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AI Financial Forecasting and Strategic Decision Quality in Emerging Market Manufacturing: Data Analytics Maturity and AI Governance

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Abstract: This study examines the relationships among AI powered financial forecasting capability, data analytics maturity, and strategic decision quality in emerging market manufacturing firms, while assessing the moderating role of the AI governance framework. Grounded in Dynamic Capabilities Theory and Organizational Information Processing Theory, the study conceptualizes strategic decision quality as an outcome of predictive intelligence, mature analytical resources, and governance mechanisms that support the responsible use of AI generated forecasts. Employing a quantitative cross sectional design, data were collected from 385 respondents working in manufacturing enterprises across Vietnam through a five point Likert scale questionnaire. The data were analyzed using IBM SPSS version 26 for reliability assessment, exploratory factor analysis, and multiple linear regression, while Hayes' PROCESS Macro Model 1 was applied to test the moderating effect. The findings revealed that AI powered financial forecasting capability ($\beta = 0.580$) and data analytics maturity ($\beta = 0.601$) both significantly enhanced strategic decision quality. Data analytics maturity produced a slightly stronger direct effect, emphasizing the importance of integrated data systems, analytical expertise, and evidence based organizational routines. Furthermore, the AI governance framework significantly strengthened the positive relationship between AI powered financial forecasting capability and strategic decision quality, as demonstrated by the positive interaction coefficient of 0.387. These results confirm that forecasting technology alone is insufficient and that reliable data capabilities, model validation, accountability, transparency, and human oversight are necessary to transform AI generated forecasts into informed, timely, comprehensive, and strategically aligned manufacturing decisions.

Keywords: Strategic decision quality; AI powered financial forecasting capability; Data analytics maturity; AI governance framework; Emerging market manufacturing firms.

1. Introduction

The quality of strategic decisions among manufacturing firms in emerging markets has become a pressing research concern because these organizations increasingly operate in unstable environments characterized by unpredictable demand, supply network disruptions, rapid technological change, and limited resources. Under such conditions, sound strategic choices are essential for sustaining competitive advantage. This quality is understood as the degree to which managerial choices prove accurate, timely, grounded in evidence, and consistent with broader organizational goals (Elbanna et al., 2016). While digital tools and artificial intelligence now deliver powerful forecasting and analytical potential, numerous emerging-market manufacturers still grapple with disjointed information systems, uneven data reliability, and constrained analytical skills, which in turn weaken the overall effectiveness of their strategic decision-making (Mikalef et al., 2019). Of particular worry is the tendency for leaders to accept predictive results without grasping the underlying algorithmic premises, a practice that risks fostering overconfidence, magnifying biases, and producing strategic misalignment (Ransbotham et al., 2019). In addition, inadequate governance arrangements and limited oversight can erode transparency, accountability, and confidence in decisions supported by AI (Dwivedi et al., 2021). Collectively, these issues indicate that elevating strategic decision quality depends not merely on sophisticated forecasting technologies but equally on well-developed data analytics competencies and strong governance structures that promote responsible and productive use of AI.

Contemporary research highlights artificial intelligence and advanced analytics as vital strategic assets that accelerate forecasting, expand information processing, and enhance executive responsiveness. While big-data analytics enables firms to distill complex datasets into actionable intelligence, performance gains hinge on complementary organizational routines rather than technology in isolation (Mikalef et al., 2020). Human–AI collaboration can sharpen strategic decision-making amid uncertainty, though opaque algorithms and poor task distribution risk eroding managerial judgment (Trunk et al., 2020). Recent insights further demonstrate that AI capabilities elevate decision outcomes primarily when supported by robust digital infrastructure and a well-defined business orientation (Guthrie et al., 2025). Furthermore, AI governance frameworks stress transparency, accountability, human oversight, data hygiene, and risk management as essential prerequisites for reliable AI integration (Papagiannidis et al., 2023, 2025). Nevertheless, existing literature remains fragmented, often examining AI, analytics, or governance separately and prioritizing broad performance metrics over decision quality; and favoring developed economies or qualitative cases.

Consequently, financial forecasting in emerging-market manufacturing remains noticeably underexplored. To address these limitations, this study evaluates the combined impact of AI-driven financial forecasting and data analytics maturity on strategic decision quality, while assessing whether AI governance reinforces this critical relationship.
Then, the three research questions can be formulated as follows:

To what extent does AI-powered financial forecasting capability influence strategic decision quality in emerging market manufacturing firms?

How does data analytics maturity affect strategic decision quality in emerging market manufacturing firms?

How does the AI governance framework moderate the relationship between AI-powered financial forecasting capability and strategic decision quality in emerging market manufacturing firms?

This study sets out three research objectives. First it seeks to gauge how far AI powered financial forecasting capability shapes strategic decision quality among emerging market manufacturing firms. Second it aims to assess the impact of data analytics maturity on strategic decision quality by checking whether solid data infrastructure analytical expertise governance practices and evidence based routines help manufacturers reach more informed timely and strategically aligned decisions. Third the work explores whether the AI governance framework positively moderates the link between AI powered financial forecasting capability and strategic decision quality especially by lifting the transparency accountability validation and responsible managerial use of AI generated forecasts. The research supplies academic and practical worth by weaving AI powered financial forecasting capability data analytics maturity AI governance and strategic decision quality into one coherent framework suited to emerging market manufacturing firms. Academically, it broadens AI capability and organizational decision making inquiry by clarifying both the direct roles of forecasting and analytics maturity and the contingent part played by governance. It further fills the sparse evidence on how these organizational capabilities together mold decision quality in emerging markets. On the practical side, the results assist manufacturing executives in deciding whether outlays should favor forecasting technologies analytics maturity or governance mechanisms. The study also offers direction for building dependable data systems analytical skills model validation steps accountability arrangements and human oversight practices that turn AI generated financial forecasts into informed timely and strategically aligned decisions.

2. Lliterature Review

2.1 Strategic decision quality

Strategic decision quality reflects how thoroughly a high-stakes, long-term choice aligns with organizational goals, rests on solid intelligence, and effectively delivers its target outcomes (Carmeli et al., 2012; Shepherd et al., 2021). Rather than measuring downstream financial performance, which external shifts can distort, it evaluates the intrinsic validity of the choice and its underlying process. Strong decision quality allows manufacturers to optimize capital allocation, target markets, select technologies, adjust capacity, and adapt smoothly to supply-demand fluctuations. This capability becomes even more essential in emerging economies, where institutional instability, limited resources, infrastructural hurdles, and volatile competition elevate decision risks and errors. Yet, decision quality remains highly variable across organizations. Analytics offers clear benefits in speed and precision, but realizing those gains demands dependable data, skilled personnel, domain expertise, and advanced tools (Ghasemaghaei et al., 2018). Indeed, findings from emerging-market firms indicate that big-data analytics alone cannot ensure sound choices; formal and relational governance critically govern data integrity and knowledge flow, while organizational culture dictates whether insights actually inform actions (Shamim et al., 2020). Consequently, emerging-market manufacturers need more than sophisticated forecasting tools that they require robust data maturity and strong governance frameworks to turn AI insights into clear, context-aware, and defensible strategic choices.

