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Generative Ai-Enabled Financial Forecasting and Strategic Financial Decision Quality in Emerging-Market SMEs

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ABSTRACT: This study investigates how generative AI enabled financial forecasting capability and business analytics capability shape strategic financial decision quality in emerging market SMEs, with particular attention to the moderating role of AI governance maturity. Grounded in organizational information processing theory and dynamic capabilities theory, the study argues that better financial decisions depend not simply on access to advanced technologies, but on how effectively firms turn AI generated forecasts and analytical information into useful financial judgment. AI governance maturity is expected to strengthen this process by providing appropriate oversight, accountability, validation, and control over the use of AI generated financial information. A quantitative cross-sectional survey was conducted with 385 respondents who possessed relevant knowledge of SME financial management, business analytics, AI applications, or organizational decision making. Data were collected using a five-point Likert scale questionnaire and analyzed with IBM SPSS version 26. Reliability analysis, exploratory factor analysis, and multiple linear regression were performed, while Hayes' Process Macro Model 1 was used to test the moderating effect. The results show that generative AI enabled financial forecasting capability (β = 0.613) and business analytics capability (β = 0.487) both have significant positive effects on strategic financial decision quality. AI governance maturity also strengthens the relationship between generative AI enabled financial forecasting capability and strategic financial decision quality, with an interaction coefficient of 0.518. These findings suggest that emerging market SMEs gain greater value from generative AI when forecasting tools are supported by sound analytical capabilities and governance practices. Effective financial decision making therefore requires not only better technology, but also the organizational capacity to interpret, review, and responsibly use AI generated financial insights.

KEYWORDS: strategic financial decision quality; generative AI enabled financial forecasting capability; business analytics capability; AI governance maturity; emerging market SMEs.

1. INTRODUCTION

Strategic financial decision quality grows ever more vital for SMEs in emerging markets as choices on investment, liquidity, financing, and resource allocation unfold amid high uncertainty and limited resources. Environmental uncertainty may undermine the effectiveness of capital budgeting and working capital management and thereby harm financial performance, so stronger financial judgment becomes especially pressing for vulnerable firms (Shah et al., 2026). These SMEs also face financing constraints and information asymmetries, yet recent findings indicate that AI adoption can lower financing costs and risks while raising financing efficiency (Bu et al., 2026). The swift advance of generative AI opens further possibilities because AI generated financial diagnostics can deliver accessible and timely insights to SMEs, although their value hinges on organizational readiness and managers' capacity to interpret and apply the analytical results (Metzger et al., 2025). In addition, analytics capabilities enhance information quality and organizational agility while business intelligence boosts decision speed and breadth (Ashrafi et al., 2019; Alzghoul et al., 2024). As a result, improving strategic financial decision quality has turned increasingly urgent since emerging market SMEs must transform growing AI and analytical resources into sound financial judgments rather than simply deploying advanced technologies

Prior research increasingly views digital analytics as a strategic capability, yet findings stay scattered on how these tools raise financial decision quality in SMEs. Business analytics capabilities improve agility and organizational performance by turning data resources into usable knowledge (Ashrafi et al., 2019), and big data analytics can boost innovation and performance in smaller firms through supporting digital strengths (Bhatti et al., 2025). More recently, Metzger et al. (2025) show that generative AI can

offer SMEs ready financial diagnostics and prompt insights, which may ease resource limits in financial management. Still, most analytics studies have looked at wide organizational results rather than strategic financial decision quality, and knowledge about decision processes stays scattered and leans heavily toward larger firms and developed economies (Mamakou, 2026). In addition, while AI governance research points to governance practices as key for handling AI risks and enabling solid applications, its function as a boundary condition for AI-enabled financial forecasting stays little examined (Mäntymäki et al., 2022). As a result, a notable gap exists around how generative AI enabled financial forecasting capability and business analytics capability together shape strategic financial decision quality in emerging market SMEs. This study fills that gap by testing both capabilities empirically and checking whether AI governance maturity strengthens the link between forecasting capability and decision quality.

Then, this research seeks to answer the three following questions:

(1) To what extent does generative AI-enabled financial forecasting capability influence strategic financial decision quality in emerging market SMEs?

(2) How does business analytics capability affect strategic financial decision quality in emerging market SMEs?

(3) How does AI governance maturity moderate the relationship between generative AI-enabled financial forecasting capability and strategic financial decision quality?

This study sets out to examine the direct effect of generative AI enabled financial forecasting capability on strategic financial decision quality among emerging market SMEs. It further investigates how business analytics capability shapes strategic financial decision quality and assesses whether AI governance maturity reinforces the link between generative AI enabled financial forecasting capability and strategic financial decision quality. Academically, the research unites generative AI forecasting, organizational analytics capability, and AI governance inside one coherent framework, thereby widening the literature on financial decision making and digital capabilities to cover the emerging market SME context. Practically, the outcomes may assist SME managers in cultivating forecasting and analytics capabilities while installing fitting AI governance mechanisms that promote reliable, informed, and strategically consistent financial decisions.

2. LITERATURE REVIEW

2.1. Strategic financial decision quality

Strategic financial decision quality denotes how far financial choices prove accurate, timely, evidence-based, and consistent with organizational aims so as to foster enduring performance and sustainability. This construct captures an organization's capacity to assess financial options, distribute resources wisely, handle uncertainty, and choose moves that generate strategic value (Bhimani et al., 2019). For emerging market SMEs, the construct holds special weight since these enterprises commonly face scarce resources, unstable markets, and limited reliable financial data that heighten the difficulty of investment and financing choices (Brinckmann et al., 2019). Sound financial decisions help such firms build resilience, make better use of available means, and adapt promptly to shifting conditions through stronger information handling and analytical skills (Mikalef et al., 2019). Digital tools together with advanced analytics have reshaped financial decision work by supplying predictive signals and sharpening managerial judgment amid uncertainty (Mishra et al., 2022). Yet, many emerging market SMEs still find it hard to turn technology outlays into better financial results because analytical abilities and governance arrangements remain inadequate (Kraus et al., 2022). Strengthening strategic financial decision quality therefore forms a vital capacity that lets SMEs weave generative AI forecasting, business analytics, and responsible AI governance into sound financial management practices.

