Jurnal Publikasi Ilmu Manajemen
Volume 5, Nomor 3, September 2026
e-ISSN :2963-766X ; p-ISSN :2963-8712, Hal. 99-108
DOI: https://doi.org/10.55606/jupiman.v5i3.6727
Tersedia: https://ejurnal.politeknikpratama.ac.id/index.php/jupiman

The Impact of Artificial Intelligence Capability on Corporate Financial Performance through the Mediating Role of Financial Decision-Making Quality

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Abstract. This study examines the impact of Artificial Intelligence Capability (AIC) on Corporate Financial Performance (CFP) through the mediating role of Financial Decision-Making Quality (FDMQ). A simulation-based quantitative explanatory design was applied to 200 computer-generated Likert-scale observations calibrated to represent finance and accounting decision contexts in AI-enabled organizations. The analysis uses instrument validity and reliability testing, multiple linear regression, and mediation analysis following PROCESS Model 4 logic with 5,000 bootstrap resamples in IBM SPSS Statistics. The results show that AIC positively affects FDMQ ($\beta = 0.617$, $p < 0.001$) and retains a significant direct effect on CFP after the mediator is included ($\beta = 0.316$, $p < 0.001$). FDMQ also has a positive effect on CFP ($\beta = 0.473$, $p < 0.001$), while the outcome model explains 50.8% of the variance in CFP. The indirect effect is significant (B = 0.319; 95% bootstrap CI [0.231, 0.412]), indicating partial mediation. The findings support the proposed mechanism that AI capability creates financial value when technological resources are translated into timely, evidence-based, and economically sound financial decisions.

Keywords: Artificial Intelligence Capability; Corporate Financial Performance; Financial Decision-Making Quality; Mediation Analysis; SPSS.

1. INTRODUCTION

Artificial intelligence (AI) is increasingly embedded in corporate finance because finance functions are expected to process larger data volumes while shortening planning, reporting, and control cycles. The shift is visible in recent finance-industry evidence. Gartner's 2025 AI in Finance Survey, based on 183 CFOs and senior finance leaders, reported that 59% of finance functions were already using AI. Among organizations that had implemented AI, the most common use cases included knowledge management for better decision support (49%), accounts-payable automation (37%), and error or anomaly detection (34%). The same survey found that 67% of finance leaders using AI had become more optimistic about its potential than in the previous year, although organizations still faced data-quality, technical-skill, and implementation barriers (Gartner, 2025). These figures show that AI has moved beyond experimental analytics and is becoming part of the infrastructure through which financial information is interpreted and acted upon.

The scale and intensity of adoption are also increasing. McKinsey's 2025 survey of 102 CFOs across industries and regions found that 44% used generative AI in more than five finance use cases, compared with only 7% in the previous year's survey, while 65% expected their organizations to increase generative-AI investment. Finance teams were applying AI to forecasting, working-capital monitoring, reporting, cost optimization, scenario analysis, and decision support. McKinsey also documented examples in which AI-supported finance tools

Naskah Masuk: 22 Juli 2026; Revisi: 23 Agustus 2026; Diterima:24 Agustus 2026; Terbit: 02 September 2026

reduced manual analysis time by around 30% and helped identify material cost and contract inefficiencies (McKinsey & Company, 2025). The managerial issue, therefore, is no longer simply whether firms adopt AI, but whether they develop a coherent capability that integrates infrastructure, data, human expertise, and organizational routines in ways that improve financial judgment and performance.

Indonesia provides a relevant emerging-market setting for this question. Research released by Amazon Web Services and Strand Partners reported that 18 million Indonesian businesses, equivalent to 28% of businesses, had adopted AI by 2024; 5.9 million firms were new adopters during that year, representing 47% year-on-year growth. However, much adoption remained concentrated in efficiency-oriented applications rather than deeper strategic transformation (Amazon Web Services, 2025). PwC Indonesia subsequently reported that 69% of Indonesian workers had used AI in their jobs during the previous year, compared with 54% globally, although only 16% used generative AI daily. Daily users were substantially more likely to report productivity benefits than infrequent users (PwC Indonesia, 2026). Together, these data indicate rapid diffusion but uneven capability maturity, creating a strong rationale for examining whether organizational AI capability is actually converted into better financial outcomes.

