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Artificial Intelligence Adoption and Financial Decision-Making Quality among SMEs in Freetown, Sierra Leone: The Moderating Role of Digital Capability

Kalie Marah, & Arni Surwanti*

Department of Management, Universitas Muhammadiyah Yogyakarta, Indonesia

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Corresponding Author:

arni_surwanti@umy.ac.id

ABSTRACT

This study investigates the impact of artificial intelligence (AI) adoption on financial decision-making quality (FDMQ) among small and medium enterprises (SMEs) in Freetown, Sierra Leone. It examines the moderating role of digital capability. The study used a quantitative, cross-sectional survey design with a sample of 250 owner-managers and finance officers from SMEs in formal and semi-formal business clusters in Freetown, based on the Technology–Organization–Environment (TOE) framework and Resource-Based View (RBV). The data were analyzed using SPSS with descriptive statistics, correlation analysis, and hierarchical moderated multiple regression. Findings showed that AI adoption ($\beta = .573$, $p < .001$) and digital capability ($\beta = .283$, $p < .001$) were significant, positive predictors of FDMQ. The AI adoption–FDMQ relationship was also significantly moderated by digital capability ($\beta = .195$, $\Delta R^2 = .035$, $p < .001$). Simple slopes analysis showed that the effect of AI adoption was more than doubled when digital capability increased from low to high. AI adoption enhances SME financial decision-making, but its impact relies on supporting digital capabilities. The study builds on the TOE and RBV frameworks in an under-researched West African context. It emphasizes the importance of integrating AI provision with digital capability development. Findings suggest associations, not causal or broadly generalizable effects, because of the cross-sectional, self-reported design and the Freetown sample.

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■ INTRODUCTION

Artificial intelligence (AI) has moved from a peripheral information-technology concern to a central determinant of how organizations sense opportunities, process financial information, and commit resources under uncertainty. Firms of all sizes increasingly rely on machine-learning-powered forecasting, natural-language analytics, robotic process automation, and algorithmic credit-scoring tools to create, understand, and respond to financial data (Al-Hattami, 2026; Artene et al., 2024). In large corporations, AI in finance and accounting has been used in applications such as audit reporting, credit-risk assessment, and enterprise fintech management (Kliestik et al., 2024; Mohammad et al., 2026). Small and medium enterprises (SMEs), however, remain relatively under-researched, even though they are the main source of employment and value added in most developing countries, including Sierra Leone.

This study defines the quality of financial decision-making (FDMQ) as the accuracy, timeliness, evidence base, and responsiveness of decisions on working capital, credit, pricing, investment, and risk, and it remains a recurring problem for SMEs in resource-poor, informally organized markets. Limited access to affordable digital infrastructure, unreliable electricity, and weak institutional support (Rahman, 2025) continue to reinforce reliance on intuition, informal bookkeeping, and fragmented record-keeping among many SME owner-managers in Freetown. Similar infrastructural, skills, and cost barriers to AI use have been documented among smallholder producers in other resource-constrained developing-country settings, reinforcing that the challenge is not unique to Sierra Leone but a broader feature of AI diffusion in low-income economies (Yuan & Sun, 2025). Meanwhile, the increasing availability of mobile money services, cloud-based accounting software, and AI-powered financial advisory solutions is slowly reducing the barriers to digitally aided decision-making, even in low-income areas (Rawat et al., 2025; Lukash et al., 2025).

Recent research indicates that AI can significantly enhance decision-making quality

within organizations by providing timely access to financial information, mitigating information asymmetry, and supporting informed managerial judgments (Al-Hattami, 2026; Artene et al., 2024; Wang et al., 2026). Algorithmic decision pipelines have been shown to influence how risk is evaluated and to make credit decisions more transparent and defensible, particularly in lending and credit scenarios (Abbas, 2025; Mohammad et al., 2026). AI-powered financial ecosystems have also been shown to enable more inclusive, data-driven financial services in emerging-market banking systems (Alzubi, 2026; Lakshmi et al., 2026). However, the impact of AI usage on better decision-making is not guaranteed: several studies warn that the advantages of AI are dependent on other organizational factors, such as data infrastructure, digitally competent staff, and integration capabilities, which otherwise limit the use of AI tools and their value (Chaudhuri et al., 2024; Kubiczek et al., 2025; Oyenubi & Oyeyipo, 2026).

The present study focuses on this conditionality. We believe that digital capability, defined as the capacity of an organization to acquire, integrate, and deploy digital technologies, data, and digitally competent people to achieve its goals (Adiguzel et al., 2024; Franco et al., 2024), is a likely boundary condition that can explain the link between AI adoption and better financial outcomes. SMEs with high digital capability are more likely to understand the outputs of AI, incorporate them into their workflows, and tailor them to their specific financial needs, while those with low digital capability might use AI tools without realizing the improvements in decision-making (Ristyawan et al., 2026; Wenting et al., 2026).

Sierra Leone offers a theoretically and practically important context for examining this relationship. Sierra Leone's SME sector operates in a low-income, post-conflict economy with a fledgling digital finance system; it is concentrated in trade, services, and light manufacturing in Freetown and is characterized by institutional fragility, limited access to formal credit, and constrained managerial capacity (Yesuf & Fields, 2025). The findings of this study have direct implications for SME competitiveness, financial inclusion policy, and donor-funded digitalization programs across West Africa, as they will help clarify whether, and under what organizational conditions, AI adoption can enhance financial decision-making in this context. To guide the empirical testing that follows, the study is framed around three research questions:

RQ1: What is the effect of AI adoption on the financial decision-making quality (FDMQ) of SMEs in Freetown, Sierra Leone?

RQ2: What is the effect of digital capability on the financial decision-making quality of SMEs in Freetown, Sierra Leone?

RQ3: Does digital capability moderate the relationship between AI adoption and financial decision-making quality among SMEs in Freetown, Sierra Leone, such that the effect of AI adoption is stronger for SMEs with higher digital capability?

Correspondingly, this study thus aims at three things: (1) to investigate the impact of AI adoption on financial decision-making quality among SMEs in Freetown; (2) to investigate the impact of digital capability on financial decision-making quality; and (3) to test the moderating effect of digital capability between AI adoption and financial decision-making quality. In doing so, the study contributes to the literature by examining AI adoption and financial decision-making quality among SMEs in Freetown, Sierra Leone, an under-researched West African context. It uniquely positions digital capability as a moderator, showing that the benefits of AI adoption depend on SMEs' ability to integrate digital technologies, skills, and data effectively. The study further integrates the TOE framework and RBV to explain how AI resources translate into improved financial decision-making through organizational capabilities. Empirically, the significant moderating effect of digital capability confirms that higher digital capability strengthens the positive effect of AI adoption on FDMQ. Thus, the study shifts the focus from whether SMEs adopt AI to the conditions under which AI adoption produces better financial decisions.

Literature Review and Theoretical Framework

Conceptual clarification

For the scope of this study, AI tool use is defined as the extent to which an SME has adopted AI tools in its day-to-day financial processes, including automated bookkeeping software, algorithmic credit or cash-flow forecasting tools, chatbot financial advisory services, and AI fraud or anomaly detection tools. This conceptualization aligns with recent research that views AI adoption as a multidimensional phenomenon, ranging from awareness and trial use to institutionalized use in core business processes (Rahman, 2025; Yesuf & Fields, 2025). Importantly, AI use in SMEs is often not a complete overhaul, but a gradual integration of individual tools into

existing manual or semi-digital processes (Kubiczek et al., 2025).

