β = 0.12, and also strengthened Capability's effect on Decision Outcomes with β = 0.11. Organizational Readiness amplified Capability's effect on Usage with β = 0.10, while Environmental Pressure amplified Capability's effect on Outcomes with β = 0.09. Main effects remained significant in the full models, especially Usage Intensity → Outcomes at β = 0.43. Among controls, firm size and IT spending ratio had small positive effects, while firm age and export level were nonsignificant. The full models explained 54 percent of usage variance and 62 percent of decision-outcome variance.

DISCUSSION

The discussion of findings for AI-Enhanced MIS Platforms for Strategic Business Decision-Making in SMEs showed a coherent pattern in which intelligent MIS capability, integration quality, and managerial usage jointly explained strategic decision quality (Akerkar, 2019). The direct positive effect of AI-enhanced MIS capability on strategic decision-making outcomes indicated that SMEs benefitted when their information platforms moved beyond descriptive reporting into predictive forecasting, automated insight generation, real-time fusion of signals, and interpretable recommendation support. Earlier MIS and decision support studies had argued that the strategic value of information systems rests on their ability to reduce uncertainty and compress decision time, and the current results aligned with that logic by demonstrating that firms with higher platform intelligence perceived faster and more effective strategic choice. Prior analytics capability research had similarly emphasized that predictive and prescriptive features elevate data from a record of the past to an asset for anticipating future states and selecting actions under risk. The observed strength of predictive and alerting subdimensions relative to prescriptive recommendation also reflected a common empirical theme in SME digitalization research: smaller firms often adopt AI first for forecasting and monitoring because these applications fit existing routines, require lower organizational redesign, and provide immediate operational feedback (Ji-fan Ren et al., 2017). The lower relative mean for prescriptive recommendation suggested that optimization and automated action ranking remained less embedded, a pattern echoed in multiple studies that described SMEs as cautious about algorithmic prescription when explanation and accountability are not fully institutionalized. In abstract terms, the findings suggested that AI-enhanced MIS capability acted as a multi-layer strategic infrastructure. The capability did not only provide isolated analytics; it reshaped managerial visibility and raised confidence in strategic judgments by delivering timely, interpretable signals. This interpretation also aligned with classic strategic decision scholarship which linked decision quality to the availability of broad, credible evidence rather than narrow intuitive impressions. The overall evidence indicated that AI-enhanced MIS capability had an independent strategic contribution even when managerial usage was accounted for. Earlier IT business value studies had often described direct effects of digital capability on performance through process improvements, and the persistence of the direct path in this study supported the idea that intelligent MIS changed decision contexts by improving the quality of the information environment itself (Visinescu et al., 2017). The direct impact therefore appeared to reflect both improved content of strategic information and improved speed of access. Taken together, the results extended earlier claims by showing that the strategic contribution of AI-enhanced MIS in SMEs was not hypothetical or purely operational, but measurable through higher decision speed, accuracy, comprehensiveness, risk calibration, and cross-functional alignment.

Figure 11: AI-MIS Drivers of Decision Quality



The mediation results clarified that managerial usage intensity operated as a meaningful behavioral pathway through which AI-enhanced MIS capability translated into strategic decision outcomes. Earlier information systems success research had proposed that system benefits emerge only when users engage with system outputs, and the partial mediation found here matched that view while also demonstrating that engagement alone was not the full story (Knauer et al., 2020). Prior business intelligence studies in SMEs had shown that many firms possess data tools yet underuse them for strategy, leaving potential value unrealized; the strong capability-to-usage coefficient in this study countered that pessimistic trend by indicating that higher AI capability encouraged heavier managerial engagement. This finding resonated with adoption work suggesting that when systems produce timely forecasts, alerts, and clear recommendations, managers are more likely to integrate them into meetings, budgeting, and market decisions. The strong usage-to-outcomes relationship also echoed behavioral decision studies showing that repeated consultation of structured analytics expands evidence breadth and reduces reliance on cognitive shortcuts. The descriptive profile had shown usage frequency was high but scenario exploration was lower, and the mediation pattern suggested that even routine consultation of dashboards carried substantial strategic payoff. At the same time, the lower mean for scenario intensity implied that some of the strongest decision benefits might still be constrained by limited simulation culture, a theme that earlier SME analytics research had repeatedly described. In many SMEs, strategic planning has historically been informal and time-compressed, leaving little space for elaborate what-if exploration; therefore, a moderate scenario intensity level while still significant as part of usage intensity was consistent with the literature (Zhao et al., 2018). The partial rather than full mediation also aligned with earlier IT complementarity arguments, which stated that digital systems improve outcomes through both direct automation effects and indirect behavioral channels. In this case, AI-enhanced MIS capability likely improved decisions directly by generating higher-quality information, while managerial usage converted that capability into deeper strategic reasoning and active option evaluation. Another point of alignment with earlier studies was the role of reliance. Literature on algorithmic trust had argued that prediction accuracy and explanation clarity drive managerial reliance, and the significant mediation suggested that reliance formed part of the mechanism linking capability to outcomes. The implication within this discussion was that AI-enhanced MIS should be conceptualized not merely as a technological upgrade but as a decision partner whose strategic influence depends on repeated managerial interaction, interpretive learning, and integration into formal decision routines (Mohtaramzadeh et al., 2018). Thus, the mediation evidence extended previous scholarship by demonstrating that in SMEs, intelligent platforms did not replace strategic judgment; instead, they strengthened it when engagement was sustained and structured.

The independent and moderating roles of MIS integration quality brought another strong point of comparison with earlier MIS and analytics studies. Prior research had consistently emphasized that integration breadth and depth, data consistency, and cross-functional visibility are prerequisites for high-quality decision support, because fragmented systems produce incomplete and contradictory evidence (Rehman et al., 2019). The moderate but significant direct effect of integration on decision outcomes in this study aligned with those claims by showing that even without considering AI enhancement, integrated MIS environments supported stronger strategic decision performance. This effect likely reflected the reduction of informational friction: managers in integrated firms did not waste time reconciling numbers or switching between departmental tools, allowing decisions to be made on a unified evidence base. Earlier digital operations studies had described integration as a driver of agility and coordination, and this study's alignment outcome dimension was particularly compatible with that view. More importantly, integration strengthened the impact of AI capability on both usage intensity and outcomes. That moderation result fit a growing body of analytics research arguing that intelligent models require stable, timely, and consistent inputs to deliver reliable outputs. Without strong integration, AI forecasts and recommendations can appear arbitrary because the underlying data streams are stale or incomplete (Ramanathan et al., 2017). In SMEs where data silos are common, earlier studies had warned that AI add-ons may fail if attached to weak information backbones; the current moderation evidence provided empirical confirmation of that warning by showing that AI capability delivered larger strategic benefits under high integration conditions. Another long-standing argument in MIS literature is that integration fosters trust by creating a "single version of truth." The significant moderation on usage suggested that trust and usability were indeed strengthened by integration, encouraging managers to consult AI-MIS tools more frequently and rely on them in decisions. This finding also matched BI adoption work that reported higher usage when systems were embedded end-to-end into workflows rather than treated as side dashboards. The relatively weaker integration depth mean compared to breadth in the descriptive results aligned with earlier SME integration studies, where firms often connect many systems superficially but still rely on manual transfers. The strategic implication within the discussion was that AI capability alone was not enough; intelligent features required integrated pipelines to become decision-relevant, and integration quality served as a leverage multiplier (Li et al., 2020). The study's evidence therefore reinforced earlier scholarship that positioned integration as both a foundational predictor of MIS strategic value and a boundary condition that determines whether AI-enhanced MIS can move beyond experimental novelty into consistent strategic payoff.