Artificial Intelligence Capability (AIC) refers to an organization's ability to mobilize and coordinate AI-related tangible resources, human skills, and intangible organizational resources. Mikalef and Gupta (2021) conceptualize AIC as a multidimensional capability rather than the simple ownership of algorithms or software. This distinction is important because firms can purchase similar technologies but obtain different outcomes depending on data quality, technical expertise, managerial coordination, learning routines, and the ability to embed AI in business processes. Subsequent research confirms that AI capability contributes to firm performance when it is supported by complementary organizational mechanisms such as a data-driven culture and decision processes (Fosso Wamba et al., 2024; Neiroukh et al., 2025). From a resource-based and dynamic-capability perspective, AI therefore becomes economically valuable when it is configured as a firm-specific capability that competitors cannot easily replicate.

Corporate Financial Performance (CFP) is a central outcome because investments in AI must ultimately be justified through improvements in profitability, revenue growth, cost efficiency, cash-flow stability, return on investment, and financial resilience. Empirical evidence increasingly connects AI orientation and capability with measurable performance outcomes. Mishra et al. (2022), using firm-level evidence, found that stronger organizational focus on AI was associated with improvements in net profitability and operating efficiency. Fosso Wamba et al. (2024) likewise found that AI capability directly enhances firm performance and that this relationship is strengthened through organizational data-driven mechanisms. These findings suggest that the financial value of AI is plausible, but they do not imply that technology automatically improves performance. The pathway from AI resources to financial results remains dependent on how managers use AI-generated information when allocating capital, controlling costs, forecasting cash flows, and responding to financial risk.

Financial Decision-Making Quality (FDMQ) is proposed as the principal mechanism linking AIC to CFP. High-quality financial decisions are characterized by accuracy, timeliness, comprehensiveness, consistency, appropriate use of evidence, and alignment with organizational objectives. AI can improve these attributes by integrating large and heterogeneous datasets, detecting weak signals, producing forecasts, generating alternative scenarios, and reducing routine cognitive burden. Awan et al. (2021) show that analytics capability creates value through data-driven insight and decision processes, while Herath Pathirannehelage et al. (2025) emphasize that effective AI-augmented decision making requires deliberate design principles that preserve meaningful human judgment. In the specific context of organizational AI, Neiroukh et al. (2025) found that AI capability significantly improves decision quality and decision speed, which in turn contribute to organizational performance.

The importance of decision quality is especially pronounced in finance because the consequences of poor judgments can be immediate and material. Budget allocations, investment choices, financing structures, working-capital policies, risk limits, and pricing decisions all require managers to synthesize uncertain information under time pressure. Giachino et al. (2025) demonstrate that AI-driven decision making is positively associated with firm performance, while human-AI complementarity research argues that competitive value increasingly emerges at the intersection of algorithmic analysis and managerial interpretation (Krakowski et al., 2023). Recent accounting research is even more directly aligned with the present model: Ellelly et al. (2026) found that financial decision-making quality mediates the relationship between AI adoption in accounting systems and organizational performance. This evidence supports the proposition that financial performance is not merely a direct technological outcome but also the consequence of better managerial decisions enabled by AI.

Despite these advances, three gaps remain. First, adoption-based measures do not fully capture whether firms possess the integrated resources and routines needed to exploit AI; a capability perspective is therefore more theoretically demanding than a binary or intensity measure of adoption. Second, prior studies often examine broad organizational performance, innovation, or decision speed, whereas the financial-performance consequences of AI capability require more explicit attention. Third, although decision quality has been identified as a mechanism in general AI and accounting research, evidence remains limited on the specific mediating role of financial decision-making quality between AIC and corporate financial performance, particularly in an Indonesian corporate context. Addressing these gaps is relevant for both scholarship and practice because it distinguishes investment in AI from the organizational capability to turn AI-supported analysis into sound financial actions.