Financial decision-making quality reflects the timeliness, evidence-based nature, consistency, and responsiveness of financial decisions on pricing, credit extension, inventory investment, expenditure control, and risk management to changing market conditions. The construct draws on the broader decision-quality literature in financial reporting and audit, where improved timeliness, reliability, and traceability of data lead to more informed, evidence-based managerial action (Al-Hattami, 2026; Artene et al., 2024). In an SME, FDMQ is more likely a characteristic of the decision-making process itself: the extent to which decisions are based on accurate, up-to-date information rather than intuition or incomplete records. This process-based view is reinforced by evidence from women-owned SMEs in Indonesia, where investment decisions were shown to mediate the effect of cognitive and emotional biases on financial performance, underlining that the quality of the underlying decision process, not only its outcome, is what ultimately drives SME financial performance (Tubastuvi et al., 2024).

Digital capability is an organization's capacity to leverage digital infrastructure, data, and human resources to create value from digital technologies. It is not the same as simply owning the technology; two SMEs can have the same AI tool, but have very different capabilities to incorporate the output of the tool into decision-making processes due to variations in staff digital literacy, data governance, and organizational routines for leveraging technology-generated insights (Adiguzel et al., 2024; Franco et al., 2024; Ristyawan et al., 2026). This is the conceptual pivot of the moderation hypothesis advanced below: the distinction between having a technology and being able to exploit it.

The Technology–Organization–Environment (TOE) framework

The TOE framework describes the process of technology adoption and its implications in terms of three contextual dimensions: technological context (the perceived attributes of the technology, including relative advantage, complexity, and compatibility); organizational context (firm characteristics, including size, managerial support, and resource slack); and environmental context (industry structure, competitive pressure, and regulatory conditions). In this context, the technological characteristics of AI, such as its ability to process large amounts of data quickly, recognize patterns, and make predictions, offer a relative advantage to SMEs aiming to enhance financial decision-making (Al-Hattami, 2026; Wang et al., 2026). However, TOE research has consistently highlighted that technological potential is mediated by organizational readiness; firms with less organizational capacity to produce a technology's outputs experience less successful adoption outcomes (Chaudhuri et al., 2024; Kubiczek et al., 2025; Oyenubi & Oyeyipo, 2026). Evidence from financial institutions in Jordan similarly shows that the performance benefits of AI and blockchain adoption are indirect, operating through a digital-absorptive-capacity mechanism that mediates the technology–performance link, which is conceptually consistent with the organizational-readiness logic proposed here (Afaneh et al., 2026). From the environmental perspective, Sierra Leone's institutional and infrastructural environment, such as limited digital infrastructure, an emerging regulatory framework for fintech, and restricted access to formal credit markets, are contextual constraints that influence the speed and extent of AI use by SMEs (Rahman, 2025; Rawat et al., 2025). This environmental constraint is not unique to Sierra Leone; research on financing mechanisms for local community development elsewhere shows that the effectiveness of digital technologies for financial decision-making is itself contingent on the surrounding digital-infrastructure environment (Radynskyy et al., 2024).

The digital-capability moderator proposed in this study is theoretically grounded in the organizational dimension of TOE. Digital capability operationalizes organizational readiness: it measures whether an SME has the internal conditions (skilled personnel, data infrastructure, integrative routines) needed to transform a technological input (AI) into an improved organizational outcome (decision quality). This aligns with previous TOE studies, which find that organizational digital readiness and data-driven culture influence the relationship between emerging technology adoption and organizational performance outcomes (Chaudhuri et al., 2024).

The Resource-Based view (RBV)

The RBV is based on the premise that SCA comes from resources and capabilities that are valuable, rare, imperfectly imitable, and non-substitutable (VRIN). In this study, AI adoption is treated as a technological resource, and digital capability as a complementary organizational capability needed to transform that resource into a valuable, firm-specific

outcome. The resource–capability distinction is also a well-documented finding in recent research on digital transformation that has adopted the RBV approach, which demonstrates that digital resources alone do not necessarily lead to performance improvements, but rather to performance improvements when they are integrated into governance structures and organizational capabilities that allow them to be used effectively (Franco et al., 2024; Ristyawan et al., 2026). In a banking and financial-services context, resource and capability configurations have also been found to work together, not separately, to shape institutional performance outcomes, further supporting the notion that technology resources must be complemented by capabilities to create value (Ristyawan et al., 2026).

Similarly, tourism-sector research that combines RBV with dynamic-capability and technology-acceptance theories finds that the impact of AI adoption on firm-level decision-making and competitiveness depends on the firm's ability to incorporate AI outputs into its existing capability configurations (Wenting et al., 2026). The capability-contingent logic proposed here is also supported by findings that big-data-analytics capability is associated with the innovation outcomes of technology firms, which are also contingent on technology-management investments (Adiguzel et al., 2024). Consistent with this, RBV-based evidence from Indonesian MSMEs shows that internal capabilities translate into export capability only through complementary organizational mechanisms, not directly, reinforcing the general RBV point that a firm-level resource is performance-relevant mainly insofar as it is channeled through a firm-specific capability (Anggadwita et al., 2026).

Combined, RBV implies that adopting AI as a resource is not enough to enhance financial decision-making; digital capability is the complementary firm-specific capability needed without which the resource cannot be fully exploited. This logic dovetails with and supports the TOE organizational-readiness argument presented above, and offers complementary theoretical support for the two hypotheses that follow: direct effect and moderation.

This resource–capability logic also applies to the production and dissemination of AI itself in organizational ecosystems. The studies conducted at the enterprise level reveal that generative AI, IoT, and blockchain-based fintech management technologies generate the highest value for the organization when integrated into the overall "cognitive algorithmic economy" of the organization's complementary digital assets and skills, and not as standalone technologies (Kliestik et al., 2024). Likewise, studies on knowledge models for AI-based fraud detection highlight the importance of human–technology interaction in the organization, suggesting that the value of an AI resource is not just in the technology itself, but in its complementariness with organizational capability (Mofarreh et al., 2025). This capability-contingent logic is particularly relevant for resource-constrained SMEs in Freetown, where formal digital infrastructure and specialist personnel are limited: the same AI tool can produce materially different decision-quality outcomes based on the SME's underlying digital capability.

Integrating TOE and RBV: A combined theoretical model

TOE addresses the why and under what contextual conditions SMEs adopt AI, while RBV addresses how the adopted technology is transformed into a performance-relevant outcome for the firm. The two frameworks are thus not mutually exclusive, but complementary: TOE treats digital capability as a condition of organizational readiness within the adoption context, while RBV treats digital capability as the factor that determines whether the AI resource provides a competitive, decision-quality advantage. This integration aligns with recent research that integrates technology-adoption and capability-based approaches to understand the diverse outcomes of AI and digital transformation efforts in organizations (Kubiczek et al., 2025; Wenting et al., 2026; Kliestik et al., 2024).