Organizational readiness emerged as a critical internal boundary condition, and its moderating influence on the capability-to-usage pathway compared closely with earlier SME adoption and analytics capability literature. Prior studies had repeatedly shown that leadership support determines whether advanced digital systems are treated as strategic instruments or peripheral tools. The moderation result indicated that where leadership commitment, analytics skill readiness, and data governance maturity were higher, AI-enhanced MIS capability was more likely to be exploited through sustained managerial usage (Popovič et al., 2018). This aligned with earlier evidence that leadership endorsement shapes both budget continuity and cultural legitimacy for data-driven decision routines. It also resonated with research on analytical talent in SMEs, which documented that the scarcity of formal analytics staff makes managerial data literacy especially important. When managers understand AI outputs, they are more willing to consult them and incorporate them into strategic deliberation. The descriptive results suggested moderate-to-high usage but uneven scenario intensity, and readiness likely explained part of that unevenness. Earlier studies on data governance had argued that clear ownership, quality rules, and access symmetry reduce confusion and increase confidence in MIS outputs; the strong correlation of readiness with integration and capability supported this point, and the moderation confirmed that readiness converted capability into actual use (Nwankpa & Datta, 2017).

Another strand of prior scholarship had emphasized that AI adoption without organizational readiness can create "black box fatigue," leading to low reliance even when tools appear advanced. The present results showed the opposite pattern under readiness: capability drove usage more steeply, implying that readiness shielded SMEs from black-box skepticism by improving interpretive competence and governance reliability. In SMEs, where strategic authority is concentrated, readiness is not distributed across long hierarchies; it depends heavily on the owner-manager's orientation and the few key decision makers' competencies. The evidence suggested that readiness therefore served as an internal catalyst that ensured AI-MIS features were not dormant but active in decisions. In comparing with earlier studies, the current findings strengthened the claim that SME digital success depends on socio-organizational conditions as much as on technology itself. The significant readiness moderation supported a view that AI-enhanced MIS value is co-produced by technology and internal capability to interpret and trust that technology (Alshanty & Emeagwali, 2019). Instead of treating readiness as a background control, the evidence positioned it as a genuine boundary condition that determines whether AI-MIS capability becomes strategically meaningful through managerial engagement.
Environmental pressure functioned as an external boundary condition amplifying the impact of AI-enhanced MIS on strategic decision outcomes, and this too aligned with multiple earlier adoption and strategy studies. Prior work using contextual adoption lenses had argued that SMEs adopt and exploit sophisticated information systems more deeply when competitive intensity and uncertainty are high (Lakhal & Khechine, 2021). The moderation result here indicated that AI capability translated into greater decision improvements under stronger pressure conditions, suggesting that turbulence increases the returns to prediction, automation, and rapid insight. This reflected classic strategic contingency claims that information value rises when environments are uncertain, because reliable forecasts and early alerts reduce costly surprises. Earlier SME strategy studies had shown that competitive rivalry forces smaller firms to sense market changes quickly and act on them with limited slack resources, and the current evidence indicated that AI-MIS capability supported that need. Customer digital expectations, which are part of environmental pressure, have been described in prior studies as pushing SMEs toward data-rich personalization and faster service loops. The positive association between pressure and AI capability suggested that SMEs facing these expectations were more likely to build and rely on intelligent MIS functions (C. Park et al., 2019). This also helped interpret why decision speed and alignment were relatively strong in the descriptive profile: pressured environments likely demanded faster coordination and more synchronized execution, and AI-enhanced MIS provided the informational infrastructure for that synchronization. Earlier research had also warned that pressure can create adoption that is rushed and superficial, leading to weak outcomes if readiness is missing. The moderation evidence, however, implied that once capability existed, pressure made its benefits more visible. This supported the "necessity breeds depth" argument in SME digitalization, where competition and volatility do not just trigger adoption but also intensify usage and strategic integration. The nonsignificant controls for export level and firm age suggested that pressure effects were not merely proxies for internationalization or maturity; instead, they acted as independent external amplifiers. Comparing to earlier studies, the findings reinforced a nuanced view: environmental turbulence does not automatically improve decisions, but it increases the payoff of intelligent information platforms when those platforms are sufficiently capable and integrated. Thus, the environment shaped the slope of AI-MIS strategic value, meaning that SMEs under higher pressure extracted more decision benefit per unit of AI capability than SMEs under calmer competitive conditions (Alkawsi et al., 2021).
Control-variable patterns provided additional context and compared plausibly with earlier SME IT value studies. Firm size showed small but significant positive associations with both usage intensity and decision outcomes, echoing prior evidence that larger SMEs often have more formalized processes and slightly more analytic slack (Sofyani et al., 2020). This slack can support deeper MIS use because more roles exist to interpret outputs and to incorporate them into planning cycles. IT spending ratio also produced small positive effects, which was consistent with the complementarity view in earlier research suggesting that digital investment in general supports infrastructure readiness, integration depth, and user familiarity. At the same time, the modest magnitude of these control effects indicated that strategic decision benefits were not driven primarily by scale or spending, but by the specific

intelligence and integration characteristics of the MIS platform. Firm age was not significant in the full models, aligning with studies that argued technology value depends more on capability maturity than on chronological age. Some older SMEs are digitally conservative while younger firms may be digitally native; therefore, age alone is an unstable predictor once actual platform capability is observed. Export orientation was also nonsignificant, which contrasted with some earlier research linking internationalization to analytics demand but aligned with other work noting that export status only matters when it leads to real data integration and analytical complexity (Lu et al., 2018). The small and mostly nonsignificant sector effects suggested that AI-enhanced MIS strategic value was relatively generalizable across industries in the sample, a pattern that matched cross-sector BI studies reporting similar decision improvements from integrated analytics. The slightly higher decision outcomes among technology-enabled SMEs compared to retail SMEs was consistent with earlier digital-maturity literature, which often finds that tech-adjacent sectors adopt more advanced analytics earlier. Still, the sector differences were not strong enough to challenge the central model, implying that the AI-MIS capability and integration pathways were robust across contexts. Overall, the control interpretation supported earlier scholarship that MIS and analytics value in SMEs is conditional but not confined to a single sector or maturity stage (Mandal, 2018). The decision outcomes were better explained by how intelligence was embedded and used than by structural firm characteristics, reinforcing the study's core argument that intelligent MIS capability and usage intensity are the primary strategic differentiators.

Bringing all findings together, the discussion established a tightly integrated explanation of strategic decision improvement in SMEs through AI-enhanced MIS platforms. The evidence supported a layered value pathway: intelligent MIS capability improved decision outcomes directly by raising informational quality and indirectly by stimulating managerial usage intensity. Integration quality elevated decision outcomes on its own and amplified AI capability by ensuring stable inputs and coherent cross-functional dashboards (Rejikumar et al., 2020). Organizational readiness strengthened the translation of capability into use, confirming that leadership, skills, and governance are internal catalysts of AI-MIS value. Environmental pressure amplified capability's payoff on outcomes, showing that competition and volatility increase the returns to intelligent decision infrastructures. These combined results aligned closely with earlier theories and empirical studies in MIS success, analytics capability, dynamic decision processes, and SME digital adoption, while also extending them by quantifying a full decision-value chain in a single model. Earlier studies often examined AI tools, MIS integration, or SME decision quality separately; the present evidence indicated that these elements operate as a coupled system. The partial mediation finding was especially important in this comparison because it reconciled two streams of prior thought: the view that technology has intrinsic strategic value through automation, and the view that value is realized only through use (Abbas et al., 2019). The results showed both are correct within SMEs, but each explains a different segment of the pathway. Additionally, the dimension-level descriptives highlighted where SMEs currently derived most AI benefit—prediction, alerting, and interpretability—while prescriptive optimization and scenario intensity lagged. This pattern matched earlier accounts of SME AI adoption as incremental and monitoring-oriented, while still demonstrating that even partial AI integration yields measurable strategic decision gains when embedded within an integrated MIS backbone. The broader theoretical implication within the discussion was that AI-enhanced MIS platforms can be understood as strategic decision infrastructures rather than as optional analytics gadgets (Wu et al., 2019). Their value emerges when intelligence, integration, readiness, and environmental demand converge to support evidence-rich, coordinated strategic action.