2.2 Critical Analysis of Theoretical Frameworks

2.2.1 Dynamic Capabilities Theory

Dynamic Capabilities Theory (Teece et al., 1997) explains how organizations coordinate, construct, and realign internal and external competencies to adapt to volatile markets, later expanding this into three core mechanisms: sensing opportunities and threats, seizing chosen options, and transforming resource foundations (Teece, 2018). This lens fits this study well because raw AI software, historical financial records, data infrastructure, and technical staff cannot guarantee superior choices on their own; value materializes only when a firm weaves these assets into repeatable routines that track shifts, evaluate choices, and adjust resources. Modern scholarship underscores that competitive advantages stem from actively orchestrating and renewing resources rather than simply owning them (Teece, 2018). Here, AI-driven financial forecasting functions as a digital sensing and seizing apparatus, using machine learning to detect demand swings, cost changes, cash-flow shifts, exchange rate fluctuations, and investment risks across datasets far beyond human cognitive limits. By enabling clear comparisons across sourcing, pricing, capacity, and market-entry choices, this capability becomes strategic when firms continuously update models, combine outputs with human expertise, and anchor predictions within formal decision routines rather than just purchasing tools. Indeed, analytics yields value precisely by converting data into strategic insight, organizational agility, and concrete action (Mikalef et al., 2020; Wamba et al., 2017). Data analytics maturity provides the organizational bedrock for this transition, as mature firms align data hygiene, platform integration, skilled talent, domain expertise, and evidence-guided routines so algorithms learn from clean data and executives interpret predictions within real-world manufacturing constraints. Ghasemaghaei et al. (2018) show that data quality, technical skills, domain context, and tool sophistication collectively elevate decision performance, validating data analytics maturity as an organizational capability rather than a simple IT feature. Strategic decision quality then reflects how effectively sensing and analytical interpretation translate into high-stakes resource commitments, characterized by well-informed choices, strategic alignment, and defensible execution under uncertainty. For emerging-market manufacturers, this flexibility is crucial given that currency shifts, infrastructural hurdles, supply chain gaps, and shifting regulations demand ongoing resource realignment. Manufacturing studies confirm that predictive analytics enhances performance when backed by supportive capabilities and a data-focused mindset (Dubey et al., 2019), while emerging-market evidence ties analytics capabilities and governance directly to better decision outcomes (Shamim et al., 2020). Dynamic Capabilities Theory thus anchors both direct pathways in the model: AI forecasting sharpens decision quality through forward-looking sensing and option testing, while analytics maturity embeds the structures needed to generate, interpret, and act on trustworthy insights. Finally, AI governance guides how forecasting tools are deployed and renewed through validation, accountability, human oversight, and data stewardship rules that keep automated sensing aligned with firm goals positioning strategic decision quality as the product of synchronized sensing, analytical learning, human judgment, opportunity seizure, and resource reconfiguration.

2.2.2 Organizational Information Processing Theory

Organizational Information Processing Theory posits that firm effectiveness hinges on matching information-processing capacity with environmental processing demands, noting that elevated task uncertainty forces organizations to gather, analyze, share, and apply more data during decision-making (Galbraith, 1974). In response, firms build information systems, decision protocols, lateral connections, and coordination structures to boost their processing reach, with modern applications proving that analytical tools, data visibility, and operational agility collectively empower organizations to navigate volatile conditions (Srinivasan & Swink, 2018). This rationale fits emerging-market manufacturing exceptionally well, where strategic choices demand merging financial projections with shifting data on demand, production, suppliers, logistics, currencies, policy, and technology. When these signals fluctuate, remain patchy, or conflict, intuition alone cannot process alternatives consistently; AI-driven financial forecasting fills this gap by aggregating vast datasets, detecting nonlinear patterns, refreshing forecasts, and projecting financial scenarios. However, the theory views processing capacity as extending beyond computing power or data volume because information must also be visible, trustworthy, integrated, relevant, and connected to flexible execution. Indeed, supply and demand visibility supply the baseline inputs for analytics, while organizational agility enables firms to translate analytical output into operational action (Srinivasan & Swink, 2018). Thus, data analytics maturity forms the broader information architecture that renders AI forecasts practical, relying on data standards, integrated IT systems, technical talent, domain knowledge, and cross-functional routines to ground forecasts in operational realities and deliver them to decision-makers. This logic clarifies why AI forecasting capability and analytics maturity independently drive strategic decision quality: forecasting expands predictive power, whereas analytics maturity enhances data reliability, accessibility, context, and organizational alignment. Strategic decision quality improves when this combined capacity satisfies the heavy information demands surrounding capital, capacity, sourcing, pricing, and expansion choices, mirroring evidence that analytical competency boosts both decision quality and efficiency (Ghasemaghaei et al., 2018) while driving quality through knowledge-sharing routines (Ghasemaghaei, 2019). Within this setup, AI governance acts as a key moderator governing how effectively raw processing capacity becomes decision-ready intelligence. By establishing data ownership, validation protocols, error margins, documentation standards, authority limits, human oversight, and escalation paths, governance filters noise, clarifies forecast intents, and directs outputs to managers equipped to interpret them. Because human and automated decision-making vary in interpretability, speed, consistency, and scale, firms must consciously design structures to blend their complementary strengths (Shrestha et al., 2019). Strong governance builds these boundaries and feedback loops so errors continuously refine future models, ultimately amplifying the positive impact of AI forecasting on strategic decision quality, especially in emerging markets where data gaps, institutional shifts, and volatile conditions heighten uncertainty and ambiguity. Ultimately, Organizational Information Processing Theory unites the model around the strategic fit between information requirements and the combined processing capacity supplied by AI forecasting, analytics maturity, human judgment, and governance control.

