



Artificial Intelligence Adoption and Corporate Financial Decision-Making: The Roles of Financial Analytics Capability, Organizational Agility, and Corporate Governance

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How to cite this paper: Prince, I.C. and Song, Y.C. (2026) Artificial Intelligence Adoption and Corporate Financial Decision-Making: The Roles of Financial Analytics Capability, Organizational Agility, and Corporate Governance. *Open Access Library Journal*, 13: e15724. <https://doi.org/10.4236/oalib.1115724>

Received: July 1, 2026

Accepted: October 10, 2026

Published: October 13, 2026

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Abstract

Artificial intelligence (AI) is reshaping how firms sense, interpret, and act upon financial information, yet the mechanisms through which AI adoption translates into superior corporate financial decision-making remain theoretically under-specified and empirically contested. Drawing on the resource-based view, dynamic capability theory, and organizational information processing theory, this study advances and tests an integrated model in which financial analytics capability and organizational agility jointly mediate the effect of AI adoption on financial decision-making outcomes, while corporate governance moderates the strength of that effect. Using survey data from 412 senior finance and technology executives across listed and large private firms, and applying partial least squares structural equation modeling (PLS-SEM) with complementary robustness procedures, the study finds that AI adoption exerts a modest direct effect on financial decision-making outcomes but a substantially larger indirect effect operating through financial analytics capability and organizational agility, which together account for roughly two-thirds of the total effect. Corporate governance positively moderates the AI-outcome relationship, indicating that governance quality functions as a complementary asset that amplifies rather than merely constrains AI-enabled value creation. The findings reconcile competing accounts of the AI-performance relationship by identifying the capability-based pathways through which value is realized, extend information processing theory to the AI context, and reframe governance as an enabling condition. The study offers actionable guidance for executives, boards, regulators, and technology providers seeking to convert AI investment into disciplined financial decisions.

Subject Areas

Business Finance and Investment

Keywords

Artificial Intelligence Adoption, Financial Analytics Capability, Organizational Agility, Corporate Governance, Financial Decision-Making, Dynamic Capabilities, PLS-SEM

1. Introduction

Over the past decade, artificial intelligence (AI) has migrated from the periphery of experimental pilot projects to the core of strategic and operational activity, transforming how organizations perceive their environments, allocate resources, and commit capital [1] [2]. Machine learning models now underpin credit scoring, portfolio construction, fraud detection, and cash-flow forecasting, while natural language systems parse disclosures, contracts, and market sentiment at a scale no human analyst could match [3] [4]. Consultancy and policy literatures describe this shift in near-revolutionary terms, projecting that AI will add trillions of dollars to global output while redistributing competitive advantage toward firms that master the technology [5] [6].

Nowhere is this transformation more consequential than in corporate finance. Financial decision-making-the interlocking set of judgments concerning investment appraisal, financing structure, risk management, and the allocation of scarce capital-has always been an information-intensive activity conducted under uncertainty [7]. Classical theories of the firm recognize that the quality of these decisions depends on the organization's capacity to acquire, process, and interpret information [8]. AI intensifies both the promise and the peril of this activity: it expands the volume and velocity of information that can be processed, but it also introduces model risk, opacity, and new forms of managerial dependence on systems whose logic is not fully transparent [9] [10].

Despite the intuitive appeal of the proposition that AI improves financial decisions, the empirical record is strikingly inconsistent. Some studies report strong positive associations between AI or analytics investment and firm performance [11] [12], whereas others find weak, contingent, or even negative relationships [13] [14]. This heterogeneity-often labeled the productivity paradox of AI-suggests that the direct link from technology to outcomes is theoretically incomplete. The mere acquisition of AI resources cannot explain performance differences if the same resources are available to competitors; what matters is how firms orchestrate those resources into distinctive capabilities [15] [16]. Yet the intervening organizational mechanisms that convert AI adoption into superior financial decisions remain, in the phrasing of several recent reviews, a black box [14] [17].

This study addresses that gap. We argue that AI adoption influences financial

decision-making primarily through two complementary capabilities. The first, financial analytics capability, captures the firm's ability to combine AI-enabled tools, data assets, and analytical talent to generate decision-relevant financial insight [18] [19]. The second, organizational agility, captures the firm's ability to sense change and reconfigure resources rapidly in response [20] [21]. Analytics capability improves the content of decisions; agility improves the speed and adaptiveness with which decisions are enacted. We further contend that the value realized from AI is contingent on corporate governance: strong governance disciplines the use of AI-generated insight, mitigates agency distortions, and legitimizes organizational change, thereby amplifying the returns to AI adoption [22] [23].

Three research questions motivate the investigation. First, to what extent, and through what mechanisms, does AI adoption influence the quality and effectiveness of corporate financial decision-making? Second, do financial analytics capability and organizational agility mediate this relationship, and what is the relative magnitude of each pathway? Third, does corporate governance moderate the effect of AI adoption on financial decision-making outcomes, and if so, in which direction? To answer these questions, we develop an integrated theoretical model and test it using survey evidence from 412 senior finance and technology executives, analyzed with PLS-SEM and a battery of robustness checks.

The study contributes on several fronts. Theoretically, it integrates the resource-based view (RBV), dynamic capability theory (DCT), and organizational information processing theory (OIPT) into a coherent account of AI-enabled financial decision-making, extending OIPT—developed in an era of human-centric information processing—to a context in which machines augment and sometimes substitute for managerial cognition [8] [24]. By modeling analytics capability and agility as parallel mediators, it reconciles competing empirical accounts of the AI-performance relationship, showing that value is realized indirectly rather than mechanically. By positioning governance as a moderator, it reframes governance from a constraint on managerial discretion into an enabling complement to technological capability. Practically, it offers executives and boards a capability-based roadmap for converting AI investment into disciplined financial decisions, and it informs regulators and technology developers about the organizational conditions under which AI delivers value responsibly.