Accordingly, this study examines a parsimonious mediation model with AIC as the independent variable, FDMQ as the mediator, and CFP as the dependent variable. Four hypotheses are proposed: H1, Artificial Intelligence Capability has a positive and significant effect on Corporate Financial Performance; H2, Artificial Intelligence Capability has a positive and significant effect on Financial Decision-Making Quality; H3, Financial Decision-Making Quality has a positive and significant effect on Corporate Financial Performance; and H4, Financial Decision-Making Quality significantly mediates the relationship between Artificial Intelligence Capability and Corporate Financial Performance. By testing these relationships with a regression-based mediation framework, the study seeks to explain not only whether AI capability matters for financial performance but also how that effect is transmitted through the quality of financial decisions.

2. RESEARCH METHODOLOGY

This study employs a quantitative explanatory simulation design to evaluate the proposed mediation structure linking Artificial Intelligence Capability, Financial Decision-Making Quality, and Corporate Financial Performance. The model is calibrated to the organizational setting of finance managers, accounting managers, controllers, financial planning and analysis professionals, senior accountants, and other decision makers who work with AI-supported financial systems. The analytical sample consists of 200 computer-generated observations scored on a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. The simulation was designed to reproduce realistic variation and moderate-to-strong positive associations among the three constructs, consistent with prior empirical evidence on AI capability, decision quality, and organizational performance. Because the observations are simulation-generated rather than collected from field respondents, the statistical estimates should be interpreted as model-based evidence about the proposed mediation mechanism rather than population estimates for Indonesian firms.

Artificial Intelligence Capability is operationalized using seven indicators adapted from the capability framework of Mikalef and Gupta (2021), covering AI-related infrastructure and data resources, technical expertise, managerial understanding, cross-functional coordination, and the ability to integrate AI into organizational routines. Financial Decision-Making Quality is measured with five indicators reflecting accuracy, timeliness, comprehensiveness, evidence use, and consistency of financial decisions, drawing on analytics and AI decision-making literature (Awan et al., 2021; Neiroukh et al., 2025; Ellelly et al., 2026). Corporate Financial Performance is measured with five perceptual indicators assessing profitability improvement, revenue growth, cost efficiency, return on investment, and cash-flow stability relative to key competitors, consistent with capability-performance research (Mikalef & Gupta, 2021; Fosso Wamba et al., 2024). The simulation dataset was generated at the item level with values constrained to the 1-5 Likert range and calibrated so that higher AIC is associated with higher FDMQ and CFP while retaining indicator-specific variation. Composite scores are calculated as the arithmetic mean of the indicators for each construct.

Data analysis is conducted using IBM SPSS Statistics 29. Instrument quality is assessed through corrected item-total correlations and Cronbach's alpha, with item-total correlations above 0.30 and alpha values above 0.70 interpreted as acceptable. Descriptive statistics and Pearson correlations are followed by classical regression diagnostics, including residual normality, multicollinearity, heteroscedasticity, and independence. Hypotheses H1-H3 are tested with simple and multiple linear regression. Mediation is evaluated using the regression-based procedure summarized by Hayes (2022) and the bootstrap logic of Preacher and Hayes (2008). The total effect (c), path a (AIC -> FDMQ), path b (FDMQ -> CFP controlling for AIC), and direct effect (c') are estimated, followed by 5,000 bootstrap resamples for the indirect effect a x b. Mediation is significant when the 95% bootstrap confidence interval excludes zero; partial mediation is concluded when the indirect effect is significant and the direct effect remains significant in the same direction.

3. RESULTS AND DISCUSSION

The simulation-based analysis begins with instrument evaluation. The three constructs show strong internal consistency. AIC has a Cronbach's alpha of 0.918, FDMQ 0.885, and CFP 0.908. Corrected item-total correlations range from 0.699 to 0.788 for AIC, 0.695 to 0.761 for FDMQ, and 0.723 to 0.785 for CFP, all well above the minimum criterion of 0.30. The composite means are 3.462 for AIC (SD = 0.929), 3.530 for FDMQ (SD = 0.963), and 3.453 for CFP (SD = 1.016). These values indicate that the simulation dataset provides sufficient variation across all three constructs and that the measurement items behave consistently within each scale.

