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Artificial Intelligence Adoption, Financial Decision-Making, and Organizational Performance in Somali Financial Institutions

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Abstract
Artificial intelligence (AI) is increasingly used in financial services, but evidence from fragile and developing financial systems remains limited. This study examines the relationships among AI adoption, financial decision-making, organizational performance, and implementation challenges in Somali financial institutions. Drawing on the Technology Acceptance Model, Resource-Based View, and Dynamic Capabilities Theory, the study used a quantitative cross-sectional design. Questionnaire data were collected from 100 employees of banks, Islamic financial institutions, fintech firms, insurance companies, and investment firms in Mogadishu. The analysis used descriptive statistics, Pearson correlations, reliability analysis, and multiple regression in SPSS version 27. Respondents reported moderate to high AI adoption. AI adoption was strongly and positively correlated with financial decision-making ($r = .809$, $p < .01$) and organizational performance ($r = .796$, $p < .01$). A regression model with AI adoption as the dependent variable explained 69.9% of its variance ($R^2 = .699$, $p < .001$). Financial decision-making ($\beta = .469$, $p < .001$) and organizational performance ($\beta = .368$, $p = .009$) were significant positive predictors, whereas contextual challenges were not significant ($\beta = .035$, $p = .778$). These cross-sectional findings show strong associations rather than causal effects. They suggest that Somali financial institutions could support responsible AI adoption through clearer regulation, stronger data governance, staff capability development, and continued investment in digital infrastructure.

Keywords: Artificial intelligence, Financial decision-making, Organizational performance, Financial institutions, Somalia

1. Introduction

The financial services industry is undergoing a profound transformation driven by artificial intelligence (AI), machine learning, and data-driven decision systems. AI has become a core technological enabler that reshapes how financial institutions perform credit assessment, fraud detection, investment analysis, risk management, and strategic decision-making (Duan et al., 2019; Huang & Rust, 2021). Unlike traditional statistical models, AI systems continuously learn from large datasets, improving prediction accuracy and enabling real-time decision support in complex financial environments.

Recent literature holds that AI is no longer a supportive tool but a strategic capability that influences organizational competitiveness and sustainability (Chatterjee et al., 2021).

Financial decision-making quality, covering credit allocation, liquidity management, investment decisions, and operational budgeting, is increasingly supported by AI-driven analytics, predictive modeling, and advanced operational research techniques in banking (Doumpos et al., 2023). Firm-level evidence shows AI capability improves internal business-process performance chiefly when embedded within a coherent business-value strategy rather than adopted as an isolated tool (Wamba-Taguimdje et al., 2020), and big-data-analytics capability strengthens competitive performance primarily through the mediating roles of dynamic and operational capabilities (Mikalef et al., 2020). AI-driven digital transformation also enhances organizational agility, enabling firms to respond quickly to changing market and regulatory conditions (Verhoef et al., 2021).

However, despite global advancements, the adoption and impact of AI in developing economies remain uneven. In fragile financial systems such as Somalia, institutions face structural constraints including limited digital infrastructure, low data maturity, shortage of skilled AI professionals, and evolving regulatory frameworks, raising the question of how far AI actually improves financial decision-making and organizational performance in Somali financial institutions.

Existing evidence largely emphasizes AI's benefits in enhancing predictive accuracy, automating financial processes, and improving organizational outcomes; however, these conclusions are predominantly derived from advanced economies where digital infrastructure, data maturity, and institutional capacity are relatively well developed (Davenport & Ronanki, 2018; Verhoef et al., 2021). Even in emerging-market settings more digitally advanced than Somalia, such as Saudi Arabia, researchers report that AI's financial pay-off is mediated by decision-making quality and organizational readiness rather than automatic (Badghish & Soomro, 2024), underscoring that mediation and contextual moderation, not direct technology effects, dominate the literature.

Four critical gaps remain evident. First, there is limited empirical evidence on the extent of AI adoption in fragile and developing economies. Second, the mechanisms through which AI enhances financial decision-making quality remain under-theorized in such contexts. Third, the direct and indirect effects of AI adoption on organizational performance have not been sufficiently disentangled within integrated empirical models. Fourth, institutional and infrastructural barriers shaping AI adoption decisions have not been adequately incorporated into explanatory frameworks.