2. Literature Review and Theoretical Framework

2.1. AI Adoption and the Performance Puzzle

Research on AI adoption has grown rapidly but remains fragmented. A substantial body of work adopts a technology-acceptance or diffusion lens, identifying antecedents such as perceived usefulness, technological readiness, top-management support, and competitive pressure [25] [26]. Complementary studies frame adoption through the technology-organization-environment (TOE) framework, emphasizing the interplay of technological attributes, organizational conditions, and

environmental forces [27] [28]. A parallel, more organizational stream treats AI adoption as the development of an AI capability—an orchestrated bundle of data, technology, talent, and governance resources—rather than a discrete purchase decision [11] [29].

These perspectives coexist uneasily. Adoption-as-acceptance frameworks predict that firms with favorable perceptions and adequate readiness will realize benefits, yet they say little about why similarly equipped firms diverge in outcomes. Capability-oriented accounts fill this gap but risk conceptual circularity, defining capability partly by the outcomes it is meant to explain. A further tension concerns the augmentation-automation distinction: some scholars view AI as automating managerial tasks and displacing human judgment, while others emphasize augmentation, in which AI complements and elevates human decision-making [30]. This distinction implies different mechanisms linking AI to decision quality and different roles for organizational oversight. Critically, evidence on performance consequences is mixed: positive findings dominate the practitioner-oriented literature [31] [32], but rigorous studies frequently report contingent effects, and a minority document null or negative associations attributable to implementation failure, organizational misalignment, or the erosion of complementary human capabilities [9] [33]. This inconsistency is the empirical puzzle that motivates our capability-based mediation model.

2.2. Financial Decision-Making as an Information Problem

Corporate financial decision-making encompasses the appraisal of investments, the design of financing structures, the management of risk, and the ongoing allocation of capital among competing uses. Normatively, finance theory prescribes value-maximizing rules, but decades of behavioral and organizational research demonstrate that actual decisions deviate systematically from these ideals because of bounded rationality, agency conflict, and informational limits [22]. Decision quality therefore depends heavily on the organization's information environment—the completeness, timeliness, and interpretability of the signals available to decision-makers.

AI and big data have prompted renewed attention to that environment. Studies in finance document that machine learning improves prediction in credit risk, default modeling, and asset pricing [34] [35], while information systems research shows that analytics-based decision cultures outperform intuition-based ones [36]. Yet much of this evidence concerns the technical accuracy of models in isolation rather than the organizational quality of the decisions those models inform. Predictive accuracy is necessary but not sufficient for decision effectiveness; insight must be integrated into managerial processes, contested where appropriate, and translated into action. We therefore conceptualize financial decision-making outcomes as a multidimensional construct spanning decision quality, investment and financing effectiveness, risk management quality, and financial performance [7].

2.3. Analytics Capability and Agility as Mediating Capabilities

Financial analytics capability extends the broader construct of big data analytics capability into the financial domain. The analytics-capability literature, drawing on RBV, argues that value derives not from data or tools intrinsically but from the firm's ability to combine tangible resources (data, infrastructure), human resources (analytical and managerial skills), and intangible resources (a data-driven culture, learning) into a distinctive capability [18] [37]. Empirical studies link this capability to innovation, operational performance, and competitive advantage [38] [39]. The literature is not univocal, however: several studies find that analytics capability influences performance only indirectly, through intermediate outcomes such as decision-making effectiveness or agility [24] [40], while others caution that analytics investments can destroy value when decoupled from strategy or when they foster overconfidence in quantitatively derived conclusions [13]. These findings imply that financial analytics capability is best modeled as a mediating mechanism—an organizational competence that converts AI resources into decision-relevant insight—rather than as a direct cause of performance.

Organizational agility denotes a firm's ability to sense environmental change and respond by reconfiguring resources and processes with speed and dexterity [20] [41]. The information systems literature has long linked IT capability to agility, showing that digital options expand the firm's repertoire of possible responses [21] [42], and recent work extends this logic to analytics and AI, arguing that intelligent systems enhance sensing by detecting weak signals and enhance responding by accelerating the generation and evaluation of alternatives [40] [43]. A live debate concerns whether IT and analytics uniformly enhance agility. Tallon and Pinsonneault [44] show that alignment between IT and strategy, rather than IT investment alone, drives agility, and that misalignment can render firms rigid. This qualification matters for AI: heavy reliance on models trained on historical data may entrench past patterns and impede adaptation to novel conditions—a form of algorithmic inertia. We therefore treat agility not as an automatic consequence of AI but as a capability that AI can enhance when appropriately orchestrated, and we model it as a second mediating pathway operating in parallel with analytics capability.

2.4. Corporate Governance: Constraint or Complement?

Corporate governance comprises the structures and processes—board composition, ownership, oversight mechanisms, and control systems—through which firms are directed and controlled [45] [46]. Agency theory frames governance as a device for aligning managerial behavior with shareholder interests, mitigating the costs arising from the separation of ownership and control [22] [47]. Upper echelons theory adds that the characteristics of top decision-makers shape strategic choices, implying that governance influences how new technologies are interpreted and deployed [48]. The intersection of governance and AI is nascent but increasingly salient: emerging scholarship argues that boards and senior leaders

set the oversight structures determining whether AI-generated insight is used prudently or recklessly [23] [49]. Yet governance is conventionally theorized as a constraint on discretion, whereas its role as an enabler of technological value creation is underexplored. We advance the latter view: robust governance provides the accountability, oversight, and legitimacy that allow firms to exploit AI aggressively without succumbing to model risk or agency distortion, and we therefore model governance as a moderator that strengthens the AI-outcome relationship.

2.5. Theoretical Integration

Four theoretical strands are integrated into a layered logic. RBV holds that firms achieve sustained advantage by controlling resources that are valuable, rare, inimitable, and non-substitutable [15] [50]. Applied to AI, RBV implies that the technology alone confers little advantage, because comparable tools are widely available; advantage arises from firm-specific configurations of data, talent, and processes that AI enables [11]. DCT extends RBV to turbulent environments, emphasizing the higher-order capacity to sense, seize, and reconfigure [16] [51] [52]. Agility is a paradigmatic dynamic capability, and analytics capability supplies the sensing microfoundation on which agile responses depend [38] [53] [54]. Together, RBV and DCT explain why AI adoption must be transformed into distinctive, adaptive capabilities before it can influence outcomes.