2.3 The Impact of AI-Powered Financial Forecasting Capability

AI-powered financial forecasting capability denotes a firm's capacity to deploy AI tools alongside financial and operational data, analytical skills, and routines so as to produce, interpret, validate, and refine forecasts that guide strategic resource decisions; this view extends beyond mere software ownership and aligns with Mikalef & Gupta's (2021) portrayal of AI capability as the coordinated use of tangible, human, and intangible assets. Drawing on Dynamic Capabilities Theory, such forecasting helps organizations sense financial risks and opportunities and seize them through timely choices on investment, pricing, capacity, and financing (Teece, 2018), an advantage especially valuable for manufacturers confronting intertwined shifts in demand, costs, cash flows, exchange rates, and supply chains. A critical-realist stance treats the capability as a latent organizational mechanism whose outcomes surface via data structures, managerial expertise, and operating conditions, while pragmatism judges its worth by whether probabilistic forecasts improve action rather than display technical elegance alone (Mikalef et al., 2023). When the capability is enhanced, emerging-market manufacturers can handle heterogeneous data, uncover nonlinear patterns, revise projections more rapidly, and weigh the financial implications of alternative strategies, thereby lowering informational uncertainty and raising the comprehensiveness, speed, and evidential coherence of decisions on capacity, sourcing, working capital, technology, and market entry. Organizational Information Processing Theory indicates that forecasting expands the firm's ability to meet the information demands generated by uncertainty (Srinivasan & Swink, 2018); AI further complements managerial judgment by supplying speed, scale, and consistency while humans address ambiguity, institutional settings, stakeholder concerns, and novel events (Jarrahi, 2018; Shrestha et al., 2019). From a fallibilist perspective, forecasts remain revisable, model-dependent claims whose contribution to decision quality grows when managers treat them as disciplined evidence, probe assumptions, and blend them with contextual insight. Empirical support for a strong direct effect includes Ghasemaghaei et al. (2018), who reported a large positive link between data-analytics competency and decision performance, and Mikalef & Gupta (2021) together with Mikalef et al. (2023), who showed that AI-resource configurations foster creativity, cognitive insight, and automation; manufacturing studies likewise confirm that AI analytics bolsters outcomes under environmental dynamism (Dubey et al., 2020). A more conditional view holds that benefits travel through complementary processes: Ghasemaghaei (2019) found analytics use improves decisions only via knowledge sharing, while Mikalef et al. (2023) and Enholm et al. (2022) emphasize that value arises from the interplay of data, skills, processes, and managerial arrangements. Both positions nevertheless converge on a positive relationship: as the capability matures, forecast information grows more timely, diagnostic, and strategically actionable, thereby fostering higher-quality commitments. Therefore:

H1: AI-powered financial forecasting capability has a positive impact on strategic decision quality in emerging market manufacturing firms.

2.4 The Impact of Data Analytics Maturity

Data analytics maturity refers to the extent to which an organization has embedded the strategy, governance, data quality, infrastructure, methods, skills, culture, and repeatable routines needed to convert data into dependable, actionable knowledge; it therefore represents a developmental condition rather than the simple ownership of databases or software. Grossman (2018) outlines progressive levels from elementary reporting to strategy-oriented, firm-wide analytics, and Langer's (2025) review confirms that maturity spans organizational, technological, and data-related domains. In manufacturing settings this maturity matters because production, financial, supplier, inventory, and market data must first be governed and made interpretable before they can shape high-stakes choices; Gökalp et al. (2021) accordingly frame data-science maturity as a foundational capability for data-driven manufacturing. Philosophically, critical realism views maturity as a socio-technical mechanism whose effects hinge on organizational structures, while pragmatism evaluates analytical knowledge by its usefulness for action rather than by the mere accumulation of data. As maturity rises, emerging-market manufacturers shift from scattered spreadsheets and backward-looking reports toward unified platforms, systematic model building, predictive and prescriptive techniques, cross-functional sense-making, and governance aligned with strategy. The resulting gains in completeness, consistency, accessibility, and diagnostic power enable managers to assess capital projects, capacity, sourcing, pricing, liquidity, and market-entry options on firmer evidential grounds. Organizational Information Processing Theory suggests that greater maturity enlarges the firm's capacity to meet the information demands created by uncertainty, thereby enhancing decision comprehensiveness, speed, and coherence (Srinivasan & Swink, 2018). Dynamic Capabilities Theory likewise implies that mature analytics aids the sensing of environmental shifts, the seizing of opportunities, and the reconfiguration of manufacturing resources (Mikalef et al., 2020). Epistemologically, a positivist stance stresses measurement and replicable evidence, yet a fallibilist outlook reminds us that datasets remain incomplete representations; decision quality improves when analytical outputs stay testable and revisable and are filtered through managerial and institutional understanding. Advocates of a strong direct effect refer to Shamim et al. (2019), who demonstrated that big data decision making capability, developed through leadership, talent, technology, and organizational culture, substantially enhances decision quality in Chinese firms. They also cite Ghasemaghaei et al. (2018), who identified a strong positive relationship between analytics competency and decision performance. Szukits & Móricz (2024) further observe that strategic emphasis on analytics cultivates an analytical culture and broader data use across decision stages, while maturity itself enables scalable, governed model deployment rather than isolated experiments (Grossman, 2018; Gökalp et al., 2021). A more moderate view accepts the positive direction but attributes much of the influence to complementary processes: Fattah (2024) finds that business-analytics capability improves decision performance only through big-data literacy and competency, and Szukits & Móricz (2024) show managerial support working via analytical culture and organizational arrangements. This pattern accords with interpretive pragmatism, in which data gain strategic significance through users, routines, dialogue, and purpose. Consequently, higher maturity should raise decision quality, yet the strength of that effect depends on managers' ability to situate evidence and convert insight into commitment; both perspectives nonetheless converge on a positive relationship because greater maturity renders evidence more reliable, integrated, timely, and usable. Accordingly:

H2: Data analytics maturity has a positive impact on strategic decision quality in emerging market manufacturing firms.

2.5 The Moderating Role of AI Governance Framework

An AI governance framework comprises the rules, decision rights, roles, practices, processes, and technical controls that oversee AI throughout its lifecycle, ensuring alignment with strategy, legal requirements, and ethical standards; this conceptualization follows Mäntymäki et al. (2022), with Schneider et al. (2023) emphasizing oversight of data, machine-learning models, and AI systems, and Papagiannidis et al. (2025) organizing responsible governance into structural, relational, and procedural elements. Its dual role is both enabling and constraining: through validation, data stewardship, explainability, human oversight, and accountability it renders AI outputs more trustworthy and usable. Philosophically, deontological ethics stresses duties of fairness, transparency, and answerability irrespective of results, while consequentialism judges governance by its capacity to improve decisions and curb harm (Madanchian & Taherdoost, 2025); critical realism, in turn, regards governance as a latent mechanism whose effects surface in model reliability, managerial trust, and decision outcomes (Stohr et al., 2024). The framework is expected to positively moderate the link between AI-powered financial forecasting capability and strategic decision quality because forecasting generates predictions, yet governance decides whether those predictions are valid, interpretable, properly channeled, and used responsibly. In emerging-market manufacturing, models integrate financial data with fluctuating demand, input costs, exchange rates, and supplier information; robust governance therefore sets data-quality thresholds, model ownership, validation routines, error tolerances, decision authority, and escalation paths, lowering the chance that biased, stale, or contextually unsuitable forecasts shape investment, capacity, sourcing, pricing, or financing choices. Organizational Information Processing Theory suggests that governance elevates the quality and control of information flows, allowing forecasting capacity to meet strategic information needs more effectively, while human–AI research underscores the necessity of allocating tasks according to AI's computational strengths and managers' contextual and ethical judgment (Shrestha et al., 2019; Berente et al., 2021). Proponents of strong moderation contend that governance converts AI capability into reliable decision infrastructure: Papagiannidis et al. (2023) highlight accountability, transparency, fairness, data management, and human oversight as enablers of robust applications; Rana et al. (2022) show that opacity in AI–business analytics produces suboptimal decisions, elevated risk, inefficiency, and competitive disadvantage, implying that greater traceability and explainability safeguard the forecasting–decision pathway; and Kordzadeh & Ghasemaghaei (2022) demonstrate that algorithmic bias can emerge across data, model, and use contexts, reinforcing the need for lifecycle controls. Parallel emerging-market findings indicate that contractual and relational governance strengthen analytics-driven decision performance (Shamim et al., 2020). Together these results point to a substantial positive interaction whereby strong governance enables the same forecasting capability to yield more credible and defensible strategic choices. A more moderate stance holds that governance strengthens rather than guarantees the relationship. Keding & Meissner (2021) observed that AI advice can shape strategic choices while inflating perceived decision quality, thereby indicating the possibility of excessive reliance on AI; moreover, governance principles deliver value only when embodied in operational structures, relationships, and procedures (Papagiannidis et al., 2025). Overly rigid controls may retard responsiveness, and purely symbolic policies cannot remedy poor data or managerial misreading. From fallibilist and pragmatist standpoints, no framework transforms forecasts into certain knowledge; governance instead establishes disciplined conditions for testing, challenging, and revising AI claims. Its moderating influence should therefore remain positive yet contingent on implementation quality, analytical maturity, and genuine human oversight. Although direct evidence for this precise interaction is still emerging, H3 represents a theory-informed extension of governance, analytics, and human–AI decision research; both perspectives nevertheless anticipate that stronger governance heightens the degree to which forecasting capability enhances strategic decision quality.Accordingly, H3 is proposed:

H3: AI governance framework positively moderates the influence of AI-powered financial forecasting capability on strategic decision quality in emerging market manufacturing firms.

Grounded in established theoretical foundations, this study advances existing knowledge through the conceptual framework presented in Figure 1:

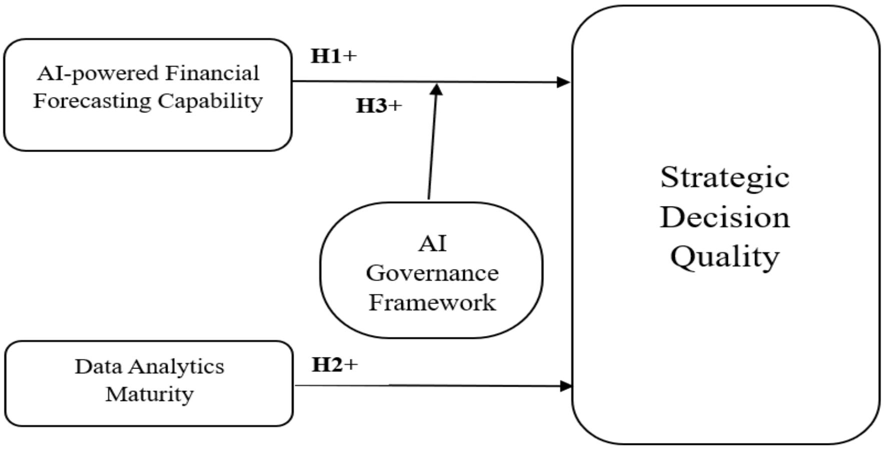

Figure 1: The Paper Conceptual Framework

3. Methods

2.1 Sampling Strategy

This research adopted a quantitative cross sectional approach to explore the influence of AI powered financial forecasting capability and data analytics maturity on strategic decision quality in manufacturing firms located in Vietnam while also testing the moderating role of the AI governance framework. Vietnam was chosen as it stands as a fast growing emerging economy where manufacturing organizations are progressively turning to AI and data analytics for better financial forecasting and strategic planning. The quantitative strategy enabled thorough testing of hypotheses along with statistical evaluation of direct effects and interaction effects drawn from standardized survey responses. Gathering information at a single moment in time made it possible to capture efficiently the perceptions of participants concerning forecasting practices analytics maturity AI governance and strategic decisions (Bryman, 2016).

Purposive sampling was applied to identify individuals who held sufficient organizational knowledge and were actively involved in financial forecasting analytics AI applications or strategic decision processes inside manufacturing businesses operating in Vietnam. Even though the individual respondent served as the unit of analysis the constructs captured organizational level features through the informed views each person held about their own firm. Eligible respondents included business owners senior and middle managers finance professionals accountants data and business analysts information technology specialists production and supply chain managers together with employees taking part in AI assisted planning or strategic decision making. All participants had to work for Vietnamese manufacturing enterprises or manufacturing firms operating within Vietnam and needed familiarity with how their organizations applied financial data analytics or AI generated forecasts. Recruitment reached companies situated in key industrial and economic zones throughout Vietnam and included diverse manufacturing sectors different firm sizes varied professional roles and differing degrees of technological experience so as to broaden sample diversity. Data collection relied on a structured self administered questionnaire adapted from established academic measures. AI powered financial forecasting capability measured the firm capacity to combine AI technologies financial and operational data analytical expertise and organizational routines in order to generate interpret validate and refine forecasts (Mikalef & Gupta, 2021; Mikalef et al., 2023). Data analytics maturity assessed how far analytics strategy infrastructure data quality technical skills organizational culture and repeatable analytical processes had become embedded throughout the firm (Grossman, 2018; Gökalp et al., 2021). The AI governance framework covered formal rules accountability data stewardship model validation transparency human oversight risk controls and continuous monitoring across the full AI lifecycle (Mäntymäki et al., 2022; Schneider et al., 2023). Strategic decision quality examined whether major organizational decisions proved informed timely comprehensive strategically aligned and defensible when facing uncertainty (Carmeli et al., 2012; Ghasemaghaei et al., 2018).

All questionnaire items used a five point Likert scale that ranged from 1 for strongly disagree to 5 for strongly agree. Academic experts and practitioners based in Vietnam with experience in finance manufacturing analytics and AI governance reviewed the questionnaire to ensure clarity and content validity. A pilot survey conducted with eligible respondents from Vietnamese manufacturing firms supported minor refinements in wording before the final electronic distribution took place through professional networks manufacturing associations organizational contacts and online channels across Vietnam. Participation was voluntary and anonymous and respondents were informed about the academic purpose of the study along with the confidentiality protections in place. Once incomplete duplicate patterned and disengaged responses had been removed 385 valid questionnaires completed by individuals employed in manufacturing enterprises in Vietnam remained available for analysis.

3.2 Data analysis

Analysis of the data relied on IBM SPSS version 26 together with Hayes PROCESS macro. Descriptive statistics initially outlined the demographic and professional profiles of respondents. Internal consistency was evaluated through Cronbach alpha where values of 0.70 or higher along with corrected item total correlations surpassing 0.30 signaled satisfactory reliability (Tavakol & Dennick, 2011). Exploratory factor analysis followed employing principal component extraction and Varimax rotation. Retention of items occurred only if factor loadings surpassed 0.50 and no notable cross loadings appeared (Hair et al., 2009). Multiple linear regression assessed the direct influences of AI powered financial forecasting capability and data analytics maturity upon strategic decision quality. Significance was judged using a threshold of p less than 0.05. Hayes PROCESS Model 1 was applied last to determine if the AI governance framework moderated the link between AI powered financial forecasting capability and strategic decision quality (Hayes, 2022).