In Somalia, these gaps are particularly pronounced. The financial sector is undergoing rapid transformation, characterized by expanding mobile money platforms and gradual formalization of banking institutions, yet there remains a near absence of systematic empirical research on AI adoption and its implications for decision-making and performance, limiting the ability of policymakers and managers to make informed AI investment decisions. Addressing this gap is essential not only for advancing theoretical understanding of AI in financial services but also for providing practical insights that can support effective digital transformation, regulatory development, and strategic decision-making in a fragile and emerging financial ecosystem.

1.1 Research Objectives

General objective: To examine the relationships among artificial intelligence adoption, financial decision-making, and organizational performance in Somali financial institutions.

Specific objectives

- Assess the extent of AI technology adoption in Somali financial institutions.
- Examine the relationship between AI adoption and financial decision-making.
- Examine the relationship between AI adoption and organizational performance.

• Identify the principal challenges associated with AI adoption in Somalia's financial sector.

2. Literature Review

2.1 Theoretical Foundations

The Resource-Based View (RBV) posits that organizational performance is primarily determined by the possession and effective utilization of valuable, rare, inimitable, and non-substitutable resources (Barney, 1991). AI is conceptualized as a strategic digital resource that enhances organizational capability through advanced analytics, automation, and knowledge integration. Firms that develop AI-enabled capabilities, such as predictive analytics and real-time risk monitoring, are more likely to sustain competitive advantage in dynamic markets (Mikalef et al., 2019; Wamba et al., 2017). RBV further suggests that AI-driven resources create value only when combined with skilled human capital, governance mechanisms, and data quality systems; without these, AI investments may underperform (Chatterjee et al., 2021). TOE-based evidence corroborates this view, showing that relative advantage and compatibility of AI systems translate into operational and economic performance gains only when paired with sustainable human capital and governance arrangements, moderated by firm size (Badghish & Soomro, 2024).

Dynamic Capabilities Theory extends RBV by emphasizing an organization's ability to integrate, build, and reconfigure competencies amid rapid change (Teece et al., 1997). In financial services, AI facilitates real-time data processing, predictive modeling, and continuous learning. Mikalef et al. (2020) demonstrate that a firm's big-data-analytics capability affects competitive performance only indirectly, fully mediated by dynamic and operational capabilities, a finding relevant to understanding why AI adoption in Somali institutions should operate through, rather than independently of, decision-making quality. Dynamic capabilities are especially critical where regulatory instability, currency fluctuations, and infrastructure limitations are common, enabling institutions to anticipate risk and redesign processes more effectively than traditional systems (Kshetri, 2021).

The Technology Acceptance Model (TAM) explains adoption behavior based on perceived usefulness and ease of use (Davis, 1989). Perceived usefulness is the strongest determinant of AI adoption intention in data-intensive industries such as banking (Huang & Rust, 2021), while organizational readiness, leadership support, and digital literacy moderate adoption behavior (Shrestha et al., 2019). Together, TAM, RBV, and Dynamic Capabilities Theory offer complementary lenses: TAM explains individual acceptance, RBV explains why AI functions as a strategic resource, and Dynamic Capabilities Theory explains how that resource is continually reconfigured under changing conditions. Integrated technology-organization-environment perspectives show AI adoption in financial-service-oriented firms is jointly shaped by organizational readiness, relative advantage, top-management support, and innovation climate (Bin-Nashwan & Li, 2025), while an extended UTAUT model shows bankers' willingness to embrace AI-based tools depends heavily on organizational readiness and perceived ethical governance (Bouteraa et al., 2024). Resistance to AI adoption is not only technical but psychological, as employees may fear job displacement (Akerkar, 2019).