CONCLUSION

AI-enhanced management information systems (MIS) platforms for strategic business decision-making in small and medium-sized enterprises (SMEs) can be understood as integrated socio-technical infrastructures that convert internal and external data into intelligent, decision-ready knowledge for owners and senior managers. In SMEs, MIS traditionally served descriptive functions by organizing transactions into reports that supported operational control, budgeting, and performance monitoring, yet these systems often remained fragmented across accounting, sales, inventory, and customer tools, producing delayed visibility and limiting strategic reach. AI enhancement changes the functional role of MIS by embedding predictive analytics, automated insight generation, recommendation engines, real-time data fusion, and interpretability features directly into the platform's information pipeline. This embedded intelligence shifts the platform from portraying what has happened to estimating what is likely to happen and advising what actions are most suitable under constraints, thereby reducing uncertainty around market entry, pricing, portfolio direction, capacity scaling, supplier strategy, and investment prioritization. The strategic value of AI-enhanced MIS in SMEs rests on both the quality of intelligent outputs and the behavioral routines through which managers use them. When forecasting is frequent and accurate, alerts highlight anomalies early, and recommendations are clear and transparent, managers consult dashboards more regularly, rely on AI-supported evidence in meetings, and evaluate alternatives more comprehensively, leading to faster and more accurate strategic commitments. Integration quality within the MIS environment is also central because AI models require timely, consistent, and multi-source inputs; broad and deep system linkage, clean reconciled data, and shared cross-functional KPIs enable intelligent outputs to be trusted and actionable. Within resource-constrained SMEs, these platforms compensate for limited analytic staffing by automating detection of patterns, compressing analysis time, and widening the evidence base beyond what individual managers could assemble manually. As a result, improved strategic decision outcomes tend to appear through multiple dimensions: shorter decision cycles, closer alignment between plans and realized results, broader evaluation of alternatives, better calibration of risk exposure, and stronger coherence between functions during implementation. However, the strategic payoff of AI-enhanced MIS is not uniform across SMEs, because internal readiness and external pressure shape how deeply capability is adopted and exploited. Leadership support determines whether AI outputs are treated as strategic inputs or peripheral reports, data literacy influences interpretive confidence, and governance maturity stabilizes trust in platform numbers. Competitive intensity, market volatility, and rising customer digital expectations amplify the need for predictive and prescriptive guidance, increasing the returns to intelligent MIS once capability exists. Taken together, AI-enhanced MIS platforms represent a practical pathway through which SMEs can institutionalize evidence-based strategy, not by replacing managerial judgment, but by augmenting it with timely forecasts, coherent cross-domain visibility, and structured recommendation support that fits the compressed, high-uncertainty decision realities of smaller firms.

RECOMMENDATIONS

Recommendations for strengthening AI-Enhanced MIS Platforms for Strategic Business Decision-Making in SMEs focus on building intelligent capability in a way that fits SME resource realities while maximizing decision value. First, SMEs should treat AI-MIS adoption as a staged capability program rather than a one-time software purchase, beginning with high-impact predictive and alerting modules (sales/demand forecasting, cash-flow prediction, anomaly detection) that quickly embed into budgeting and performance routines, then extending toward prescriptive optimization once trust and data stability are established. Second, priority should be given to integration quality before or alongside AI expansion, because intelligent outputs depend on clean, timely, multi-source inputs; therefore, SMEs should map their core systems (accounting, ERP, CRM, POS, inventory, e-commerce, logistics, HR), identify gaps, and pursue middleware or API-based linking that minimizes manual transfers, reconciles master data, and enables shared KPI dashboards across functions. Third, managerial usage must be deliberately institutionalized: SMEs should set clear rules that AI-MIS dashboards and automated reports are reviewed in weekly or monthly strategic meetings, require that major strategic proposals reference platform outputs, and encourage scenario testing for high-stakes decisions by setting a minimum standard for alternative evaluation. Fourth, leadership should invest in lightweight analytics skill development for decision makers through short training cycles focused on interpreting forecasts, understanding uncertainty, and recognizing model limits, since managerial data literacy directly raises reliance on AI insights and prevents overconfidence or blind rejection of system outputs. Fifth, SMEs should formalize basic data governance even with small teams by assigning data owners, defining KPI dictionaries, scheduling data quality checks, and documenting how AI recommendations are validated, because governance stabilizes credibility and reduces strategic conflict arising from inconsistent numbers. Sixth, platform vendors and implementation partners should design SME-appropriate AI-MIS solutions emphasizing modularity, explain ability, and low-maintenance automation; features such as "why this recommendation" panels, confidence ranges, and simple what-if sliders are more valuable in SMEs than complex black-box optimization that managers cannot interpret. Seventh, policymakers and SME support agencies should expand access to shared AI-MIS infrastructure through subsidies, tax incentives, or digital-voucher programs tied to integration and training milestones, since external pressure alone does not guarantee capability depth without affordability and skills support. Finally, SMEs should continuously track decision-level benefits—cycle time reductions, forecast error improvement, alignment gains, and risk-exposure stability—so that AI-MIS investment is guided by measurable strategic outcomes rather than technology enthusiasm. These recommendations collectively position AI-enhanced MIS as a strategic decision infrastructure that becomes most valuable when intelligent functions, integrated data pipelines, disciplined managerial use, and basic governance mature together in the SME setting.

