

Research Article

Enhancing Financial Decision Quality in Smart Organizations through Explainable AI and Real Time Analytics with AI Governance Maturity

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Abstract

This study investigates the links among explainable AI capability, real time financial analytics capability, and financial decision quality within smart organizations while assessing how AI governance maturity moderates those links. Drawing on organizational information processing theory and dynamic capabilities theory, it frames financial decision quality as the product of organizational capabilities that convert clear AI outputs and timely financial data into accurate, evidence based, and strategically coherent choices. AI governance maturity serves as a boundary condition shaping whether explainability translates into stronger financial judgments. A quantitative cross sectional design gathered responses on a five point Likert scale from 385 Vietnamese professionals knowledgeable in AI, financial analytics, governance, or organizational decision making. Analysis relied on IBM SPSS version 26 for reliability checks, exploratory factor analysis, and multiple linear regression, with Hayes Process Macro Model 1 testing the moderation. Findings show that explainable AI capability ($\beta = 0.636$) and real time financial analytics capability ($\beta = 0.580$) both raise financial decision quality, the former exerting a modestly larger direct influence that underscores the value of interpretable and actionable algorithmic advice. AI governance maturity further amplifies the positive path from explainable AI capability to financial decision quality through a significant interaction term of 0.436. The results indicate that explainability by itself cannot guarantee high quality financial decisions; smart organizations must therefore pair

understandable AI systems and timely analytics with model validation, human oversight, continuous monitoring, auditability, and explicit accountability.

Keywords: Financial decision quality; explainable AI capability; real time financial analytics capability; AI governance maturity; smart organizations.

Introduction

Financial decision quality in smart organizations centers on the accuracy, timeliness, evidence base, transparency, and strategic alignment of financial choices. Its decline carries serious weight, since investment, liquidity, budgeting, and risk decisions now rest ever more heavily on algorithmic outputs and data. Smart organizations process information effectively; however, neither speed nor sophistication guarantees sound judgment. Data driven decision processes demand interpretation and human evaluation rather than technological deployment alone (Elgendy et al., 2022). Opaque models may hide bias, unstable assumptions, and errors, thereby eroding accountability in settings where financial stakes run high. Although explainability can strengthen transparency and agile decision making (Sadeghi et al., 2024), experimental evidence indicates that explanations do not consistently raise trust or appropriate reliance (Leichtmann et al., 2023). Baron (2025) further questions the premise that explainability is essential for justified trust and draws a clear line between understanding a model and confirming its reliability. The issue grows urgent as organizations adopt artificial intelligence and real time analytics more rapidly than they build the governance capacity needed to validate outputs, assign responsibility, and stop poorly governed decisions from generating financial losses and strategic misdirection.

Prior research shows that analytics can improve organizational decisions. Li et al. (2022) demonstrated that big data analytics usage raised decision quality through enhanced capabilities, while Chatterjee et al. (2023) connected analytics adoption to stronger forecasting, decision processes, and firm performance. However, both studies focused on analytics in general rather than real time financial analytics inside smart organizations. Research on explainable artificial intelligence likewise indicates that transparency aids agile decision making and resilience (Sadeghi et al., 2024). Explanation nevertheless fails to generate consistent trust or suitable human behavior in high stakes decisions (Leichtmann et al., 2023). Current work, therefore, tends to exaggerate technological gains while giving insufficient attention to whether explanations remain understandable, faithful, and usable for financial managers. These studies further measure broad organizational performance, agility,

or trust instead of financial decision quality and rely on cross sectional data drawn from single industries or countries. Analytics, explainability, and governance are in addition typically studied in isolation, so their combined effects stay unclear. This paper should close this gap by testing the joint impact of explainable artificial intelligence capability and real time financial analytics capability on financial decision quality in smart organizations. It should further treat AI governance maturity as a moderator to determine whether oversight, accountability, validation, and risk controls together raise the decision value of explainable systems.

Accordingly, this study seeks to address the following three research questions:

- (1) To what extent does explainable AI capability influence financial decision quality in smart organizations?
- (2) How does real time financial analytics capability affect financial decision quality in smart organizations?
- (3) How does AI governance maturity moderate the relationship between explainable AI capability and financial decision quality?

Accordingly, the first objective examines the direct effect of explainable AI capability on financial decision quality by testing whether interpretable and transparent AI outputs foster accurate accountable and strategically relevant financial decisions. The second objective explores how real time financial analytics capability improves financial decision quality through timely data processing continuous monitoring and swift generation of financial insights. The third objective assesses the moderating role of AI governance maturity to establish whether governance mechanisms amplify the contribution of explainable AI capability to financial decision quality. The academic contribution of this research rests on uniting technological explainability real time analytical capability and organizational governance inside a single framework. Through simultaneous examination of these elements, the study advances work on intelligent decision support past mere technology adoption and broad organizational performance. It further illuminates the conditions under which governance shapes the conversion of explainable AI capabilities into superior financial decisions inside smart organizations.

2. LITERATURE REVIEW

2.1. Financial Decision Quality

Financial decision quality describes the degree to which choices about investment financing budgeting liquidity and risk prove accurate timely evidence based transparent and aligned

with organizational goals. The concept embraces both outcome effectiveness and process integrity since a profitable result that stems from weak reasoning can still prove unreliable. Strong financial decision quality supports disciplined resource allocation risk recognition accountability and adaptability amid uncertainty. Within smart organizations, its significance grows sharper because connected systems produce continuous data and progressively hand analysis over to artificial intelligence. Collaboration between human and artificial intelligence can surpass the limits of human information processing yet managerial judgment stays vital for handling ambiguity and contextual exceptions (Jarrahi, 2018). Decision structures must therefore balance algorithmic speed and scale with human expertise interpretability and responsibility instead of treating automation as automatically superior (Shrestha et al., 2019). Present conditions stay troubling because sophisticated systems can speed up flawed choices when data contain bias explanations stay shallow or governance remains underdeveloped. Recent findings show that ethics transparency and explainability promote responsible artificial intelligence adoption and decision efficacy although rising decision complexity may dilute these gains (Cao et al., 2026). As a result, financial decision quality in smart organizations hinges on turning technological intelligence into accountable understandable and strategically sound managerial action.