2.2 Empirical Literature Review

2.2.1 AI and Financial Decision-Making

AI has transformed financial decision-making by improving speed, accuracy, and predictive capability in credit scoring, fraud detection, and risk management (Berg et al., 2020; Doumpos et al., 2023; Duan et al., 2019). A structural equation modeling study found that machine-learning tools improved decision-making effectiveness relative to manual methods, particularly in forecasting and risk scoring (Sujith et al., 2022). Huang and Rust (2021) argue that AI

augments rather than replaces human decision-makers, a view supported by evidence that AI-based credit scoring can improve predictive accuracy while retaining the role of professional judgment (Berg et al., 2020). Evidence from developing economies also associates AI-supported tools with faster and more accurate decisions, although benefits depend on data governance and model-risk oversight (Akour et al., 2024; Doumpos et al., 2023; Kadam et al., 2025). In customer-facing financial services, acceptance depends strongly on trust, transparency, and perceived value (Hentzen et al., 2022).

2.2.2 AI and Organizational Performance

Organizational performance is multidimensional, spanning profitability, efficiency, innovation, risk management, and customer satisfaction. Wamba et al. (2017) show big data and analytics capabilities enhance firm performance through improved operational efficiency, while Mikalef et al. (2019) find data-driven capabilities improve performance through decision quality and agility. AI-enabled marketing capability has been found to enhance SME performance in emerging economies through customer targeting and responsiveness (Abrokwah-Larbi & Awuku-Larbi, 2023). Chatterjee et al. (2021) provide evidence that AI adoption enhances organizational performance by improving productivity and reducing costs; in the banking sector, AI-driven innovation contributes positively to financial performance through better risk management, operational efficiency, and enhanced credit assessment capabilities (Baffour Gyau et al., 2024). Firm-level banking evidence using panel GMM estimation shows AI technology innovation significantly boosts return on assets, though the dividend can be eroded by non-performing loans and weak regulatory updating (Baffour Gyau et al., 2024). A bibliometric review finds performance-oriented AI studies concentrated on efficiency and risk outcomes, with few yet examining sustained profitability in low-income markets (Pattnaik et al., 2024), while risk-governance research cautions that AI-driven gains are contingent on explainable, auditable practices, since opaque decisions can themselves become a risk source (Fritz-Morgenthal et al., 2022).

2.2.3 AI Adoption in Financial Institutions

AI adoption is influenced by technological, organizational, and environmental factors; institutions with strong digital infrastructure and leadership support integrate AI more successfully (Verhoef et al., 2021). TOE-based studies find relative advantage, compatibility, government support, and sustainable human capital are the strongest predictors of adoption, with firm size moderating the adoption–performance relationship (Badghish & Soomro, 2024). In developing economies, adoption is constrained by inadequate infrastructure, limited skilled personnel, and weak institutional frameworks (Kshetri, 2021), while successful adoption also requires organizational restructuring, upskilling, and governance mechanisms (Akerkar, 2019).

2.2.4 Challenges in Developing Economies

The literature consistently identifies shortages of AI-skilled human capital, fragmented data ecosystems, and weak data-governance frameworks as primary constraints (Kshetri, 2021; Mikalef et al., 2019). Financial constraints also slow adoption given the cost of hardware, cybersecurity, and training (Duan et al., 2019; Chatterjee et al., 2021), compounded by regulatory uncertainty and concerns over algorithmic bias and accountability (Huang & Rust, 2021). For Islamic finance institutions, legal analyses of robo-advisory tools find the absence of explicit Shariah-compliance protocols is a binding constraint on adoption, recommending explicit supervisory-board oversight of algorithmic investment logic (Kharisma et al., 2025). Conceptual work similarly concludes algorithmic transparency, fairness, and avoidance of gharar remain underdeveloped in Islamic-finance AI governance (Arsyad et al., 2025), while evidence from Saudi Islamic banking shows AI strengthens efficiency only when integrated within an explicit Shariah-governance architecture (Shalhoob, 2025). Organizational resistance

to change remains an added barrier (Shrestha et al., 2019), and these challenges are more pronounced in fragile economies such as Somalia.