Empirical review and hypotheses development

There has been a rapid increase in empirical evidence that shows how adopting AI can lead to better financial and decision outcomes across sectors and regions. In the accounting and audit context, AI-powered digital innovations have been identified as a means to improve the quality of real-time reporting, which can, in turn, boost decision-making by ensuring timely, reliable, and traceable financial information (Al-Hattami, 2026). Likewise, AI use in financial reporting decision-making has been linked to improvements in the quality and defensibility of financial reporting decisions (Artene et al., 2024). Algorithmic decision pipelines and AI-driven credit-risk models have been found to influence lending decisions in credit markets, but concerns remain about opacity and fairness where the capacity to interpret and govern these models is limited (Abbas, 2025; Mohammad et

al., 2026). Findings from platform-based financial ecosystems also suggest that AI use is linked to more inclusive, data-driven service delivery in emerging-market banks (Alzubi, 2026; Lakshmi et al., 2026). Evidence closer to the informal, owner-managed enterprise context of this study shows that AI accounting tools improve the quality of financial reporting among women artisan-entrepreneurs (U. S. Yadav et al., 2025), while generative-AI collaboration has also been shown to shape consumer trust and financial decision-making more broadly (Oza et al., 2026), lending further support to a positive AI–decision-quality link outside large-firm settings. Based on this evidence, the following hypothesis is proposed:

H1: AI adoption has a positive and significant effect on financial decision-making quality among SMEs in Freetown, Sierra Leone.

A second line of research connects digital capability to better decision and performance outcomes, without focusing on the technology inputs. Digital capability (data infrastructure, digitally skilled personnel, and integrative routines) has been linked to better resource and capability configurations in financial institutions (Ristyawan et al., 2026) and to higher innovation outcomes in technology companies with higher analytics capability (Adiguzel et al., 2024). The digital-transformation literature has demonstrated that hybrid governance structures that integrate digital resources into organizational processes are key to digital transformation in supply chain and operational settings (Franco et al., 2024). Accordingly:

H2: Digital capability has a positive and significant effect on financial decision-making quality among SMEs in Freetown, Sierra Leone.

Organizational readiness and capability are common themes in the literature reviewed above and relate to TOE and RBV. An organizational data-driven culture moderates the relationship between emerging technology adoption and organizational growth trajectories, such that the positive impact of technology adoption is stronger when organizational data orientation is greater (Chaudhuri et al., 2024). Similarly, research on barriers to AI adoption in resource-constrained project settings indicates that the gains from AI adoption are limited when there is a lack of complementary organizational and institutional capacity (Oyenubi & Oyeyipo, 2026), and research on harnessing AI suggests that the benefits of AI implementation are realized when the implementation is effective, and that implementation effectiveness is determined by organizational digital readiness (Kubiczek et al., 2025). Most directly, evidence from the tourism sector combining the RBV and dynamic-capability perspectives indicates that AI's value for the firm's decision-making and competitiveness depends on the firm's dynamic-capability configuration (Wenting et al., 2026). Comparable evidence from the banking sector shows that AI-assisted practices translate into improved employee performance and institutional profitability only where organizational implementation capacity supports them, again pointing to organizational readiness as the binding constraint on AI's value (Gajanand & Trivedi, 2026). Based on this, it is hypothesized that:

H3: Digital capability positively moderates the relationship between AI adoption and financial decision-making quality, such that the positive effect of AI adoption on financial decision-making quality is stronger for SMEs with higher digital capability.

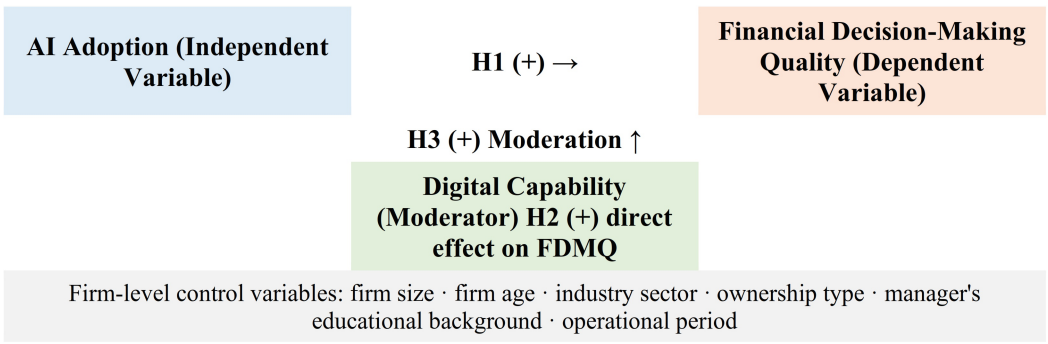


Figure 1. Conceptual model of ai adoption, digital capability, and financial decision-making quality among smes in freetown, sierra leone

Table 1. Demographic profile of study participants (n = 180)

The control variables shown (firm size, firm age, sector, ownership type, managerial education, and years of operation) are contextual factors identified from the SME technology-adoption literature as theoretically relevant to FDMQ. Consistent with the scope of the final data-collection instrument, these variables were not retained as separate measured items and were therefore not entered into the hierarchical regression models. Their omission from the empirical model is acknowledged as a limitation that may affect the precision of the estimated coefficients; future studies are encouraged to measure and control for these firm-level characteristics.

■ METHOD

Research Design

The study used a quantitative, cross-sectional survey design within a positivist research paradigm, suitable for testing the hypothesized relationship between measurable constructs using a structured instrument at a single point in time (Rahman, 2025; M. Yadav et al., 2025). The cross-sectional design is chosen because it efficiently captures the current status of AI adoption, digital capability, and the quality of financial decision-making across a wide cross-section of SMEs in Freetown; however, as a limitation, it does not allow strong causal inferences about the direction of the observed relationships.

Participants (Population and Sample)

The target population includes registered and semi-formal SMEs in Freetown's main commercial districts, including trade, retail, hospitality, light manufacturing, and financial and professional services. The unit of analysis is the firm, and the key informant is the owner-manager or, if specified, the finance officer or senior accounting staff member, because this group is likely best positioned to report on both the use of AI-related tools and the firm's financial decision processes.

Since there was no single comprehensive sampling frame for SMEs in Freetown, a multi-stage sampling approach was used. The commercial areas of Freetown were first divided into major business clusters (e.g., central business district, Congo Town, Wellington, and other main trading areas) to provide sectoral and geographic coverage. Within each cluster, the sampling technique applied depended on whether a usable listing of firms was available. For business clusters where reasonably complete, up-to-date registers of formally and semi-formally registered SMEs could be compiled from local trade-association membership rolls and municipal business-registration records, systematic random sampling was applied: firms were listed and every kth firm meeting the inclusion criteria (formally or semi-formally registered, operating for at least one year, and having between 5 and 99 employees, as is typical in the region for SMEs) was selected. For clusters and market segments where no such listing existed, mainly informally organized trading areas with high firm turnover, convenience sampling supplemented by a snowball referral technique was used instead, a pragmatic approach often employed in SME research in data-poor developing-country settings (Yesuf & Fields, 2025). This means the two techniques were applied to different, non-overlapping parts of the sampling frame rather than combined within the same stratum. The resulting sample is nevertheless not a true probability sample overall: the listed strata approximate random selection, while the unlisted strata are filled through convenience and snowball sampling and are likely to over-represent more visible, better networked, or more cooperative firms than less accessible or informally operating SMEs. Therefore, inferential statistics (regression coefficients, significance tests) should be understood as describing relationships within this achieved sample, not as formally generalizable population estimates. Treat the external validity of the results to the broader Freetown SME population and to SMEs in other parts of Sierra Leone with caution until replicated with a fully enumerated sampling frame.