2.2. Critical Analysis of Theoretical Frameworks

2.2.1. Organizational Information Processing Theory

Organizational information processing theory originated with Jay Galbraith as a framework for understanding how organizations design structures and systems to handle uncertainty and information demands effectively. Galbraith (1974) maintained that uncertainty widens the gap between the information an organization already holds and the information it needs to complete a task successfully. When uncertainty increases organizations must either lower their information requirements or raise their capacity to gather interpret distribute and apply information. The theory, therefore, provides a solid basis for explaining financial decision quality in smart organizations since financial managers work amid volatile markets continuous data streams complex regulations and shifting risk conditions. In such settings, high quality financial decisions require close alignment between information processing needs and organizational information processing capacity. Explainable artificial intelligence capability enlarges this capacity by turning complex algorithmic predictions into information that financial managers can grasp evaluate and use in their decisions. Explanations about

model logic influential variables confidence levels and alternative outcomes lessen ambiguity around artificial intelligence recommendations and thereby support informed human judgment because managers can judge whether an output matches economic realities organizational priorities and acceptable risk assumptions. Studies rooted in organizational information processing theory show that digital technologies create value when they enhance the availability integration and interpretation of information needed for organizational action (Srinivasan & Swink, 2018). Therefore, explainability should be regarded not merely as a technical attribute but as an organizational information processing mechanism that links algorithmic intelligence with managerial understanding verification and action. Real time financial analytics capability likewise expands information processing capacity by continuously collecting integrating and analyzing financial and operational data. It allows managers to identify liquidity pressures budget deviations cost shifts investment risks and emerging market opportunities earlier than traditional reporting systems would permit. Advanced analytics can strengthen forecasting and decision processes by converting large datasets into timely managerial insights (Chatterjee et al., 2023). Inside smart organizations, this capability shortens information delays and enables quicker revision of financial plans. Yet information speed yields value only when the data remain relevant reliable and interpretable. Organizational information processing theory consequently stresses the fit between information requirements and processing capacity rather than the sheer volume of information produced. The theory also illuminates the moderating role of ai governance maturity. Governance structures set data standards validation routines accountability duties model monitoring and escalation procedures. These structures raise the reliability of explanations and help managers recognize when algorithmic recommendations call for further scrutiny or human intervention. Mature governance thus bolsters the capacity of explainable artificial intelligence capability to improve financial decision quality by turning explanations into controlled and auditable information. Without such arrangements, explanations may enlarge information availability without guaranteeing accuracy responsibility or proper use. Therefore, organizational information processing theory unites all constructs through a coherent logic. Explainable artificial intelligence capability and real time financial analytics capability enlarge information processing capacity financial decision quality reflects the effectiveness of information use and AI governance maturity strengthens the organizational conditions that allow explainable outputs to support accountable financial judgment.

The theory assumes that financial uncertainty heightens organizational information requirements and that financial decision quality rises when information processing capacity matches those requirements. Explainable artificial intelligence capability and real time financial analytics capability are presumed to increase this capacity through interpretation integration and timely insight while ai governance maturity is presumed to enhance the reliability and controlled application of explainable outputs thereby amplifying their positive effect on financial decision quality in smart organizations.

2.2.2. The Dynamic Capabilities Theory

Dynamic capabilities theory was introduced by David Teece Gary Pisano and Amy Shuen to explain how organizations maintain effectiveness in changing environments by integrating developing and reconfiguring internal and external competences (Teece et al., 1997). The theory separates dynamic capabilities from ordinary capabilities. Ordinary capabilities sustain established activities while dynamic capabilities allow organizations to detect environmental change mobilize suitable resources and reshape existing routines. Later, Teece (2018) structured this logic around sensing opportunities and threats seizing valuable opportunities and transforming organizational assets and processes. This perspective supplies a fitting foundation for explaining financial decision quality in smart organizations because merely owning artificial intelligence systems or analytics platforms does not by itself improve managerial decisions. Value appears when organizations continually combine these technologies with financial expertise data resources decision routines and governance arrangements. Explainable artificial intelligence capability constitutes a dynamic capability since it requires more than purchasing interpretable software. Organizations must create procedures for choosing appropriate models producing meaningful explanations validating algorithmic reasoning and blending these explanations with managerial expertise. This capability aids sensing by uncovering patterns risks and financial relationships that complex datasets might, otherwise, conceal. It aids seizing by helping managers assess recommendations and commit resources with deeper understanding. It also supports transformation because insights drawn from explainable systems can prompt organizations to adjust budgeting routines investment criteria risk controls and performance monitoring practices. Artificial intelligence capabilities generate organizational value when technological resources are joined with human skills coordination and organizational learning rather than treated as standalone assets (Mikalef & Gupta, 2021). Real time financial analytics capability

serves a complementary dynamic role. Continuous financial information lets organizations sense shifts in cash flows costs market conditions and operational performance. Then, managers can seize opportunities through timely investment financing pricing or resource allocation decisions. Repeated use of current information further supports transformation by allowing organizations to revise forecasts redesign financial processes and reallocate resources as conditions change. Digital transformation research shows that dynamic capabilities enable firms to renew business models structures and resources through ongoing processes of sensing seizing and transformation (Warner & Wäger, 2019). Consequently, real time analytics gains strategic worth when it becomes embedded in adaptive managerial routines rather than confined to generating dashboards or automated reports. Dynamic capabilities theory also clarifies why AI governance maturity alters the strength of the link between explainable artificial intelligence capability and financial decision quality. Governance maturity supplies coordinated policies expertise accountability and monitoring routines that help organizations apply explanations consistently across financial decisions. Mature governance assists managers in judging whether models stay accurate whether explanations mirror actual model behaviour and whether outputs meet ethical and regulatory standards. It further allows the organization to update artificial intelligence systems when data risks or institutional conditions shift. Therefore, governance functions as an enabling capability that supports the disciplined reconfiguration of technological and human resources. The theoretical framework, thus, regards explainable artificial intelligence capability and real time financial analytics capability as adaptive organizational competences financial decision quality as the decision outcome of their effective use and ai governance maturity as the condition that strengthens the conversion of explainability into strategically useful financial judgment.

The assumptions of dynamic capabilities theory hold that smart organizations function in changing environments where static technological resources cannot preserve financial decision quality. Explainable artificial intelligence capability and real time financial analytics capability are assumed to support sensing seizing and transforming activities. Their value rests on integration with managerial expertise and organizational routines. AI governance maturity is assumed to reinforce this integration by coordinating accountability validation learning and resource reconfiguration around explainable artificial intelligence supported financial decisions.