2.3 Research Gap

Most empirical studies concentrate in developed or moderately developed economies (Verhoef et al., 2021; Chatterjee et al., 2021), leaving a lack of context-specific evidence from fragile, post-conflict systems such as Somalia. Prior research has largely examined AI adoption, decision-making, and performance in isolation rather than an integrated model (Mikalef et al., 2019; Wamba-Taguimdje et al., 2020), and institutional/infrastructural barriers are rarely incorporated as explicit variables (Kshetri, 2021; Duan et al., 2019). Even recent TOE-based studies from better-resourced markets have only begun to formally incorporate governance and human-capital constraints as explicit predictors (Badghish & Soomro, 2024), and the Islamic-finance AI-governance literature remains almost entirely conceptual and legal rather than survey-based (Kharisma et al., 2025; Arsyad et al., 2025), leaving a larger gap for fragile Muslim-majority systems such as Somalia's. This study addresses these gaps by integrating AI adoption, decision-making quality, and organizational performance into a single analytical model while examining structural and organizational challenges in a fragile financial environment.

2.4 Conceptual Framework

The framework is grounded in TAM and RBV. As Figure 1 shows, financial decision-making is specified as an independent variable, AI adoption as the dependent variable, organizational performance as an outcome or mediating variable, and contextual challenges as a moderating variable. The reported regression analysis, however, estimates AI adoption as the dependent variable and does not test the mediation and moderation paths shown in the figure.