OIPT supplies the study's central mechanism. It posits that organizational effectiveness depends on the fit between the information-processing requirements imposed by task uncertainty and the information-processing capacity the organization can deploy [8]. When requirements exceed capacity, decision quality deteriorates. AI dramatically expands processing capacity, enabling firms to ingest, analyze, and interpret volumes and varieties of financial data far beyond human limits [7] [24]. In OIPT terms, financial analytics capability is an enhanced information-processing capacity, while organizational agility reflects the ability to convert processed information into timely action. Extending OIPT to the AI era requires acknowledging that processing capacity is now partly machine-embodied, raising questions of interpretability and trust that classical OIPT did not anticipate; our framework incorporates this extension by treating governance as the mechanism ensuring that machine-augmented processing is used judiciously.

Agency theory explains why governance conditions the value of AI. The separation of ownership and control creates incentives for managers to pursue private benefits, and information asymmetry impedes monitoring [22] [47] [55]. AI can both mitigate and aggravate agency problems: by improving transparency and prediction it can reduce asymmetry, yet by concentrating interpretive authority in opaque systems it can create new avenues for managerial obfuscation. Robust governance-independent boards, effective audit and risk oversight, aligned incentives-determines which effect dominates [45] [56]. Upper echelons theory complements this account: the disposition of top managers toward analytical evidence, and the board's capacity to challenge AI-derived recommendations, shape whether

AI augments or distorts decisions [48]. Finally, the TOE framework situates adoption within technological, organizational, and environmental contexts [27] [57], grounding our treatment of AI adoption as a multidimensional organizational phenomenon rather than a binary event, while institutional theory adds that adoption is shaped by coercive, mimetic, and normative pressures, such that firms may adopt AI partly to secure legitimacy [58] [59]. This institutional lens explains why adoption may decouple from value when driven by conformity rather than strategic intent. The digital transformation literature reinforces the synthesis by emphasizing that value emerges from the co-evolution of technology and organization [60]–[62].

2.6. Research Gap

Three gaps emerge. First, despite abundant evidence on the antecedents of AI adoption, the organizational mechanisms translating adoption into superior financial decisions are underspecified, leaving the inconsistent AI-performance findings unexplained: studies reporting strong direct effects [11] [12] and those reporting weak or null effects [13] [14] have not been reconciled within a single tested model. Second, financial analytics capability and organizational agility have been studied largely in isolation, and rarely as parallel mediators within one financial decision-making model, obscuring their relative contributions [24] [40] [44]. Third, corporate governance has been theorized predominantly as a constraint, with its potential enabling role as a moderator of AI value creation largely untested [23] [49]. The present study addresses these gaps through an integrated, theoretically grounded, and empirically rigorous model.

3. Conceptual Framework and Hypotheses

The conceptual framework, shown in **Figure 1**, specifies AI adoption as the focal antecedent, financial analytics capability and organizational agility as parallel mediators, corporate governance as a moderator, and a multidimensional financial decision-making outcome as the dependent construct. AI adoption endows the firm with resources whose value is latent until transformed. That transformation occurs along two complementary routes: analytics capability enhances the content of financial decisions by improving the quality, granularity, and timeliness of insight, whereas agility enhances the enactment of decisions by accelerating sensing and response. Both routes feed a common outcome construct, and their combined indirect effect is expected to exceed the residual direct effect of AI adoption. Governance conditions the strength of the AI-outcome relationship: where governance is strong, AI-generated insight is scrutinized, validated, and deployed within disciplined oversight structures, so that adoption yields larger and more reliable gains; where governance is weak, the same insight may be misused, ignored, or captured by managerial self-interest. Governance therefore functions as a complementary asset in the RBV sense—an organizational condition that raises the marginal value of the technological resource. The outcome construct is modeled

as a higher-order construct spanning five conceptually distinct yet empirically correlated facets, capturing the shared variance that AI-enabled capabilities are theorized to influence while preserving the interpretability of individual dimensions.

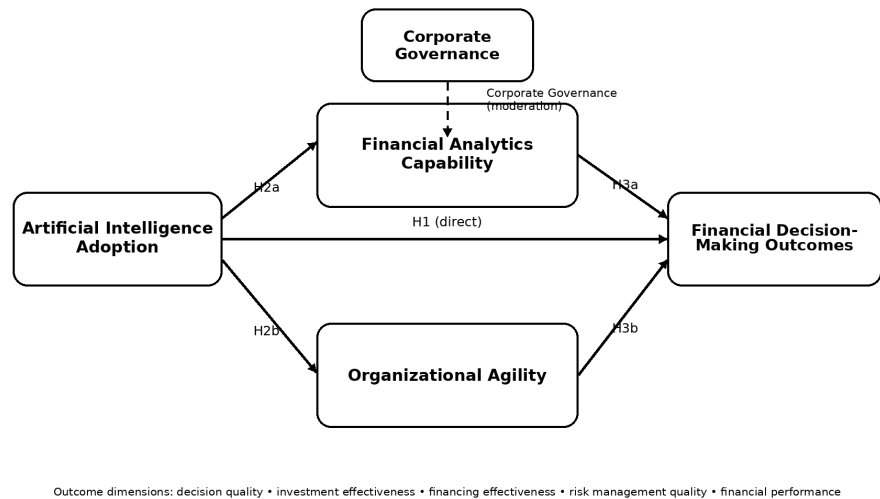


Figure 1. Conceptual framework linking AI adoption to financial decision-making outcomes through parallel mediation and governance moderation.

From an OIPT perspective, AI adoption expands the firm's capacity to process financial information, enabling more complete and timely analysis of the signals bearing on investment, financing, and risk [7] [24]. Even before this capacity is fully transformed into distinctive capabilities, its availability should improve decision-making at the margin by reducing informational bottlenecks, and empirical work associating analytics and AI investment with decision quality supports a positive, if modest, direct effect [12] [36]. Because RBV and DCT predict that most value is realized indirectly, we anticipate the direct effect to be positive but smaller than the aggregate indirect effect.