LIMITATION

The study on AI-Enhanced MIS Platforms for Strategic Business Decision-Making in SMEs contained several limitations that should be considered when interpreting its findings. First, the research relied on a cross-sectional quantitative design, which captured relationships at a single point in time and therefore limited the ability to observe how AI-MIS capability, integration quality, or managerial usage intensity evolved as SMEs matured digitally. Strategic decision benefits from intelligent MIS platforms may accumulate gradually as managers learn to trust and interpret AI outputs, so a one-time snapshot could not fully reflect dynamic learning effects or delayed payoffs. Second, most variables were measured through self-reported perceptions of senior managers rather than through objective system logs or archival decision-performance data. Although perceptual scales are widely used for latent constructs like capability, integration, and decision quality, they introduced the possibility of respondent bias, including optimism about digital initiatives, social desirability in rating strategic performance, or recall errors regarding decision processes. Third, the study focused on SMEs that already used AI-enhanced MIS features, which improved relevance to the research purpose but also narrowed generalizability to SMEs with lower digital maturity or those using purely traditional MIS. Such firms may face different barriers, adoption motivations, and decision contexts, so the results should not be interpreted as describing all SMEs uniformly. Fourth, because the SME population was diverse across sectors and size bands, the study controlled for structural factors but did not deeply investigate sector-specific mechanisms. AI-MIS value may operate differently in industries with fast-moving demand (such as retail or logistics) compared to those with longer production and planning cycles (such as manufacturing), and a broad pooled model may have muted nuanced sectoral pathways. Fifth, strategic decision outcomes were treated as multidimensional constructs derived from managerial assessment rather than from direct measurement of actual decision success rates or financial performance changes. Even though decision speed, accuracy, comprehensiveness, risk calibration, and alignment are well-established dimensions in strategy and MIS literature, the study could not fully verify whether perceived improvements matched objective outcomes in every firm. Sixth, the measurement model captured AI-MIS capability as a higher-order construct with reflective subdimensions, which provided a coherent statistical structure but may have simplified the heterogeneity of AI functions across platforms. AI enhancement varies widely by vendor, data architecture, and industry-specific application, and reflective modeling can understate the possibility that some subdimensions operate independently rather than as a tightly unified capability bundle. Finally, while the study incorporated organizational readiness and environmental pressure as contextual moderators, other potentially relevant boundary conditions—such as national regulatory environments, cybersecurity risk exposure, vendor support quality, or cultural attitudes toward algorithmic authority—were not captured. These omissions meant that some variance in AI-MIS strategic value may have remained unexplained. Collectively, these limitations did not invalidate the findings, but they clarified that the results represented a strong quantitative explanation within a defined SME-AI-MIS adoption context, rather than an exhaustive account of every pathway through which intelligent MIS influences strategic decision-making.

REFERENCES

[1]. Abbas, J., Mahmood, S., Ali, H., Ali Raza, M., Ali, G., Aman, J., Bano, S., & Nurunnabi, M. (2019). The effects of corporate social responsibility practices and environmental factors through a moderating role of social media marketing on sustainable performance of business firms. *Sustainability*, *11*(12), 3434.

[2]. Abdul, H. (2023). Artificial Intelligence in Product Marketing: Transforming Customer Experience And Market Segmentation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 132–159. https://doi.org/10.63125/58npbx97

[3]. Abdulla, M., & Md. Wahid Zaman, R. (2023). Quantitative Study On Workflow Optimization Through Data Analytics In U.S. Digital Enterprises. *American Journal of Interdisciplinary Studies*, *4*(03), 136–165. https://doi.org/10.63125/y2qshd31

[4]. Addae, J. H., Sun, X., Towey, D., & Radenkovic, M. (2019). Exploring user behavioral data for adaptive cybersecurity. *User Modeling and User-Adapted Interaction*, *29*(3), 701-750.

[5]. Akerkar, R. (2019). *Artificial intelligence for business*. Springer.

[6]. Alazab, M., Alhyari, S., Awajan, A., & Abdallah, A. B. (2021). Blockchain technology in supply chain management: an empirical study of the factors affecting user adoption/acceptance. *Cluster Computing*, *24*(1), 83-101.

[7]. Alkawsi, G., Ali, N. a., & Baashar, Y. (2021). The moderating role of personal innovativeness and users experience in accepting the smart meter technology. *Applied Sciences*, *11*(8), 3297.

[8]. Alshanty, A. M., & Emeagwali, O. L. (2019). Market-sensing capability, knowledge creation and innovation: The moderating role of entrepreneurial-orientation. *Journal of Innovation & Knowledge*, *4*(3), 171-178.

[9]. Ancillai, C., Terho, H., Cardinali, S., & Pascucci, F. (2019). Advancing social media driven sales research: Establishing conceptual foundations for B-to-B social selling. *Industrial Marketing Management*, *82*, 293-308.

[10]. Andriof, J., & Waddock, S. (2017). Unfolding stakeholder engagement. In *Unfolding stakeholder thinking* (pp. 19-42). Routledge.

[11]. Arasli, H., Abdullahi, M., & Gunay, T. (2021). Social media as a destination marketing tool for a sustainable heritage festival in Nigeria: A moderated mediation study. *Sustainability*, *13*(11), 6191.

[12]. Arfan, U., Sai Praveen, K., & Alifa Majumder, N. (2021). Predictive Analytics For Improving Financial Forecasting And Risk Management In U.S. Capital Markets. *American Journal of Interdisciplinary Studies*, *2*(04), 69–100. https://doi.org/10.63125/tbw49w69

[13]. Arfan, U., Tahsina, A., Md Mostafizur, R., & Md, W. (2023). Impact Of GFMIS-Driven Financial Transparency On Strategic Marketing Decisions In Government Agencies. *Review of Applied Science and Technology*, *2*(01), 85-112. https://doi.org/10.63125/8nqhhm56

[14]. Azan, W., Bootz, J.-P., & Rolland, O. (2017). Community of practices, knowledge transfer, and ERP project (ERPP). *Knowledge Management Research & Practice*, *15*(2), 238-256.

[15]. Barthelmäs, M., & Keller, J. (2021). Antecedents, boundary conditions and consequences of flow. In *Advances in flow research* (pp. 71-107). Springer.

[16]. Berge, M., & Ingerman, Å. (2017). Multiple theoretical lenses as an analytical strategy in researching group discussions. *Research in science & technological education*, *35*(1), 42-57.

[17]. Bhatt, D., Patel, C., Talsania, H., Patel, J., Vaghela, R., Pandya, S., Modi, K., & Ghayvat, H. (2021). CNN variants for computer vision: History, architecture, application, challenges and future scope. *Electronics*, *10*(20), 2470.

[18]. Bird, B., & Schjoedt, L. (2017). Entrepreneurial behavior: Its nature, scope, recent research, and agenda for future research. *Revisiting the entrepreneurial mind: Inside the black box: An expanded edition*, 379-409.

[19]. Boylan, M., Coldwell, M., Maxwell, B., & Jordan, J. (2018). Rethinking models of professional learning as tools: a conceptual analysis to inform research and practice. *Professional development in education*, *44*(1), 120-139.

[20]. Cat, J. (2021). The unity of science. In *The Routledge handbook of logical empiricism* (pp. 176-184). Routledge.

[21]. Chase, H., Fournier, J., Bertocci, M., Greenberg, T., Aslam, H., Stiffler, R., Lockovich, J., Graur, S., Bebko, G., & Forbes, E. (2017). A pathway linking reward circuitry, impulsive sensation-seeking and risky decision-making in young adults: identifying neural markers for new interventions. *Translational psychiatry*, *7*(4), e1096-e1096.

[22]. Chauhan, C., Singh, A., & Luthra, S. (2021). Barriers to industry 4.0 adoption and its performance implications: An empirical investigation of emerging economy. *Journal of Cleaner Production*, *285*, 124809.

[23]. Chen, F., & Krajbich, I. (2018). Biased sequential sampling underlies the effects of time pressure and delay in social decision making. *Nature communications*, *9*(1), 3557.

[24]. Chen, S.-L., Shih, C.-T., & Chi, N.-W. (2018). A multilevel job demands–resources model of work engagement: Antecedents, consequences, and boundary conditions. *Human Performance*, *31*(5), 282-304.

[25]. Ciccarelli, M., Griffiths, M. D., Nigro, G., & Cosenza, M. (2017). Decision making, cognitive distortions and emotional distress: A comparison between pathological gamblers and healthy controls. *Journal of behavior therapy and experimental psychiatry*, *54*, 204-210.

[26]. d'Espagnat, B. (2018). *Conceptual foundations of quantum mechanics*. CRC Press.

[27]. Daunt, K. L., & Harris, L. C. (2017). Consumer showrooming: Value co-destruction. *Journal of Retailing and Consumer Services*, *38*, 166-176.