2.2. Critical Analysis of Theoretical Frameworks

2.2.1. Organizational Information Processing Theory

Organizational Information Processing theory supplies a robust theoretical base for clarifying how generative AI-enabled financial forecasting capability and business analytics capability advance strategic financial decision quality. Drawing from Galbraith's conception of organizations as information processing systems whose success hinges on matching information processing demands with available capacity (Galbraith, 1974), later work continues to extend this reasoning into analytics rich settings even though the foundational statement lies outside the recent fifteen-year span. The core claim holds that rising uncertainty elevates information needs and thereby raises the capacity organizations must possess to gather, interpret, integrate, and share information for effective decisions (Song et al., 2020). This logic fits strategic financial choices in emerging market SMEs especially well because managers confront uncertainty over cash flows, financing terms, customer demand, investment returns, inflation, and shifting competitive pressures. Generative AI-enabled financial forecasting capability expands processing capacity by synthesizing financial data, identifying patterns, creating forward scenarios, and delivering forecasts that aid prospective judgments, while recent findings further show that generative AI can ease financing constraints for SMEs and thereby underscore its practical value in their financial management (Zhang et al., 2026). From the same theoretical stance, however, extra information alone does not secure better

decisions, what counts is whether the firm can convert that information into clear and usable knowledge. Business analytics capability therefore acts as a complementary processing route that lets firms blend data, analytical tools, expertise, and routines into actionable insights. Evidence links big data analytics capability and data driven insights to higher decision quality (Awan et al., 2021), and newer results indicate that technical, human, and contextual analytics resources shape decision quality which in turn channels analytics strengths into organizational performance (Mamakou, 2026). In this light, generative AI-enabled financial forecasting capability enlarges the supply of prospective financial intelligence while business analytics capability supplies the wider organizational means to process, interpret, and apply data. The theory further justifies strategic financial decision quality as the fitting outcome because greater processing capacity helps decision makers lower uncertainty, compare financial options more systematically, and reach better informed choices. Studies guided by Organizational Information Processing theory confirm that analytics capabilities enlarge organizational information processing capacity and strengthen responses to complex information settings (Yu et al., 2021). Consequently, this study treats strategic financial decision quality as the decision level result of aligning high financial information demands with technologically and organizationally strengthened processing capacity.

The paper assumes that emerging market SMEs face financial uncertainty that generates substantial information processing needs and that strategic financial decision quality rises when processing capacity matches those needs. Generative AI-enabled financial forecasting capability and business analytics capability raise this capacity by producing, analyzing, interpreting, and integrating pertinent information and thereby allow managers to reach more accurate, timely, informed, and strategically coherent financial decisions (Song et al., 2020; Yu et al., 2021).

2.2.2. Dynamic Capabilities theory

Dynamic Capabilities theory supplies the second theoretical pillar by clarifying how organizations deliberately combine, develop and reshape resources and competencies when environments shift. Originally advanced by Teece Pisano and Shuen, the concept frames dynamic capabilities as the organizational capacity to integrate build and reconfigure competencies amid change (Teece et al., 1997). Later refinements highlight the processes of sensing opportunities and threats, seizing those opportunities and transforming or reconfiguring organizational resources. Current scholarship continues to draw on this lens to show how firms convert digital and analytical resources into strategically valuable capabilities instead of regarding technologies as inherently productive assets (Ameen et al., 2024). This line of reasoning holds particular weight for emerging market SMEs because simply owning generative AI tools does not guarantee superior strategic financial decisions. Such firms must cultivate organizational abilities that enable them to detect relevant financial signals, exploit technological insights and adapt financial strategies as conditions evolve. Generative AI-enabled financial forecasting capability can heighten sensing by uncovering patterns and generating forward looking interpretations of financial trends. Managers can then seize these insights when assessing financing investment liquidity and resource allocation options. Strategic financial decision quality serves as a key indicator of whether technological intelligence has been successfully turned into informed managerial action.

Business analytics capability further supports this conversion because dynamic capabilities rest on the coordinated use of resources rather than their mere possession. Recent evidence indicates that the value of business analytics arises from complementary sets of technical, human and contextual capabilities with decision quality functioning as the central pathway that links analytics capabilities to performance (Mamakou, 2026). Parallel work on organizational AI reveals that AI capability encompasses not only data and technology but also human skills and intangible resources such as coordination and change capacity (Mikalef & Gupta, 2021). These insights reinforce the dynamic capability view that technological resources yield strategic value only when they become embedded in organizational competencies and decision routines. Dynamic capabilities theory also offers a useful explanation for the moderating effect of AI governance maturity. Mechanisms of accountability, oversight, validation, risk management and appropriate AI use shape whether AI-generated forecasts are reliably absorbed into managerial decisions. Contemporary AI studies increasingly stress that realized benefits hinge on aligned processes governance and organizational integration rather than technological strength alone (Zhang & Dong 2026). AI governance maturity can therefore be understood as an organizational condition that fosters the disciplined orchestration of AI resources. Greater maturity equips SMEs to evaluate and control AI-generated financial intelligence more systematically thereby amplifying the degree to which generative AI-enabled financial forecasting capability translates into strategic financial decision quality.

The study assumes that competitive financial decision making requires SMEs to continually sense financial developments seize pertinent opportunities and reconfigure resources as conditions change. Generative AI-enabled financial forecasting capability supplies forward looking intelligence while business analytics capability facilitates its organizational use. AI governance maturity is assumed to reinforce the disciplined application of AI resources by aligning technological intelligence with organizational oversight accountability and decision processes thereby elevating strategic financial decision quality (Ameen et al. 2024; Mikalef & Gupta 2021).

To account for strategic financial decision quality in emerging market SMEs, the theoretical framework integrates Organizational Information Processing theory which clarifies how generative AI-enabled financial forecasting capability and business analytics capability enlarge firms capacity to process complex financial information and reduce decision uncertainty with Dynamic Capabilities theory which explains how SMEs mobilize integrate and reconfigure these technological and analytical capabilities while AI governance maturity conditions the effective translation of AI-generated financial intelligence into strategic financial decisions.

2.3. The impact of generative AI-enabled financial forecasting capability

Generative AI-enabled financial forecasting capability refers to an organizational capacity for applying generative AI models that combine and make sense of financial data, create forward looking diagnostics along with predictions, and turn those results into practical guidance for planning and choices. This view moves financial forecasting, past simple automated estimates by highlighting the firm's ability to understand and use the intelligence that AI produces. Metzger et al. (2025) show that generative AI delivers clear and timely financial diagnostics suited to SMEs, and Eisfeldt & Schubert (2025) position generative AI as a technology of rising importance for financial analysis and everyday practice.