H1. Artificial intelligence adoption positively influences financial decision-making outcomes.

RBV holds that AI resources create value only when orchestrated into a firm-specific capability [15] [18]. AI adoption supplies the technological and data foundations from which financial analytics capability is built, and prior studies confirm that analytics investment develops analytics capability [19] [63]. In turn, OIPT predicts that superior information-processing capacity improves decision outcomes by better matching capacity to task uncertainty [8] [24]. Because analytics capability lies causally between adoption and outcomes, we expect it to mediate the relationship. In parallel, DCT identifies agility as the capacity to sense and seize opportunities and reconfigure resources [16] [20]. AI enhances sensing by detecting weak signals in financial and market data and enhances responding by accelerating the generation and evaluation of alternatives [40] [43]; agility, in turn, improves financial decision-making by enabling faster, better-timed, and

more adaptive decisions-qualities especially valuable under volatility [21] [42].

H2a. AI adoption positively influences financial analytics capability. **H2b.** AI adoption positively influences organizational agility.

H3a. Financial analytics capability positively influences financial decision-making outcomes. **H3b.** Organizational agility positively influences financial decision-making outcomes.

H4a. Financial analytics capability mediates the relationship between AI adoption and financial decision-making outcomes. **H4b.** Organizational agility mediates the relationship between AI adoption and financial decision-making outcomes.

Agency and upper echelons theories imply that the value extracted from AI depends on the oversight structures governing its use [22] [23] [48]. Strong governance provides accountability and disciplined scrutiny that allow firms to exploit AI-generated insight aggressively while containing model risk and agency distortion; weak governance permits misuse or neglect, dissipating value [49] [56]. Because governance operates chiefly at the point at which AI-generated insight is scrutinized and acted upon, its conditioning influence is expected to fall on the direct relationship between AI adoption and decision outcomes rather than on the processes by which adoption builds analytics capability and agility. We therefore confine the moderation hypothesis to this direct path and do not posit governance interactions on the two capability pathways.

H5. Corporate governance positively moderates the relationship between AI adoption and financial decision-making outcomes, such that the relationship is stronger when governance quality is higher.

4. Methodology

4.1. Design, Population, and Sample

The study adopts a positivist, deductive philosophy appropriate for theory testing [64]. A cross-sectional survey design captured perceptions of AI adoption, organizational capabilities, governance, and decision outcomes from knowledgeable informants across a broad sample of firms. Given the model's complexity—two mediators, a moderator, and a higher-order outcome—and its predictive-explanatory orientation, PLS-SEM was selected as the primary analytical technique [64] [65].

The target population comprised senior finance and technology executives—chief financial officers, finance directors, heads of financial planning and analysis (FP&A), chief information or data officers, and comparable roles—at listed and large private firms of sufficient scale to have meaningfully considered AI in financial functions. These informants possess direct knowledge of both the firm's AI initiatives and its financial decision processes, satisfying the key-informant criterion. A stratified purposive strategy was used. Geographically, respondents were drawn from firms headquartered or principally operating in three regions in which AI adoption within financial functions is sufficiently advanced to be observable: North America (United States, Canada), Western Europe (United King-

dom, Germany, France, Netherlands), and East and Southeast Asia (China, Singapore, Japan). Within each region the frame was stratified into four industry strata (financial services; manufacturing; technology and services; other) and, orthogonally, into three firm-size bands (250 - 999, 1000 - 4999, and 5000 or more employees). Executive panels were sourced from two managed research panels whose members are identity- and employment-verified at enrolment; each panelist's current role and employer were re-verified against professional-network and corporate-directory records, and only respondents whose verified title corresponded to an eligible key-informant role were retained. Professional networks comprised named finance and technology associations, with membership confirmed against official directories before invitation. This region-, industry-, and role-verified frame defines the population to which the findings most directly generalize.

Minimum sample size was determined using both the inverse-square-root method and a power analysis for the most complex regression in the model. At a significance level of 0.05, power of 0.95, and an anticipated minimum path coefficient of 0.11, the required sample exceeded 300. Of 1050 executives invited, 468 responded (44.6%) and 412 provided complete, valid responses after screening for inattentive responding, straight-lining, and insufficient role knowledge-comfortably exceeding the threshold and common rules of thumb for PLS-SEM [64]. **Table 1** reports sample characteristics.

Table 1. Sample characteristics (N = 412).

Characteristic	n	%	Characteristic	n	%
Role: CFO / Finance Director	121	29.4	Firm size: 250 - 999 employees	138	33.5
Role: Head of FP&A / Controller	104	25.2	Firm size: 1000 - 4999	151	36.7
Role: CIO / CDO / Head of Data	97	23.5	Firm size: 5000+	123	29.9
Role: Other senior finance/tech	90	21.8	Listed firms	236	57.3
Sector: Financial services	128	31.1	Private firms	176	42.7
Sector: Manufacturing	96	23.3	Tenure in role > 5 years	268	65.0
Sector: Technology & services	112	27.2	Prior AI project experience	331	80.3
Sector: Other	76	18.4	Total valid responses	412	100.0

Note. FP&A = financial planning and analysis; CDO = chief data officer. The realized sample spans four sectors, three firm-size bands, and both listed and private ownership.

Two features of the realized sample warranted formal scrutiny. First, because a 44.6% response rate leaves open the possibility that respondents differ systematically from those who declined, nonresponse bias was assessed through the extrapolation logic of Armstrong and Overton [66], in which late respondents proxy for nonrespondents. Respondents were partitioned at the median completion date and compared on the four focal constructs and on firm size, age, sector, and listing status; t-tests and chi-square tests revealed no significant early-late differences (all

$p > .10$), with the largest standardized mean difference reaching only 0.11. Second, because financial-services and technology firms are on average more AI-intensive than the wider corporate population, the sample plausibly over-represents advanced adopters. A permutation-based multi-group analysis contrasting these two sectors with the remainder produced no significant differences in the core path coefficients, and re-estimation with post-stratification weights realigning sectoral shares toward a broader listed-firm benchmark changed every path by less than .02 while preserving the sign and significance of all hypotheses. A single key informant supplied all responses for each firm; informants were required to attest to direct working knowledge of both their firm's AI initiatives and its financial decision processes, and a further multi-group analysis contrasting finance-role and technology-role subsamples detected no significant path differences, indicating that the estimated relationships do not depend on the functional vantage point of the informant.