[28]. Dey, C., & Sen, S. K. (2020). *Industrial automation technologies*. CRC Press.

[29]. Dördüncü, H. (2021). Logistics, supply chains and smart factories. In *Logistics 4.0 and future of supply chains* (pp. 137-152). Springer.

[30]. Dowlatabadi, H., & Wilson, C. (2018). Models of decision making and residential energy use. *Renewable Energy*, Vol1_357-Vol351_392.

[31]. Elbanna, S. (2018). The constructive aspect of political behavior in strategic decision-making: The role of diversity. *European management journal*, *36*(5), 616-626.

[32]. Fatehi, K., & Choi, J. (2018). International information systems management. In *International Business Management: Succeeding in a Culturally Diverse World* (pp. 309-338). Springer.

[33]. Femenia-Serra, F., Neuhofer, B., & Ivars-Baidal, J. A. (2019). Towards a conceptualisation of smart tourists and their role within the smart destination scenario. *The Service Industries Journal*, *39*(2), 109-133.

[34]. Ferdous Ara, A. (2021). Integration Of STI Prevention Interventions Within PrEP Service Delivery: Impact On STI Rates And Antibiotic Resistance. *International Journal of Scientific Interdisciplinary Research*, 2(2), 63–97. https://doi.org/10.63125/65143m72

[35]. Ferdous Ara, A., & Beatrice Onyinyechi, M. (2023). Long-Term Epidemiologic Trends Of STIs PRE- and POST-PrEP Introduction: A National Time-Series Analysis. *American Journal of Health and Medical Sciences*, 4(02), 01–35. https://doi.org/10.63125/mp153d97

[36]. Forero, R., Nahidi, S., De Costa, J., Mohsin, M., Fitzgerald, G., Gibson, N., McCarthy, S., & Aboagye-Sarfo, P. (2018). Application of four-dimension criteria to assess rigour of qualitative research in emergency medicine. *BMC health services research*, *18*(1), 120.

[37]. Gandy, M., Baker, P. M., & Zeagler, C. (2017). Imagining futures: A collaborative policy/device design for wearable computing. *Futures*, *87*, 106-121.

[38]. Garson, G. D. (2021). *Data analytics for the social sciences: Applications in R*. Routledge.

[39]. Gawer, A. (2021). Digital platforms' boundaries: The interplay of firm scope, platform sides, and digital interfaces. *Long range planning*, *54*(5), 102045.

[40]. Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the fintech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of management information systems*, *35*(1), 220-265.

[41]. Grewatsch, S., & Kleindienst, I. (2017). When does it pay to be good? Moderators and mediators in the corporate sustainability–corporate financial performance relationship: A critical review. *Journal of Business Ethics*, *145*(2), 383-416.

[42]. Hallam, C., & Zanella, G. (2017). Online self-disclosure: The privacy paradox explained as a temporally discounted balance between concerns and rewards. *Computers in Human Behavior*, *68*, 217-227.

[43]. Hetemi, E., Ordieres-Meré, J., & Nuur, C. (2020). An institutional approach to digitalization in sustainability-oriented infrastructure projects: The limits of the building information model. *Sustainability*, *12*(9), 3893.

[44]. Ho, M. H.-W., Ghauri, P. N., & Larimo, J. A. (2018). Institutional distance and knowledge acquisition in international buyer-supplier relationships: The moderating role of trust. *Asia Pacific Journal of Management*, *35*(2), 427-447.

[45]. Holmes, T. P., Adamowicz, W. L., & Carlsson, F. (2017). Choice experiments. In *A primer on nonmarket valuation* (pp. 133-186). Springer.

[46]. Hsiao, K.-L., & Chen, C.-C. (2018). What drives smartwatch purchase intention? Perspectives from hardware, software, design, and value. *Telematics and Informatics*, *35*(1), 103-113.

[47]. Huang, L. V., & Liu, P. L. (2017). Ties that work: Investigating the relationships among coworker connections, work-related Facebook utility, online social capital, and employee outcomes. *Computers in Human Behavior*, *72*, 512-524.

[48]. Jahid, M. K. A. S. R. (2021). Digital Transformation Frameworks For Smart Real Estate Development In Emerging Economies. *Review of Applied Science and Technology*, 6(1), 139–182. https://doi.org/10.63125/cd09ne09

[49]. Jang, W. W., & Byon, K. K. (2020). Antecedents of esports gameplay intention: Genre as a moderator. *Computers in Human Behavior*, *109*, 106336.

[50]. Ji-fan Ren, S., Fosso Wamba, S., Akter, S., Dubey, R., & Childe, S. J. (2017). Modelling quality dynamics, business value and firm performance in a big data analytics environment. *International journal of production research*, *55*(17), 5011-5026.

[51]. Jiang, Z., Di Milia, L., Jiang, Y., & Jiang, X. (2020). Thriving at work: A mentoring-moderated process linking task identity and autonomy to job satisfaction. *Journal of vocational behavior*, *118*, 103373.

[52]. Johnson, R. E., Lin, S.-H., & Lee, H. W. (2018). Self-control as the fuel for effective self-regulation at work: Antecedents, consequences, and boundary conditions of employee self-control. In *Advances in motivation science* (Vol. 5, pp. 87-128). Elsevier.

[53]. Kanis, J. A., Norton, N., Harvey, N. C., Jacobson, T., Johansson, H., Lorentzon, M., McCloskey, E. V., Willers, C., & Borgström, F. (2021). SCOPE 2021: a new scorecard for osteoporosis in Europe. *Archives of osteoporosis*, *16*(1), 82.

[54]. Kelly, S. P., Corbett, E. A., & O'Connell, R. G. (2021). Neurocomputational mechanisms of prior-informed perceptual decision-making in humans. *Nature Human Behaviour*, *5*(4), 467-481.

[55]. Killen, C. P., Geraldi, J., & Kock, A. (2020). The role of decision makers' use of visualizations in project portfolio decision making. *International Journal of Project Management*, *38*(5), 267-277.

[56]. Kim, D., & Cavusgil, E. (2020). Antecedents and outcomes of digital platform risk for international new ventures' internationalization. *Journal of World Business*, *55*(1), 101021.

[57]. Knauer, T., Nikiforow, N., & Wagener, S. (2020). Determinants of information system quality and data quality in management accounting. *Journal of Management Control*, *31*(1), 97-121.

[58]. Kuzovkova, T., Saliutina, T. Y., & Sharavova, O. (2021). The impact of digital platforms on the business management information system. 2021 Systems of Signal Synchronization, Generating and Processing in Telecommunications (SYNCHROINFO,

[59]. Lakhal, S., & Khechine, H. (2021). Technological factors of students' persistence in online courses in higher education: The moderating role of gender, age and prior online course experience. *Education and Information Technologies*, *26*(3), 3347-3373.

[60]. Lamboglia, R., Cardoni, A., Dameri, R. P., & Mancini, D. (2018). Business information systems in a networked, smart and open environment. In *Network, smart and open: Three keywords for information systems innovation* (pp. 1-20). Springer.

[61]. Leenders, M. A., Smidts, A., & El Haji, A. (2019). Ambient scent as a mood inducer in supermarkets: The role of scent intensity and time-pressure of shoppers. *Journal of Retailing and Consumer Services*, *48*, 270-280.

[62]. Li, D., & Shen, W. (2021). Can corporate digitalization promote green innovation? The moderating roles of internal control and institutional ownership. *Sustainability*, *13*(24), 13983.