Conceptually, this capability matters because financial forecasting serves as a core information channel that lets managers foresee future states and decide how to assign resources. Wasserbacher & Spindler (2022) note that sound forecasting and planning gain special value in turbulent settings since firms must pull meaningful signals from ever more complex data. Generative AI strengthens that process by handling varied financial inputs and producing understandable forward oriented insights. Metzger et al. (2025) offer especially useful SME findings that AI generated financial diagnostics can strengthen financial management and reduce business as well as financial risks. Newer work further reveals that ChatGPT generated financial factors, carry predictive power (Cheng et al., 2026), and Pelster & Val (2024) report that ChatGPT processes financial details and yields judgments linked to later earnings and stock returns. From an epistemological angle, the capability signals a shift from largely experience based financial understanding toward knowledge that is enriched by data. Forecasts ought not be treated as fixed truths about a future that cannot be known but rather as probability-based pictures that help managers weigh possible results. The difference counts because accuracy in prediction and sound strategic judgment is not the same in philosophical terms. Wasserbacher & Spindler (2022) warn that prediction alone does not supply the causal links needed for planning and resource decisions. Generative AI is therefore best seen as a support for rather than a substitute for managerial thinking. Such human-machine partnership matches recent finance studies that treat AI as one element inside hybrid financial decision systems instead of a standalone prediction device (Kou et al., 2026). Theoretically, greater generative AI enabled financial forecasting capability should raise the quality of strategic financial decisions since better information handling lets managers spot patterns, foresee risks, weigh options, and react faster when conditions change. Clear empirical backing appears in Neiroukh et al. (2025), who show that organizational AI capability markedly lifts both decision quality and speed. Metzger et al. (2025) likewise judge that generative AI can meaningfully strengthen SME financial management through ready and prompt insights. Cao & You (2024) add related forecasting results indicating that machine learning yields more accurate out of sample earnings forecasts than conventional models or analyst consensus.

Still, the literature points to a finer discussion about how large the effect may be. A sizable impact seems reasonable when AI capability greatly widens forecasting precision and information handling power, as Neiroukh et al. (2025) and Cao & You (2024) suggest. A milder impact also makes theoretical sense because technological forecasts gain value for decisions only after managers interpret and apply them properly. Metzger et al. (2025) find directly that generative AI usefulness for SMEs rests on organizational readiness, skill in reading the data, and readiness to act on automated alerts. Behavioral findings add weight to this limit. Logg et al. (2019) document algorithm appreciation while Dietvorst et al. (2015) show that decision makers may turn algorithm averse once they see errors. The link is therefore expected to stay positive yet its size hinges on whether AI generated forecasts become trusted and usable managerial knowledge. Then the first hypothesis is as follows:

H1: Generative AI-enabled financial forecasting capability has a positive impact on strategic financial decision quality in emerging market SMEs.

2.4. The Impact of business analytics capability

Business analytics capability can be understood as an organizational capacity to bring together and deploy technological, human, data, and managerial resources so that organizational data are systematically turned into analytical insights that guide decisions and actions. It is not simply the ownership of analytical tools but the ability to place analytics inside everyday routines and convert data resources into knowledge that matters for decisions. Ashrafi et al. (2019) treat business analytics capability as a multidimensional organizational capability and show that it raises information quality as well as innovative capability. More recently, Mamakou (2026) stresses that the value of business analytics arises from complementary technical, human, and contextual capabilities rather than from technology investments taken alone.

Conceptually, business analytics capability holds strategic weight because firms now face large amounts of varied information that intuition alone cannot handle effectively. Analytics lets organizations detect patterns, bring together scattered information, assess options, and change data into insights that support managerial judgment. Ashrafi et al. (2019) demonstrate that analytics capability builds organizational agility by improving information quality and innovative capability, showing that its contribution reaches beyond data handling into responsiveness. Awan et al. (2021) further find that big data analytics capability and business intelligence and analytics are positively linked with decision making quality, with data driven insights serving as a key path through which analytical resources become useful for decisions. From an epistemological standpoint, business analytics capability marks a shift from mainly intuitive knowledge toward organizational knowledge grounded in evidence. This does not mean that quantitative findings offer a perfect picture of organizational reality. Analytics instead yields empirically based interpretations from which managers build strategic meaning. The philosophical contribution of business analytics therefore rests on joining a positivist focus on observable data with managerial interpretation. Analytical results shape judgment without replacing it. The distinction carries special weight for strategic financial decisions because historical patterns, predictive signals, and measured alternatives still require interpretation against organizational aims and shifting external conditions. A stronger business analytics capability should therefore improve strategic financial decision quality in emerging market SMEs. Organizations that are able to combine financial and operational data can assess investment choices, financing needs, liquidity positions, and resource allocation options on the basis of richer evidence. Direct empirical backing for the wider decision process comes from Awan et al. (2021), who report that big data analytics capability is positively related to decision making quality. Parallel work on business analytics and strategic decision processes shows that decision comprehensiveness and decision speed mediate the link between business analytics capability and decision quality, indicating that analytics raises not only the amount of information but also the thoroughness and speed with which organizations form decisions. The connection proves especially meaningful for SMEs. Bhatti et al. (2025) find that big data analytics capability supports innovation and financial performance among micro, small, and medium enterprises through complementary organizational capabilities. Newer results from Mamakou (2026) identify decision quality as a main route through which business analytics capabilities translate into firm performance and, notably, show that smaller firms can gain considerable advantages from lean data to decision systems. These results point toward a potentially strong effect because analytics can offset informational limits by expanding the evidence available to SME decision makers.

Nevertheless, a moderate rather than uniformly strong effect also makes theoretical sense. Mamakou (2026) shows that analytics success rests on complementary sets of capabilities and organizational context, meaning that analytics resources by themselves are not enough. Awan et al. (2021) likewise indicate that data driven insights reinforce the connection between analytical resources and decision processes. Business analytics capability should therefore raise strategic financial decision quality, yet the size of that improvement hinges on whether analytical information is properly interpreted and woven into financial judgments. This line of reasoning underpins the hypothesis that follows:

H2: Business analytics capability has a positive impact on strategic financial decision quality in emerging market SMEs.