Table 1. Instrument Validity and Reliability Test

Construct	Items	Corrected Item-Total Correlation	Cronbach's Alpha	Result
Artificial Intelligence Capability (AIC)	7	0.699-0.788	0.918	Valid and Reliable
Financial Decision-Making Quality (FDMQ)	5	0.695-0.761	0.885	Valid and Reliable
Corporate Financial Performance (CFP)	5	0.723-0.785	0.908	Valid and Reliable

Regression diagnostics indicate that the model is statistically suitable for interpretation. The standardized residuals do not depart significantly from normality in the Kolmogorov-Smirnov test ($p = 0.519$). Multicollinearity is not problematic because the VIF values for AIC and FDMQ are both 1.616. The Glejser test also does not indicate heteroscedasticity, with $p = 0.946$ for AIC and $p = 0.552$ for FDMQ. The Durbin-Watson statistic for the final outcome model is 2.012, which is close to the ideal value of 2 and suggests no material residual autocorrelation. In the mediator regression, AIC explains 38.1% of the variance in FDMQ ($R^2 = 0.381$; adjusted $R^2 = 0.378$; $F = 121.944$; $p < 0.001$). In the final outcome regression, AIC and FDMQ jointly explain 50.8% of the variance in CFP ($R^2 = 0.508$; adjusted $R^2 = 0.503$; $F = 101.682$; $p < 0.001$).

Hypothesis Testing

The hypothesis test combines standardized regression coefficients with the bootstrap mediation result. The total effect of AIC on CFP before the mediator is introduced is positive and significant ($B = 0.665$; $SE = 0.062$; $\beta = 0.608$; $t = 10.776$; $p < 0.001$). After FDMQ is included, the direct effect remains significant but becomes smaller ($B = 0.346$; $SE = 0.069$; $\beta = 0.316$; $t = 4.978$; $p < 0.001$). AIC also has a strong positive effect on FDMQ ($B = 0.640$; $SE = 0.058$; $\beta = 0.617$; $t = 11.043$; $p < 0.001$), while FDMQ significantly improves CFP when AIC is controlled ($B = 0.499$; $SE = 0.067$; $\beta = 0.473$; $t = 7.439$; $p < 0.001$). The unstandardized indirect effect is 0.319 and its 95% bootstrap confidence interval ranges from 0.231 to 0.412, excluding zero. The standardized indirect effect is approximately 0.292. Thus, all four hypotheses are supported in the simulation-based analysis and FDMQ acts as a partial mediator.

Table 2. Regression and Mediation Hypothesis Testing

Hypothesis	**Relationship**	**β**	**t-statistic**	**p-value**	**Decision**
H1	AIC -> CFP	0.316	4.978	<0.001	Supported
H2	AIC -> FDMQ	0.617	11.043	<0.001	Supported
H3	FDMQ -> CFP	0.473	7.439	<0.001	Supported
H4	AIC -> FDMQ -> CFP	0.292	6.169	<0.001	Supported

H1 is supported because AIC retains a positive direct relationship with CFP after decision quality is controlled ($\beta = 0.316$; $p < 0.001$). This result is consistent with the argument that AI capability has financial value beyond a single decision mechanism. Firms with stronger AI resources can automate routine analytical work, detect anomalies earlier, improve forecasting, and create more responsive monitoring systems. Mikalef and Gupta (2021) show that AI capability functions as a bundle of organizational resources that contributes to firm performance, while Fosso Wamba et al. (2024) demonstrate a direct performance effect alongside complementary organizational mechanisms. Mishra et al. (2022) similarly associate stronger AI focus with higher net profitability and operating efficiency. In corporate finance, these benefits can appear through lower processing costs, better working-capital visibility, earlier identification of financial deviations, and more disciplined resource allocation.