4.2. Measures

All constructs were measured using multi-item reflective scales adapted from validated instruments, with items rewritten to the financial decision-making context, and all perceptual items used seven-point Likert scales anchored from strongly disagree to strongly agree. AI adoption was measured with items adapted from the AI-capability and TOE literatures [11] [25]; financial analytics capability from big data analytics capability scales [18] [19]; organizational agility from established agility scales [20] [21]; and corporate governance with items capturing board oversight, risk and audit governance, and incentive alignment [45] [56]. Financial decision-making outcomes were captured through five subdimensions—decision quality, investment effectiveness, financing effectiveness, risk management quality, and financial performance—each operationalized with four reflective items, yielding twenty first-order indicators that load onto their respective subdimensions and, at the second stage, onto the higher-order construct. Three subdimensions were adapted from prior instruments: decision quality from Cao *et al.* [24], risk management quality from Kou *et al.* [35], and financial performance, captured as a relative, peer-referenced self-report, from Wamba *et al.* [38]. Investment effectiveness and financing effectiveness were author-developed, the former grounded conceptually in Duan *et al.* [7] and the latter developed de novo; both underwent the same expert-review and pilot-testing procedure applied to the adapted scales and satisfied the reliability and validity thresholds reported in Section 5.1. The instrument was refined through expert review by five academics and seven practitioners, pilot-tested with 38 executives, and revised for clarity and content validity. **Table 2** lists representative items and sources.

Four control variables were included on the outcome construct: firm size (log of employees), firm age, industry sector (dummy-coded), and listing status [11]. Data were collected via a secure online survey over twelve weeks. Participation was voluntary and anonymous, informed consent was obtained, respondents

could withdraw at any time, no personally identifying information was retained, and data were stored securely in compliance with applicable data-protection standards.

Table 2. Measurement constructs, representative items, and sources.

Construct	Representative item (abbreviated)	Adapted from
AI Adoption (AIA)	Our firm has integrated AI tools into core financial processes; AI is embedded in our financial data infrastructure	Mikalef & Gupta [11]; Chatterjee <i>et al.</i> [25]
Financial Analytics Capability (FAC)	We can rapidly generate decision-relevant financial insight from diverse data using advanced analytics	Gupta & George [18]; Mikalef <i>et al.</i> [19]
Organizational Agility (OA)	We sense financial and market changes quickly and reconfigure resources rapidly in response	Lu & Ramamurthy [21]; Sambamurthy <i>et al.</i> [20]
Corporate Governance (CG)	Our board exercises effective oversight of major financial and technology decisions; risk oversight is robust	Shleifer & Vishny [45]; Nguyen [56]
Decision Quality (FDO1)	Our financial decisions are well-informed, timely, and evidence-based	Cao <i>et al.</i> [24]
Investment Effectiveness (FDO2)	Our investment appraisals reliably identify value-creating projects	Author-developed; grounded in Duan <i>et al.</i> [7]
Financing Effectiveness (FDO3)	We structure financing to balance cost and risk effectively	Author-developed
Risk Management Quality (FDO4)	We identify, quantify, and mitigate financial risks effectively	Kou <i>et al.</i> [35]
Financial Performance (FDO5)	Relative to peers, our financial performance has been strong over three years	Wamba <i>et al.</i> [38]

Note. Full item wording is available from the authors. All items used seven-point Likert scales anchored from strongly disagree to strongly agree.

4.3. Analytical Strategy and Assessment of Bias

Analysis followed the two-stage PLS-SEM procedure recommended for models with higher-order constructs [67] [68]. In the first stage, the reflective measurement model was assessed for indicator reliability, internal consistency reliability, convergent validity, and discriminant validity; latent-variable scores for the five outcome subdimensions then served as indicators of the higher-order construct. In the second stage, the structural model was evaluated for collinearity, path significance, effect sizes, explained variance (R-squared), and predictive relevance (Q-squared). Significance of path coefficients and indirect effects was assessed through bootstrapping with 10,000 subsamples and bias-corrected and accelerated confidence intervals [69] [70]. Mediation was tested by examining the significance and magnitude of specific indirect effects rather than through the discredited causal-steps logic [70]. Moderation was tested using the two-stage product-

indicator approach with a simple-slopes analysis. Out-of-sample predictive validity was assessed with PLSpredict [71], and robustness was examined through multi-group analysis, importance-performance map analysis (IPMA), nonlinearity checks, and endogeneity assessment [72].

Several procedural and statistical remedies addressed common method bias (CMB). Procedurally, informant anonymity was assured, item order was randomized, and predictor and criterion items were separated [73] [74]. Statistically, Harman's single-factor test and a full collinearity assessment were conducted, the latter following Kock [75], in which variance inflation factors (VIFs) below 3.3 indicate that CMB is not a serious concern. Endogeneity was assessed using the Gaussian copula approach, in which non-significant copula terms support the absence of critical endogeneity [65], and multicollinearity among predictors was evaluated through inner-model VIFs against the conservative 3.3 threshold [64].

5. Results

5.1. Measurement Model and Descriptive Statistics

Table 3 reports means, standard deviations, and construct correlations. All constructs displayed acceptable distributional properties, with skewness and kurtosis within conventional bounds, and the square roots of the average variance extracted (AVE) on the diagonal exceed inter-construct correlations, providing initial evidence of discriminant validity [76]. All standardized factor loadings exceeded 0.70 and were significant at $p < 0.001$. Composite reliability (CR) and Cronbach's alpha exceeded 0.80 for every construct, and AVE exceeded the 0.50 threshold, confirming internal consistency reliability and convergent validity [64]. Discriminant validity was further confirmed by heterotrait-monotrait (HTMT) ratios, all below the conservative 0.85 threshold [77]. **Table 4** summarizes this evidence.