2.5 The moderating role of AI governance maturity

AI governance maturity can be understood as the extent to which an organization has built, formalized, and regularly applied rules, structures, processes, responsibilities, and technological tools for overseeing AI systems in line with organizational goals, ethical standards, and legal demands. Mäntymäki et al. (2022) describe organizational AI governance as a system of rules, practices, processes, and technological tools that keeps AI use consistent with strategies, objectives, values, legal requirements, and ethical principles. Papagiannidis et al. (2025) expand the idea of responsible AI governance through structural, relational, and procedural practices, indicating that maturity means moving past general principles toward their consistent application across AI activities.

Conceptually, AI governance maturity has grown in importance because the strategic benefit of AI rests not only on technical strength but also on the ability of organizations to create accountability, transparency, oversight, and control around AI-supported work. AI governance therefore acts as an organizational bridge that links technological capacities with responsible use. Mäntymäki et al. (2022) highlight strategic alignment as an essential part of organizational AI governance, while Almeida & dos Santos Júnior (2025) show that more developed governance is tied to formalized processes, practices, stakeholder training, strategies, policies, and standards. Recent causal findings further reveal that firms applying responsible AI governance practices record clear gains in corporate performance, suggesting that governance adds organizational value rather than serving only as a compliance tool (Xia et al., 2026). From an ontological view, AI-generated financial forecasts should not be treated as independent pictures of a financial future that can be known with certainty. They are technologically produced interpretations that arise from models, data, assumptions, and probabilistic links. Epistemologically, their usefulness therefore rests on organizational routines through which managers judge whether AI-generated knowledge is clear enough, credible, relevant, and suitable for strategic action. AI governance maturity supplies an institutional framework for this judgment by defining responsibility, monitoring, validation, and

acceptable AI practices. This philosophical stance favors a human centered approach in which AI supplies computational power while organizational actors keep responsibility for strategic financial judgment. Current research likewise holds that organizational AI governance supports how members discuss whether and how AI should be used responsibly rather than automatically dictating responsible choices (Sturm et al., 2026).

This line of thought is especially relevant to the link between generative AI-enabled financial forecasting capability and strategic financial decision quality. Strong forecasting capability can give managers quick forward-looking financial insights, yet such information gains strategic worth only when organizations have ways to check its reliability, transparency, accountability, and proper use. Higher AI governance maturity should reinforce this conversion by placing AI forecasting inside defined responsibilities, review steps, risk controls, and decision protocols. Papagiannidis et al. (2025) show that responsible AI governance needs structural, relational, and procedural practices across AI implementation, while Liu et al. (2026) find that governance maturity forms a key element of responsible AI performance. The moderating role may prove especially significant in emerging market SMEs because technology uptake can advance more quickly than governance capacity. Recent SME findings indicate that AI adoption can move ahead of governance development and leave smaller firms open to risks that are not fully understood (Chen et al., 2026). In addition, research focused on emerging market SMEs questions the idea that more AI use automatically yields better results and instead shows that AI governance, skills, leadership, ethics, and data infrastructure work as complementary sets that support strategic decision quality and other organizational outcomes (Sturm et al., 2026).

The literature still indicates that the moderating influence should not be read as always strong. Solid governance can raise reliability and accountability, yet excessively strict governance may limit experimentation or delay responses. Sturm et al. (2026) maintain that responsible AI governance cannot fully dictate responsible AI use because organizational actors must continue to apply contextual judgment. This favors a contingent rather than fixed reading. AI governance maturity should therefore reinforce the positive contribution of generative AI-enabled financial forecasting capability by building conditions in which AI-generated information can be trusted, assessed, and responsibly brought into financial judgments while leaving room for managerial discretion.

H3: AI governance maturity positively moderates the relationship between generative AI-enabled financial forecasting capability and strategic financial decision quality in emerging market SMEs.

Drawing on established theoretical foundations, this study proposes the conceptual framework presented in Figure 1 to advance and enrich the existing body of knowledge.

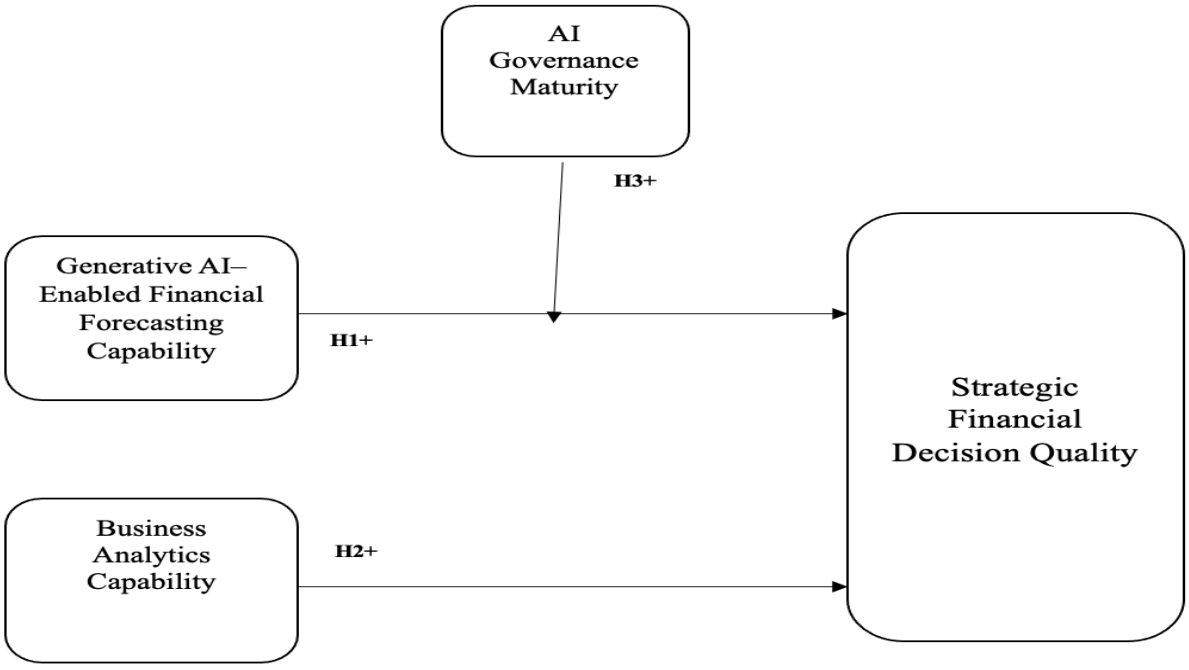


Figure 1: The Paper Conceptual Framework

3. METHODS

3.1. Sampling Strategy

This study used a quantitative cross sectional research design to examine how generative AI-enabled financial forecasting capability and business analytics capability shape strategic financial decision quality in emerging market SMEs while also testing the moderating role of AI governance maturity. The design aligned well with the conceptual framework because the work advanced