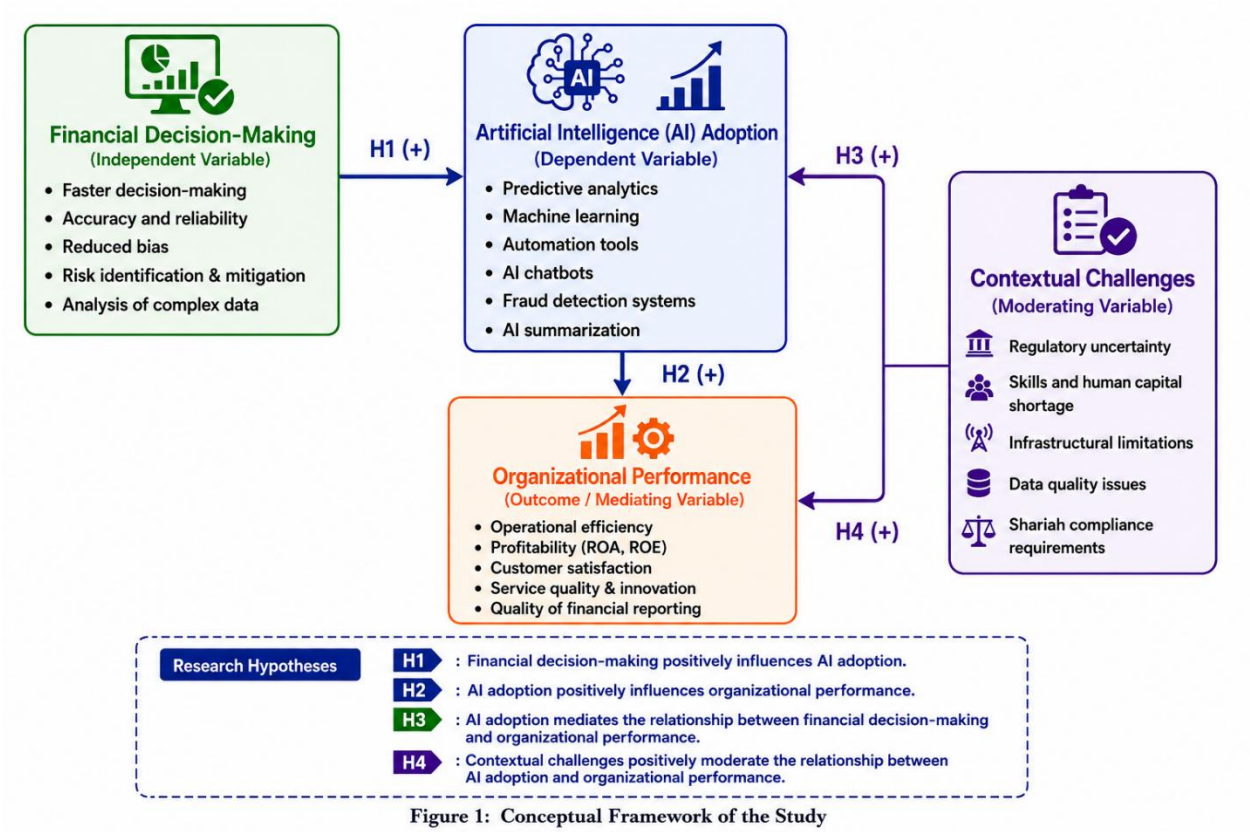


Figure 1: Conceptual framework of the study

3. Methods

This study used a quantitative, cross-sectional explanatory design within a positivist paradigm to examine relationships among AI adoption, financial decision-making, and organizational performance in financial institutions in Mogadishu, Somalia. The deductive approach drew on TAM, RBV, and Dynamic Capabilities Theory.

The target population comprised employees of commercial banks, Islamic banks, microfinance institutions, fintech and mobile money providers, insurance companies, and investment firms in Mogadishu. Simple random sampling was used to select 100 respondents. Primary data were collected with a structured questionnaire covering respondent characteristics, AI adoption, financial decision-making, organizational performance, and contextual challenges. Construct items used a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). A pilot test assessed the questionnaire's clarity and reliability before the main survey.

Data were analyzed in SPSS version 27. Frequencies and percentages summarized respondent characteristics, while means and standard deviations summarized study variables. Pearson correlations assessed bivariate relationships among the constructs. Multiple regression estimated AI adoption as the dependent variable, with financial decision-making, organizational performance, and contextual challenges as predictors. Cronbach's alpha assessed internal consistency using .70 as the minimum threshold; the overall scale coefficient was .958.

3.1 Ethical Considerations

Participants provided informed consent, participation was voluntary, and responses were anonymous and confidential. The study was approved by the Institutional Review Board of Hormuud University.

4. Results

4.1 Respondent Profile

Table 1 presents the demographic and institutional profile of the 100 respondents. The sample was predominantly male (75.0%), and the largest age group was 26–35 years (37.0%). Many respondents held a master's degree (37.0%) or a professional qualification such as CFA or CPA (32.0%). Supervisory staff (18.0%) and middle managers (17.0%) were the largest specified position groups, although 26.0% reported another position. The largest experience group had one to five years of work experience (38.0%). Commercial banks accounted for the largest institutional group (35.0%), followed by Islamic banks and finance houses (21.0%). The largest institution-size category was 500–999 employees (29.0%).

Table 1. Demographic and Institutional Profile of Respondents (N = 100)

Variable	Category	Freq.	%
Gender	Male	75	75.0
	Female	25	25.0
Age Group	18–25 years	21	21.0
	26–35 years	37	37.0
	36–45 years	22	22.0

Variable	Category	Freq.	%
	46–55 years	12	12.0
	56 years and above	8	8.0
Highest Education	Secondary school	8	8.0
	Bachelor degree	2	2.0
	Master degree	37	37.0
	Professional qualification (CFA, CPA, etc.)	32	32.0
	PhD	8	8.0
	Unspecified/other	13	13.0
Current Position	Executive / Senior management	14	14.0
	Middle management	17	17.0
	Supervisory level	18	18.0
	Operational / Technical staff	16	16.0
	IT / Technology specialist	9	9.0
	Other	26	26.0
Years of Experience	Less than 1 year	17	17.0
	1–5 years	38	38.0
	6–9 years	21	21.0
	Above 10 years	23	23.0
	Unspecified	1	1.0
Institution Type	Commercial bank	35	35.0
	Microfinance institution	13	13.0

Variable	Category	Freq.	%
	Mobile money / Fintech company	9	9.0
	Islamic bank / Finance house	21	21.0
	Insurance company	9	9.0
	Investment / Asset management firm	13	13.0
Institution Size (Employees)	Fewer than 50	19	19.0
	50–199	16	16.0
	200–499	19	19.0
	500–999	29	29.0
	1,000 or more	17	17.0

4.2 Descriptive Patterns Across Constructs

The descriptive statistics indicate a moderate to high level of AI technology adoption among the surveyed organizations, with mean scores ranging from 3.38 to 3.65, while the standard deviations (1.174–1.208) suggest a moderate level of variation in respondents' perceptions.