This multi-layered approach balances statistical soundness with the practical challenges of studying informally structured SME populations, where business registries are often incomplete or outdated. As mentioned above, this mapping step reduced, but did not eliminate, sampling bias toward more visible or accessible firms, consistent with mapping in other African SME and financial-inclusion surveys. To maintain the target sample size without altering the stratification structure, firms that were inactive, seasonal-only, or refused to provide financial decision-making information were not included, and replacement firms with the same stratum characteristics were selected when an intended respondent declined to participate.

The sample size was calculated using the general rule of at least 10-15 observations per estimated parameter for multiple regression analysis with an interaction term, resulting in a

minimum of 250-300 usable responses. We collected and used 250 valid, fully completed responses as the analytic sample. This sample size is comparable to similar studies on AI adoption in financial and organizational settings, which have used samples ranging from 250 to 300 respondents to assess AI adoption and its organizational impacts (Gandrita et al., 2026; Rawat et al., 2025).

To accommodate differences in respondent literacy and language preference, primary data were gathered using structured, face-to-face and, if needed, telephone-administered surveys, with research assistants trained and bilingual in English and Krio. Face-to-face administration was prioritized because connectivity and digital-access constraints among Freetown SMEs make it difficult to rely solely on online survey administration (Rawat et al., 2025). Informed consent was obtained from each respondent before data collection. Participation was voluntary, anonymous, and without any financial incentive, except a token of appreciation where customary in the local context.

Instruments

A structured, closed-ended questionnaire adapted from validated scales in the literature and modified for the Freetown SME context was used to collect data. The instrument consists of four parts: (i) firm and respondent demographic and background characteristics; (ii) AI adoption; (iii) digital capability; and (iv) financial decision-making quality. All substantive items are rated on a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree), as is common in the literature on AI adoption and digital capability (Adiguzel et al., 2024; Kubiczek et al., 2025).

AI adoption is measured as a multi-item scale that reflects the degree of use of AI-enabled financial tools such as automated bookkeeping, algorithmic forecasting, AI-assisted credit or risk assessment, and AI-based customer or supplier analytics, based on constructs of AI adoption in previous studies (Rahman, 2025; Yesuf & Fields, 2025). Digital capability is defined as a multi-item scale that measures data infrastructure capability, staff digital competence, and the firm's processes for incorporating digital or AI-generated outputs into decision-making, based on digital- and analytics-capability constructs previously used in organizational capability studies (Adiguzel et al., 2024; Franco et al., 2024; Ristyawan et al., 2026).

The quality of financial decision-making is measured using a multi-item scale reflecting the timeliness, evidence-based nature, consistency, and responsiveness of the firm's financial decision-making process, adapted from decision-quality constructs in previous studies on accounting and financial-reporting decision-making (Al-Hattami, 2026; Artene et al., 2024). The literature on SMEs reveals that firm size (number of employees), firm age, and sector are known correlates of technology adoption and financial decision practices (M. Yadav et al., 2025); the firm-level background section of the instrument therefore captured these characteristics descriptively, although they were not carried forward as measured control variables in the regression models. The instrument was pre-tested with 30 SME respondents outside the main sample to check item clarity and obtain preliminary reliability data before administration; items were then modified based on pilot feedback and expert review by two academics with relevant subject-matter expertise. The items were back-translated and contextually adapted to ensure relevance and comprehensibility for Freetown SME owner-managers, many of whom use AI-enabled functionality embedded in mobile money and point-of-sale applications, but not dedicated enterprise AI systems (Lukash et al., 2025; Lakshmi et al., 2026).

Content validity was established through the expert review and pilot testing described above. To confirm the appropriateness of the items for the constructs, exploratory factor analysis (principal axis factoring with varimax rotation) was used to confirm the items' factor loadings, and the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (threshold > 0.70) and Bartlett's test of sphericity ($p < .05$) were used to confirm the suitability of the data for factor analysis. Internal consistency reliability of the multi-item scales was measured using Cronbach's alpha, interpreted as acceptable if the value is 0.70 or higher (Adiguzel et al., 2024; Ristyawan et al., 2026).

Data Analysis

Quantitative data were analyzed using SPSS (Statistical Package for the Social Sciences), in line with the study's positivist, hypothesis-testing approach. The analysis is carried out in four steps. First, data screening and cleaning are performed, including checks for missing data, outliers, and normality (using skewness, kurtosis, and Kolmogorov–Smirnov/ Shapiro–Wilk tests), and common method bias diagnostics (Harman's single-factor test) are conducted because all constructs are measured by a single self-report instrument. Second, descriptive statistics (mean, standard deviation, frequencies) are calculated to describe the sample and study variables. Third, reliability

and construct validity are assessed via Cronbach's alpha, composite reliability, and exploratory/confirmatory factor analysis, and bivariate relationships among constructs are examined using Pearson correlation analysis. Fourth, and most centrally, the study's hypotheses are tested through the use of hierarchical moderated multiple regression analysis.

Hierarchical moderated multiple regression is identified as the most theoretically and statistically appropriate test for this study because the central research question of this study is not only the direct effect of AI adoption and digital capability on the quality of financial decision-making (H1 and H2) but also whether digital capability conditions the relationship between AI adoption and financial decision-making quality (H3). This selection follows previous research that examines organizational culture and readiness as a boundary condition on the technology-adoption–outcome relationship, rather than assuming that the effects of technology adoption are uniform across firms (Chaudhuri et al., 2024).

The analysis is done in two steps in SPSS. The mean-centered main-effect predictors (AI adoption and digital capability) are entered in Step 1 to test H1 and H2 (whether each predictor explains variance in FDMQ independently and significantly). To avoid multicollinearity, the interaction term (AI adoption × digital capability) is calculated from the mean-centered predictors and entered in Step 2 to test H3. In moderated regression, predictor variables are usually mean-centered before computing the interaction term, which reduces unnecessary multicollinearity between the main-effect and interaction terms and allows the interaction coefficient to be interpreted with confidence. Firm-level control variables (firm size, firm age, sector, ownership type, managerial education, and years of operation) were not entered into these models because, although they are shown as contextual factors in the conceptual model (Figure 1) and captured descriptively in the demographic section of the instrument, they were not retained as separate measured items suitable for regression control in the final instrument used for hypothesis testing. This is not a design choice but an acknowledged limitation of the present analysis, discussed further, together with its implications for estimation bias.

Moderation is supported when the interaction term is statistically significant ($p < .05$) and when the change in R^2 (ΔR^2) between Step 1 and Step 2 is significant, suggesting that the interaction term accounts for more variance in FDMQ than the main effects alone. Simple slopes analysis explores the form of the moderation (at one standard deviation below and above the mean of digital capability) and determines whether the relationship between AI adoption and FDMQ is stronger for SMEs with higher digital capability, as predicted. Standard regression diagnostics are examined first, including the Variance Inflation Factor (VIF, < 10) and tolerance statistics to check for problematic multicollinearity, the Durbin–Watson statistic to check independence of residuals, and residual scatterplots to check for homoscedasticity and linearity, as recommended for moderated regression in management and financial-decision research (Al-Hattami, 2026; Wang et al., 2026).