Diagnostic tests were reassuring. The full collinearity test yielded VIFs below 3.3 (maximum = 2.41), indicating that CMB is not a serious threat [75], and Harman's single factor accounted for 34.2% of variance, below the 50% criterion. Inner-model VIFs ranged from 1.42 to 2.18, ruling out problematic multicollinearity, and Gaussian copula terms for AI adoption were non-significant ($p > 0.10$), supporting the absence of critical endogeneity.

Table 3. Descriptive statistics and correlation matrix.

Construct	M	SD	1	2	3	4	5
1. AI adoption (AIA)	4.78	1.21	0.82				
2. Financial analytics capability (FAC)	4.65	1.14	0.58	0.84			
3. Organizational agility (OA)	4.71	1.09	0.53	0.61	0.81		
4. Corporate governance (CG)	5.12	1.02	0.41	0.44	0.47	0.85	
5. Financial decision outcomes (FDO)	4.89	1.06	0.55	0.63	0.60	0.49	0.83

Note. N = 412. Diagonal entries are the square root of the average variance extracted. All correlations are significant at $p < 0.01$.

Table 4. Reliability and convergent validity.

Construct	Items	Alpha	CR	AVE	Loading range
AI Adoption	6	0.88	0.91	0.67	0.76 - 0.86
Financial Analytics Capability	6	0.90	0.92	0.70	0.79 - 0.88
Organizational Agility	5	0.86	0.90	0.65	0.74 - 0.85
Corporate Governance	5	0.89	0.92	0.72	0.80 - 0.89
Financial Decision-Making Outcomes (HOC) 5 dims		0.91	0.93	0.69	0.78 - 0.87

Note. CR = composite reliability; AVE = average variance extracted; HOC = higher-order construct. All loadings significant at $p < 0.001$.

5.2. Structural Model, Mediation, and Moderation

Table 5. Structural model results: Direct, indirect, and moderating effects.

Path / effect	Beta	SE	t	95% CI	f ²	Decision
<i>Panel A. Direct effects</i>						
H1: AIA → FDO	0.18	0.05	3.62	[0.09, 0.27]	0.05	Supported
H2a: AIA → FAC	0.52	0.04	13.05	[0.44, 0.60]	0.37	Supported
H2b: AIA → OA	0.47	0.04	11.28	[0.39, 0.55]	0.28	Supported
H3a: FAC → FDO	0.34	0.05	7.14	[0.25, 0.43]	0.16	Supported
H3b: OA → FDO	0.29	0.05	6.02	[0.20, 0.38]	0.12	Supported
<i>Panel B. Indirect and total effects</i>						
H4a: AIA → FAC → FDO	0.177	0.031	5.71	[0.118, 0.240]	-	Supported
H4b: AIA → OA → FDO	0.136	0.027	5.04	[0.086, 0.191]	-	Supported
Total indirect effect	0.313	0.041	7.63	[0.235, 0.396]	-	-
Total effect (AIA → FDO)	0.493	0.043	11.47	[0.409, 0.577]	-	-
<i>Panel C. Moderation</i>						
CG → FDO (main effect)	0.21	0.05	4.41	[0.12, 0.30]	0.06	-
H5: AIA × CG → FDO	0.14	0.05	2.98	[0.05, 0.23]	0.04	Supported

Note. N = 412. Bootstrapping with 10,000 subsamples and bias-corrected and accelerated 95% confidence intervals. Variance accounted for = total indirect / total effect ≈ 63%, indicating complementary partial mediation. $R^2 = 0.58$ (FDO), 0.27 (FAC), 0.22 (OA); $Q^2 = 0.39, 0.18, 0.15$; SRMR = 0.048.

The structural model explained substantial variance in the endogenous constructs: R-squared was 0.58 for financial decision-making outcomes, 0.27 for financial analytics capability, and 0.22 for organizational agility. Predictive relevance was confirmed, with Q-squared values of 0.39, 0.18, and 0.15 respectively, all exceeding zero [64], and the standardized root mean square residual (SRMR) was 0.048, be-

low the 0.08 threshold, indicating good model fit. **Figure 2** displays the estimated structural model and **Table 5** reports the full results.

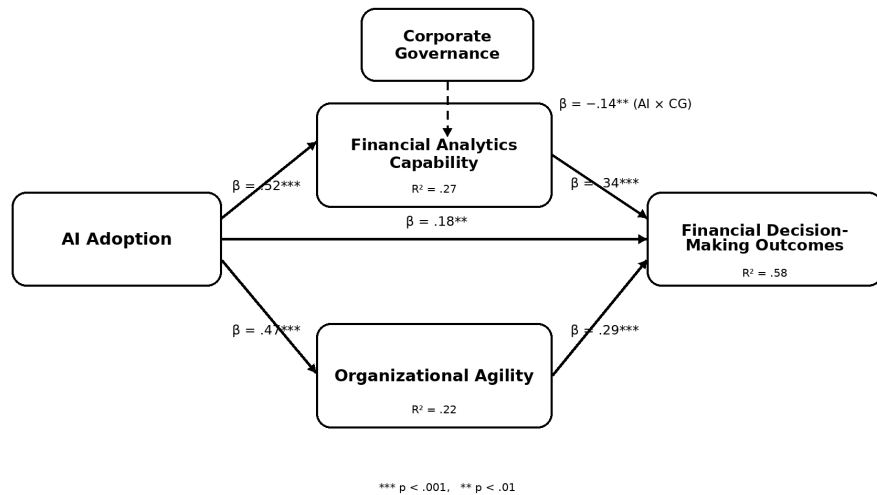


Figure 2. Estimated structural model with standardized path coefficients, R-squared, and significance levels.