4. Results

4.1 Descriptive Statistical Analysis

The sample covered manufacturing firms situated in the principal economic regions of Vietnam. In particular 44.2 percent of respondents were employed by companies in Southern Vietnam while 31.9 percent worked in Northern Vietnam and 23.9 percent belonged to firms in Central Vietnam. Turning to organizational roles middle or functional managers formed the biggest category at 24.9 percent followed by owners directors or senior managers at 22.1 percent finance or accounting professionals at 21.6 percent data analytics or information technology specialists at 17.1 percent and production or supply chain professionals at 14.3 percent. With respect to firm size organizations that employed 50 to 249 people made up the largest share at 33.5 percent whereas companies with 250 to 999 employees represented 30.1 percent. Smaller enterprises with fewer than 50 staff accounted for 16.1 percent and large organizations employing at least 1000 people constituted 20.3 percent. In addition 37.7 percent of participants stated high familiarity with their firms use of AI powered financial forecasting and data analytics while 21.0 percent reported very high familiarity and 30.9 percent noted moderate familiarity. Only 10.4 percent had limited familiarity. Taken together these figures show that the sample included diverse organizational settings and that the majority of respondents held enough professional knowledge to assess AI forecasting capability data analytics maturity AI governance and strategic decision quality.

4.2 Reliability analysis

Table 1 below presents the measurement items used to operationalize the study constructs. Each construct was measured using four items adapted from established academic literature to ensure theoretical relevance and adequate coverage of its underlying dimensions. All items were assessed using a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree.

Table 1: Measurement Items

Code	Survey item	Theoretical source
AI-Powered Financial Forecasting Capability		
AI1	Our firm integrates financial and operational data when producing AI-supported financial forecasts.	(Mikalef & Gupta, 2021; Mikalef et al., 2023)
AI2	Our firm can use AI tools to generate financial forecasts for different strategic scenarios.	(Mikalef & Gupta, 2021; Shrestha et al., 2019)
AI3	AI-generated financial forecasts are regularly validated and updated using newly available information.	(Mikalef et al., 2023; Ghasemaghaei et al., 2018)
AI4	Employees responsible for forecasting can interpret AI-generated financial outputs within the firm's operating context.	(Jarrahi, 2018; Shrestha et al., 2019)
Data Analytics Maturity		
DAM1	Our firm has integrated data infrastructure that supports analytics across relevant business functions.	(Grossman, 2018; Gökalp et al., 2021)
DAM2	Our firm follows established procedures for maintaining the accuracy, consistency, and accessibility of data.	(Ghasemaghaei et al., 2018; Gökalp et al., 2021)
DAM3	Our firm has employees with the technical and business knowledge required to conduct and interpret data analytics.	(Ghasemaghaei et al., 2018; Shamim et al., 2019)

DAM4	Data analytics is embedded in repeatable organizational processes rather than being used only for isolated tasks.	(Grossman, 2018; Szukits & Móricz, 2024)
AI Governance Framework		
GF1	Our firm has clearly assigned roles and responsibilities for governing AI systems.	(Mäntymäki et al., 2022; Papagiannidis et al., 2025)
GF2	Our firm applies formal procedures for validating and monitoring AI models throughout their lifecycle.	(Schneider et al., 2023; Papagiannidis et al., 2023)
GF3	The data sources, assumptions, and limitations of AI-generated outputs are documented within our firm.	(Rana et al., 2022; Schneider et al., 2023)
GF4	Our firm requires appropriate human oversight when AI outputs are used in important organizational activities.	(Berente et al., 2021; Papagiannidis et al., 2023)
Strategic Decision Quality		
SDQ1	Our firm's strategic decisions are based on relevant and sufficiently reliable information.	(Carmeli et al., 2012; Ghasemaghaei et al., 2018)
SDQ2	Strategic decisions in our firm are made within a timeframe appropriate to the situation.	(Elbanna et al., 2016; Ghasemaghaei et al., 2018)
SDQ3	Relevant strategic alternatives are carefully considered before major decisions are finalized.	(Carmeli et al., 2012; Shepherd et al., 2021)
SDQ4	Our firm's strategic decisions are consistent with its broader organizational objectives.	(Carmeli et al., 2012; Elbanna et al., 2016)

Table 2: Reliability analysis of "Strategic Decision Quality"

Reliability Statistics

Cronbach's Alpha	N of Items
.756	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SDQ1	10.842	5.216	.586	.741
SDQ2	10.765	5.084	.641	.711
SDQ3	10.913	5.327	.647	.708
SDQ4	10.806	5.145	.579	.744

Source: (The authors, 2026)

Where the four survey items, labeled SDQ1 to SDQ4, corresponded to Questions 1 through 4 and were developed to measure strategic decision quality.

As presented in Table 2, all items recorded corrected item total correlation values above the recommended threshold of 0.30. The overall scale achieved a Cronbach's alpha of 0.756, exceeding the minimum acceptable level of 0.70 and confirming satisfactory internal consistency. Moreover, the Cronbach's alpha values obtained after deleting individual items ranged from 0.708 to 0.744, all of which were lower than the overall alpha. This finding indicates that removing any item would reduce the reliability of the scale. Therefore, all four items contributed meaningfully to the construct and were retained for subsequent analyses. Comparable levels of reliability were also identified for the other measurement scales employed in the study (Hair et al., 2009; Tavakol & Dennick, 2011).

4.3 Exploratory factor analysis (EFA)

Table 3: Factor Loading Matrix.

Rotated Component Matrix[a]							
Component with loading factors							
1		2		3		4	
AI1	0.782	DAM1	0.746	GF1	0.769	SDQ1	0.738
AI2	0.815	DAM2	0.791	GF2	0.811	SDQ2	0.701
AI3	0.754	DAM3	0.713	GF3	0.728	SDQ3	0.776

AI4	0.697	DAM4	0.684	GF4	0.693	SDQ4	0.722
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.							
a. Rotation converged in 7 iterations.							

Source: (The authors, 2026)

Where the measurement items labeled AI1–AI4, DAM1–DAM4, GF1–GF4, and SDQ1–SDQ4 were developed to measure AI-powered financial forecasting capability, data analytics maturity, AI governance framework, and strategic decision quality, respectively, with each construct represented by four indicators.

Table 3 presents the exploratory factor analysis results, which identified four distinct factors corresponding to the dependent variable, two independent variables, and moderating variable. All 16 items loaded strongly on their intended factors, with coefficients ranging from 0.684 to 0.815, thereby exceeding the recommended threshold of 0.50 (Hair et al., 2009). The Varimax rotation converged after seven iterations, indicating a stable factor solution. Therefore, no items were removed, and all 16 indicators were retained for subsequent analysis, providing satisfactory support for the proposed four-factor structure and construct validity of the measurement model.

4.4 Multiple linear regression model

Table 4: Coefficients[a].

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
Constant	0.352	0.141		2.496	0.013
AI	0.452	0.024	0.580	18.833	0.000
DAM	0.468	0.024	0.601	19.500	0.000
a. Dependent Variable: SDQ					

Source: (The authors, 2026)

Where AI represents the mean of AI1–AI4, DAM represents the mean of DAM1–DAM4, and SDQ represents the mean of SDQ1–SDQ4.