two direct relationships and one interaction effect. Generative AI-enabled financial forecasting capability and business analytics capability were expected to raise strategic financial decision quality, and AI governance maturity was predicted to strengthen the link between generative AI-enabled financial forecasting capability and strategic financial decision quality. A quantitative approach suited the goals since standardized numerical data support systematic hypothesis testing and estimation of both direct and moderating effects, and a cross-sectional design allows organizational perceptions to be recorded at a single point in time (Bryman, 2016).

Purposive sampling was chosen to select respondents who held enough organizational knowledge and practical experience with financial decision making, analytics, or AI-enabled tools. The unit of analysis was the individual organizational member even though the core constructs were judged through respondents' informed views of their SMEs. Eligible participants comprised SME owners, senior and middle managers, finance and accounting professionals, financial analysts, data analysts, information technology specialists, and staff engaged in AI-supported financial, analytical, or managerial work. Respondents needed to work in SMEs based in emerging markets and to understand how their firms applied financial forecasting, business analytics, or AI tools in decision processes. This profile mattered because the paper frames strategic financial decision quality around choices on investment, liquidity, financing, and resource allocation under uncertainty. Recruitment aimed for variation across industries, SME sizes, managerial levels, and levels of AI and analytics experience so that sample diversity would increase and overreliance on any single occupational group would decrease.

Data were gathered with a structured self-administered questionnaire built from established academic sources and measures adapted to the conceptual meanings used in the study. Generative AI-enabled financial forecasting capability captured the organizational ability to apply generative AI for integrating and interpreting financial information, producing forward looking financial diagnostics and predictions, and converting those outputs into useful input for financial planning and decisions, following the conceptualization drawn from Metzger et al. (2025) and related forecasting work. Business analytics capability measured the firm's capacity to combine technological, human, data, and managerial resources and turn organizational data into analytical insights that support managerial action (Ashrafi et al., 2019; Awan et al., 2021). AI governance maturity reflected the degree to which formalized governance rules, responsibilities, processes, oversight arrangements, and technological mechanisms were applied consistently to keep AI use aligned with organizational, ethical, and legal requirements (Mäntymäki et al., 2022; Papagiannidis et al., 2025). Strategic financial decision quality assessed how far organizational financial decisions proved accurate, timely, evidence based, strategically aligned, and able to support effective evaluation of financial alternatives and resource allocation.

All construct items used a five-point Likert scale from 1 for strongly disagree to 5 for strongly agree. Before the main survey the questionnaire was reviewed by academic experts and practitioners familiar with SME financial management, AI, business analytics, and organizational governance to check wording clarity, construct relevance, and content validity. A pilot study with eligible respondents then identified ambiguous wording and allowed minor refinement ahead of full data collection. The final questionnaire was distributed electronically through professional networks, SME associations, business contacts, and relevant online channels. Participation was voluntary and anonymous, and respondents learned of the academic purpose of the study and the confidentiality of their answers. After screening for incomplete responses, duplicates, patterned answers, and low engagement, 385 valid questionnaires remained for statistical analysis.

3.2. Data Analysis

Data analysis proceeded in sequence with IBM SPSS Statistics version 26 and Hayes' Process macro. Initial screening checked missing values, response patterns, possible outliers, and overall suitability of the data for multivariate work. Descriptive statistics next summarized respondents' demographic and professional traits and offered an overview of the distributions of the study variables. Internal consistency reliability was evaluated with Cronbach's alpha. A coefficient of at least 0.70 was treated as satisfactory, and corrected item total correlations above 0.30 showed adequate consistency between individual items and their constructs (Tavakol & Dennick, 2011). Exploratory factor analysis then inspected the underlying structure of the measurement items. Principal component extraction with Varimax rotation was applied, and factor loadings of at least 0.50 served as the main criterion for retaining items while problematic cross loadings were reviewed before the final measurement structure was set (Hair et al., 2009). The analysis checked whether items for generative AI-enabled financial forecasting capability, business analytics capability, AI governance maturity, and strategic financial decision quality showed clear empirical distinction. This step was especially useful because the conceptual framework separates forecasting capability from the broader organizational capacity to convert data into analytical knowledge. Multiple linear regression next tested the direct effects stated in H1 and H2. Generative AI-enabled financial forecasting capability and business analytics capability entered as predictors of strategic financial decision quality, with statistical significance judged at $p < 0.05$ (Shrestha, 2020). Finally, Hayes' Process Model 1 tested H3 on the moderating

effect of AI governance maturity on the relationship between generative AI-enabled financial forecasting capability and strategic financial decision quality. The analysis estimated the interaction term between generative AI-enabled financial forecasting capability and AI governance maturity while accounting for their main effects. A statistically significant interaction coefficient at $p < 0.05$ was taken as evidence of moderation (Hayes, 2022).

4. RESULTS

4.1. Descriptive Statistical Analysis

The sample covered SMEs from multiple emerging market regions, with 34.0% of respondents based in Southeast Asia, 23.6% in South Asia, 17.7% in East Asia, 14.5% in Latin America, and 10.1% in other emerging markets. Middle or functional managers formed the largest occupational group at 26.5%, followed by owners, directors, or senior managers at 22.6%, finance or accounting professionals at 21.0%, data analytics or information technology specialists at 17.9%, and other employees engaged in relevant AI-supported activities at 11.9%. Organizational size showed SMEs with 10 to 49 employees as the biggest share at 31.9%, then firms with 50 to 99 employees at 27.0%, those with 100 to 249 employees at 26.0%, and micro enterprises with fewer than 10 employees at 15.1%. On familiarity, 40.8% of participants reported high familiarity with their organizations' use of generative AI-enabled financial forecasting and business analytics, 23.4% indicated very high familiarity, 26.2% reported moderate familiarity, and only 9.6% reported limited familiarity. Taken together, the sample reflected diverse emerging market SME settings, and the fact that 64.2% of respondents held high or very high familiarity shows that most participants brought substantial organizational knowledge suited to assessing AI forecasting capability, business analytics capability, AI governance maturity, and strategic financial decision quality.

