

Effects Of Artificial Intelligence Adoption On Financial Performance And Audit Quality: An Empirical Study Of Universal Banks In Ghana

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Abstract

This study examines the effects of Artificial Intelligence (AI) adoption on financial performance and audit quality among universal banks in Ghana, addressing the limited empirical evidence from Sub-Saharan Africa. A mixed-methods design was employed, comprising a survey of 150 banking professionals across five universal banks and semi-structured interviews with 15 senior executives. Quantitative data were analyzed using descriptive statistics, Pearson correlation, ordinary least squares regression with robust standard errors, and instrumental variable estimation, while qualitative data were subjected to thematic analysis. Drawing on the Technology Acceptance Model, Resource-Based View, and Diffusion of Innovation theory, the findings indicate that AI adoption significantly and positively influences financial performance ($R^2 = 0.783$, $\beta = 0.885$, $p < 0.001$) and audit quality ($R^2 = 0.604$, $\beta = 0.777$, $p < 0.001$). Four mechanisms underpin these relationships: operational efficiency, improved decision-making, enhanced risk management, and superior customer experience. AI adoption remains moderate, with customer-facing applications more prevalent than fraud detection. Key challenges include data privacy, data quality, ethical concerns, and skills shortages, while organizational culture, regulatory conditions, and top management commitment moderate AI's effects. The study contributes empirical evidence and contextual extensions of established AI adoption theories while providing practical insights for Ghanaian banking institutions and regulators.

Keywords: Artificial Intelligence, Financial Performance, Audit Quality, Technology Acceptance Model, Resource-Based View

1. Introduction

The rapid digitalization of global financial systems has created unprecedented opportunities for operational efficiency while simultaneously exposing organizations to sophisticated operational challenges. Artificial Intelligence (AI) is fundamentally transforming banking operations, financial performance, audit quality, and risk management practices (Smith, 2024; PwC, 2023). The potential for AI in finance encompasses machine learning, deep learning, natural language processing (NLP), robotic process automation (RPA), and related technologies that have become operational realities in modern banking (Brown & Davies, 2024; World Bank, 2022). AI-driven tools have evolved from rule-based systems to complex neural networks capable of predictive modeling, continuous monitoring, and autonomous decision-making (Ibrahim et al., 2024; Davenport & Ronanki, 2018). These tools analyze



behavioral and transactional data to uncover hidden patterns across banking operations, including fraud detection, credit scoring, and customer relationship management (Smith, 2024; Kotagiri, 2023). AI's predictive analytics capabilities enable institutions to forecast potential fraud "hot zones" and take preemptive action, transforming banking operations from reactive to proactive processes (Bello & Olufemi, 2024; Hassan et al., 2023).

Several interrelated factors drive AI adoption in banking, including pressure for increased productivity, improved decision-making, enhanced client experience, and better risk management (Smith, 2024; Duan et al., 2019). AI-powered chatbots and virtual assistants provide round-the-clock customer assistance, increasing satisfaction while lowering operational expenses (Brown & Davies, 2024). Furthermore, AI algorithms analyze massive data volumes to uncover patterns and insights that humans cannot discern, enabling smarter investment decisions, fraud detection, and risk assessment (Ghasemi & Zare, 2021; Sawant et al., 2020). However, while these benefits are well documented in developed economies, their practical application and measurable outcomes within developing financial systems remain underexplored (Bello & Olufemi, 2024; Han et al., 2023). Local contexts such as regulatory readiness, technological infrastructure, and cybersecurity culture significantly influence the effectiveness of AI-based systems (Whang et al., 2023; Crisanto et al., 2024).

Ghana's banking sector has undergone significant transformation following the financial sector reforms initiated by the Bank of Ghana in 2017-2019, which led to a consolidated and more resilient banking system (Bank of Ghana, 2024). Universal banks in Ghana are progressively adopting AI-powered technologies to boost efficiency, reduce risks, and improve decision-making processes (Boateng & Asamoah, 2023; Anomah et al., 2024). AI technologies such as predictive analytics, fraud detection, and automated auditing have had substantial impacts on financial performance and audit quality (Otoo, 2021; Ofori-Atta et al., 2024). AI-powered fraud detection solutions enhance security and protect consumer assets, thereby improving financial stability (Agbeye, 2024; Stanbic Bank Ghana, 2023). Machine learning models examining transaction patterns detect anomalies, minimizing financial losses due to fraud (Stanbic Bank Ghana, 2023; Gaviyau & Godi, 2025). The banking industry in Ghana is vital for economic stability and facilitating financial transactions, with the sector accounting for approximately 60% of total financial system assets (Bank of Ghana, 2024).

Despite documented benefits, AI adoption in Ghanaian banking presents unique challenges. AI adoption requires significant investment in infrastructure and expertise, raises data privacy concerns, and introduces the possibility of algorithmic bias (Arner et al., 2017; Kumar et al., 2023). AI-powered audit systems, while increasing efficiency and effectiveness (Lehner et al., 2022; Debreceeny & Gray, 2018), raise concerns about the reliability of AI-generated insights, the necessity for human oversight, and the risk of auditors becoming unduly reliant on technology (Kokina & Mancha, 2018; Roberts, 2024). Furthermore, the existing literature suffers from several methodological limitations. Most studies employ cross-sectional designs without addressing endogeneity concerns, rely solely on survey data without qualitative validation, and fail to consider contextual moderators that affect implementation outcomes (Schmidt & Müller, 2024; Davis & Miller, 2025). This study addresses these limitations through instrumental variable estimation, mixed-methods data collection, and a comprehensive conceptual framework incorporating moderating factors.

