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AI Governance and Corporate Financial Decision-Making: A Conceptual Framework for Sustainable Value Creation

Zeren Jamal*

Abstract

The rapid integration of artificial intelligence into corporate finance alters how capital is allocated, risk is assessed, and value is measured. Without deliberate governance, algorithmic decision systems can amplify bias, obscure accountability, and privilege short-term gains over durable performance. This paper develops a conceptual framework linking AI governance mechanisms to the quality of AI-augmented financial decisions and, ultimately, to sustainable value creation. Drawing on interdisciplinary scholarship in AI ethics, corporate governance, and sustainable finance, the framework identifies five governance dimensions: board-level oversight, algorithmic transparency, fairness audits, accountability structures, and ethical principles integration. These dimensions are proposed to enhance decision quality by reducing opacity, mitigating bias, and reinforcing long-term orientation. The model posits that decision quality mediates the relationship between AI adoption and sustainable value, while governance strength moderates this indirect path. The framework yields testable propositions and offers practical guidance for boards and regulators navigating the intersection of algorithmic capability and fiduciary duty. The paper contributes a governance-centric lens to the emerging literature on AI in corporate finance, moving the conversation from technical deployment toward institutional conditions that enable responsible, value-sustaining outcomes.

Keywords

AI governance, corporate financial decisions, sustainable value, algorithmic accountability, ESG, decision quality

Independent Research

INTRODUCTION

Capital allocation, credit assessment, risk pricing, and investment selection increasingly rely on predictive models that learn from vast datasets without explicit human instruction. Machine learning algorithms now screen loan applicants, generate trading signals, and calibrate enterprise risk metrics with speed and granularity that manual processes cannot match. These technical gains do not automatically translate into better corporate financial outcomes. Amplified model opacity, embedded historical bias, and the erosion of reasoned deliberation can distort decisions and expose firms to reputational, legal, and strategic harm. Scholars and practitioners have therefore called for robust AI governance, the structures, principles, and practices that ensure algorithmic systems align with organizational values and societal expectations.

Despite the proliferation of ethical AI guidelines and boardroom discussions, conceptual work that explicitly connects AI governance to the quality of financial decision-making and long-term value creation remains scarce. Existing research tends to treat governance as a compliance concern separate from the mechanics of financial choice. The present paper bridges this gap by asking: How do AI governance mechanisms shape corporate financial decisions, and through what pathways do they foster sustainable value? The question is consequential because institutional investors, rating agencies, and regulators increasingly demand evidence that firms can manage algorithmic risks without sacrificing performance. Without a clear theoretical model, boards lack the analytical scaffolding to design governance interventions that protect and create value.

This article proposes a conceptual framework that positions AI governance as a multidimensional enabler of high-quality financial decisions, which in turn drive sustainable value creation. Sustainable value is defined here as the generation

***Corresponding Author:** Zeren Jamal

of risk-adjusted financial returns while maintaining or improving environmental, social, and governance (ESG) performance over multi-year horizons. The framework draws on recent advances in AI ethics (Jobin et al., 2019; Fjeld et al., 2020), algorithmic management (Raisch & Krakowski, 2021; Kellogg et al., 2020), and sustainable finance (Whelan et al., 2021; Grewal et al., 2021). It yields four testable propositions and a visual model intended to guide empirical work and board-level design. The remainder of the paper reviews the pertinent literature, constructs the framework, develops propositions, and discusses implications for theory and practice.

LITERATURE REVIEW

AI Governance: From Principles to Institutional Mechanisms

The landscape of AI governance has expanded rapidly, moving from high-level ethical principles to concrete oversight instruments. A global mapping of AI ethics guidelines reveals convergence around transparency, fairness, non-maleficence, accountability, and privacy (Jobin et al., 2019). Principled frameworks such as the OECD AI Principles and the European Commission's Ethics Guidelines for Trustworthy AI translate these values into operational requirements for organizations (Fjeld et al., 2020). Parallel legal and regulatory developments, including the EU Artificial Intelligence Act, codify risk-based obligations for high-stakes algorithmic systems. While these instruments shape the external environment, firms must internalize governance through board mandates, audit functions, and management controls.