This choice of test is preferred over structural equation modeling (SEM/PLS-SEM), which is commonly used in similar studies on the adoption of AI (Gandrita et al., 2026), as the model in this study is relatively simple (three main latent constructs and one interaction term) and does not require the simultaneous estimation of multiple structural paths or higher-order constructs. SPSS hierarchical moderated regression analysis is clear, broadly interpretable, and sufficiently powered for the sample sizes expected in this study, and it aligns with the positivist, variable-based research design used throughout the study.

Ethical Considerations

The study adhered to standard ethical research principles, including informed consent, voluntary participation, anonymity and confidentiality of respondent data, and the right to withdraw at any stage without penalty. Before data collection, verbal and written informed consent to participate was obtained directly from each respondent (the owner-manager, or finance officer where designated), and separate authorization to approach staff and access firm-level information was obtained from the business owner or senior manager where the respondent was not the owner. All collected data were anonymized at the point of entry, securely stored on password-protected devices, and used solely for this research.

This firm-level consent process, however, is not equivalent to independent ethical review, and formal clearance from an institutional research ethics committee was not obtained for the data-collection protocol used in this study. This is acknowledged as a limitation: future data collection involving Freetown SME owner-managers should be reviewed and approved in advance by the institutional research ethics committee of the authors'

affiliated university (or another appropriately constituted ethics board), with the resulting approval reference reported in the manuscript, in order to meet the independent ethical-oversight standard expected of survey research involving human participants.

■ RESULT AND DISCUSSION

Data Screening and Preliminary Diagnostics

The number of usable responses received was 250, which is in line with the sampling target. No data were missing for any of the eighteen substantive items, and no univariate outliers fell outside the plausible range of 1–5. The skewness and kurtosis statistics for the three composite variables were within the conventional ±1 range (AI adoption: skewness = 0.03, kurtosis = −0.56; financial decision-making quality: skewness = 0.06, kurtosis = −0.42; digital capability: skewness = −0.01, kurtosis = −0.03), suggesting that there was no serious departure from normality. The Shapiro–Wilk test showed a marginal departure from normality for AI adoption (W = .987, p = .024) and financial decision-making quality (W = .989, p = .046), but not for digital capability (W = .992, p = .205); with the sample size (N = 250) and near zero skewness/kurtosis values, these marginal results are consistent with the known sensitivity of the test to minor deviations in larger samples, and ordinary least squares regression was judged appropriate to proceed. To evaluate common method bias, all eighteen items were entered into a single-factor test with Harman's single-factor test, where the first factor accounted for 34.3% of the total variance, which is below the 50% threshold generally used to identify a dominant method factor. Although this result is encouraging, it is not conclusive, as Harman's test is a relatively weak diagnostic tool that may fail to detect common method variance even when it is present. All three constructs were measured via self-report from a single informant per firm; this evidence alone cannot rule out common method bias. The three-factor structure found in the exploratory factor analysis is another indirect source of reassurance, as items loaded cleanly onto their intended constructs and no evidence of a dominant general factor emerged.

Reliability and Validity

Internal consistency reliability was assessed using Cronbach's alpha for the three multi-item scales. All three scales exceeded the conventional 0.70 threshold: AI adoption (six items) had α = .852, financial decision-making quality (six items) had α = .910, and digital capability (six items) had α = .868 (Table 1). The values obtained show good internal consistency across all constructs, which is comparable with the reliability values reported in similar studies on AI adoption and digital capability (Adiguzel et al., 2024; Ristyawan et al., 2026).

The Kaiser–Meyer–Olkin (KMO) measure yielded an overall value of .914, well above the recommended .70, and Bartlett's test of sphericity was significant ($\chi^2 = 2247.20$, $p < .001$), indicating that the correlation matrix was adequate for factor analysis. Exploratory factor analysis (principal axis factoring) was performed on all eighteen items, with three factors extracted that aligned with the hypothesized constructs of AI adoption, financial decision-making quality, and digital capability, together accounting for 62.8% of total variance (Factor 1: 23.2%; Factor 2: 20.4%; Factor 3: 19.1%). Because the composite scores of the three constructs are appreciably correlated (r = .572 between AI adoption and FDMQ; Table 2), an orthogonal (Varimax) rotation would misrepresent the underlying factor structure. The EFA was therefore re-estimated using an oblique Promax rotation (κ = 4), which allows the factors to correlate. As presented in Appendix A (Table A1), the Promax pattern matrix confirms the same simple structure as the original solution: all items loaded significantly (>.60) on their intended construct, no cross-loading exceeded .40, and the resulting factor correlation matrix shows a moderate-to-strong association between AI adoption and FDMQ (r = .652), a weak association between AI adoption and digital capability (r = -.052), and a weak-to-moderate association between FDMQ and digital capability (r = .288), confirming that an oblique rotation was the appropriate choice.

To test convergent and discriminant validity within a confirmatory framework, a three-factor confirmatory factor analysis (CFA) was subsequently estimated by maximum likelihood, with each item constrained to load on its hypothesized construct only and the three factors allowed to correlate. The measurement model showed an excellent fit to the data: $\chi^2(150) = 153.23$, $p = .412$, $\chi^2/df = 1.02$, CFI = .999, TLI = .998, RMSEA = .009 (90% CI essentially at zero), and SRMR = .042. Standardized loadings ranged from .635 to .826, all significant. Composite reliability (CR) and average variance extracted (AVE) are reported in Table 1. AVE for AI adoption is marginally below the conventional .50 threshold, which is a noted measurement limitation. Discriminant validity was assessed with the Fornell-Larcker criterion using the CFA inter-factor correlations (Fornell & Larcker, 1981): the square root of AVE for each

construct (.701, .793, and .724, respectively) exceeds its correlation with the other two constructs, supporting the empirical distinctiveness of the three constructs even under this stricter, disattenuated test.

Table 1. Reliability and discriminant validity of study constructs

Construct	Items	Cronbach's α	AVE	1. AIA	2. FDMQ	3. DC
1. AIA	6	α=.852 / CR=.852	.491	**.701**		
2. FDMQ	6	α=.910 / CR=.910	.628	.652	**.793**	
3. DC	6	α=.868 / CR=.869	.525	-.052	.288	**.724**

Source: Field Data, 2026
Note: α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted; diagonal values (italicized) are the square root of AVE. α, CR, AVE, and the correlations above are derived from the confirmatory factor analysis (CFA), not from the exploratory Varimax loadings in the original submission. AIA = AI Adoption; FDMQ = Financial Decision-Making Quality; DC = Digital Capability. Item-level Promax factor loadings underlying this table are reported in Appendix A (Table A1).

Descriptive Statistics and Correlation Analysis

Descriptive statistics and Pearson correlation coefficients for the three study variables (item-mean scores) are shown together in Table 2. The mean scores for the five-point scale were moderate for AI adoption (M = 3.28, SD = 0.64), digital capability (M = 3.25, SD = 0.65), and financial decision-making quality (M = 3.12, SD = 0.79). The values indicate that, on average, the Freetown SMEs in the sample have started to use AI tools and have a moderate level of digital competence, but are not yet making consistently high-quality financial decisions, reflecting a step-by-step adoption of AI tools rather than a full digital transformation as seen in previous studies on SMEs and AI (Kubiczek et al., 2025; Rahman, 2025).