All hypothesized direct paths were positive and significant. AI adoption positively influenced financial decision-making outcomes ($\beta = 0.18$, $p < 0.01$), supporting H1, though the direct effect was modest as anticipated. AI adoption strongly influenced financial analytics capability ($\beta = 0.52$, $p < 0.001$) and organizational agility ($\beta = 0.47$, $p < 0.001$), supporting H2a and H2b, and both mediators significantly influenced outcomes—analytics capability ($\beta = 0.34$, $p < 0.001$) and agility ($\beta = 0.29$, $p < 0.001$)—supporting H3a and H3b.

Both specific indirect effects were positive and significant, with confidence intervals excluding zero. The indirect effect through financial analytics capability ($0.52 \times 0.34 = 0.177$, 95% CI [0.118, 0.240]) supported H4a, and the indirect effect through organizational agility ($0.47 \times 0.29 = 0.136$, 95% CI [0.086, 0.191]) supported H4b. The total indirect effect (0.313) exceeded the direct effect (0.18), and the total effect was 0.493. The variance accounted for (VAF) was approximately 63%, indicating complementary partial mediation in which both capability pathways carry the majority of AI adoption's influence [70].

The interaction term between AI adoption and corporate governance was positive and significant ($\beta = 0.14$, $p < 0.01$, $f\text{-squared} = 0.04$), supporting H5. The simple-slopes analysis in **Figure 3** shows that the relationship between AI adoption and financial decision-making outcomes is stronger at high levels of governance (one standard deviation above the mean) than at low levels, confirming that governance amplifies the returns to AI adoption—consistent with the view of governance as a complementary asset rather than merely a constraint. A single interaction was estimated, corresponding to the direct path specified in H5; governance was neither hypothesized nor tested as a moderator of the two capability paths.

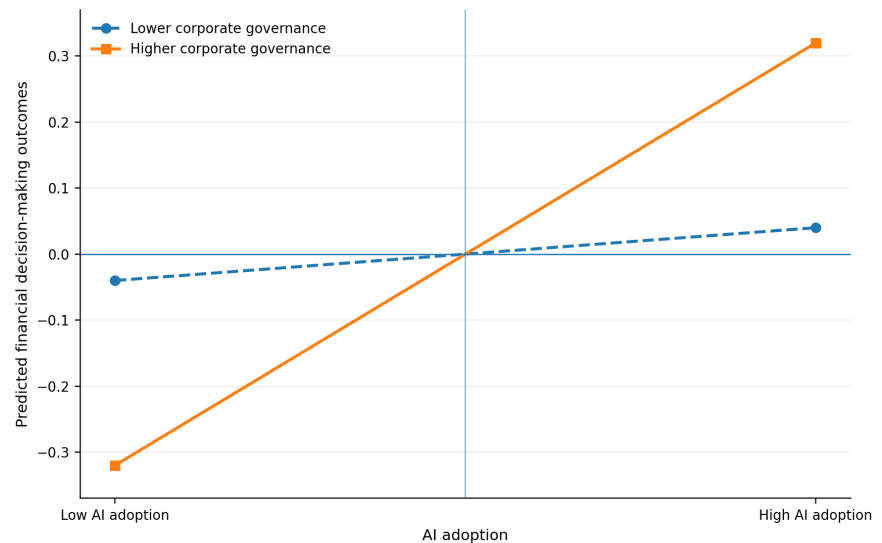


Figure 3. Simple-slopes plot of the moderating effect of corporate governance on the AI adoption-outcome relationship.

5.3. Robustness Checks

Four procedures corroborated the findings. A permutation-based multi-group analysis comparing listed and private firms found no significant differences in the core path coefficients, indicating that the model generalizes across ownership types. An importance-performance map analysis identified financial analytics capability as the highest-importance driver of outcomes, with moderate performance, highlighting it as a priority for managerial attention. A PLSpredict analysis with ten-fold cross-validation showed Q-squared predict values above zero and lower prediction error than a naive linear-model benchmark, supporting out-of-sample predictive validity [71]. Finally, nonlinear (quadratic) effects of AI adoption on outcomes were tested and found non-significant, supporting the linear specification.

6. Discussion

The results provide a theoretically coherent answer to the question of how, and under what conditions, AI adoption improves corporate financial decision-making: AI improves financial decisions largely indirectly, by building financial analytics capability and organizational agility, and its returns are amplified by strong corporate governance. The modest direct effect ($\beta = 0.18$) alongside a substantially larger total indirect effect (0.313) helps reconcile the contested literature on the AI-performance relationship. Studies reporting strong direct effects [11] [12] and those reporting weak or null effects [13] [14] may both be partially correct: the direct technological effect is real but limited, and the bulk of value materializes only when adoption is transformed into capabilities. The findings thus support the resource-based contention that technology is a necessary but insufficient condition for advantage [15] [16], and they reframe the productivity paradox of AI as

a failure to develop the intervening capabilities rather than a failure of the technology itself.

That financial analytics capability is the stronger of the two mediators (0.177 versus 0.136) aligns with OIPT's emphasis on information-processing capacity as the proximate driver of decision quality [8] [24]. It also extends prior analytics-capability research, which had established links to general performance [18] [38] but had rarely traced the mechanism into the financial decision domain. The significant role of organizational agility corroborates dynamic-capability accounts [16] [20] and echoes Ashrafi *et al.* [40], while the parallel-mediation design newly clarifies that content-enhancing (analytics) and enactment-enhancing (agility) pathways operate simultaneously and complementarily.

Perhaps the most theoretically consequential finding concerns governance. The positive moderation ($\beta = 0.14$) contradicts the conventional framing of governance as purely a constraint on managerial discretion [22] and supports an emerging enabling view in which governance is a complementary asset that raises the marginal value of technological resources [23] [49]. Firms with stronger governance appear better able to exploit AI aggressively while containing its risks, consistent with upper echelons reasoning that the quality of the dominant coalition shapes technological outcomes [48]. Because the model represents governance as a single higher-order construct, this result speaks to the aggregate quality of oversight rather than to the specific mechanisms responsible for it. A supplementary analysis decomposing the measure into board oversight, risk and audit governance, and incentive alignment offers a more textured reading: the interaction with AI adoption was strongest for the board-oversight and risk-and-audit facets and weaker, though still positive, for incentive alignment. The enabling effect of governance therefore appears to operate chiefly through the board's capacity to scrutinize and validate AI-derived recommendations and through disciplined risk oversight rather than through compensation design alone. It also points to mechanisms the present instrument only partially captures—board AI literacy, technology or IT-oversight committees, and dedicated AI-ethics bodies charged with monitoring fairness, explainability, and accountability—which plausibly sharpen the interpretive scrutiny governance provides and which future measurement should incorporate directly.