As shown in Table 4, the significance values for the relationships between AI-powered financial forecasting capability and strategic decision quality and between data analytics maturity and strategic decision quality were both 0.000, which is well below the 0.05 threshold. AI-powered financial forecasting capability had a significant positive effect on strategic decision quality with $\beta = 0.580$, $t = 18.833$, and $p < 0.001$. Data analytics maturity also exerted a significant positive effect with $\beta = 0.601$, $t = 19.500$, and $p < 0.001$. These findings provide strong empirical support for accepting H1 and H2.

4.5 Moderator analysis

Table 5: Results analysis of "AI Governance Framework".

Model: 1 Y: SDQ X: AI W: GF Sample Size: 385

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OUTCOME VARIABLE: BA Model Summary

R	R-sq	MSE	F	dl1	dl2	p
.732	.536	0.285	146.707	3.000	381.000	.000

Model	Coeff.	SE	t	p	LLCI	ULCI
Constant	3.462	0.035	98.914	0.000	3.393	3.531
AI	0.631	0.044	14.341	0.000	0.545	0.717
GF	0.597	0.043	13.884	0.000	0.512	0.682
Int_1	0.387	0.037	10.459	0.000	0.314	0.460

Source: (The authors, 2026)

Where GF was calculated as the mean score of items GF1 to GF4.

The positive interaction coefficient (B = 0.387) indicates that a stronger AI governance framework amplifies the positive influence of AI powered financial forecasting capability on strategic decision quality. In other words, the contribution of AI based financial forecasts to informed, timely, comprehensive, and strategically aligned decisions becomes more pronounced when firms establish clear accountability, model validation, data stewardship, transparency, continuous monitoring, and human oversight. Such governance arrangements enable managers to evaluate AI generated forecasts more carefully and apply them within appropriate organizational and strategic contexts. Furthermore, the confidence interval for the interaction effect, ranging from LLCI = 0.314 to ULCI = 0.460, does not include zero, confirming the significance and stability of the moderating effect. Overall, the results establish the AI governance framework as an important boundary condition that strengthens the influence of AI powered financial forecasting capability on strategic decision quality in Vietnamese manufacturing firms. Therefore, Hypothesis H3 is empirically supported.

5. Discussion

5.1Result Summary

AI powered financial forecasting capability and data analytics maturity both showed marked positive influences on strategic decision quality through standardized regression coefficients of 0.580 and 0.601 respectively. These outcomes reveal that generating timely reliable AI based financial forecasts combined with mature data infrastructure analytical expertise and evidence based decision processes markedly elevates strategic decision quality among emerging market manufacturing firms. Moreover the AI governance framework exerted a significant positive moderating effect that reinforced the link between AI powered financial forecasting capability and strategic decision quality as shown by the interaction coefficient of 0.387 together with a confidence interval from 0.314 to 0.460. Such evidence implies that the decision value of AI powered forecasting grows clearer once firms adopt clear accountability model validation data stewardship transparency continuous monitoring and human oversight. In short, the results furnish robust empirical backing for all three proposed hypotheses and affirm the conceptual framework that connects AI powered financial forecasting capability data analytics maturity AI governance framework and strategic decision quality.

Concerning the research questions the findings settle the first by verifying that AI powered financial forecasting capability meaningfully raises strategic decision quality. They settle the second by showing that data analytics maturity exerts a slightly stronger positive effect on strategic decision quality. They settle the third by confirming that a stronger AI governance framework notably intensifies the beneficial contribution of AI powered financial forecasting capability to strategic decision quality. In sum, these outcomes establish that manufacturing firms need advanced forecasting technologies mature analytical capabilities and sound governance arrangements alike to convert AI generated insights into informed timely comprehensive and strategically aligned decisions.

5.2 Theoretical Implications

The empirical findings strongly support H1 since AI powered financial forecasting capability markedly elevates strategic decision quality with $\beta = 0.580$. This outcome closely matches Teece (2018) and Srinivasan & Swink (2018) who hold that advanced forecasting broadens organizational sensing and information processing capacity. It likewise aligns with Ghasemaghaei et al. (2018), Mikalef & Gupta (2021), and Dubey et al. (2020) who link analytical capabilities to better decision results. Yet it only partly agrees with Ghasemaghaei (2019) and Enholm et al. (2022) who claim AI mainly creates value through knowledge sharing and complementary organizational arrangements. While those routes may boost effectiveness the large direct coefficient shows that forecasting capability itself adds real weight to decision quality. Still the study challenges pure technological determinism for managerial interpretation stays vital amid contextual ambiguity (Jarrahi, 2018; Shrestha et al., 2019). In theoretical terms the work adds by framing AI powered financial forecasting as an organizational capability that turns predictive intelligence straight into stronger strategic decisions in emerging market manufacturing firms.

The empirical findings further uphold H2 given that data analytics maturity produces a clear positive effect on strategic decision quality shown by $\beta = 0.601$. This result firmly agrees with Shamim et al. (2019) and Ghasemaghaei et al. (2018) who stress that integrated analytical competencies sharply improve decision outcomes. It also backs Grossman (2018), Gökalp et al. (2021), and Szukits & Móricz (2024) because mature data governance infrastructure analytical expertise and organizational culture let firms convert scattered information into usable evidence. On the other hand it only partly backs Fattah (2024) and Szukits & Móricz (2024) who argue that analytics mainly aids decisions through intervening factors such as data literacy competency and analytical culture. Although those factors matter the solid direct effect proves analytics maturity carries its own explanatory force. Its coefficient even edges past that of AI powered forecasting and thereby questions technology centered views. Theoretically, the study adds by treating data analytics maturity as a separate information processing and dynamic capability that directly lifts strategic decision quality amid emerging market uncertainty.

At the same time the empirical findings firmly support H3 because the positive interaction coefficient of 0.387 shows that the AI governance framework heightens the effect of AI powered financial forecasting capability on strategic decision quality. This result firmly matches Papagiannidis et al. (2023), Rana et al. (2022), and Kordzadeh & Ghasemaghaei (2022) who stress that accountability explainability data controls and human oversight shield decisions from algorithmic opacity bias and misuse. The outcome also builds on Shamim et al. (2020) by proving that governance does more than aid analytics in general and specifically raises the decision value drawn from forecasting capability. Yet, it only partly matches Keding & Meissner (2021) who caution that AI advice can raise perceived decision quality through managerial overreliance. The clear interaction implies that sound governance can curb that risk via systematic validation and managerial challenge. The study rejects purely symbolic or overly rigid governance since weak controls may curb responsiveness (Papagiannidis et al., 2025). Theoretically, the work adds by casting AI governance as an enabling boundary condition rather than a mere restrictive compliance device.