Because the mean and standard deviation alone do not show the spread of individual responses, Figure 2 supplements Table 2 with the five-number summary (minimum, Q1, median, Q3, maximum) of each construct's item-mean scores, computed directly from the raw responses of all 250 SMEs. All three constructs show a broadly symmetric spread across roughly two-thirds of the five-point scale range, consistent with the near-zero skewness, with digital capability showing the narrowest interquartile spread and financial decision-making quality the widest, indicating relatively more disagreement among respondents about the quality of their firm's financial decision-making than about their level of digital capability.

Table 2. Descriptive statistics and correlations for study variables (N = 250)

Variable	M	SD	Min	Max	1	2	3
1. AIA	3.28	0.64	1.67	5.00	—		
2. FDMQ	3.12	0.79	1.17	5.00	.572	—	
3. DC	3.25	0.65	1.33	5.00	−.050	.256	—

Source: Field Data, 2026 Note. AIA = AI Adoption; FDMQ = Financial Decision-Making Quality; DC = Digital Capability. $p < .01$ (two-tailed).

The bivariate correlations in Table 2 indicate that financial decision-making quality was positively and significantly correlated with AI adoption ($r = .572$, $p < .001$), providing preliminary support for H1. Financial decision-making quality was also positively and significantly correlated with digital capability ($r = .256$, $p < .001$), providing preliminary support for H2. Interestingly, AI adoption and digital capability were not significantly correlated ($r = −.050$, $p = .434$), suggesting that, in this sample, AI tool use is not significantly related to digital capability. This near-zero correlation is analytically helpful: it helps minimize the risk of multicollinearity in the subsequent regression analysis and suggests that AI adoption and digital capability are conceptually and empirically different firm attributes, not two measures of the same construct as the RBV distinction between a technological resource and the organizational capability to use it would imply (Franco et al., 2024; Ristyawan et al., 2026).

Hierarchical Moderated Regression Analysis

H1, H2, and H3 were tested using hierarchical moderated multiple regression in SPSS. The interaction term (AI adoption ×

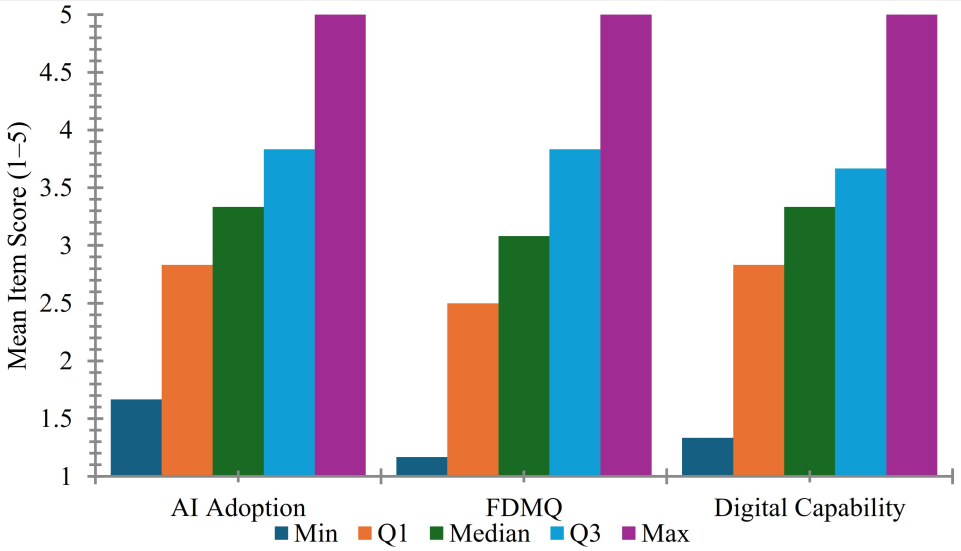


Figure 2. Five-Number summary (minimum, Q1, median, Q3, maximum) of the three study variables, computed directly from the raw item-mean scores of all 250 respondents. Note; Values are computed directly from the raw item-mean scores of all 250 respondents (Min, Q1, Median, Q3, and Max per construct), replacing the normal-theory approximation (mean ± 0.6745·SD) used in the original submission. A small number of respondents fall outside the Tukey 1.5×IQR fence on the Digital Capability variable; these are retained in the analysis and do not materially change the results

digital capability) was calculated from the centered variables, and AI adoption and digital capability were mean-centered before the analysis. The results for both regression steps are shown in Table 3.

Step 1 (Main effects): AI adoption and digital capability together accounted for about 41% of the variance in financial decision-making quality (R^2 = .409, adjusted R^2 = .404), $F(2, 247) = 85.36$, $p < .001$. The effect of AI adoption on financial decision-making quality was positive and significant (B = .721, SE = .060, β = .586, t = 11.97, $p < .001$), supporting H1. Digital capability was also a positive and significant predictor of financial decision-making quality (B = .345, SE = .059, β = .285, t = 5.82, $p < .001$), supporting H2.

Step 2 (Interaction effect): The AI adoption × digital capability interaction term was entered in the second step. Its addition significantly improved model fit, raising the explained variance to R^2 = .444, adjusted R^2 = .437, $F(3, 246) = 65.51$, $p < .001$. The change in R^2 from Step 1 to Step 2 was significant (ΔR^2 = .035, $\Delta F(1, 246) = 15.68$, $p < .001$), and the interaction term itself was a significant positive predictor of financial decision-making quality (B = .367, SE = .093, β = .195, t = 3.96, $p < .001$). This result supports H3: digital capability significantly and positively moderates the relationship between AI adoption and financial decision-making quality.

Regression diagnostics. Multicollinearity was not an issue: variance inflation factors

Table 3. Hierarchical moderated regression results (DV: financial decision-making quality)

Predictor	Step 1: B (SE)	β	Step 2: B (SE)	β
Constant	3.119 (.039)		3.127 (.038)	
AI Adoption (centered)	.721 (.060)	.586	.704 (.059)	.573
Digital Capability (centered)	.345 (.059)	.285	.343 (.058)	.283
AI Adoption × Digital Capability			.367 (.093)	.195
R^2	.409		.444	
Adjusted R^2	.404		.437	
ΔR^2			.035	
F	85.36		65.51	

Source: Field Data, 2026
Note. N = 250. Unstandardized coefficients (B) with standard errors in parentheses; β = standardized coefficient. $p < .001$.

(VIFs) for all predictors in the final model were close to 1.00 (AI adoption = 1.01, digital capability = 1.00, interaction term = 1.01), below the conventional threshold of 10. The Durbin–Watson statistic (2.13) fell within the acceptable range (1.5–2.5), suggesting no serious autocorrelation in the residuals. Residual plots verified that the relationships between the variables were approximately linear and that the error variance was homoscedastic, so the OLS regression model was appropriate for these data.