2.3. The Impact of Explainable AI capability

Explainable AI capability denotes an organization's integrated capacity to design, deploy, interpret, communicate, validate, and govern AI models so that their reasoning, key inputs, uncertainty, and recommendations become clear and usable for the decision makers concerned. This capacity reaches beyond mere possession of an explanation tool, since effective explanations must match the knowledge, duties, and information needs of varied organizational stakeholders (Meske et al., 2022). It, therefore, unites explanation techniques, accessible interfaces, financial expertise, validation practices, human oversight, and organizational learning. Viewed through organizational information processing, explainable AI capability turns complex algorithmic results into practical managerial insight, lowers ambiguity, and heightens the ability to weigh uncertain financial options. Its value is especially clear in investment, lending, liquidity, budgeting, and risk choices, which demand solid reasoning for executives, auditors, regulators, and other parties. Explainability can aid error detection, model challenge, accountability, transparency, and well-calibrated trust rather than passive acceptance of automated advice (Longo et al., 2024). Senoner et al. (2022) illustrated its operational worth by showing that explainable AI uncovered previously unseen performance drivers and guided interventions that sharply cut production yield loss. Although this evidence came from manufacturing, the same mechanism holds for financial decisions because interpretable links let managers spot material drivers, question implausible forecasts, and direct resources toward justified actions. As explainable AI capability matures, smart organizations can link predictive accuracy with managerial reasoning more tightly. Financial managers can match model explanations against economic knowledge, probe anomalies, gauge uncertainty, and convey the rationale behind their choices. These steps should raise the accuracy, speed, consistency, transparency, and strategic fit of financial decisions. Lu & Zhang (2025) observed that machine explanations paired with rich information prompted active human review, corrected missed relationships, lowered bias, and lifted prediction accuracy in a microloan firm. Von Zahn et al. (2025) likewise showed that explanations raised experts' metacognitive accuracy and enabled better delegation to AI, especially when machine reasoning diverged from human judgment. From a positivist stance, explainable AI capability stands as an observable organizational construct whose impact on financial decision quality can be gauged through standardized measures and hypothesis testing. This view assumes that clearer and more usable explanations systematically strengthen verification, confidence

calibration, and decision results. A critical realist stance supplies a more conditional reading by treating explainability as a genuine causal force whose effects rest on underlying structures such as financial expertise, explanation fidelity, data quality, cognitive bias, and governance practices (Zachariadis et al., 2013). A pragmatic stance further judges explainability by whether it helps managers resolve financial problems and reach defensible decisions rather than by technical transparency alone (Goldkuhl, 2012). Empirical findings reinforce this conditional logic. Strong evidence indicates that explanations ease knowledge transfer, productive delegation, and complementary human and machine reasoning. Yet, Fügner et al. (2022) found that working with a superior AI system failed to lift performance when users could not accurately judge their own abilities. Bauer et al. (2023) also showed that feature-based explanations could heighten confirmation bias, warp mental models, and harm investment performance. Explainability may therefore remain neutral or even harmful when explanations are inaccurate, cognitively overloaded, misunderstood, or selectively adopted. Still, framing explainability as an organizational capability embeds the expertise, validation, oversight, and learning routines required to manage these risks. Stronger explainable AI capability should therefore raise financial decision quality by enabling smart organizations to convert complex algorithmic forecasts into understandable, verifiable, and contextually fitting financial judgments. On this basis, the following hypothesis is advanced:

H1: Explainable AI capability has a positive impact on financial decision quality in smart organizations.

2.4. The Impact of Real Time Financial Analytics Capability

Real time financial analytics capability denotes an organization's integrated capacity to continuously gather, combine, process, analyze, visualize, and interpret present financial and operational data so as to produce prompt and usable insights for managerial choices. This view aligns with the broader understanding that analytics capability joins data quality, analytical skill, domain knowledge, data resources, and advanced tools rather than simply reflecting the presence of analytical software (Ghasemaghaei et al., 2018). Its real time aspect stresses the ability to handle continually refreshed information and to support immediate or swiftly revised organizational responses (Elgendy et al., 2022). As a result, real time financial analytics capability goes beyond mere access to live dashboards. It demands solid data infrastructure, financial expertise, data governance, cross functional integration, and organizational routines that convert ongoing information streams into purposeful financial

action. Analytics capability yields organizational value when technological, managerial, and human resources are strategically aligned (Akter et al., 2016). From an organizational information processing standpoint, real time financial analytics capability enlarges the organization's ability to cope with uncertainty by shortening the gap between financial events, managerial reading, and corrective steps. It lets managers keep constant watch on cash flows, liquidity, costs, revenues, budget variances, credit exposure, investment results, and market swings. Decision makers can therefore detect financial issues sooner, update forecasts, weigh alternative actions, and shift resources before stale data erodes decision usefulness. Ghasemaghaei et al. (2018) showed that data quality, analytical skills, domain knowledge, data scale, and tool sophistication markedly raised decision quality. As real time financial analytics capability grows stronger, smart organizations should reach more accurate, timely, evidence based, and strategically coherent financial decisions. Continuous analytics substitutes retrospective reports with present situational awareness, speeds anomaly detection, and allows managers to gauge the likely effects of financial options. Chatterjee et al. (2023) observed that big data analytics adoption reinforced decision processes, forecasting, and firm performance. Aydiner et al. (2019) likewise found that business analytics improved organizational outcomes through enhanced business processes. Hjelle et al. (2024) further indicated that information currency, completeness, and presentation shaped decision quality by lowering perceived task complexity. These results point to a clear positive influence because timely analytical insights strengthen both the informational base and the processing efficiency of financial judgment. From a positivist angle, real time financial analytics capability stands as a measurable organizational construct whose impact on financial decision quality can be assessed through standardized indicators and statistical hypothesis testing. This stance assumes that greater analytical capability produces visible gains in decision accuracy, speed, and consistency. A critical realist angle treats analytics capability as a causal mechanism whose results hinge on deeper organizational structures such as data quality, employee expertise, technological integration, managerial cognition, and knowledge sharing. Access to current information therefore does not by itself ensure better decisions, since these contextual factors decide whether analytical outputs are properly read and applied. A pragmatic angle judges real time analytics by whether it assists managers in tackling financial problems, reacting to emerging risks, and assigning resources effectively. Empirical findings uphold this conditional reading. Ghasemaghaei (2019) reported that analytics use raised

decision quality through knowledge sharing, suggesting that its direct technological effect may stay limited without supporting organizational processes. Roetzel (2019) also showed that surplus information can exceed human processing limits and impair decision performance. Real time analytics may therefore yield neutral or even negative results when continuous data flows are inaccurate, fragmented, irrelevant, or cognitively burdensome. Still, framing real time financial analytics as an organizational capability embeds the resources and routines needed to filter, contextualize, communicate, and apply current information. Stronger real time financial analytics capability should therefore allow smart organizations to convert continually updated financial data into relevant insights, prompt responses, and defensible financial judgments. The following hypothesis is consequently advanced:

H2: Real time financial analytics capability has a positive impact on financial decision quality in smart organizations.