Table 2. Descriptive Statistics for the Extent of AI Technology Adoption

Item	Mean	Std. Dev.
Predictive analytics for forecasting market trends and customer behavior	3.52	1.193
Machine learning for credit scoring and loan default assessment	3.47	1.176
Automation tools for repetitive back-office tasks	3.57	1.208
AI-driven chatbots for automated customer support	3.38	1.196
Fraud detection systems for real-time transaction monitoring	3.58	1.174
AI summarization of financial transactions in statements	3.65	1.184

The descriptive statistics indicate that respondents generally agreed that AI has a positive impact on financial decision-making, with mean scores ranging from 3.48 to 3.71, while the standard deviations (1.058–1.202) indicate moderate variability in respondents' opinions.

Table 3. Descriptive Statistics for Financial Decision-Making

Item	Mean	Std. Dev.
AI tools have improved the efficiency and speed of financial decision-making	3.50	1.202
AI provides more accurate, reliable financial information than manual methods	3.54	1.058
Use of AI has reduced human bias, leading to more objective financial choices	3.53	1.132
AI-driven models help proactively identify and mitigate liquidity and credit risks	3.48	1.150
AI enables analysis of complex datasets previously too large for manual oversight	3.71	1.172

The descriptive statistics suggest that AI has a positive impact on organizational performance, with mean scores ranging from 3.46 to 3.67, while the standard deviations (1.016–1.218) indicate moderate variation in respondents' perceptions.

Table 4. Descriptive Statistics for Organizational Performance

Item	Mean	Std. Dev.
AI integration has reduced operational costs and time for accounting procedures	3.49	1.168
Improvement in Return on Assets due to AI-driven optimization	3.46	1.218
AI has enhanced operational resilience and faster response to market uncertainties	3.55	1.067
AI-based customer analytics have improved customer satisfaction and retention	3.67	1.016
AI tools assist in producing higher-quality, more understandable financial reports	3.64	1.087

The descriptive statistics indicate that respondents generally agreed that challenges and contextual factors moderately influence AI adoption in Somalia, with mean scores ranging from 3.35 to 3.72, while the standard deviations (1.045–1.175) suggest moderate variation in respondents' perceptions.

Table 5. Descriptive Statistics for Contextual Challenges in Somalia

Item	Mean	Std. Dev.
Lack of specialized AI and data analysis skills among staff	3.46	1.158
Limited access to high-quality, structured data in Somalia	3.67	1.045
Inconsistent internet connectivity and power supply limit AI deployment	3.35	1.175
Ensuring AI algorithms strictly follow Islamic finance principles	3.48	1.096
Absence of a clear national regulatory framework for AI adoption	3.72	1.055

4.3 Reliability of the Measurement Instrument

Internal consistency was assessed using Cronbach's alpha for each construct and for the full 21-item instrument. All coefficients exceeded the conventional .70 threshold, and the full-scale coefficient of .958 indicated excellent internal consistency.

Table 6. Reliability Statistics by Construct

Construct	No. of Items	α
Extent of AI Technology Adoption	6	.875
Impact on Financial Decision-Making	5	.876
Impact on Organizational Performance	5	.858
Challenges and Contextual Factors in Somalia	5	.836
Overall Instrument	21	.958

4.4 Bivariate Relationships Among Constructs

Pearson correlations showed strong, positive, and statistically significant relationships among all study constructs ($r = .736–.883$, $p < .01$). AI adoption was positively associated with financial decision-making ($r = .809$) and organizational performance ($r = .796$). Because the data are cross-sectional, these correlations do not establish causal direction.

Table 7. Pearson Correlation Matrix Among Study Constructs

Construct	AI Adoption	Financial Decision-Making	Organizational Performance	Contextual Challenges
AI Technology Adoption	1.000	.809**	.796**	.736**
Financial Decision-Making	.809**	1.000	.846**	.803**
Organizational Performance	.796**	.846**	1.000	.883**
Contextual Challenges	.736**	.803**	.883**	1.000

Note. ** Correlation is significant at the .01 level (two-tailed).