Simple Slopes Analysis

Simple slopes were estimated at three conditional levels of digital capability (one standard deviation below the mean (low DC), at the mean, and one standard deviation above the mean (high DC)) to probe the form of the significant interaction. The positive association between AI adoption and financial decision-making quality increased gradually as digital capability increased, as illustrated in Table 4 and Figure 3. At low digital capability, the simple slope of AI adoption on FDMQ was positive but relatively small (B = .465, p < .001). The slope at mean digital capability was .704 (p < .001), which is close to the Step 2 (not Step 1) coefficient for AI adoption reported in Table 3 (B = .704), because the simple-slope-at-the-mean is mathematically equivalent to the centered main-effect coefficient from the model that includes the interaction term. The slope was significantly steeper at high digital capability (B = .944, p < .001) than at low digital capability, where it was less than half the slope at high digital capability. This pattern suggests that the benefits of AI adoption are significantly higher for more digitally capable SMEs, supporting the hypothesized moderation and the RBV-informed proposition that AI is a resource whose value depends on complementary firm capability (Adiguzel et al., 2024; Wenting et al., 2026).

Table 4. Simple slopes of AI adoption on financial decision-making quality at conditional values of digital capability

Level of Digital Capability	Simple slope (B)	SE	t	p
Low (−1 SD)	.465	.082	5.67	< .001
Mean	.704	.059	11.97	< .001
High (+1 SD)	.944	.085	11.14	< .001

Taken together, the hierarchical regression results reported in Table 3 support all three hypotheses. H1 is supported: AI adoption has a positive and significant direct effect on FDMQ (β = .573, p < .001). H2 is supported: digital capability has a positive and significant direct effect on FDMQ (β = .283, p < .001). H3 is supported: digital capability positively moderates the AI adoption–FDMQ relationship (β = .195, ΔR^2 = .035, p < .001), such that the benefit of AI adoption for financial decision-making is substantially larger for SMEs with high digital capability than for those with low digital capability. No hypothesis was rejected in this sample.

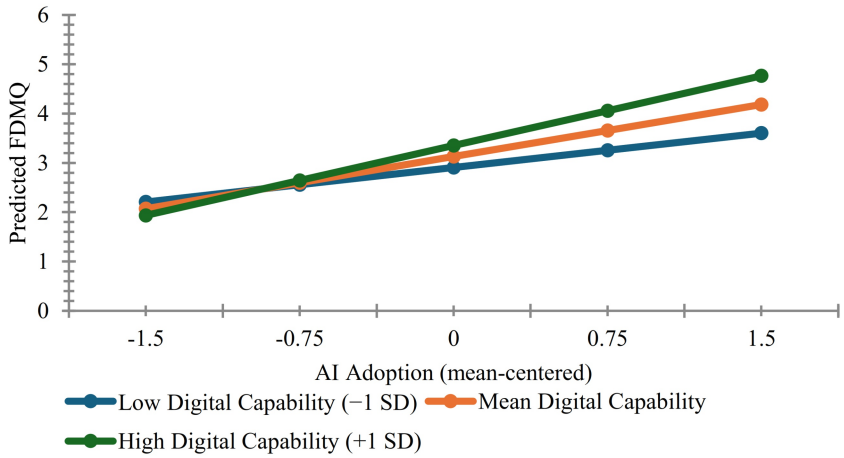


Figure 3. Moderating effect of digital capability on the AI adoption–financial decision-making quality relationship

Interpretation of Findings

The findings support the study's hypothesized model: AI adoption is positively related to the financial decision-making quality of SMEs in Freetown, Sierra Leone, and organizational digital capability significantly strengthens the relationship between the two variables. The design is cross-sectional, so these results are interpreted throughout as evidence of association and predictive relationship, not as causal effects of the underlying process; the regression "effects" are statistical effects in the estimated model, not causal effects of the underlying process. Three findings are of special interest.

The strong direct impact of AI adoption on the quality of financial decision-making (H1: β = .573–.586) validates the link established mainly in larger companies and more digitally advanced markets, in the low-resource West African SME setting. This impact is comparable to findings in accounting and audit contexts, where AI-driven digital innovation has been shown to enhance the timeliness, reliability, and traceability of financial information, thereby improving decision-making quality (Al-Hattami, 2026). It is also consistent with evidence that the integration of AI into financial reporting systems brings measurable benefits to the quality and defensibility of financial decisions (Artene et al., 2024), and with evidence from digital lending and credit-risk contexts, where algorithmic decision pipelines have been shown to reshape and, under suitable governance, enhance the quality and transparency of financial decisions (Abbas, 2025; Mohammad et al., 2026). This relationship is also observed in the SME sector in Freetown, where AI is more likely to be embedded in mobile money and point-of-sale systems than used as an enterprise system, suggesting that even limited, tool-level AI use can improve the evidence base and timeliness of SME financial decisions.

Second, the strong direct relationship between digital capability and financial decision-making quality (H2: β = .283–.285) beyond AI adoption further supports the RBV proposition that firm-specific capabilities are performance relevant in their own right, not just as a conduit for technology. This finding is consistent with the evidence that resource and capability configurations are complementary in influencing institutional performance in financial-sector organizations (Ristyawan et al., 2026) and with the evidence that big-data-analytics capability is a positive influence on innovation outcomes among technology firms, regardless of the specific technologies used (Adiguzel et al., 2024). It also aligns with research on digital transformation, which indicates that hybrid governance arrangements the organizational practices by which digital resources are governed play a key role in the process of realizing the operational value of digital resources (Franco et al., 2024). In practice, this means that even without targeted investments in AI, capacity-building programs focused on technology provision can benefit from a broader approach that includes staff digital skills, data management processes, and adaptive capacity.

Third, and most central to this study's contribution, the significant positive interaction between AI adoption and digital capability (H3: $\beta = .195$, $\Delta R^2 = .035$, $p < .001$) indicates that digital capability is not just an independent predictor of financial decision-making quality, but a true boundary condition on the value of AI adoption. This pattern is made concrete in the simple slope analysis: The relationship between AI adoption and FDMQ more than doubles (from B = .465 to B = .944) when digital capability moves from one standard deviation below to one standard deviation above the mean. Practically, this means two SMEs with the same level of AI tool adoption can see very different improvements in the quality of financial decision-making, depending on their digital capability. This finding supports the integrated TOE–RBV model developed: AI's technological potential is moderated by the firm's organizational capacity to absorb and act on its outputs, as per TOE's organizational-readiness logic (Chaudhuri et al., 2024; Kubiczek et al., 2025; Oyenubi & Oyeyipo, 2026); and, as per RBV's resource–capability distinction, AI is a technological resource whose value depends on the complementary, firm-specific capability needed to leverage it (Wenting et al., 2026). This is also in line with enterprise-level evidence that generative AI and related digital technologies are most valuable when integrated into a wider ecosystem of complementary digital assets and skills, not used as standalone tools (Kliestik et al., 2024), and with knowledge-model research that suggests the value of AI-enabled financial controls is contingent on human–technology interaction within the organization (Mofarreh et al., 2025).

The correlation between AI adoption and digital capability is near zero and not significant ($r = -.050$), which is itself a significant finding. It suggests that, in this sample, SMEs are not necessarily becoming more digitally capable as they use more AI tools; the two seem to be moving in different directions. This decoupling aligns with other

observations that AI adoption in SMEs is often incremental and tool-driven, and not necessarily integrated into a comprehensive digital-transformation strategy (Kubiczek et al., 2025; Rahman, 2025), reinforcing the practical need for the moderation finding: deliberate investments in digital capability are needed to ensure that increased AI adoption among Freetown SMEs will lead to proportionately improved financial decision-making.