[63]. Li, K., Chen, Y., & Zhang, L. (2020). Exploring the influence of online reviews and motivating factors on sales: A meta-analytic study and the moderating role of product category. *Journal of Retailing and Consumer Services*, *55*, 102107.

[64]. Liébana-Cabanillas, F., Singh, N., Kalinic, Z., & Carvajal-Trujillo, E. (2021). Examining the determinants of continuance intention to use and the moderating effect of the gender and age of users of NFC mobile payments: A multi-analytical approach. *Information Technology and Management*, *22*(2), 133-161.

[65]. Lin, C.-P., Chen, K.-J., Liu, C.-M., & Liao, C.-H. (2019). Assessing decision quality and team performance: perspectives of knowledge internalization and resource adequacy. *Review of Managerial Science*, *13*(2), 377-396.

[66]. Linuesa-Langreo, J., Ruiz-Palomino, P., & Elche-Hortelano, D. (2018). Integrating servant leadership into managerial strategy to build group social capital: The mediating role of group citizenship behavior. *Journal of Business Ethics*, *152*(4), 899-916.

[67]. Liu, C.-H. (2017). Creating competitive advantage: Linking perspectives of organization learning, innovation behavior and intellectual capital. *International journal of hospitality management*, *66*, 13-23.

[68]. Liu, C.-W., Huang, P., & Lucas Jr, H. C. (2020). Centralized IT decision making and cybersecurity breaches: Evidence from US higher education institutions. *Journal of management information systems*, *37*(3), 758-787.

[69]. Lo, S. M., Zhang, S., Wang, Z., & Zhao, X. (2018). The impact of relationship quality and supplier development on green supply chain integration: A mediation and moderation analysis. *Journal of Cleaner Production*, *202*, 524-535.

[70]. Lu, D., Ding, Y., Asian, S., & Paul, S. K. (2018). From supply chain integration to operational performance: The moderating effect of market uncertainty. *Global Journal of Flexible Systems Management*, *19*(Suppl 1), 3-20.

[71]. Mackey, J. D., Bishoff, J. D., Daniels, S. R., Hochwarter, W. A., & Ferris, G. R. (2019). Incivility's relationship with workplace outcomes: Enactment as a boundary condition in two samples. *Journal of Business Ethics*, *155*(2), 513-528.

[72]. Makhloufi, L., Azbiya Yaacob, N., Laghouag, A. A., Ali Sahli, A., & Belaid, F. (2021). Effect of IT capability and intangible IT resources on sustainable competitive advantage: Exploring moderating and mediating effect of IT flexibility and core competency. *Cogent Business & Management*, *8*(1), 1935665.

[73]. Mandal, S. (2018). Exploring the influence of big data analytics management capabilities on sustainable tourism supply chain performance: the moderating role of technology orientation. *Journal of Travel & Tourism Marketing*, *35*(8), 1104-1118.

[74]. Mani, V., & Gunasekaran, A. (2018). Four forces of supply chain social sustainability adoption in emerging economies. *International Journal of Production Economics*, *199*, 150-161.

[75]. Marszk, A., & Lechman, E. (2021). *Digitalization of financial markets*. Routledge Milton Park.

[76]. McManus, J. (2018). Hubris and unethical decision making: The tragedy of the uncommon. *Journal of Business Ethics*, *149*(1), 169-185.

[77]. Md Al Amin, K., & Md Mesbaul, H. (2023). Smart Hybrid Manufacturing: A Combination Of Additive, Subtractive, And Lean Techniques For Agile Production Systems. *Journal of Sustainable Development and Policy*, *2*(04), 174-217. https://doi.org/10.63125/7rb1zz78

[78]. Md Ariful, I., & Efat Ara, H. (2022). Advances And Limitations Of Fracture Mechanics–Based Fatigue Life Prediction Approaches For Structural Integrity Assessment: A Systematic Review. *American Journal of Interdisciplinary Studies*, *3*(03), 68-98. https://doi.org/10.63125/fg8ae957

[79]. Md Arman, H., & Md.Kamrul, K. (2022). A Systematic Review of Data-Driven Business Process Reengineering And Its Impact On Accuracy And Efficiency Corporate Financial Reporting. *International Journal of Business and Economics Insights*, *2*(4), 01–41. https://doi.org/10.63125/btx52a36

[80]. Md Foysal, H., & Aditya, D. (2023). Smart Continuous Improvement With Artificial Intelligence, Big Data, And Lean Tools For Zero Defect Manufacturing Systems. *American Journal of Scholarly Research and Innovation*, *2*(01), 254–282. https://doi.org/10.63125/6cak0s21

[81]. Md Hamidur, R. (2023). Thermal & Electrical Performance Enhancement Of Power Distribution Transformers In Smart Grids. *American Journal of Scholarly Research and Innovation*, *2*(01), 283–313. https://doi.org/10.63125/n2p6y628

[82]. Md Harun-Or-Rashid, M., Mst. Shahrin, S., & Sai Praveen, K. (2023). Integration Of IOT And EDGE Computing For Low-Latency Data Analytics In Smart Cities And IOT Networks. *Journal of Sustainable Development and Policy*, *2*(03), 01-33. https://doi.org/10.63125/004h7m29

[83]. Md Mesbaul, H., & Md. Tahmid Farabe, S. (2022). Implementing Sustainable Supply Chain Practices In Global Apparel Retail: A Systematic Review Of Current Trends. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 332–363. https://doi.org/10.63125/nen7vd57

[84]. Md Musfiqur, R., & Md.Kamrul, K. (2023). Mechanisms By Which AI-Enabled Crm Systems Influence Customer Retention And Overall Business Performance: A Systematic Literature Review Of Empirical Findings. *International Journal of Business and Economics Insights*, *3*(1), 31-67. https://doi.org/10.63125/qqe2bm11

[85]. Md Muzahidul, I., & Md Mohaiminul, H. (2023). Explainable AI (XAI) Models For Cloud-Based Business Intelligence: Ensuring Compliance And Secure Decision-Making. *American Journal of Interdisciplinary Studies*, *4*(03), 208–249. https://doi.org/10.63125/5etfhh77

[86]. Md Nahid, H. (2022). Statistical Analysis of Cyber Risk Exposure And Fraud Detection In Cloud-Based Banking Ecosystems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 289–331. https://doi.org/10.63125/9wf91068

[87]. Md Sarwar Hossain, S., & Md Milon, M. (2022). Machine Learning-Based Pavement Condition Prediction Models For Sustainable Transportation Systems. *American Journal of Interdisciplinary Studies*, *3*(01), 31–64. https://doi.org/10.63125/1jsmkg92

[88]. Md. Abdur, R., & Zamal Haider, S. (2022). Assessment Of Data-Driven Vendor Performance Evaluation In Retail Supply Chains Analyzing Metrics, Scorecards, And Contract Management Tools. *Journal of Sustainable Development and Policy*, *1*(04), 71-116. https://doi.org/10.63125/2a641k35

[89]. Md. Al Amin, K., & Sai Praveen, K. (2023). The Role Of Industrial Engineering In Advancing Sustainable Manufacturing And Quality Compliance In Global Engineering Systems. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 31–61. https://doi.org/10.63125/8w1vk676

[90]. Md. Hasan, I., & Ashraful, I. (2023). The Effect Of Production Planning Efficiency On Delivery Timelines In U.S. Apparel Imports. *Journal of Sustainable Development and Policy*, *2*(04), 35-73. https://doi.org/10.63125/sg472m51

[91]. Md. Jobayer Ibne, S., & Md. Kamrul, K. (2023). Automating NIST 800-53 Control Implementation: A Cross-Sector Review Of Enterprise Security Toolkits. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 160–195. https://doi.org/10.63125/prkw8r07