4.2. Reliability analysis

Table 1 summarizes the measurement items employed to assess the study constructs. Each construct was operationalized through four items adapted from established scholarly sources to maintain theoretical consistency and capture its essential dimensions comprehensively. Respondents evaluated all items using a five-point Likert scale, ranging from 1, strongly disagree, to 5, strongly agree.

Table 1: Measurement Items

Code	Survey item	Theoretical source
Strategic Financial Decision Quality		
SFDQ1	Our organization makes strategic financial decisions based on relevant and sufficient financial information.	Mikalef et al. (2019); Mishra et al. (2022)
SFDQ2	Our organization evaluates financial alternatives systematically before making major financial decisions.	Mikalef et al. (2019); Mishra et al. (2022)
SFDQ3	Our organization makes strategic financial decisions in a timely manner when financial conditions change.	Mikalef et al. (2019); Mishra et al. (2022)
SFDQ4	Our organization's strategic financial decisions are consistent with its financial and organizational objectives.	Brinckmann et al. (2019); Mikalef et al. (2019)
Generative AI Enabled Financial Forecasting Capability		
GAIFC1	Our organization uses generative AI to analyze financial information for forecasting purposes.	Metzger et al. (2025); Eisfeldt & Schubert (2025)
GAIFC2	Our organization uses generative AI to generate forward looking financial forecasts or diagnostics.	Metzger et al. (2025); Cheng et al. (2026)
GAIFC3	Our organization can use generative AI to identify patterns and signals relevant to future financial conditions.	Cheng et al. (2026); Pelster & Val (2024)
GAIFC4	Our organization can interpret generative AI generated financial forecasts for financial planning purposes.	Metzger et al. (2025); Wasserbacher & Spindler (2022)

Business Analytics Capability		
BAC1	Our organization can integrate data from relevant sources for business analysis.	Ashrafi et al. (2019); Awan et al. (2021)
BAC2	Our organization possesses the analytical resources needed to transform business data into useful insights.	Ashrafi et al. (2019); Mamakou (2026)
BAC3	Our organization can systematically analyze business data to identify meaningful patterns and trends.	Ashrafi et al. (2019); Awan et al. (2021)
BAC4	Our organization can incorporate analytical insights into its managerial decision processes.	Awan et al. (2021); Mamakou (2026)
AI Governance Maturity		
AIGM1	Our organization has clearly defined responsibilities for the governance and oversight of AI applications.	Mäntymäki et al. (2022); Papagiannidis et al. (2025)
AIGM2	Our organization has established procedures for monitoring and reviewing the use of AI applications.	Mäntymäki et al. (2022); Papagiannidis et al. (2025)
AIGM3	Our organization applies formal practices to evaluate risks associated with the use of AI applications.	Mäntymäki et al. (2022); Papagiannidis et al. (2025)
AIGM4	Our organization regularly reviews its AI governance practices to ensure alignment with organizational, ethical, and legal requirements.	Mäntymäki et al. (2022); Papagiannidis et al. (2025)

Table 2: Reliability analysis of "Strategic Financial Decision Quality".

Reliability Statistics				
Cronbach's Alpha	N of Items			
.846	4			
Item-Total Statistics				
	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
SFDQ1	10.918	5.137	.684	.812
SFDQ2	10.764	4.886	.701	.805
SFDQ3	10.847	5.024	.653	.824
SFDQ4	10.691	4.752	.728	.794

Source: (The authors, 2026)

As presented in Table 2, all four items recorded corrected item total correlation values ranging from 0.653 to 0.728, substantially exceeding the recommended threshold of 0.30. The overall scale achieved a Cronbach's alpha of 0.846, surpassing the minimum acceptable level of 0.70 and confirming strong internal consistency. Moreover, the Cronbach's alpha values obtained after deleting individual items ranged from 0.794 to 0.824, all of which remained lower than the overall alpha. This finding indicates that removing any item would reduce the reliability of the scale. Therefore, SFDQ1 to SFDQ4 contributed meaningfully to the measurement of strategic financial decision quality and were retained for subsequent analyses. Comparable reliability assessment criteria were also applied to the other measurement scales included 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	
SFDQ1	.742	GAIFC1	.775	BAC1	.731	AIGM1	.764

SFDQ2	.786	GAIFC2	.823	BAC2	.792	AIGM2	.801
SFDQ3	.815	GAIFC3	.758	BAC3	.816	AIGM3	.837
SFDQ4	.773	GAIFC4	.714	BAC4	.746	AIGM4	.779
Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.							
a. Rotation converged in 7 iterations.							

Source: (The authors, 2026)

Table 3 presents the exploratory factor analysis results, which identified four distinct factors representing strategic financial decision quality, generative AI enabled financial forecasting capability, business analytics capability, and AI governance maturity. All 16 measurement items loaded strongly on their intended factors, with coefficients ranging from 0.714 to 0.837, exceeding the recommended threshold of 0.50 (Hair et al., 2009). The Varimax rotation converged after six iterations, indicating a stable factor solution. Consequently, no measurement items were removed, and all 16 indicators were retained for subsequent statistical analyses. Overall, the findings provide satisfactory evidence supporting the proposed four factor structure and the 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	0.284	0.078		3.641	0.000
GAIFC	0.521	0.030	0.613	17.367	0.000
BAC	0.438	0.026	0.487	16.846	0.000
a. Dependent Variable: SFDQ					

Source: (The authors, 2026)

Where GAIFC represents the mean of GAIFC1 to GAIFC4, BAC represents the mean of BAC1 to BAC4, and SFDQ represents the mean of SFDQ1 to SFDQ4.

As shown in Table 4, the significance values for the relationships between generative AI enabled financial forecasting capability and strategic financial decision quality and between business analytics capability and strategic financial decision quality were both 0.000, which is well below the 0.05 threshold. Generative AI enabled financial forecasting capability had a significant positive effect on strategic financial decision quality, with $\beta = 0.613$, $t = 17.367$, and $p < 0.001$. Business analytics capability also exerted a significant positive effect, with $\beta = 0.487$, $t = 16.846$, and $p < 0.001$. These findings provide strong empirical support for H1 and H2.