Within the corporate sphere, AI governance refers to the allocation of decision rights, monitoring procedures, and accountability mechanisms that guide the lifecycle of algorithmic models (Buiten, 2019; Taeihagh, 2021). Scholarly work distinguishes between formal compliance structures and substantive governance that shapes how algorithms influence real-world choices. Kriebitz and Lütge (2020) argue that corporate human rights responsibilities extend to algorithmic systems, necessitating due diligence processes that assess systemic bias. Martin (2019) emphasizes that algorithmic accountability requires answerability beyond technical explainability; it demands clear lines of human responsibility for outcomes. Similarly, Wieringa (2020) reviews algorithmic accountability practices and finds that auditability, traceability, and remedial mechanisms constitute the operational core of governance.

Despite rich conceptual work, limited research has examined how these governance mechanisms influence the caliber of financial decisions. Most AI governance studies remain anchored in public policy, technology ethics, or general management, with sparse attention to the distinctive pressures of corporate finance. This omission is critical because financial decisions allocate resources that shape firm survival, stakeholder welfare, and societal outcomes.

AI-Augmented Financial Decision-Making

The deployment of AI in corporate finance spans credit scoring, fraud detection, investment analysis, working capital management, and mergers and acquisitions due diligence. Machine learning models identify non-linear patterns in structured and unstructured data, offering predictive accuracy that often surpasses traditional econometric methods (Dastile et al., 2020). Eisfeldt et al. (2023) document that generative AI tools can enhance productivity in financial analysis, while algorithmic trading systems now execute a substantial fraction of equity volume. The OECD (2021) highlights both efficiency gains and emergent risks, including pro-cyclicality, data leakage, and model fragility.

Organizational scholars caution that the mere presence of predictive power does not guarantee decision quality. Raisch and Krakowski (2021) theorize an automation–augmentation paradox: substituting human judgment with algorithmic recommendations can erode the cognitive diversity and ethical reasoning that support robust choices. Shrestha et al. (2019) propose that effective AI adoption requires redesigned decision-making structures that preserve human oversight for consequential judgments. Kellogg et al. (2020) show that algorithmic control systems can undermine employee autonomy and moral engagement, effects that plausibly extend to financial managers who rely on opaque model outputs. Consequently, decision quality in AI-augmented finance should be conceptualized not solely as predictive accuracy but as a composite of accuracy, bias mitigation, interpretability, and long-term goal alignment.

Sustainable Value Creation

Sustainable value creation integrates financial performance with durable contributions to environmental and social welfare. A growing body of evidence indicates that firms with strong ESG profiles exhibit lower cost of capital, higher operational efficiency, and greater resilience during crises (Whelan et al., 2021). Material sustainability information enhances stock price informativeness, suggesting that markets reward genuine integration rather than symbolic disclosure (Grewal et al., 2021). The conceptual foundation rests on stakeholder theory and enlightened shareholder value, which posit that long-term shareholder returns depend on managing relationships with employees, communities, regulators, and the natural environment.

Connecting AI to sustainable value is not straightforward. Algorithmic systems optimized for narrow short-term financial metrics can erode stakeholder trust. Discriminatory credit models, aggressive trading algorithms that disregard market stability, and automated capital budgeting tools that ignore environmental externalities exemplify how ungoverned AI can destroy value over extended horizons. Conversely, AI systems that incorporate ESG data, audit for fairness, and expose long-term risk scenarios can enhance the quality of corporate decisions in ways that sustain value. Governance, therefore, acts as the mechanism that tilts the balance from value extraction to value building.