2.5 The Moderating Role of AI Governance Maturity

AI governance maturity denotes the degree to which an organization has built, formalized, embedded, and steadily refined the structures, policies, processes, responsibilities, competencies, and technological safeguards needed to oversee AI systems across their entire life cycles. Organizational AI governance consists of linked rules, practices, processes, and tools that keep AI use consistent with organizational strategies, legal duties, ethical standards, and stakeholder expectations (Birkstedt et al., 2023). The maturity element sets apart firms that only state responsible AI principles from those that reliably put them into practice through clear decision rights, model documentation, data controls, validation steps, human oversight, risk assessment, performance tracking, incident handling, and ongoing learning. AI governance maturity, therefore, reaches further than the mere presence of an AI ethics policy. It constitutes an organizational capacity for applying governance mechanisms steadily throughout AI design, development, deployment, use, monitoring, and retirement. Schneider et al. (2023) note that effective AI governance calls for coordinated control over data, machine learning models, and full AI systems. Papagiannidis et al. (2025) likewise frame responsible AI governance through structural, procedural, and relational practices that secure the safe, trustworthy, and ethical operation of AI across its life cycle. AI governance maturity holds special weight in smart organizations because financial managers increasingly depend on explainable AI outputs when assessing investments, liquidity, credit exposure, budgets, financing options, and financial risks. Although explainable AI capability can render model

reasoning clearer, explanations by themselves do not ensure predictive accuracy, fairness, reliability, or suitable managerial reliance. Explanations may prove incomplete, technically unfaithful, cognitively demanding, or selectively read. Therefore, explainability must sit inside governance arrangements that validate models, check data quality, assign responsibility, and define acceptable conditions for AI supported financial decisions (Schneider et al., 2023). Mature governance settles whether explanations truly mirror model behaviour, whether underlying data stay reliable, and whether AI recommendations meet financial, ethical, and regulatory standards. When AI governance maturity stands high, clear responsibilities, model documentation, validation protocols, audit trails, continuous monitoring, and escalation procedures help managers separate trustworthy explanations from misleading or unstable ones. Governance also fosters employee training, stakeholder communication, and interdisciplinary review, allowing financial managers to read explanations critically rather than accept them by default. Cao et al. (2026) show that ethics, transparency, and explainability aid trustworthy AI adoption and managerial decision efficacy, though decision complexity can shape the strength of these effects. Therefore, mature governance should heighten the worth of explainable AI capability by turning technical explanations into validated, accountable, and managerially usable knowledge. From a dynamic capabilities view, AI governance maturity lets organizations integrate and reconfigure technological, financial, human, and managerial resources as AI risks, regulations, and market conditions change. It shifts explainability from an isolated system trait into an organizationally managed decision resource. Raisch & Krakowski (2021) contend that organizations must balance automation with human augmentation, which means governance should safeguard human judgment while still enabling AI based value creation. From a positivist stance, AI governance maturity can be gauged through standardized indicators of policy formalization, accountability, documentation, monitoring, oversight, risk control, employee competence, and organizational learning. Its moderating role can be examined by testing whether the interaction between explainable AI capability and AI governance maturity significantly forecasts financial decision quality. A critical realist stance regards governance maturity as an underlying enabling mechanism whose visible effects rest on leadership commitment, organizational culture, professional expertise, power relations, and enforcement practices (Zachariadis et al., 2013). Formal policies may therefore yield limited gains when they stay detached from daily routines or amount to symbolic compliance. A pragmatic stance judges

governance maturity by whether it assists managers in spotting model failures, assigning responsibility, justifying decisions, reacting to financial risks, and avoiding harm (Goldkuhl, 2012). The moderating influence may not always prove strong. Papagiannidis et al. (2025) indicate that coordinated governance practices reinforce responsible organizational use of AI. By contrast, Birkstedt et al. (2023) point to weak operationalization, uncertain implementation effectiveness, and limited governance competence as lasting issues. Overly rigid governance may also slow decisions, limit innovation, and curb managerial flexibility. Yet, mature governance differs from restrictive compliance because it balances control with adaptability and ensures that explanations remain validated, relevant, and usable. The positive contribution of explainable AI capability to financial decision quality should therefore grow stronger when AI governance maturity is higher. On this basis, the following hypothesis is advanced:

H3: AI governance maturity positively moderates the relationship between explainable AI capability and financial decision quality in smart organizations.

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

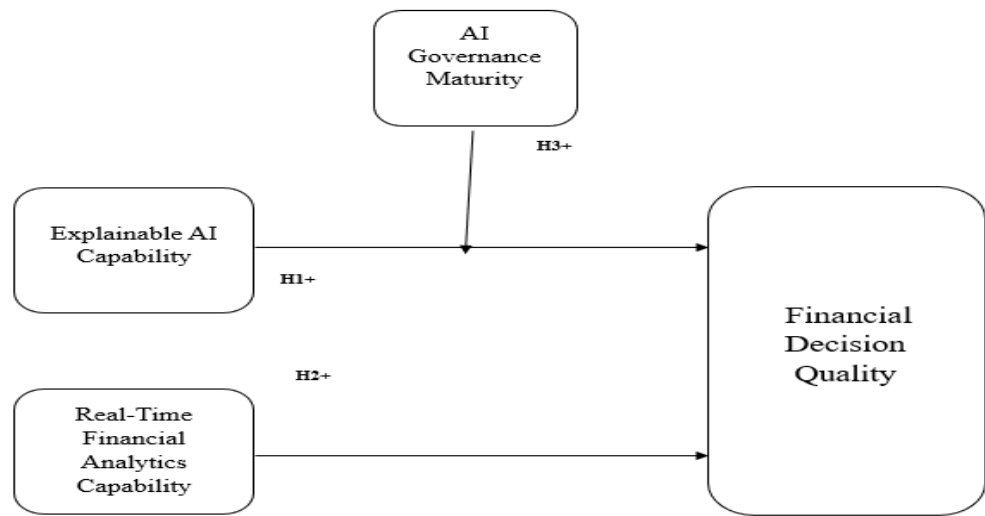


Figure 1: The Paper Conceptual Framework

METHODS

3.1. Sampling Strategy

This study adopted a quantitative cross sectional design to examine how explainable AI capability and real time financial analytics capability shape financial decision quality in smart organizations while testing the moderating role of AI governance maturity. Vietnam was chosen as organizations there increasingly apply artificial intelligence, business intelligence,

automated reporting, and advanced analytics in financial management. The quantitative approach supported hypothesis testing and evaluation of direct and interaction effects via standardized survey responses, and the cross sectional design captured perceptions of explainable AI, financial analytics, governance maturity, and financial decision quality at a single point in time (Bryman, 2016). Individual organizational members served as the unit of analysis. Purposive sampling targeted participants able to assess AI supported financial decision processes. Eligible respondents were at least 18 years old, employed by a Vietnamese organization, and experienced in financial management, accounting, business analytics, artificial intelligence, information technology, risk management, auditing, or governance. The sample included senior managers, middle managers, finance and accounting professionals, data analytics and information technology specialists, and risk, audit, or compliance staff drawn from varied regions, industries, organizational sizes, roles, and levels of technological familiarity to enhance diversity.