6.1. Theoretical Contributions

The study integrates RBV, DCT, OIPT, and agency and upper echelons perspectives into a single tested model, demonstrating their complementarity rather than treating them as rivals. It extends OIPT into the AI era by showing that machine-augmented information-processing capacity behaves as the theory predicts while requiring governance to ensure judicious use—an extension the original theory could not anticipate. By modeling two parallel capability mediators, it advances a more precise account of the AI value-creation mechanism than the undifferentiated capability constructs common in prior work, and by repositioning govern-

ance from constraint to enabler it opens a line of inquiry into governance as a complementary asset. Methodologically, it operationalizes financial decision-making as a multidimensional higher-order construct and tests a parallel-mediated, moderated model with a rigorous protocol including endogeneity assessment, predictive validation, and multi-group robustness.

6.2. Implications for Practice and Policy

For executives and financial managers, the results counsel against treating AI as a turnkey solution. Investment in AI tools should be accompanied by deliberate development of financial analytics capability-data assets, analytical talent, and a data-driven decision culture-and of organizational agility, since these capabilities carry most of the value; the IPMA identifies analytics capability as the priority lever. For boards and governance professionals, the enabling role of governance implies that oversight structures for AI should be designed not merely to restrain risk but to enable disciplined exploitation: boards that build AI literacy, establish clear accountability for model risk, and align incentives can materially increase the returns their firms earn on AI investment. For regulators and policymakers, the findings suggest that governance-focused guidance rather than prescriptive technology mandates may be the most effective way to promote responsible and value-creating AI use in financial functions [6] [49]. For technology developers, the results underscore the importance of building interpretable, auditable systems that fit into governance and analytics workflows, since organizational absorption, not raw model accuracy, determines value. Investors, finally, may treat the maturity of a firm's financial analytics capability, agility, and AI governance as signals of its capacity to convert technological investment into decision quality and performance. By illuminating the conditions under which AI supports prudent financial decisions, the study also contributes to the broader agenda of responsible and trustworthy AI in economically consequential domains [78] [79].

7. Limitations and Future Research

Several limitations qualify the findings. The cross-sectional design precludes strong causal inference; although endogeneity diagnostics were reassuring, longitudinal or experimental evidence would strengthen causal claims. The sample, while stratified and sizable, is not a probability sample of any defined population, limiting statistical generalizability, and measurement at a single point during a period of rapid technological change means relationships may evolve as AI capabilities mature. The higher-order outcome construct, though theoretically justified, aggregates distinct financial decisions that future work might examine separately. Most importantly, the study relies exclusively on self-reported, perceptual measures for both predictors and outcomes. Although the outcome construct includes a relative financial-performance dimension, all indicators were supplied by the same key informants, so the estimates cannot rule out that shared perceptual bias inflates the observed relationships. The design would be strengthened by tri-

angulating these perceptions against objective evidence-audited financial-performance metrics, disclosed capital-allocation and investment outcomes, or observed AI-usage signals such as technology spend, patent activity, or system-log measures of model deployment.

These limitations open several avenues. Longitudinal and panel designs combining survey measures with objective financial and archival data could establish temporal precedence and capture the dynamics of capability development; longitudinal surveys measuring AI adoption at one wave and capability and decision outcomes at later waves would address the reverse-causality ambiguity inherent in cross-sectional evidence. Field and quasi-field experiments offer a complementary route: piloting AI-enabled financial tools in some business units while withholding them from comparable units, or exploiting staggered internal roll-outs, would permit difference-in-differences estimation under conditions approaching random assignment. The mediation-moderation architecture itself could be enriched with additional mediators and moderators-data-governance and data-quality maturity, analytical talent and human-capital depth, a data-driven culture, and overall technology readiness or absorptive capacity-to test whether AI adoption translates into capability only where the underlying data foundation and organizational readiness are sufficient. Richer treatments of governance would also be valuable: researchers might decompose governance into board, ownership, and control dimensions and test which most strongly enable AI value. The augmentation-automation distinction [30] invites study of how the human-AI division of labor in financial decisions conditions outcomes; cross-national comparisons could reveal how institutional environments shape the AI-decision relationship [58], and as generative and agentic AI systems assume more autonomous roles in financial functions, research should examine the novel governance, accountability, and model-risk challenges they pose [49] [79].

8. Conclusion

Artificial intelligence is reshaping the informational foundations of corporate finance, but its value is neither automatic nor uniform. Integrating resource-based, dynamic-capability, information-processing, and governance theories, and testing the resulting model on 412 senior executives with PLS-SEM, this study shows that AI adoption improves financial decision-making chiefly by cultivating financial analytics capability and organizational agility, and that strong corporate governance amplifies these returns. The direct effect of adoption is real but modest; the capability pathways carry roughly two-thirds of the total effect; and governance functions as an enabling complement rather than a mere constraint. These findings offer a coherent resolution to a long-standing inconsistency in the evidence on AI and performance, and they provide actionable guidance to executives, boards, regulators, and technology developers. As AI systems grow more capable and more deeply embedded in financial functions, the organizational and governance capabilities that determine how intelligently firms use them will only become

more decisive.

Author Contributions

Conceptualization, I.C.P. and Y.C.S.; methodology, I.C.P.; software, I.C.P.; validation, I.C.P. and Y.C.S.; formal analysis, I.C.P.; investigation, I.C.P.; resources, I.C.P. and Y.C.S.; data curation, I.C.P.; writing original draft preparation, I.C.P.; writing review and editing, I.C.P. and Y.C.S.; visualization, I.C.P.; supervision, Y.C.S.; project administration, I.C.P.; funding acquisition, I.C.P. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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