Theoretical Implications

The results of this study have two main theoretical implications. First, they extend the TOE framework's organizational-readiness logic beyond the decision to adopt AI to the value SMEs gain from adoption, showing that the value of the adoption–outcome relationship is conditioned by organizational context (operationalized as digital capability). Second, the findings provide empirical evidence for the theoretical distinction between the two RBV constructs of AI adoption and digital capability, rather than reducing them to a single "digital maturity" construct, as their empirical independence in this sample ($r = -.050$) suggests. This resource–capability distinction, and its interaction effect on a firm-level performance-relevant outcome, replicates capability-contingent findings previously documented in banking, tourism, and technology-sector settings (Adiguzel et al., 2024; Ristyawan et al., 2026; Wenting et al., 2026).

Practical Implications

The results indicate that while AI can be a valuable tool for SME owner-managers in Freetown, it is not a standalone solution for enhancing financial decision-making. Companies should invest in AI-powered financial products and take proactive steps to enhance their employees' digital skills, improve data management practices, and increase their capacity to analyze and utilize AI-generated content to make informed decisions (firms with higher digital capability gain about twice the benefit in terms of decision quality for the same level of AI use). The results indicate that for financial technology providers and digital-service platforms targeting the SME market in Sierra Leone, adding AI-powered capabilities to a simple digital-literacy support or guided-use offering could meaningfully enhance the value of these tools for client companies, not just provide the tools themselves. The findings warn against digital-inclusion policies that focus on distributing AI or fintech tools without investing in SME digital skills development, and indicate that such investment is not a mere add-on to providing digital tools, but an important factor in the success of digital tools in improving financial decision-making.

Limitations

These findings are limited by several factors. The cross-sectional design does not allow for strong causal inferences. However, the hypothesized direction of the relationships is theoretically supported; reverse and/or reciprocal relationships (e.g., firms that invest more in AI tools subsequently investing more in financial decision-making processes) cannot be excluded. The strong regression and interaction effects should therefore be interpreted as associations rather than causalities. While the Harman single-factor test and the clean three-factor structure found in the exploratory factor analysis are encouraging, neither test can completely rule out the possibility of common method variance, and future studies could benefit from using multi-informant designs (e.g., owner-manager self-report combined with independently verified financial data) or from measuring predictors and outcomes at different times. The achieved sample used a mixed sampling approach of systematic random sampling and convenience and snowball sampling in strata that were not fully listed, which may over-represent more visible, accessible, and cooperative firms. The results should therefore be considered as relationships within the achieved sample, not as formally generalizable estimates for the overall Freetown SME population. The sample is also limited to Freetown, and although this offers depth in Sierra Leone's main commercial center, the results may not apply to SMEs in other Sierra Leonean districts where infrastructural and market conditions differ, or to SME populations in other developing-economy contexts.

A further limitation concerns the firm-level control variables shown in the conceptual model (Figure 1): firm size, firm age, sector, ownership type, managerial education, and years of operation. These were identified in the literature as theoretically relevant to FDMQ. However, they were not retained as measured items in the final instrument and were therefore not entered into the hierarchical regression models. Their absence means that the reported regression coefficients for AI adoption, digital capability, and their interaction may be subject to omitted-variable bias if any of these firm characteristics is correlated with both the predictors and FDMQ; the true magnitude and, in principle, the significance of the H1–H3 effects could change once these controls are included. Readers should therefore treat the

effect sizes reported here as unadjusted associations, and future replications of this model should measure these six characteristics directly and enter them as covariates.

Finally, the ethical clearance obtained for this study was limited to firm-level informed consent and did not include formal review and approval by an independent institutional research-ethics committee. This is a procedural limitation of the present study rather than a substantive threat to the findings themselves. However, it falls short of the independent ethical-oversight standard normally expected of survey research involving human participants, and it is reported here transparently so that readers can weigh the study's ethical safeguards accordingly.

Directions for Future Research

Future studies may be longitudinal to explore the co-evolution of AI adoption and digital capability over time, and how the moderation effect intensifies, diminishes, or remains consistent as SMEs progress in their digital journeys. These findings could be complemented by qualitative or mixed-method designs that shed light on the specific organizational mechanisms that enable digital capability to turn AI use into better decisions, such as staff training practices or data-governance routines. Comparative studies across several districts in Sierra Leone, or across West African SME populations more broadly, could determine the boundary conditions of these findings. The interaction effect size was found to be relatively large (ΔR^2 = .035) in this study, suggesting that future research could consider other or alternative moderators and mediators that could further explain the conditions under which AI adoption leads to improved financial decision-making among SMEs in resource-limited environments; behavioral factors such as owner-manager cognitive and emotional biases are one plausible candidate, given their demonstrated role in mediating SME financial performance elsewhere (Purwidianti et al., 2026). Future replications of this model should also measure the six firm-level control variables identified in Figure 1 (firm size, firm age, sector, ownership type, managerial education, and years of operation) directly, so that they can be entered as covariates in the regression model, and should be reviewed in advance by an independent institutional research-ethics committee, with the resulting approval reference reported in the manuscript, to address the two methodological limitations. Given that financial-decision quality is conceptually adjacent to financial literacy, future work could also draw on the growing financial-literacy literature (Idris et al., 2023) to examine whether owner-manager financial literacy is itself a further boundary condition on, or a substitute for, the digital-capability effect identified here.

■ CONCLUSION

This study set out to answer three research questions on AI adoption, digital capability, and the quality of financial decision-making (FDMQ) among SMEs in Freetown, Sierra Leone. In answer to RQ1, AI adoption was found to have a positive and significant effect on FDMQ (H1 supported), confirming that even the relatively basic, tool-embedded forms of AI use observed in this setting, such as AI-enabled features within mobile money and point-of-sale platforms, are associated with more timely, evidence-based financial decisions. In answer to RQ2, digital capability was also found to have an independent positive and significant effect on FDMQ (H2 supported), showing that a firm's digital infrastructure, staff skills, and data-management practices matter for decision quality in their own right, not merely as a channel for AI. In answer to RQ3, digital capability significantly and positively moderated the AI adoption–FDMQ relationship (H3 supported): the benefit of AI adoption for financial decision-making more than doubled as digital capability moved from one standard deviation below to one standard deviation above the sample mean. Taken together, these findings support the study's integrated TOE–RBV model and show that AI adoption is not, by itself, a sufficient condition for better SME financial decisions in a resource-constrained environment; its value is contingent on the complementary organizational capability to absorb and apply what it produces.

For SME owner-managers, the managerial implication is that spending on AI-enabled tools should be paired with, rather than substituted for, investment in staff digital skills, data-management routines, and IT support, since firms with low digital capability realize substantially less benefit from the same level of AI use. For policymakers, donor agencies, and fintech providers engaged in SME digitalization and financial-inclusion programs in Sierra Leone and comparable West African settings, the findings caution against distributing AI-enabled financial tools in isolation; program design should build in a digital-capability-building component, such as guided-use training, data-literacy support, or IT-support services, if AI-related investments are to translate into measurably better financial

decision-making. Policy and donor support aimed at SME competitiveness should therefore treat AI-tool provision and digital-capability development as complementary, jointly funded components of the same intervention rather than as separate or sequential program tracks.

These conclusions should be read in light of the study's cross-sectional, Freetown-specific design and its unmeasured firm-level control variables, and are offered as an evidence-based starting point for both practice and further research rather than as a generalizable causal claim.

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