5.3 Practical Implications

The empirical findings firmly uphold H1 and show that manufacturing executives ought to regard AI powered financial forecasting as a strategic decision capability instead of a pure technology purchase. With its clear effect on strategic decision quality $\beta = 0.580$ firms need to fold AI forecasts into capital budgeting capacity planning sourcing pricing cash flow management and market expansion choices. Managers should set up rolling forecasting routines that merge operational and financial data weigh alternative scenarios and revise model assumptions whenever demand exchange rates or input costs shift. Yet automated forecasts must guide rather than displace managerial judgment. Cross functional review teams that bring together finance production supply chain and technology specialists should inspect forecast assumptions and place probabilistic outputs in context before any strategic commitment is approved. This practice mirrors the complementary strengths of algorithmic processing and human judgment noted by Jarrahi (2018) and Shrestha et al. (2019). Firms should also judge forecasting investments by gains in decision timeliness evidential breadth and strategic fit rather than technical accuracy alone because AI yields business value only when paired with fitting organizational resources and routines (Mikalef & Gupta, 2021; Enholm et al., 2022).

The empirical findings likewise firmly support H2 as data analytics maturity yields the strongest direct effect on strategic decision quality $\beta = 0.601$. In practical terms this outcome cautions firms against buying ever more advanced AI tools while their data stay fragmented inconsistent hard to reach or weakly governed. Manufacturing leaders should first gauge maturity across data quality system integration analytical expertise organizational culture governance and evidence based routines. Investment focus should cover linking financial production inventory supplier and market databases setting shared data definitions raising real time access and training managers to read analytical evidence. Such steps can shift firms from isolated spreadsheets and descriptive reports toward scalable predictive and prescriptive analysis in line with the maturity view of Grossman (2018) and Gökalp et al. (2021). Senior management should further form cross functional analytics teams and build evidence use into decision protocols and performance reviews. These habits matter because technical assets alone cannot lift decisions when staff lack analytical literacy or when culture resists data use (Fattah, 2024; Szukits & Móricz, 2024). Analytics maturity must therefore come before or run alongside major AI outlays.

Finally the empirical findings firmly support H3 and reveal that AI governance reinforces the forecasting and decision quality link with an interaction coefficient of 0.387. Manufacturing firms should therefore put governance in place before relying on AI forecasts for high stakes choices. A multidisciplinary governance committee should assign model ownership set approval authority record data sources and assumptions fix validation thresholds track forecast errors and define escalation steps when outputs look unreliable. Human review must stay mandatory for major investment financing capacity and market entry decisions. These safeguards tackle the risks of algorithmic opacity and bias flagged by Rana et al. (2022) and Kordzadeh & Ghasemaghaei (2022). Still governance must match decision risk. Overly rigid rules may delay reactions to market shocks while purely symbolic policies offer scant protection. Firms should therefore apply tighter checks to high impact decisions and allow quicker review for routine forecasts. Governance should function as an enabling device that raises transparency accountability and managerial confidence in keeping with the structural relational and procedural stance advanced by Papagiannidis et al. (2025).

5.4 Limitations

This study has several limitations. First, its cross sectional design captures perceptions at one point in time and therefore cannot establish definitive causal relationships or reveal how forecasting, analytics maturity, and governance evolve. Second, self reported measures may be affected by social desirability, common method bias, and differences in respondents' understanding of organizational practices. Third, although the sample of 385 respondents provides adequate statistical power, its focus on Vietnamese manufacturing firms limits generalization to other emerging economies, industries, and institutional environments. Fourth, purposive sampling may underrepresent firms with limited digital capability. Finally, the model examines only two direct predictors and one moderator, leaving possible mediating mechanisms and contextual conditions unexplored.

5.5 Future Research Directions

Future research should employ longitudinal or panel designs to determine whether improvements in forecasting capability and analytics maturity produce sustained gains in strategic decision quality. Comparative studies across emerging economies could examine whether institutional quality, digital infrastructure, industry turbulence, or firm size changes the identified relationships. Researchers should combine managerial surveys with objective indicators, including forecast accuracy, decision speed, investment outcomes, and model error rates, to reduce common method bias. Future models could investigate knowledge sharing, managerial trust, analytical culture, and human AI collaboration as mediators. Additional moderators, such as environmental uncertainty, leadership support, or regulatory pressure, may explain when governance becomes most valuable. Qualitative case studies could also clarify how firms translate formal governance principles into operational decision routines.

5.6 Conclusion

This study demonstrates that strategic decision quality in manufacturing firms is strengthened by the combined development of AI powered financial forecasting capability, data analytics maturity, and effective AI governance. AI forecasting and analytics maturity exerted significant positive effects, with standardized coefficients of 0.580 and 0.601, respectively, while the positive interaction coefficient of 0.387 confirmed that governance amplifies the decision value of forecasting capability. These findings answer all three research questions and support the proposed hypotheses. The study concludes that advanced forecasting technology alone is insufficient. Manufacturers must integrate reliable data, analytical expertise, cross functional routines, accountability, validation, and human oversight to convert AI generated predictions into informed and strategically aligned decisions. The resulting framework extends understanding of responsible AI enabled decision making within emerging market manufacturing contexts.

Reference

[1]. Berente, N., Gu, B., Recker, J., & Santhanam, R. (2021). Managing artificial intelligence. *MIS quarterly*, *45*(3), 1433-1450. https://doi.org/10.25300/MISQ/2021/16274

[2]. Bryman, A. (2016). *Social Research Methods*. Oxford University Press.

[3]. Carmeli, A., Tishler, A., & Edmondson, A. C. (2012). CEO relational leadership and strategic decision quality in top management teams: The role of team trust and learning from failure. *Strategic Organization*, *10*(1), 31-54. https://doi.org/10.1177/1476127011434797

[4]. Dubey, R., Gunasekaran, A., Childe, S. J., Blome, C., & Papadopoulos, T. (2019). Big data and predictive analytics and manufacturing performance: integrating institutional theory, resource-based view and big data culture. *British journal of management*, *30*(2), 341-361. https://doi.org/10.1111/1467-8551.12355

[5]. Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., ... & Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International journal of production economics*, *226*, 107599. https://doi.org/10.1016/j.ijpe.2019.107599

[6]. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. International journal of information management, 57, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

[7]. Elbanna, S., Andrews, R., & Pollanen, R. (2016). Strategic planning and implementation success in public service organizations: Evidence from Canada. *Public management review*, *18*(7), 1017-1042. https://doi.org/10.1080/14719037.2015.1051576

[8]. Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information systems frontiers*, *24*(5), 1709-1734. https://doi.org/10.1007/s10796-021-10186-w

[9]. Fattah, I. A. (2024). Decision making performance of business analytics capabilities: the role of big data literacy and analytics competency. *Business Process Management Journal*, *30*(6), 2096-2126. https://doi.org/10.1108/BPMJ-11-2023-0894

[10]. Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, *4*(3), 28-36. https://doi.org/10.1287/inte.4.3.28

[11]. Ghasemaghaei, M. (2019). Does data analytics use improve firm decision making quality? The role of knowledge sharing and data analytics competency. *Decision Support Systems*, *120*, 14-24. https://doi.org/10.1016/j.dss.2019.03.004

[12]. Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems*, *27*(1), 101-113. https://doi.org/10.1016/j.jsis.2017.10.001

[13]. Gökalp, M. O., Gökalp, E., Kayabay, K., Koçyiğit, A., & Eren, P. E. (2021). Data-driven manufacturing: An assessment model for data science maturity. *Journal of Manufacturing Systems*, *60*, 527-546. https://doi.org/10.1016/j.jmsy.2021.07.011

[14]. Grossman, R. L. (2018). A framework for evaluating the analytic maturity of an organization. *International Journal of Information Management*, *38*(1), 45-51. https://doi.org/10.1016/j.ijinfomgt.2017.08.005

[15]. Guthrie, C. H., Fosso-Wamba, S., Queiroz, M. M., & Cai, H. (2025). The Impact of Artificial Intelligence Capabilities on Decision-Making Performance: A Longitudinal Study. *Journal of Global Information Management (JGIM)*, *33*(1), 1-27.