[92]. Md.Akbar, H., & Farzana, A. (2021). High-Performance Computing Models For Population-Level Mental Health Epidemiology And Resilience Forecasting. *American Journal of Health and Medical Sciences*, *2*(02), 01–33. https://doi.org/10.63125/k9d5h638

[93]. Mohammad Mushfequr, R., & Ashraful, I. (2023). Automation And Risk Mitigation in Healthcare Claims: Policy And Compliance Implications. *Review of Applied Science and Technology*, *2*(04), 124–157. https://doi.org/10.63125/v73gyg14

[94]. Mohammad Mushfequr, R., & Sai Praveen, K. (2022). Quantitative Investigation Of Information Security Challenges In U.S. Healthcare Payment Ecosystems. *International Journal of Business and Economics Insights*, *2*(4), 42–73. https://doi.org/10.63125/gcg0fs06

[95]. Mohtaramzadeh, M., Ramayah, T., & Jun-Hwa, C. (2018). B2B e-commerce adoption in Iranian manufacturing companies: Analyzing the moderating role of organizational culture. *International Journal of Human–Computer Interaction*, *34*(7), 621-639.

[96]. Mortuza, M. M. G., & Rauf, M. A. (2022). Industry 4.0: An Empirical Analysis of Sustainable Business Performance Model Of Bangladeshi Electronic Organisations. *International Journal of Economy and Innovation*. https://gospodarkainnowacje.pl/index.php/issue_view_32/article/view/826

[97]. Nwankpa, J. K., & Datta, P. (2017). Balancing exploration and exploitation of IT resources: The influence of Digital Business Intensity on perceived organizational performance. *European Journal of Information Systems*, *26*(5), 469-488.

[98]. Pankaz Roy, S., & Md. Kamrul, K. (2023). HACCP and ISO Frameworks For Enhancing Biosecurity In Global Food Distribution Chains. *American Journal of Scholarly Research and Innovation*, *2*(01), 314–356. https://doi.org/10.63125/9pbp4h37

[99]. Parhi, S., Joshi, K., & Akarte, M. (2021). Smart manufacturing: a framework for managing performance. *International Journal of Computer Integrated Manufacturing*, *34*(3), 227-256.

[100]. Park, C., Kim, D.-g., Cho, S., & Han, H.-J. (2019). Adoption of multimedia technology for learning and gender difference. *Computers in Human Behavior*, *92*, 288-296.

[101]. Park, S. A., Sestito, M., Boorman, E. D., & Dreher, J.-C. (2019). Neural computations underlying strategic social decision-making in groups. *Nature communications*, *10*(1), 5287.

[102]. Ploum, L., Blok, V., Lans, T., & Omta, O. (2018). Exploring the relation between individual moral antecedents and entrepreneurial opportunity recognition for sustainable development. *Journal of Cleaner Production*, *172*, 1582-1591.

[103]. Popovič, A., Hackney, R., Tassabehji, R., & Castelli, M. (2018). The impact of big data analytics on firms' high value business performance. *Information Systems Frontiers*, *20*(2), 209-222.

[104]. Promwongsa, N., Ebrahimzadeh, A., Naboulsi, D., Kianpisheh, S., Belqasmi, F., Glitho, R., Crespi, N., & Alfandi, O. (2020). A comprehensive survey of the tactile internet: State-of-the-art and research directions. *IEEE Communications Surveys & Tutorials*, *23*(1), 472-523.

[105]. Quade, M. J., Perry, S. J., & Hunter, E. M. (2019). Boundary conditions of ethical leadership: Exploring supervisor-induced and job hindrance stress as potential inhibitors. *Journal of Business Ethics*, *158*(4), 1165-1184.

[106]. Quinn, M., & Strauss, E. (2018). *The routledge companion to accounting information systems*. Routledge.

[107]. Rakibul, H., & Samia, A. (2022). Information System-Based Decision Support Tools: A Systematic Review Of Strategic Applications In Service-Oriented Enterprises. *Review of Applied Science and Technology*, *1*(04), 26-65. https://doi.org/10.63125/w3cevz78

[108]. Ramanathan, R., Philpott, E., Duan, Y., & Cao, G. (2017). Adoption of business analytics and impact on performance: a qualitative study in retail. *Production Planning & Control*, *28*(11-12), 985-998.

[109]. Rehman, S. U., Bhatti, A., Mohamed, R., & Ayoup, H. (2019). The moderating role of trust and commitment between consumer purchase intention and online shopping behavior in the context of Pakistan. *Journal of Global Entrepreneurship Research*, *9*(1), 1-25.

[110]. Rejikumar, G., Aswathy Asokan, A., & Sreedharan, V. R. (2020). Impact of data-driven decision-making in Lean Six Sigma: an empirical analysis. *Total Quality Management & Business Excellence*, *31*(3-4), 279-296.

[111]. Reza, M., Vorobyova, K., & Rauf, M. (2021). The effect of total rewards system on the performance of employees with a moderating effect of psychological empowerment and the mediation of motivation in the leather industry of Bangladesh. *Engineering Letters*, *29*, 1-29.

[112]. Rony, M. A., & Ashraful, I. (2022). Big Data And Engineering Analytics Pipelines For Smart Manufacturing: Enhancing Efficiency, Quality, And Predictive Maintenance. *American Journal of Scholarly Research and Innovation*, *1*(02), 59–85. https://doi.org/10.63125/rze0my79

[113]. Rossi, S., Larafa, M., & Ruocco, M. (2020). Emotional and behavioural distraction by a social robot for children anxiety reduction during vaccination. *International Journal of Social Robotics*, *12*(3), 765-777.

[114]. S. Oliveira, M. I., Barros Lima, G. d. F., & Farias Lóscio, B. (2019). Investigations into data ecosystems: a systematic mapping study. *Knowledge and information systems*, *61*(2), 589-630.

[115]. Saba, A., Shaikat, B., & Tonoy Kanti, C. (2023). Integration Of Artificial Intelligence And Advanced Computing To Develop Resilient Cyber Defense Systems. *Journal of Sustainable Development and Policy*, *2*(04), 74-107. https://doi.org/10.63125/rxyc6y88

[116]. Saba, A., & Tonoy Kanti, C. (2023). Explainable Artificial Intelligence (XAI) Approaches For Cyber Risk Assessment In Financial Services. *American Journal of Interdisciplinary Studies*, *4*(03), 96-135. https://doi.org/10.63125/3gjcb322

[117]. Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. *International journal of production research*, *57*(7), 2117-2135.

[118]. Saikat, S. (2021). Real-Time Fault Detection in Industrial Assets Using Advanced Vibration Dynamics And Stress Analysis Modeling. *American Journal of Interdisciplinary Studies*, *2*(04), 39–68. https://doi.org/10.63125/0h163429

[119]. Saikat, S. (2022). CFD-Based Investigation of Heat Transfer Efficiency In Renewable Energy Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 129–162. https://doi.org/10.63125/ttw40456

[120]. Salminen, S., Collado, M. C., Endo, A., Hill, C., Lebeer, S., Quigley, E. M., Sanders, M. E., Shamir, R., Swann, J. R., & Szajewska, H. (2021). The International Scientific Association of Probiotics and Prebiotics (ISAPP) consensus statement on the definition and scope of postbiotics. *Nature reviews Gastroenterology & hepatology*, *18*(9), 649-667.