Data collection used a structured self administered questionnaire built from established scales. Explainable AI capability measured whether organizations could render AI logic, inputs, uncertainty, and recommendations clear and actionable for financial decision makers, drawing on AI capability and explainability studies (Mikalef & Gupta, 2021; Meske et al., 2022). Real time financial analytics capability assessed the ability to continuously collect, integrate, analyze, visualize, and interpret financial and operational data, with items adapted from work on analytics resources, data quality, expertise, and decision performance (Akter et al., 2016; Ghasemaghaei et al., 2018). AI governance maturity captured the formalization and refinement of AI policies, accountability, validation, monitoring, risk controls, and human oversight, grounded in governance frameworks (Schneider et al., 2023; Papagiannidis et al., 2025). Financial decision quality evaluated whether financial choices were accurate, timely, evidence based, transparent, consistent, and aligned with organizational goals (Ghasemaghaei et al., 2018; Hjelle et al., 2024). All items used a five point Likert scale ranging from 1 for strongly disagree to 5 for strongly agree. Academic experts in finance, analytics, artificial intelligence, governance, and quantitative methods reviewed the instrument for relevance and clarity, while finance managers and analytics professionals confirmed that the items matched organizational practice. Because the questionnaire was administered in Vietnamese, translation followed by back translation secured conceptual equivalence with the English measures. Distribution occurred through universities, professional networks, business

communities, organizational contacts, and digital channels. Participation was voluntary and anonymous. Respondents received details on the academic purpose, confidentiality, and right to withdraw. Screening questions and attention checks strengthened data quality. After removal of incomplete, duplicate, patterned, unusually rapid, and disengaged responses, 385 valid questionnaires remained for analysis.

3.2. Data analysis

Data analysis employed IBM SPSS version 26 and Hayes' Process Macro. Descriptive statistics summarized organizational regions, professional roles, organizational sizes, and familiarity with explainable AI, real time financial analytics, AI governance, and financial decision making. Scale reliability was assessed via Cronbach's alpha, with coefficients of 0.70 or higher and corrected item total correlations above 0.30 indicating adequate internal consistency (Tavakol & Dennick, 2011). Exploratory factor analysis then applied principal component extraction and Varimax rotation, retaining items with factor loadings above 0.50 and no cross loadings (Hair et al., 2009). Multiple linear regression tested the direct effects of explainable AI capability and real time financial analytics capability on financial decision quality at a significance level of p below 0.05. Finally, Hayes' Process Model 1 examined whether AI governance maturity moderated the link between explainable AI capability and financial decision quality (Hayes, 2022).

4. RESULTS

4.1. Descriptive Statistical Analysis

The sample represented smart organizations across the major economic regions of Vietnam. Specifically, 43.6% of respondents worked for organizations located in Southern Vietnam, 32.2% were based in Northern Vietnam, and 24.2% came from Central Vietnam. Regarding organizational roles, finance or accounting professionals constituted the largest group at 26.2%, followed by middle or functional managers at 23.4%, data analytics or information technology specialists at 20.8%, owners, directors, or senior managers at 16.9%, and risk management, internal audit, or compliance professionals at 12.7%. In terms of organizational size, organizations employing 50 to 249 people accounted for the largest proportion at 32.7%, while those with 250 to 999 employees represented 30.4%. Large organizations employing at least 1,000 people constituted 22.1%, whereas organizations with fewer than 50 employees accounted for 14.8%. Furthermore, 39.0% of participants reported high familiarity with their organizations' use of explainable AI, real time financial analytics, and AI governance in

financial decision making, while 20.5% indicated very high familiarity and 31.2% reported moderate familiarity. Only 9.3% possessed limited familiarity. Overall, the results demonstrate that the sample incorporated diverse organizational contexts, professional roles, and firm sizes. Most respondents also possessed sufficient knowledge to evaluate explainable AI capability, real time financial analytics capability, AI governance maturity, and financial decision quality in smart organizations.

4.2. Reliability analysis

Table 1 presents the measurement items used to operationalize the study constructs. Each construct was measured using four items derived and adapted from established academic literature to ensure theoretical alignment and adequate coverage of its key dimensions. Participants rated all items on a five point Likert scale ranging from 1 representing strongly disagree to 5 representing strongly agree.

Table 1: Measurement Items

Code	Survey item	Theoretical source
Financial decision quality in smart organizations		
FDQ1	Financial decisions in our organization are based on accurate and reliable information.	Ghasemaghaei et al. (2018) and Li et al. (2022)
FDQ2	Financial decisions in our organization are made within an appropriate timeframe.	Ghasemaghaei et al. (2018) and Hjelle et al. (2024)
FDQ3	Financial decisions in our organization are supported by relevant evidence and systematic analysis.	Ghasemaghaei (2019) and Li et al. (2022)
FDQ4	Financial decisions in our organization are consistent with its financial and strategic objectives.	Aydiner et al. (2019) and Ghasemaghaei et al. (2018)
Explainable AI capability		
XAIC1	Our organization's AI systems provide understandable explanations for their predictions and recommendations.	Meske et al. (2022) and Longo et al. (2024)
XAIC2	Our organization's AI systems identify the input factors that contribute most strongly to their predictions.	Bauer et al. (2023) and Meske et al. (2022)
XAIC3	Our organization's AI systems communicate the uncertainty and limitations associated with their outputs.	Longo et al. (2024) and Meske et al. (2022)

XAIC4	Our organization's AI systems present explanations in a form that decision makers can interpret and review.	Meske et al. (2022) and von Zahn et al. (2025)
Real time financial analytics capability		
RTFAC1	Our organization continuously integrates current financial and operational data into its analytics systems.	Akter et al. (2016) and Ghasemaghahi et al. (2018)
RTFAC2	Our organization's analytics tools process financial data as it becomes available.	Chatterjee et al. (2023) and Ghasemaghahi et al. (2018)
RTFAC3	Our organization has personnel with the expertise required to interpret current financial analytics.	Akter et al. (2016) and Ghasemaghahi et al. (2018)
RTFAC4	Our organization provides timely visualizations of its current financial conditions.	Chatterjee et al. (2023) and Hjelle et al. (2024)
AI governance maturity		
AIGM1	Our organization has formally documented policies governing the development and use of AI systems.	Birkstedt et al. (2023) and Schneider et al. (2023)
AIGM2	Responsibilities for approving, overseeing, and reviewing AI systems are clearly assigned in our organization.	Birkstedt et al. (2023) and Papagiannidis et al. (2025)
AIGM3	Our organization systematically validates, documents, and monitors AI models throughout their life cycles.	Papagiannidis et al. (2025) and Schneider et al. (2023)
AIGM4	Our organization periodically reviews and updates its AI governance practices in response to emerging risks and requirements.	Birkstedt et al. (2023) and Papagiannidis et al. (2025)

Table 2: Reliability analysis of “Financial decision quality in smart organizations”.