[16]. Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2009). *Multivariate Data Analysis* (7th ed.). Prentice Hall.

[17]. Hayes, A. F. (2022). *Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach* (3rd ed.). Guilford Press.

[18]. Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business horizons*, *61*(4), 577-586. https://doi.org/10.1016/j.bushor.2018.03.007

[19]. Keding, C., & Meissner, P. (2021). Managerial overreliance on AI-augmented decision-making processes: How the use of AI-based advisory systems shapes choice behavior in R&D investment decisions. *Technological Forecasting and Social Change*, *171*, 120970. https://doi.org/10.1016/j.techfore.2021.120970
[20]. Kordzadeh, N., & Ghasemaghaei, M. (2022). Algorithmic bias: review, synthesis, and future research directions. *European Journal of Information Systems*, *31*(3), 388-409. https://doi.org/10.1080/0960085X.2021.1927212
[21]. Langer, B. (2025). Understanding data & analytics maturity: a systematic review of maturity model composition. *Schmalenbach Journal of Business Research*, *77*(2), 205-227. https://doi.org/10.1007/s41471-024-00205-2
[22]. Madanchian, M., & Taherdoost, H. (2025). Ethical theories, governance models, and strategic frameworks for responsible AI adoption and organizational success. *Frontiers in Artificial Intelligence*, *8*, 1619029. https://doi.org/10.3389/frai.2025.1619029
[23]. Mäntymäki, M., Minkkinen, M., Birkstedt, T., & Viljanen, M. (2022). Defining organizational AI governance. *AI and Ethics*, *2*(4), 603-609. https://doi.org/10.1007/s43681-022-00143-x
[24]. Mikalef, P., & Gupta, M. (2021). Artificial intelligence capability: Conceptualization, measurement calibration, and empirical study on its impact on organizational creativity and firm performance. *Information & management*, *58*(3), 103434. https://doi.org/10.1016/j.im.2021.103434
[25]. Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: the mediating role of dynamic capabilities and moderating effect of the environment. *British journal of management*, *30*(2), 272-298. https://doi.org/10.1111/1467-8551.12343
[26]. Mikalef, P., Lemmer, K., Schaefer, C., Ylinen, M., Fjørtoft, S. O., Torvatn, H. Y., ... & Niehaves, B. (2023). Examining how AI capabilities can foster organizational performance in public organizations. *Government Information Quarterly*, *40*(2), 101797. https://doi.org/10.1016/j.giq.2022.101797
[27]. Papagiannidis, E., Enholm, I. M., Dremel, C., Mikalef, P., & Krogstie, J. (2023). Toward AI governance: Identifying best practices and potential barriers and outcomes. *Information Systems Frontiers*, *25*(1), 123-141. https://doi.org/10.1007/s10796-022-10251-y
[28]. Papagiannidis, E., Mikalef, P., & Conboy, K. (2025). Responsible artificial intelligence governance: A review and research framework. *The Journal of Strategic Information Systems*, *34*(2), 101885. https://doi.org/10.1016/j.jsis.2024.101885
[29]. Papagiannidis, E., Mikalef, P., & Conboy, K. (2025). Responsible artificial intelligence governance: A review and research framework. *The Journal of Strategic Information Systems*, *34*(2), 101885. https://doi.org/10.1016/j.jsis.2024.101885
[30]. Rana, N. P., Chatterjee, S., Dwivedi, Y. K., & Akter, S. (2021). Understanding dark side of artificial intelligence (AI) integrated business analytics: assessing firm's operational inefficiency and competitiveness. https://doi.org/10.1080/0960085x.2021.1955628
[31]. Ransbotham, S., Khodabandeh, S., Fehling, R., LaFountain, B., & Kiron, D. (2019). Winning with AI. MIT Sloan management review. https://sloanreview.mit.edu/projects/winning-with-ai/
[32]. Schneider, J., Abraham, R., Meske, C., & Vom Brocke, J. (2023). Artificial intelligence governance for businesses. *Information Systems Management*, *40*(3), 229-249. https://doi.org/10.1080/10580530.2022.2085825
[33]. Shamim, S., Zeng, J., Khan, Z., & Ul Zia, N. (2020). Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technological Forecasting and Social Change*, *161*. https://doi.org/10.1016/j.techfore.2020.120315
[34]. Shamim, S., Zeng, J., Shariq, S. M., & Khan, Z. (2019). Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. *Information & Management*, *56*(6), 103135. https://doi.org/10.1016/j.im.2018.12.003
[35]. Shepherd, N., Mooi, E. A., Elbanna, S., & Rudd, J. (2021). Deciding fast: examining the relationship between strategic decision speed and decision quality across multiple environmental contexts. *European Management Review*, *18*(2), 119-140. https://doi.org/10.1111/emre.12430
[36]. Shrestha, N. (2020). Detecting multicollinearity in regression analysis. American Journal of Applied Mathematics and Statistics, 8(2), 39–42. https://doi.org/10.12691/ajams-8-2-1
[37]. Shrestha, Y. R., Ben-Menahem, S. M., & Von Krogh, G. (2019). Organizational decision-making structures in the age of artificial intelligence. *California management review*, *61*(4), 66-83. https://doi.org/10.1177/0008125619862257
[38]. Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: an organizational information processing theory perspective. *Production and operations management*, *27*(10), 1849-1867. https://doi.org/10.1111/poms.12746
[39]. Stohr, A., Ollig, P., Keller, R., & Rieger, A. (2024). Generative mechanisms of AI implementation: A critical realist perspective on predictive maintenance. *Information and Organization*, *34*(2), 100503. https://doi.org/10.1016/j.infoandorg.2024.100503
[40]. Szukits, Á., & Móricz, P. (2024). Towards data-driven decision making: the role of analytical culture and centralization efforts. *Review of Managerial Science*, *18*(10), 2849-2887. https://doi.org/10.1007/s11846-023-00694-1

[41]. Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. International Journal of Medical Education, 2, 53–55. https://doi.org/10.5116/ijme.4dfb.8dfd

[42]. Teece, D. J. (2018). Business models and dynamic capabilities. *Long range planning*, *51*(1), 40-49. https://doi.org/10.1016/j.lrp.2017.06.007

[43]. Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509-533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z

[44]. Trunk, A., Birkel, H., & Hartmann, E. (2020). On the current state of combining human and artificial intelligence for strategic organizational decision making. *Business Research*, *13*(3), 875-919. https://doi.org/10.1007/s40685-020-00133-x

[45]. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of business research*, *70*, 356-365. https://doi.org/10.1016/j.jbusres.2016.08.009