4.5 Multiple Regression Analysis

The regression model (n = 99 complete cases) was statistically significant, $F(3, 95) = 73.364$, $p < .001$, and explained 69.9% of the variance in AI adoption ($R^2 = .699$, adjusted $R^2 = .689$).

Table 8. Model Summary and Analysis of Variance for AI Technology Adoption

R	R Square	Adjusted R Square	F (3, 95)	Sig.
.836	.699	.689	73.364	< .001

Table 9. Regression Coefficients Predicting AI Technology Adoption

Predictor	B	Std. Error	Beta (β)	T	Sig.
(Constant)	2.124	1.366		1.555	.123
Impact on Financial Decision-Making	0.564	0.130	.469	4.331	< .001
Impact on Organizational Performance	0.462	0.173	.368	2.673	.009
Challenges and Contextual Factors in Somalia	0.045	0.160	.035	0.282	.778

Financial decision-making (β = .469, p < .001) and organizational performance (β = .368, p = .009) were significant positive predictors of AI adoption. Contextual challenges were not statistically significant after adjustment for the other predictors (β = .035, p = .778).

5. Discussion

The findings show strong associations among AI adoption, financial decision-making, and organizational performance. This pattern is consistent with evidence that adoption depends jointly on organizational readiness, relative advantage, innovation climate, and ethical governance (Bin-Nashwan & Li, 2025; Bouteraa et al., 2024). It also accords with research showing that AI creates value when it is embedded in organizational processes and supported by complementary capabilities (Kumari et al., 2024; Wamba-Taguimdje et al., 2020). Fraud-detection systems received stronger endorsement than customer-facing chatbots, suggesting that sampled institutions may be prioritizing operational protection before wider customer-facing deployment. The comparatively modest rating for bias reduction also suggests that respondents viewed AI as supporting rather than replacing professional judgment, consistent with Berg et al. (2020). Because the regression treated AI adoption as the dependent variable, its coefficients should not be interpreted as evidence that adoption caused better decisions or performance.

Contextual challenges were strongly correlated with financial decision-making and organizational performance (r = .803 and .883, respectively), but they were not a significant predictor of AI adoption in the multivariable model. Regulatory uncertainty received the highest mean rating among the challenge items. This result is consistent with research emphasizing governance readiness and regulatory clarity (Bin-Nashwan & Li, 2025). Shariah-compliance concerns were also relevant for the Islamic finance institutions represented in the sample, in line with studies calling for explicit Shariah standards and transparent oversight of AI-supported financial decisions (Arsyad et al., 2025; Kharisma et al., 2025; Shalhoob, 2025). The findings therefore support attention to regulatory clarity, data governance, staff capability, and infrastructure, while the nonsignificant regression coefficient cautions against treating contextual challenges as an independent statistical determinant in this model.

This study has several limitations. Its cross-sectional design cannot establish causal direction, and self-reported questionnaire data may be affected by common-method and response biases. The sample was limited to 100 employees in Mogadishu, which restricts generalizability to other locations and institutions. In addition, the reported analysis did not test the mediation and moderation paths shown in Figure 1. Longitudinal, multi-city studies using objective performance measures and formal mediation or moderation analysis would provide stronger evidence.

6. Conclusion and Policy Implications

This study examined AI adoption, financial decision-making, organizational performance, and implementation challenges in Somali financial institutions. AI adoption was strongly associated with both financial decision-making and organizational performance. In the reported regression, financial decision-making and organizational performance significantly predicted AI adoption, whereas contextual challenges did not. These results indicate related patterns within the sampled institutions but do not establish causal effects. The descriptive findings nevertheless identify regulatory uncertainty, data limitations, skills shortages, and Shariah-compliance requirements as practical concerns. Policymakers and financial managers should therefore strengthen regulatory guidance, data governance, workforce capability, and digital infrastructure while requiring transparent and accountable AI use. Future studies should use longitudinal and multi-city designs, incorporate objective performance indicators, and test the proposed causal, mediating, and moderating pathways directly.

Ethics Approval and Informed Consent

This study was approved by the Institutional Review Board of Hormuud University. Written informed consent was obtained from all participants.

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None.

Conflict of Interest

The author reports no financial, institutional, or personal conflicts of interest.

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