Reliability Statistics

Cronbach's Alpha	N of Items
.826	4

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
FDQ1	10.180	5.507	0.594	0.783
FDQ2	10.160	5.361	0.632	0.755
FDQ3	10.230	5.356	0.696	0.701
FDQ4	10.250	5.423	0.692	0.700

Source: (The authors, 2026)

As presented in Table 2, all four items recorded corrected item total correlation values ranging from 0.594 to 0.696, substantially exceeding the recommended threshold of 0.30. The overall scale achieved a Cronbach's alpha of 0.826, 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 0.700 to 0.783, all of which remained lower than the overall alpha. This finding indicates that removing any item would reduce the reliability of the scale. Therefore, FDQ1 to FDQ4 contributed meaningfully to the measurement of financial decision quality in smart organizations and were retained for subsequent analyses. Comparable reliability levels were also observed across 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	
FDQ1	0.724	XAIC1	0.768	RTFAC1	0.752	AIGM1	0.739
FDQ2	0.761	XAIC2	0.811	RTFAC2	0.806	AIGM2	0.783
FDQ3	0.824	XAIC3	0.746	RTFAC3	0.771	AIGM3	0.817
FDQ4	0.819	XAIC4	0.702	RTFAC4	0.718	AIGM4	0.756
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 financial decision quality in smart organizations, explainable AI capability, real time financial analytics capability, and AI governance maturity. All 16 measurement items loaded strongly on their intended factors, with coefficients ranging from 0.702 to 0.824,

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	0.28	0.127		2.24	0.03
XAIC	0.52	0.025	0.636	20.8	0
RTFAC	0.47	0.026	0.58	18	0
a. Dependent Variable: FDQ					

Source: (The authors, 2026)

Where XAIC represents the mean of XAIC1 to XAIC4, RTFAC represents the mean of RTFAC1 to RTFAC4, and FDQ represents the mean of FDQ1 to FDQ4.

As shown in Table 4, the significance values for the relationships between explainable AI capability and financial decision quality in smart organizations and between real time financial analytics capability and financial decision quality in smart organizations were both 0.000, which is well below the 0.05 threshold. Explainable AI capability had a significant positive effect on financial decision quality with $\beta = 0.636$, $t = 20.840$, and $p < 0.001$. Real time financial analytics capability also exerted a significant positive effect, with $\beta = 0.580$, $t = 18.000$, and $p < 0.001$. These findings provide strong empirical support for accepting H1 and H2.

Moderator analysis

Table 5: Results analysis of “AI governance maturity”.

Model: 1 Y: FDQ X: XAIC W: AIGM Sample
Size: 385

**

OUTCOME VARIABLE: FDQ Model Summary

R	R-sq	MSE	F	dl1	dl2	p
0.69	0.47	0.24	112.18	3	381	0

Model

	Coeff.	SE	t	p	LLCI	ULCI
Constant	0.284	0.1	2.898	0	0.09	0.48
XAIC	0.623	0.04	15.58	0	0.54	0.7
AIGM	0.605	0.04	14.41	0	0.52	0.69
Int_1	0.436	0.04	11.47	0	0.36	0.51

Source: (The authors, 2026)

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

The positive interaction coefficient of $B = 0.436$ shows that higher AI governance maturity intensifies the beneficial effect of explainable AI capability on financial decision quality within smart organizations. Although explainable AI capability renders algorithmic predictions and recommendations clearer, its impact on financial decision quality grows stronger when organizations maintain mature AI governance arrangements. Well-defined responsibilities, structured validation routines, ongoing model monitoring, thorough documentation, and robust risk controls allow financial managers to assess AI explanations with greater care and deploy them more suitably. As a result, organizations that have advanced AI governance convert understandable AI outputs into accurate, timely, evidence based, and strategically coherent financial decisions more effectively. In addition, the confidence interval for the interaction term, spanning LLCI = 0.361 to ULCI = 0.511, excludes zero and thereby affirms both the significance and reliability of this positive moderating influence. In short, the results position AI governance maturity as a key boundary condition that heightens the favorable contribution of explainable AI capability to financial decision quality in smart organizations, providing empirical support for Hypothesis H3.

5. DISCUSSION

5.1. Result Summary

Explainable AI capability and real time financial analytics capability each exert significant positive influences on financial decision quality in smart organizations, as reflected in the standardized regression coefficients of 0.636 and 0.580. These results show that clear AI explanations together with prompt financial information help managers assess options, check algorithmic suggestions, detect rising risks, and reach more accurate evidence based financial choices. At the same time, AI governance maturity functions as a significant positive

moderator that intensifies the link between explainable AI capability and financial decision quality, confirmed by the interaction coefficient of 0.436 and the confidence interval spanning 0.361 to 0.511. The pattern indicates that explainability yields stronger decision gains when backed by well defined responsibilities, model validation routines, audit trails, continuous monitoring, documentation, and sound risk controls. In summary, the empirical evidence upholds all three hypotheses and affirms the theoretical framework that ties explainable AI capability, real time financial analytics capability, AI governance maturity, and financial decision quality in smart organizations. Turning to the research questions, the findings resolve the first by verifying that explainable AI capability markedly elevates financial decision quality. They settle the second by establishing that real time financial analytics capability likewise produces a significant positive effect, even though its standardized coefficient is modestly lower than that of explainable AI capability. They address the third by revealing that higher AI governance maturity meaningfully magnifies the positive role of explainable AI capability in shaping financial decision quality. Together, these outcomes underscore that smart organizations benefit most when they integrate understandable AI systems with current financial analytics and mature governance structures. Improving financial decision quality therefore calls for organizations to craft accessible explanations, sustain reliable up to date data, ensure human oversight, validate AI models systematically, and assign clear accountability for AI supported financial decisions.

5.2. Theoretical Implications

The empirical findings strongly support H1, as explainable AI capability significantly elevates financial decision quality with $\beta = 0.636$. This outcome aligns with Meske et al. (2022), who contend that clear explanations enable informed human oversight, and Bauer et al. (2023), who show that explainability can enhance users' grasp of algorithmic judgments. It further backs Longo et al. (2024), who regard explanation as vital for rendering AI outputs understandable and open to challenge. At the same time, the study only partly agrees with deterministic assertions that higher transparency inevitably yields superior decisions. Longo et al. (2024) warn that even technically precise explanations may stay cognitively hard to access, while von Zahn et al. (2025) illustrate that explanation effects hinge on design features and users' ability to interpret them. The robust coefficient therefore implies that explainability generates value when it forms an organizational capability that blends technical methods, financial expertise, communication, and validation practices rather than simply presenting

model details. Theoretically, this research advances organizational information processing theory by framing explainable AI capability as an interpretive processing mechanism that lowers equivocality and turns opaque predictions into usable financial knowledge. In doing so, it clarifies why AI sophistication by itself falls short of ensuring high quality financial decisions.