4.5. Moderator analysis

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

Model: 1 Y: SFDQ X: GAIFC W: AIGM Sample Size: 385

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OUTCOME VARIABLE: SFDQ Model Summary

R	R-sq	MSE	F	dl1	dl2	p
.598	.358	0.231	70.817	3.000	381.000	.000

Model

	Coeff.	SE	t	p	LLCI	ULCI
Constant	.286	.082	3.488	.001	.125	.447
GAIFC	.625	.039	16.026	.000	.548	.702
AIGM	.671	.043	15.605	.000	.586	.756
Int_1	.518	.041	12.634	.000	.437	.599

Source: (The authors, 2026)

Where AIGM was calculated as the mean score of items AIGM1 to AIGM4.

The positive interaction coefficient of B = 0.518 indicates that higher AI governance maturity strengthens the positive effect of generative AI enabled financial forecasting capability on strategic financial decision quality in emerging market SMEs. Although generative AI enabled financial forecasting capability provides forward looking financial insights that can support managers in anticipating risks, evaluating alternatives, and planning financial actions, its contribution to strategic financial decision quality becomes stronger when firms maintain mature AI governance arrangements. Clearly defined responsibilities, systematic validation procedures, continuous monitoring, accountability mechanisms, and appropriate risk controls enable managers to evaluate AI generated financial forecasts more carefully and incorporate them more appropriately into strategic financial decisions. Consequently, SMEs with stronger AI governance maturity are better positioned to translate AI generated financial intelligence into accurate, timely, evidence based, and strategically aligned financial decisions. Moreover, the confidence interval for the interaction term, ranging from LLCI = 0.437 to ULCI = 0.599, excludes zero, further confirming the significance and reliability of this positive moderating effect. Overall, the findings identify AI governance maturity as an important boundary condition that strengthens the favorable contribution of generative AI enabled financial forecasting capability to strategic financial decision quality in emerging market SMEs, thereby providing empirical support for Hypothesis H3.

5. DISCUSSION

5.1. Result Summary

The findings show that generative AI enabled financial forecasting capability and business analytics capability both have significant positive effects on strategic financial decision quality in emerging market SMEs, with standardized regression coefficients of 0.613 and 0.487, respectively. These results suggest that SMEs make better strategic financial decisions when they can generate forward looking financial insights through generative AI and combine organizational data with effective analytical capabilities. Generative AI enabled financial forecasting capability shows the larger standardized coefficient, highlighting the value of timely financial forecasts and prospective insights when managers assess risks, compare alternatives, and make financing, investment, liquidity, and resource allocation decisions. Business analytics capability also plays an important role by helping firms organize, interpret, and turn available data into evidence that can inform financial judgment. At the same time, AI governance maturity significantly strengthens the relationship between generative AI enabled financial forecasting capability and strategic financial decision quality. This moderating effect is reflected in the positive interaction coefficient of B = 0.518 and the confidence interval from 0.437 to 0.599, which does not include zero. The result indicates that AI generated financial forecasts become more useful for strategic decisions when SMEs have clearer responsibilities, appropriate oversight, validation procedures, monitoring mechanisms, and risk controls in place.

Overall, the empirical results support H1, H2, and H3 and are consistent with the proposed framework linking generative AI enabled financial forecasting capability, business analytics capability, AI governance maturity, and strategic financial decision quality. Regarding the first research question, the findings establish that generative AI enabled financial forecasting capability has a significant positive influence on strategic financial decision quality. The second research question is addressed by showing that business analytics capability also contributes positively to strategic financial decision quality, although its standardized coefficient is lower than that of generative AI enabled financial forecasting capability. For the third research question, the findings demonstrate that higher AI governance maturity strengthens the positive relationship between generative AI enabled financial forecasting capability and strategic financial decision quality. Taken together, the results suggest that emerging market SMEs gain greater value from generative AI when forecasting capability is accompanied by broader analytical competence and sound governance arrangements. Improving strategic financial decision quality therefore involves not simply adopting advanced AI tools, but developing the organizational ability to interpret financial information, apply analytical insights, maintain appropriate human oversight, validate AI generated outputs, and establish clear responsibility for AI supported financial decisions.

5.2. Theoretical Implications

The empirical findings strongly support H1, as generative AI enabled financial forecasting capability significantly improves strategic financial decision quality with β = 0.613. This result strongly concurs with Metzger et al. (2025), who argue that generative AI can provide SMEs with accessible and timely financial diagnostics, and with Cheng et al. (2026), whose evidence demonstrates the predictive value of ChatGPT generated financial factors. It also reinforces Pelster & Val (2024), who associate ChatGPT based financial assessments with subsequent earnings and stock returns. However, the findings do not support an unqualified technological determinism in which stronger predictive capability automatically guarantees better decisions. Wasserbacher & Spindler (2022) caution that prediction cannot establish the causal knowledge required for planning, while Metzger et al. (2025) emphasize organizational readiness and managers' ability to interpret AI outputs. The sizeable coefficient therefore suggests that forecasting capability matters, but not that managerial judgment becomes redundant. Theoretically, this study extends

organizational information processing theory by positioning generative AI enabled financial forecasting capability as a prospective information processing mechanism that expands SMEs' capacity to manage financial uncertainty and convert complex information into decision relevant intelligence.

The findings strongly support H2, demonstrating that business analytics capability positively affects strategic financial decision quality with β = 0.487. This result strongly concurs with Awan et al. (2021), who associate big data analytics capability with higher decision-making quality, and supports Ashrafi et al. (2019), who contend that analytics capability creates organizational value through improved information quality and agility. Nevertheless, the comparatively lower coefficient than that of generative AI enabled financial forecasting capability challenges any assumption that broader analytics capability necessarily constitutes the dominant driver of strategic financial judgment. More importantly, the findings only partially support a technology centered interpretation of analytics. Mamakou (2026) argues that analytics value emerges from complementary technical, human, and contextual capabilities, while Awan et al. (2021) emphasize data driven insights as a mechanism connecting analytical resources with decision processes. The evidence therefore favors analytics as an organizational capability rather than a technological asset operating independently. Theoretically, this study advances organizational information processing theory by showing that business analytics capability functions as an integrative processing capacity through which dispersed organizational data become decision relevant knowledge. It also extends dynamic capabilities theory by demonstrating how analytical resources acquire strategic value when embedded within organizational routines for interpreting and applying information.