H2 is supported by the strong AIC -> FDMQ coefficient ($\beta = 0.617$; $p < 0.001$). This path is the largest standardized direct effect in the model, suggesting that a substantial portion of AI capability's organizational value first appears in the decision process. AI-capable firms can combine historical accounting data, operational information, external indicators, and predictive models to produce richer financial evidence. The finding is aligned with Neiroukh et al. (2025), who report that AI capability enhances decision quality and decision speed, and with Awan et al. (2021), who emphasize the role of analytics capability in generating data-driven insight. The practical implication is that the effectiveness of AI investment should be evaluated not only through system usage but also through improvements in the accuracy, timeliness, completeness, and interpretability of financial decisions.

H3 is also supported because FDMQ has a positive effect on CFP ($\beta = 0.473$; $p < 0.001$). This result indicates that decision quality is not merely an information-system outcome; it is a managerial capability with direct financial consequences. Better financial decisions improve the selection of investments, allocation of budgets, management of liquidity, prioritization of cost-control initiatives, and response to risk. Giachino et al. (2025) show that AI-driven decision making contributes positively to firm performance, while Herath Pathirannehelage et al. (2025) emphasize the need to design AI-augmented decision processes that support rather than obscure managerial reasoning. Financial managers therefore obtain greater value from AI when outputs are translated into defensible choices rather than treated as automatic recommendations.

H4 receives support from the mediation analysis. The indirect effect AIC -> FDMQ -> CFP is statistically significant (B = 0.319; 95% bootstrap CI [0.231, 0.412]), while the direct effect AIC -> CFP remains significant. The pattern is therefore consistent with complementary partial mediation. This means that AI capability affects financial performance through at least two channels: a direct operational-capability channel and an indirect decision-quality channel. The result closely parallels the mechanism identified by Ellelly et al. (2026), who found that financial decision-making quality mediates the relationship between AI adoption in accounting systems and organizational performance. The present model extends that logic by treating AI as an organizational capability and by focusing specifically on corporate financial performance. It also supports the broader view that the source of advantage shifts toward human-AI combinations in which algorithmic processing and managerial judgment reinforce one another (Krakowski et al., 2023).

Taken together, the model provides a clear managerial interpretation. AI expenditure alone should not be treated as evidence of financial transformation. The stronger pathway runs from AIC to FDMQ and then to CFP, indicating that organizations must develop the conditions under which AI-generated analysis becomes credible managerial input. These conditions include integrated and reliable financial data, finance-domain knowledge among AI teams, AI literacy among financial managers, model validation, explainability, clear decision rights, and human oversight for material judgments. The partial mediation result also implies that some financial benefits can emerge directly from automation and analytical efficiency, but sustainable value requires decision processes that convert technical capability into economically sound action. This distinction is especially important in emerging markets, where adoption can expand faster than organizational readiness and governance maturity.

4. CONCLUSION AND RECOMMENDATIONS

This study develops and tests a focused mediation framework linking Artificial Intelligence Capability, Financial Decision-Making Quality, and Corporate Financial Performance. In the SPSS-based simulation analysis, AIC significantly improves FDMQ and CFP, FDMQ significantly improves CFP, and the indirect AIC -> FDMQ -> CFP effect is significant, indicating partial mediation. The final model explains 50.8% of the variance in corporate financial performance, showing that financial decision-making quality is a central mechanism through which AI capability can be translated into economic outcomes within the simulated model. The theoretical contribution lies in integrating an organizational AI-capability perspective with a finance-specific decision-quality mechanism, while the practical implication is that organizations should combine AI investment with high-quality data, finance expertise, governance, model validation, and human oversight. As a simulation-based study, the findings demonstrate the statistical coherence of the proposed mechanism rather than population-level effects; future research should validate the model with field survey data and longitudinal accounting indicators such as ROA, ROE, operating margin, cash conversion cycle, and revenue growth across industries and firm sizes.

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