The findings strongly support H2, given that real time financial analytics capability positively shapes financial decision quality with $\beta = 0.580$. This result agrees with Ghasemaghaei et al. (2018), who link analytical competence to better decision performance, and Akter et al. (2016), who maintain that analytics delivers value through the combination of technological, managerial, and human resources. It also bolsters Hjelle et al. (2024), who stress that timely analytics can heighten organizational responsiveness. Yet the evidence questions any technologically deterministic view that swifter information always produces better decisions. Ghasemaghaei (2019) shows that data quality and analytical skill condition the benefits drawn from large volumes of data, while Chatterjee et al. (2023) indicate that analytics capabilities produce results through complementary organizational processes. Although the coefficient remains sizable, it is lower than that of explainable AI capability, suggesting that speed cannot replace interpretation, reliability, or managerial judgment. The study therefore endorses capability based perspectives but does not favor regarding real time dashboards as a standalone remedy for financial uncertainty. Theoretically, it develops organizational information processing theory by treating real time financial analytics capability as temporal processing capacity that shortens information lags and matches present financial signals with managerial actions.

The empirical findings support H3, since the positive interaction coefficient of 0.436 demonstrates that AI governance maturity intensifies the association between explainable AI capability and financial decision quality. This outcome closely matches Birkstedt et al. (2023), who view AI governance as an organizational system of accountability, oversight, and control, and Papagiannidis et al. (2025), who highlight governance capabilities across the AI lifecycle. It also upholds Schneider et al. (2023), whose governance lens underscores the need to align technical and managerial duties. However, the results do not favor the notion that formal governance documents alone ensure responsible or effective AI application. Birkstedt et al. (2023) recognize that governance demands operational mechanisms, while Papagiannidis et al. (2025) stress ongoing organizational adjustment rather than fixed compliance. The

significant interaction implies that explanations gain greater decision relevance when validation, monitoring, auditability, escalation, and accountability are woven into daily practices. Consequently, governance does not simply exert an independent direct effect but shapes whether explainability translates into reliable financial judgment. Theoretically, the study advances dynamic capabilities theory by casting AI governance maturity as a reconfiguring capability that unites explanatory technologies, professional expertise, and control routines as risks and demands shift. In this way, it identifies governance maturity as a theoretically significant boundary condition.

5.3. Practical Implications

The support for H1 shows that smart organizations ought to regard explainable AI capability as a unified managerial capability instead of merely acquiring explanation software. Financial leaders should insist that AI systems reveal key inputs, assumptions, uncertainty levels, limitations, and the rationale behind recommendations on investment, liquidity, lending, budgeting, and risk. Yet, managers must not treat explanation visibility as equivalent to explanation quality. Highly technical explanations can overload nontechnical users or foster unwarranted confidence when they fail to mirror actual model behaviour (Longo et al., 2024). Organizations should therefore engage financial professionals, data scientists, auditors, and decision owners in crafting role suitable explanation interfaces. Scenario testing and explanation focused training can enable managers to question recommendations and adjust reliance rather than accept algorithmic outputs by default. This stance echoes Meske et al. (2022), who stress that explainability should foster understanding, control, and productive human interaction. Given that explainable AI capability yielded the strongest direct effect with $\beta = 0.636$, resources devoted to interpretability, user skill, and validation ought to form a core priority in financial transformation.

The support for H2 indicates that organizations should build real time financial analytics capability through aligned investments in data architecture, analytical tools, professional expertise, and decision processes. Managers should combine financial and operational data drawn from accounting systems, enterprise resource planning platforms, customer transactions, supply networks, and market sources to generate current pictures of cash flow, costs, credit exposure, and financial risk. Even so, accelerated analytics must not compromise data reliability. Ghasemaghaei (2019) shows that decision gains rest on analytical competence and data quality, while Akter et al. (2016) frame analytics performance as the product of

complementary technological, managerial, and human resources. Organizations should therefore put in place data quality controls, consistent definitions, automated exception alerts, and clear ownership of essential financial data. Because the effect of real time financial analytics capability was sizable yet weaker than that of explainable AI capability with $\beta = 0.580$, dashboards should aid rather than supplant professional interpretation. Decision protocols should clarify when real time signals call for immediate action, additional inquiry, or escalation to senior financial managers.

The support for H3 reveals that explainability delivers stronger financial value when situated within mature AI governance. Organizations should create model approval processes, accountability frameworks, audit trails, validation standards, monitoring schedules, incident reporting, and escalation routes. Governance duties should be allocated distinctly across finance, technology, risk, compliance, internal audit, and executive leadership. Birkstedt et al. (2023) underline that AI governance demands coordinated structures and processes, while Papagiannidis et al. (2025) stress governance throughout the AI lifecycle. Still, organizations must steer clear of symbolic governance in which policies appear without real enforcement. Periodic audits should check whether explanations stay faithful, whether model performance has declined, and whether biased or unreliable recommendations influence financial decisions. The significant interaction coefficient of 0.436 shows that governance maturity is not simply a compliance cost but a capability that unlocks value. Smart organizations should therefore link explainability investments to operational oversight, staff training, documented human review, and ongoing governance refinement.

5.4. Limitations

This study carries several limitations. Its cross sectional design records organizational perceptions at a single moment and thus cannot confirm firm temporal causality among the constructs. Purposive sampling and the Vietnamese setting may limit generalizability to other countries, industries, and regulatory contexts. Although respondents held relevant professional knowledge, self reported measures can introduce common method bias, social desirability, and overly positive views of organizational capabilities. Aggregating individual perceptions to stand for organizational constructs may also mask differences among financial managers, AI specialists, auditors, and executives. The model tests only the moderating role of AI governance maturity in the link between explainable AI capability and financial decision

quality. Other pertinent conditions, such as data quality, financial expertise, organizational culture, model complexity, and environmental uncertainty, lie beyond its empirical reach.

5.5. Future Research Directions

Future studies should adopt longitudinal or experimental designs to establish whether gains in explainability and real time analytics lead to lasting rises in financial decision quality. Cross national and multi industry work could examine whether the relationships differ across institutional, technological, and regulatory settings. Researchers should pair survey answers with objective markers such as forecasting errors, decision speed, financial losses, model overrides, and audit outcomes. Multilevel designs could separate individual expertise from organizational capability and explore divergence among managers, data scientists, and assurance professionals. Additional research should explore data quality, AI literacy, decision complexity, organizational culture, and environmental turbulence as moderators or mediators. Comparative studies could also evaluate varied explanation formats and governance setups. Finally, configurational research may uncover combinations of analytics, explainability, human judgment, and governance that yield high financial decision quality.