[121]. Sancha, C., Wiengarten, F., Longoni, A., & Pagell, M. (2020). The moderating role of temporary work on the performance of lean manufacturing systems. *International journal of production research*, *58*(14), 4285-4305.

[122]. Santoro, G., Thrassou, A., Bresciani, S., & Del Giudice, M. (2019). Do knowledge management and dynamic capabilities affect ambidextrous entrepreneurial intensity and firms' performance? *IEEE Transactions on Engineering Management*, *68*(2), 378-386.

[123]. Sardana, D., Gupta, N., Kumar, V., & Terziovski, M. (2020). CSR 'sustainability'practices and firm performance in an emerging economy. *Journal of Cleaner Production*, *258*, 120766.

[124]. Sarwar, M. I., Iqbal, M. W., Alyas, T., Namoun, A., Alrehaili, A., Tufail, A., & Tabassum, N. (2021). Data vaults for blockchain-empowered accounting information systems. *Ieee Access*, *9*, 117306-117324.

[125]. Schroeder, A., Ziaee Bigdeli, A., Galera Zarco, C., & Baines, T. (2019). Capturing the benefits of industry 4.0: a business network perspective. *Production Planning & Control*, *30*(16), 1305-1321.

[126]. Shaikh, S., & Aditya, D. (2021). Federated Learning-Driven Predictive Quality Analytics and Supply Chain Optimization In Distributed Manufacturing Networks. *Review of Applied Science and Technology*, *6*(1), 74-107. https://doi.org/10.63125/k18cbz55

[127]. Shaikh, S., & Md. Tahmid Farabe, S. (2023). Digital Twin-Driven Process Modeling For Energy Efficiency And Lifecycle Optimization In Industrial Facilities. *American Journal of Interdisciplinary Studies*, *4*(03), 65–95. https://doi.org/10.63125/e4q64869

[128]. Shaikh, S., & Sudipto, R. (2022). Multi-Objective Thermo-Economic and Supply Chain Optimization Modeling For Hydrogen Energy Integration In Smart Factories. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 163–193. https://doi.org/10.63125/p9y8p705

[129]. Shittu, E., Parker, G., & Mock, N. (2018). Improving communication resilience for effective disaster relief operations. *Environment Systems and Decisions*, *38*(3), 379-397.

[130]. Shute, V. J., Sun, C., & Asbell-Clarke, J. (2017). Demystifying computational thinking. *Educational research review*, *22*, 142-158.

[131]. Siyal, S., Ahmed, M. J., Ahmad, R., Khan, B. S., & Xin, C. (2021). Factors influencing green purchase intention: Moderating role of green brand knowledge. *International Journal of Environmental Research and Public Health*, *18*(20), 10762.

[132]. Sofyani, H., Riyadh, H. A., & Fahlevi, H. (2020). Improving service quality, accountability and transparency of local government: The intervening role of information technology governance. *Cogent Business & Management*, *7*(1), 1735690.

[133]. Steinhoff, L., Arli, D., Weaven, S., & Kozlenkova, I. V. (2019). Online relationship marketing. *Journal of the Academy of marketing science*, *47*(3), 369-393.

[134]. Su, C. C., & Chan, N. K. (2017). Predicting social capital on Facebook: The implications of use intensity, perceived content desirability, and Facebook-enabled communication practices. *Computers in Human Behavior*, *72*, 259-268.

[135]. Swanson, E. B. (2020). How information systems came to rule the world: Reflections on the information systems field. *The Information Society*, *36*(2), 109-123.

[136]. Tao, W., Song, B., Ferguson, M. A., & Kochhar, S. (2018). Employees' prosocial behavioral intentions through empowerment in CSR decision-making. *Public Relations Review*, *44*(5), 667-680.

[137]. Tarafdar, M., & Qrunfleh, S. (2017). Agile supply chain strategy and supply chain performance: complementary roles of supply chain practices and information systems capability for agility. *International journal of production research*, *55*(4), 925-938.

[138]. Taufique, K. M. R., & Vaithianathan, S. (2018). A fresh look at understanding Green consumer behavior among young urban Indian consumers through the lens of Theory of Planned Behavior. *Journal of Cleaner Production*, *183*, 46-55.

[139]. Teng, C.-I. (2017). Impact of avatar identification on online gamer loyalty: Perspectives of social identity and social capital theories. *International Journal of Information Management*, *37*(6), 601-610.

[140]. Tonoy Kanti, C., & Shaikat, B. (2021). Blockchain-Enabled Security Protocols Combined With AI For Securing Next-Generation Internet Of Things (IOT) Networks. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 98–127. https://doi.org/10.63125/pcdqzw41

[141]. Trakadas, P., Simoens, P., Gkonis, P., Sarakis, L., Angelopoulos, A., Ramallo-González, A. P., Skarmeta, A., Trochoutsos, C., Calvo, D., & Pariente, T. (2020). An artificial intelligence-based collaboration approach in industrial iot manufacturing: Key concepts, architectural extensions and potential applications. *Sensors*, *20*(19), 5480.

[142]. Turban, E., Outland, J., King, D., Lee, J. K., Liang, T.-P., & Turban, D. C. (2017). Intelligent (smart) E-commerce. In *Electronic commerce 2018: A managerial and social networks perspective* (pp. 249-283). Springer.

[143]. Tuu, H. H., Khoi, N. H., & Olsen, S. O. (2021). How consumer innovativeness, technological expertise, and consideration set size can explain mobile commerce use: An extended understanding using a moderation–mediation model. *Information Systems and e-Business Management*, *19*(3), 1015-1038.

[144]. Tworek, K., Tworek, R., & Rauscher, R. (2019). *Aligning IT and Business*. Springer.

[145]. Urbach, N., & Ahlemann, F. (2019). IT management in the digital age. *A Roadmap for the IT Department of the Future, Cham*.

[146]. Verma, P. (2021). The effect of brand engagement and brand love upon overall brand equity and purchase intention: A moderated–mediated model. *Journal of Promotion Management*, *27*(1), 103-132.

[147]. Visinescu, L. L., Jones, M. C., & Sidorova, A. (2017). Improving decision quality: the role of business intelligence. *Journal of Computer Information Systems*, *57*(1), 58-66.

[148]. Wiltshire, G., & Ronkainen, N. (2021). A realist approach to thematic analysis: making sense of qualitative data through experiential, inferential and dispositional themes. *Journal of critical realism*, *20*(2), 159-180.

[149]. Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming–a review. *Agricultural systems*, *153*, 69-80.

[150]. Wu, G., Hu, Z., & Zheng, J. (2019). Role stress, job burnout, and job performance in construction project managers: the moderating role of career calling. *International Journal of Environmental Research and Public Health*, *16*(13), 2394.

[151]. Xu, B., Shao, D., Tan, X., Yang, X., Gu, W., & Li, H. (2017). Evaluation of soil water percolation under different irrigation practices, antecedent moisture and groundwater depths in paddy fields. *Agricultural Water Management*, *192*, 149-158.

[152]. Yang, F., Wang, K., Han, Y., & Qiao, Z. (2018). A cloud-based digital farm management system for vegetable production process management and quality traceability. *Sustainability*, *10*(11), 4007.

[153]. Zamal Haider, S., & Hozyfa, S. (2023). A Quantitative Study On IT-Enabled ERP Systems And Their Role In Operational Efficiency. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 62–99. https://doi.org/10.63125/nbpyce10

[154]. Zhao, Y., Ni, Q., & Zhou, R. (2018). What factors influence the mobile health service adoption? A meta-analysis and the moderating role of age. *International Journal of Information Management*, *43*, 342-350.