CONCEPTUAL FRAMEWORK

Core Constructs

The framework comprises three focal constructs. *AI governance* is a multidimensional formative construct encompassing five mechanisms: board-level AI oversight, algorithmic transparency and explainability, fairness and bias audits, accountability frameworks, and the integration of ethical AI principles into corporate policy. These mechanisms were selected based on frequency and consensus in the ethics and governance literature (Jobin et al., 2019; Fjeld et al., 2020; Martin, 2019) and their applicability to financial contexts. *AI-augmented financial decision quality* is defined as the extent to which financial decisions supported by algorithmic systems exhibit high predictive accuracy, low bias, interpretability that allows human review, and alignment with long-term strategic objectives. *Sustainable value creation* captures the simultaneous achievement of risk-adjusted financial returns and measurable improvements in material ESG indicators over multi-year periods.

Figure 1 presents the structural relationships. AI adoption, the extent to which a firm relies on algorithmic models for financial decisions, influences decision quality. This relationship is shaped by AI governance. Decision quality, in turn, drives sustainable value creation. The model thus specifies a moderated mediation: the indirect effect of AI adoption on sustainable value through decision quality is contingent on governance strength. A direct path from governance to decision quality is also posited, reflecting the notion that robust governance elevates decision processes even at a given level of AI adoption.

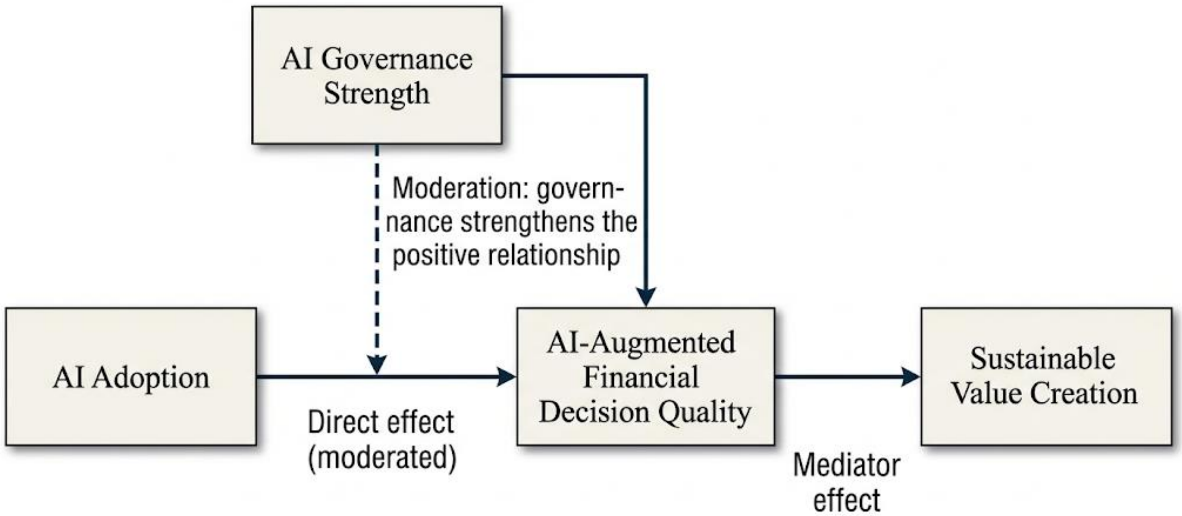

Figure 1. Conceptual framework of AI governance, financial decision quality, and sustainable value creation. The dashed line represents the moderation of the AI adoption–decision quality relationship by AI governance strength.

PROPOSITIONS

The first proposition addresses the direct effect of governance on decision quality. Boards that establish dedicated AI oversight committees, mandate model documentation standards, and link executive compensation to algorithmic fairness metrics create an institutional environment that favors careful, contestable financial decisions. Transparency allows managers to interrogate model logic rather than deferring to black-box outputs. Fairness audits surface hidden biases in credit or pricing algorithms before they cause harm. Accountability frameworks clarify who bears responsibility when automated decisions produce adverse outcomes, reducing moral hazard. These mechanisms collectively improve the information environment, lower the risk of catastrophic errors, and foster a culture where algorithmic outputs are treated as advisory inputs rather than final verdicts (Raisch & Krakowski, 2021; Shrestha et al., 2019).