5.6. Conclusion

This study shows that explainable AI capability and real time financial analytics capability markedly raise financial decision quality in smart organizations. Explainable AI capability generated the stronger direct effect, affirming that intelligibility, interpretability, and contestability are essential for turning algorithmic outputs into defensible financial judgments. Real time financial analytics capability likewise enhanced decision quality by providing timely and relevant financial information. In addition, AI governance maturity amplified the contribution of explainable AI capability, demonstrating that explanations gain value when backed by accountability, validation, monitoring, and oversight. All three hypotheses therefore received support. By combining organizational information processing theory and dynamic capabilities theory, the research clarifies how interpretive, temporal, and governance capabilities together underpin financial decisions. Smart organizations should consequently pair technological investment with professional expertise, dependable information, human judgment, and enforceable governance practices.

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References

1. Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, 182, 113–131. <https://doi.org/10.1016/j.ijpe.2016.08.018>
2. Aydiner, A. S., Tatoglu, E., Bayraktar, E., Zaim, S., & Delen, D. (2019). Business analytics and firm performance: The mediating role of business process performance. *Journal of Business Research*, 96, 228–237. <https://doi.org/10.1016/j.jbusres.2018.11.028>
3. Baron, S. (2025). Trust, explainability and AI: S. Baron. *Philosophy & Technology*, 38(1), 4. <https://doi.org/10.1007/s13347-024-00837-6>
4. Bauer, K., Von Zahn, M., & Hinz, O. (2023). Expl(AI)ned: The impact of explainable artificial intelligence on users' information processing. *Information Systems Research*, 34(4), 1582–1602. <https://doi.org/10.1287/isre.2023.1199>
5. Birkstedt, T., Minkkinen, M., Tandon, A., & Mäntymäki, M. (2023). AI governance: Themes, knowledge gaps and future agendas. *Internet Research*, 33(7), 133–167. <https://doi.org/10.1108/INTR-01-2022-0042>
6. Bryman, A. (2016). *Social research methods*. Oxford University Press.
7. Cao, G., Duan, Y., & Edwards, J. S. (2026). AI trustworthiness in managerial decision-making: Ethics, transparency, and explainability as key drivers. *Journal of Business Ethics*, 1–21. <https://doi.org/10.1007/s10551-026-06400-x>

8. Chatterjee, S., Chaudhuri, R., Gupta, S., Sivarajah, U., & Bag, S. (2023). Assessing the impact of big data analytics on decision-making processes, forecasting, and performance of a firm. *Technological Forecasting and Social Change*, 196, 122824. <https://doi.org/10.1016/j.techfore.2023.122824>
9. Elgendy, N., Elragal, A., & Päivärinta, T. (2022). DECAS: A modern data-driven decision theory for big data and analytics. *Journal of Decision Systems*, 31(4), 337–373. <https://doi.org/10.1080/12460125.2021.1894674>
10. Fügener, A., Grahl, J., Gupta, A., & Ketter, W. (2022). Cognitive challenges in human–artificial intelligence collaboration: Investigating the path toward productive delegation. *Information Systems Research*, 33(2), 678–696. <https://doi.org/10.1287/isre.2021.1079>
11. Galbraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, 4(3), 28–36. <https://doi.org/10.1287/inte.4.3.28>
12. 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>
13. 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>
14. Goldkuhl, G. (2012). Pragmatism vs interpretivism in qualitative information systems research. *European Journal of Information Systems*, 21(2), 135–146. <https://doi.org/10.1057/ejis.2011.54>
15. Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L. (2009). *Multivariate data analysis* (7th ed.). Prentice Hall.
16. Hayes, A. F. (2022). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach* (3rd ed.). Guilford Press.

17. Hjelle, S., Mikalef, P., Altwaijry, N., & Parida, V. (2024). Organizational decision making and analytics: An experimental study on dashboard visualizations. *Information & Management*, 61(6), 104011. <https://doi.org/10.1016/j.im.2024.104011>
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. Leichtmann, B., Humer, C., Hinterreiter, A., Streit, M., & Mara, M. (2023). Effects of explainable artificial intelligence on trust and human behavior in a high-risk decision task. *Computers in Human Behavior*, 139, 107539. <https://doi.org/10.1016/j.chb.2022.107539>
20. Li, L., Lin, J., Ouyang, Y., & Luo, X. R. (2022). Evaluating the impact of big data analytics usage on the decision-making quality of organizations. *Technological Forecasting and Social Change*, 175, 121355. <https://doi.org/10.1016/j.techfore.2021.121355>
21. Longo, L., Brcic, M., Cabitza, F., Choi, J., Confalonieri, R., Del Ser, J., et al. (2024). Explainable artificial intelligence (XAI) 2.0: A manifesto of open challenges and interdisciplinary research directions. *Information Fusion*, 106, 102301. <https://doi.org/10.1016/j.inffus.2024.102301>
22. Lu, T., & Zhang, Y. (2025). 1 + 1 > 2? Information, humans, and machines. *Information Systems Research*, 36(1), 394–418. <https://doi.org/10.1287/isre.2023.0305>
23. Meske, C., Bunde, E., Schneider, J., & Gersch, M. (2022). Explainable artificial intelligence: Objectives, stakeholders, and future research opportunities. *Information Systems Management*, 39(1), 53–63. <https://doi.org/10.1080/10580530.2020.1849465>
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. 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>
26. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. *Academy of Management Review*, 46(1), 192–210. <https://doi.org/10.5465/amr.2018.0072>
27. Roetzel, P. G. (2019). Information overload in the information age: A review of the literature from business administration, business psychology, and related disciplines with a bibliometric approach and framework development. *Business Research*, 12(2), 479–522. <https://doi.org/10.1007/s40685-018-0069-z>
28. Sadeghi, K., Ojha, D., Kaur, P., Mahto, R. V., & Dhir, A. (2024). Explainable artificial intelligence and agile decision-making in supply chain cyber resilience. *Decision Support Systems*, 180, 114194. <https://doi.org/10.1016/j.dss.2024.114194>
29. 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>
30. Senoner, J., Netland, T., & Feuerriegel, S. (2022). Using explainable artificial intelligence to improve process quality: Evidence from semiconductor manufacturing. *Management Science*, 68(8), 5704–5723. <https://doi.org/10.1287/mnsc.2021.4190>
31. 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>
32. 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>
33. 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>
34. 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>
 35. 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>
 36. 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](https://doi.org/10.1002/(SICI)1097-0266(199708)18:7%3C509::AID-SMJ882%3E3.0.CO;2-Z)
 37. Von Zahn, M., Liebich, L., Jussupow, E., Hinz, O., & Bauer, K. (2025). Knowing (not) to know: Explainable artificial intelligence and human metacognition. *Information Systems Research*. <https://doi.org/10.1287/isre.2024.1431>
 38. Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long Range Planning*, 52(3), 326–349. <https://doi.org/10.1016/j.lrp.2018.12.001>
 39. Zachariadis, M., Scott, S., & Barrett, M. (2013). Methodological implications of critical realism for mixed-methods research. *MIS Quarterly*, 37(3), 855–879.
<https://doi.org/10.25300/MISQ/2013/37.3.09>