The findings strongly support H3, with the positive interaction between generative AI enabled financial forecasting capability and AI governance maturity reaching B = 0.518, with a confidence interval of 0.437 to 0.599. This result strongly concurs with Papagiannidis et al. (2025), who conceptualize responsible AI governance through structural, relational, and procedural practices, and with Liu et al. (2026), who identify governance maturity as an important component of responsible AI performance. Yet the finding invites a more nuanced interpretation of governance than simple organizational control. Sturm et al. (2026) reject the assumption that governance structures can mechanically prescribe responsible AI use, emphasizing the continuing role of contextual human judgment. The present evidence therefore supports governance as an enabling boundary condition rather than a substitute for managerial discretion. This distinction is theoretically important because the significant interaction demonstrates that the value of forecasting capability is contingent on the organizational conditions surrounding its use. The study consequently extends dynamic capabilities theory by positioning AI governance maturity as a conditioning capability that strengthens the disciplined orchestration of AI resources, explaining when generative AI generated financial intelligence is more effectively translated into strategic financial decision quality.

5.3. Practical Implications

The support for H1, with generative AI enabled financial forecasting capability showing the stronger standardized effect on strategic financial decision quality (β = 0.613), suggests that emerging market SMEs should treat generative AI as a financial management capability rather than merely another digital tool. Managers should integrate generative AI into forecasting activities where forward looking information is particularly valuable, including liquidity planning, investment evaluation, financing requirements, and resource allocation. However, indiscriminate adoption would be difficult to justify. Metzger et al. (2025) demonstrate that AI generated financial diagnostics can provide SMEs with accessible real time analysis, but their usefulness depends on organizational readiness, competence in interpreting data, and willingness to respond to automated warnings. SMEs should therefore combine AI generated forecasts with financial expertise and managerial review rather than allowing automated outputs to dictate financial choices. This is particularly important because the study measures decision quality rather than forecasting accuracy alone. Managers should consequently evaluate whether AI forecasts are understandable, relevant to the decision context, and sufficiently supported by organizational financial information before incorporating them into strategic choices.

The support for H2 (β = 0.487) carries a different managerial message. SMEs should not assume that generative AI can compensate for weak underlying analytical capability. Business analytics capability requires firms to convert dispersed data into information that managers can actually use. Ashrafi et al. (2019) show that business analytics capabilities contribute to organizational agility through improved information quality and innovative capability. Accordingly, emerging market SMEs should strengthen data integration, analytical expertise, and routines through which analytical findings enter managerial discussions. Investment priorities should extend beyond analytics software toward employees capable of interpreting financial and operational data and communicating their implications to decision makers. The smaller coefficient relative to generative AI forecasting capability does not make business analytics peripheral. Instead, it suggests that analytics provides a broader organizational information infrastructure within which financial evidence can be examined systematically. For resource constrained SMEs, developing focused analytical routines around financially consequential decisions may therefore be more practical than investing indiscriminately in increasingly sophisticated analytics technologies.

H3 offers an especially consequential practical implication because the positive interaction (B = 0.518, 95% CI [0.437, 0.599]) indicates that AI governance maturity strengthens the contribution of generative AI forecasting capability. SMEs should therefore develop governance alongside AI adoption rather than treating governance as a later compliance exercise. Mäntymäki et al. (2022) argue that organizational AI governance translates ethical principles into practicable governance processes and is needed both to realize AI benefits and manage its risks. Papagiannidis et al. (2025) further organize responsible AI governance around structural, relational, and procedural practices and emphasize operationalizing responsible AI throughout implementation, monitoring, and evaluation. In practice, SMEs should clarify who is accountable for AI supported financial decisions, establish procedures for reviewing outputs, document important uses, monitor applications, and specify circumstances requiring human intervention. Governance should nevertheless enable informed use rather than become bureaucratic control. The practical priority is therefore proportional governance that makes AI generated financial intelligence more scrutinizable and responsibly actionable while preserving managerial judgment.

5.4. Limitations

Several limitations qualify the interpretation of the findings. First, the cross-sectional design captures organizational perceptions at one point in time and therefore cannot establish how generative AI forecasting, analytics capability, governance maturity, and financial decision quality evolve together. Second, the reliance on self-reported assessments may introduce common method and perceptual bias, particularly because organizational capabilities and decision quality were evaluated by individual respondents. Third, purposive sampling improves access to knowledgeable participants but restricts statistical generalization to the broader population of emerging market SMEs. Although the study covers heterogeneous organizational contexts, institutional, technological, and financial conditions can differ substantially across emerging markets. Finally, strategic financial decision quality is perceptual rather than based on objective decision outcomes. The results should therefore be interpreted as evidence of theoretically specified associations rather than definitive causal effects.

5.5. Future Research Directions

Future research should extend the framework longitudinally to determine whether improvements in generative AI forecasting capability precede sustained improvements in strategic financial decision quality. Multi respondent designs could combine assessments from owners, financial managers, and technology specialists to reduce single informant dependence. Researchers could also complement perceptual decision quality with objective indicators such as forecasting errors, financing costs, liquidity outcomes, or investment performance. Cross country studies would be particularly valuable for examining whether institutional development, regulatory environments, digital infrastructure, or financial market conditions alter the relationships identified here. Further work should also investigate whether AI governance has nonlinear effects, since increasingly formal governance may not generate proportionately greater decision benefits. Finally, extending the model to human AI collaboration, managerial financial literacy, data quality, and organizational readiness could clarify the mechanisms through which AI generated forecasts become strategically useful financial knowledge.

5.6. Conclusion

This study examined how generative AI enabled financial forecasting capability and business analytics capability shape strategic financial decision quality in emerging market SMEs and whether AI governance maturity conditions the forecasting relationship. The findings support all three hypotheses. Generative AI forecasting capability produced a positive effect (β = 0.613), while business analytics capability also contributed significantly (β = 0.487). More importantly, AI governance maturity strengthened the forecasting capability decision quality relationship, as indicated by the positive interaction coefficient (B = 0.518). Taken together, the results show that technological capability alone does not explain high quality financial judgment. Strategic value emerges when forward looking AI intelligence is accompanied by organizational analytical capacity and governance arrangements that support its responsible evaluation and use. The study therefore connects forecasting, analytics, and governance within a unified explanation of AI supported financial decision making in emerging market SMEs.

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