Proposition 1. Stronger AI governance mechanisms are positively associated with the quality of AI-augmented financial decisions, controlling for the extent of AI adoption.

The second proposition links decision quality to sustainable value. Financial decisions of higher quality allocate capital to projects that generate competitive returns without imposing excessive negative externalities. Accurate risk models that incorporate climate scenarios reduce the probability of stranded assets. Unbiased credit assessment expands access to capital for underserved but creditworthy segments, strengthening social license and market reach. Interpretable forecasts enable boards to exercise informed judgment about trade-offs between short-term profit and long-term resilience. When decision quality is high, firms are better equipped to manage the tensions between immediate financial performance and the investments in human capital, innovation, and environmental stewardship that drive durable value (Whelan et al., 2021; Grewal et al., 2021). This reasoning suggests that the quality of AI-augmented choices, not the mere fact of AI use, determines sustainable outcomes.

Proposition 2. AI-augmented financial decision quality is positively associated with sustainable value creation.

The third proposition captures the moderating role of governance in the translation of AI adoption into decision quality. In weak governance settings, AI systems may be deployed rapidly to automate existing processes without adequate scrutiny. This can entrench historical biases, produce brittle models that fail under regime shifts, and incentivize managers to game short-term metrics that algorithms optimize. Under such conditions, greater AI adoption can actually degrade decision quality. Strong governance, by contrast, channels AI adoption toward augmentation: models are validated against fairness criteria, stress-tested for edge cases, and embedded within decision structures that retain meaningful human judgment. Thus, the slope of the relationship between AI adoption and decision quality becomes more positive as governance strength increases.

Proposition 3. AI governance moderates the positive relationship between AI adoption and financial decision quality, such that the relationship is stronger when governance mechanisms are robust and weaker or negative when governance is deficient.

Integrating the three propositions yields a moderated mediation thesis. The mechanism through which AI adoption influences sustainable value runs through decision quality, yet this transmission depends on the governance infrastructure that surrounds the technology. Firms that invest heavily in AI tools but neglect governance may experience a null or negative indirect effect; firms that pair technology with rigorous oversight and ethical guardrails benefit from an enhanced indirect effect.

Proposition 4. The indirect effect of AI adoption on sustainable value creation through decision quality is moderated by AI governance strength, such that the indirect effect is positive and significant only at higher levels of governance.

Governance Mechanisms and Financial Decision Impacts

Table 1 maps each governance dimension to its hypothesized impact on financial decision quality, with supporting sources. The table is intended to guide empirical operationalization and boardroom diagnostics.

Table 1. AI Governance Mechanisms and Expected Impact on Financial Decision Quality

Governance Mechanism	Description	Impact on Financial Decision Quality	Selected Sources
Board-level AI oversight	Dedicated committee or director expertise monitors AI risk and strategy	Reduces overreliance on black-box models; aligns AI with risk appetite and long-term goals	Raisch & Krakowski (2021); Shrestha et al. (2019)
Algorithmic transparency	Documentation standards and interpretable model architectures	Enhances auditability and manager trust; enables informed override of flawed model recommendations	Martin (2019); Wieringa (2020)
Fairness and bias audits	Regular statistical testing for discriminatory outcomes across protected groups	Mitigates legal and reputational risk; improves accuracy of credit and pricing decisions for underrepresented segments	Jobin et al. (2019); Kriebitz & Lütge (2020)
Accountability frameworks	Clear assignment of human responsibility for AI-driven decisions with remediation paths	Reduces moral hazard; encourages due diligence before automating high-stakes choices	Buiten (2019); Taeihagh (2021)
Ethical principles integration	Codified AI ethics charter linked to corporate strategy and training	Aligns financial choices with stakeholder values; supports ESG-consistent capital allocation	Fjeld et al. (2020); OECD (2021)

DISCUSSION

The proposed framework advances theory by integrating previously separate streams of research. AI governance scholarship has concentrated on societal-level norms and organizational ethics but has rarely specified how governance instruments alter the micro-foundations of financial choice. The finance literature has documented AI's predictive advantages while paying limited attention to the institutional conditions that determine whether those advantages translate into enduring value. By positioning decision quality as a mediating construct and governance as a boundary condition, the framework offers a structure for cumulative empirical inquiry.

A key insight is that AI governance is not merely a defensive tool against downside risk. It can be an enabling condition that converts algorithmic capability into strategic renewal. When boards treat AI governance as a value driver rather than a compliance cost, they shift the conversation from "Can we use this model?" to "How should we design our decision processes so that AI improves the quality of choices that matter most?" This reframing resonates with recent calls to move beyond responsible AI as risk management toward responsible AI as competitive differentiation (Taeihagh, 2021).

The framework also speaks to the growing demand for ESG integration in corporate finance. AI models that ingest vast ESG datasets can help firms identify material sustainability risks and opportunities more precisely than conventional analysis. Without governance, however, such models may be manipulated to greenwash or cherry-pick favorable indicators. Governance mechanisms like transparency and fairness audits ensure that ESG-augmented models contribute to decision quality rather than to performative disclosure. This alignment can strengthen the credibility of corporate sustainability claims with investors, rating agencies, and regulators.

Practical Implications

For boards and senior executives, the framework suggests a diagnostic sequence. First, assess the firm's current AI governance maturity across the five dimensions identified. Second, map the decision areas most affected by algorithmic systems: credit origination, investment screening, capital budgeting, and risk management are prime candidates. Third, evaluate decision quality using metrics beyond accuracy, incorporating bias measures, explainability scores, and alignment with long-term strategic objectives. Fourth, link decision quality to sustainability outcomes tracked in management dashboards and external reporting. This sequence can reveal governance gaps that, when closed, materially improve both financial and non-financial performance.

Regulators and standard-setters may derive implications from the moderated mediation logic. Disclosure mandates that require firms to report AI governance practices and their connection to material financial and sustainability metrics could reduce information asymmetries and nudge investment in governance. For instance, the EU's Corporate Sustainability Reporting Directive already pushes firms to disclose how intangibles including data and algorithms relate to business model resilience. Future iterations could incorporate metrics on algorithmic fairness audits and decision oversight.

Limitations and Future Research

The framework is conceptual and awaits empirical validation. Each proposition can be tested through surveys of CFOs and board members, archival measures of governance quality (e.g., existence of AI ethics charters, board technology committee composition), and objective proxies for decision quality such as loan default rate differentials across demographic groups or the accuracy of capital project post-audits. Longitudinal designs are essential to disentangle causality, as firms with stronger governance may also be those that invest more carefully in AI. Experimental vignettes in which financial professionals make allocation decisions with and without transparency and accountability cues could isolate micro-level mechanisms.

The scope is deliberately restricted to corporate financial decisions; the generalizability to operational, marketing, or human resource algorithms remains to be explored. Moreover, cultural and institutional contexts shape the meaning and effectiveness of governance mechanisms. A next step would compare the framework's explanatory power across regulatory regimes and market environments. Finally, the rapid evolution of generative AI and foundation models warrants ongoing theoretical refinement. As models become more autonomous and capable of generating entire financial plans, the governance challenge shifts from reviewing model outputs to designing appropriate constraints at the architectural level.

CONCLUSION

AI governance is emerging as a critical determinant of whether algorithmic finance serves or subverts long-term value creation. This paper offers a conceptual model that links governance mechanisms to the quality of financial decisions and, through this pathway, to sustainable outcomes. By articulating the conditions under which AI adoption enhances rather than erodes decision quality, the framework provides a structure for scholarship that is both theoretically grounded and practically actionable. Future empirical work can refine the propositions, and boards can immediately apply the lens to evaluate their own governance readiness. The ultimate ambition is not to slow the adoption of powerful technologies but to build the institutional muscle that ensures financial decisions made with AI are decisions worth sustaining.

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