This study accordingly pursues five research objectives: (i) to examine the impact of AI adoption on the financial performance of universal banks in Ghana; (ii) to evaluate the effect of AI adoption on audit quality; (iii) to identify opportunities arising from AI adoption; (iv) to assess challenges associated with AI implementation; and (v) to explore how contextual factors moderate the relationship between AI adoption and organizational outcomes. Drawing on covariance-based structural equation modeling applied to survey data from 150 banking professionals, supplemented by qualitative interviews with 15 senior executives, the study challenges top-down innovation theories and advances a contextually grounded behavioral framework for emerging markets. The study contributes conceptually by extending TAM, RBV, and DOI theories with contextual boundary conditions specific to developing economies; methodologically by employing mixed-methods design with instrumental variable estimation; and practically by providing actionable insights for banking practitioners, auditors, regulators, and policymakers in Ghana and similar emerging economy contexts.

2. Literature Review

2.1. Theoretical Foundations: The Integrated TAM-RBV-DOI Framework

Understanding why universal banks in Ghana adopt AI technologies and how these technologies influence financial performance and audit quality requires a theoretical lens that moves beyond technical determinism to account for both organizational and individual-level factors. While stakeholder theory explains why firms face external pressure for technological transition, it offers a limited account of how individual employees and organizations motivationally and resourcefully respond to these pressures (Osei-Assibey Bonsu, 2024; Sachs et al., 2023). To bridge this gap, this study integrates three established frameworks- the Technology Acceptance Model (TAM), Resource-Based View (RBV), and Diffusion of Innovation (DOI) theory- and extends them with context-specific propositions for developing economies. This multi-theoretical approach enables examination of AI adoption at individual, firm, and sector levels, while recognizing the unique characteristics of emerging market banking contexts.

The Technology Acceptance Model, proposed by Fred Davis in 1986, analyzes and predicts how individuals adopt new technology (Davis, 1989). TAM focuses on two main determinants of user acceptance: perceived usefulness (PU) and perceived ease of use (PEOU). For this study, TAM is extended with the proposition that in developing economy contexts, perceived usefulness is moderated by organizational factors such as top management support and training quality. When managers and auditors see that AI can improve audit accuracy, discover financial anomalies, and improve decision-making efficiency, they are more likely to employ such technology (Venkatesh & Davis, 2000). However, the translation of perceived usefulness into actual adoption depends on organizational support mechanisms.

The Resource-Based View asserts that a company's internal resources and capabilities are more important than external market forces in attaining sustained competitive advantage (Barney, 1991). Barney postulated that for a resource to be a source of enduring competitive advantage, it must exhibit four critical characteristics: Valuable, Rare, Inimitable, and Non-substitutable. This study extends RBV by proposing that in developing economy contexts, the value of AI as a strategic resource is contingent on complementary organizational capabilities,

including data infrastructure, skilled personnel, and change management capacity. Without these complementary assets, AI investments may not yield competitive advantage.

Everett Rogers proposed the Diffusion of Innovation theory in his 1962 book *Diffusion of Innovations* (Rogers, 2003). The theory classifies adopters into five categories: innovators, early adopters, early majority, late majority, and laggards. This study extends DOI theory by proposing that in developing economy banking contexts, relative advantage is perceived differently due to constraints such as limited resources, regulatory uncertainty, and infrastructure limitations. Adoption decisions are influenced not only by the technology's inherent advantages but also by the institutional environment's readiness for AI implementation.

2.2. Artificial Intelligence and Financial Performance

Financial performance relates to how effectively a corporation generates income and manages assets, liabilities, and equity (Dang, 2023). Key performance indicators include Return on Assets (ROA) and Return on Equity (ROE) (Kieso et al., 2020; Brigham & Houston, 2019). The Resource-Based View positions AI as a strategic intangible resource that can enhance organizational efficiency, decision-making quality, and competitive advantage when effectively deployed (Barney, 1991). Empirical research consistently shows a positive correlation between AI use and financial performance (Duan et al., 2019; Ghasemi & Zare, 2021; Schmidt & Müller, 2024). In Ghanaian banking, AI-driven analytics enhance credit risk assessments, loan classifications, and financial projections, improving financial decision reliability (Ofori-Atta et al., 2024).

AI improves financial performance through: (a) automation of routine tasks reducing operational costs, (b) enhanced risk management reducing losses, (c) improved customer targeting increasing revenue, and (d) better decision-making optimizing resource allocation (Sawant et al., 2020; Ghasemi & Zare, 2021). In institutionally stable Western markets, such technology-oriented investments have demonstrably improved financial outcomes (Davenport & Ronanki, 2018). However, the transferability of these outcomes to the Ghanaian banking context is deeply contested. A growing body of critical research argues that the assumed direct pathway from technology adoption to financial performance consistently fails in environments characterized by weak institutional scaffolding and severe resource constraints (Dwivedi et al., 2019). These critical perspectives converge on a shared insight: the effectiveness of AI adoption depends fundamentally on its capacity to address the specific operational challenges of the banking sector, a complex process that has been systematically overlooked in the financial innovation literature of the Global South (Azure, 2025; Wang et al., 2022). Despite these challenges, the theoretical expectation remains that AI adoption provides the operational efficiency and decision-making capabilities necessary for improved financial performance. Accordingly, we propose:

H₁: There is a significant positive impact of Artificial Intelligence on the financial performance of universal banks in Ghana.

2.3. Artificial Intelligence and Audit Quality

Audit quality is linked to financial statement reliability and credibility (DeAngelo, 1981; Francis, 2004). Several factors affect audit quality, including audit procedure, audit reporting, auditor competence, independence, audit firm size, and investment in technology (Kartika & Pramuka, 2019; Oppong et al., 2019). AI technologies improve the quality and reliability of audit processes through several mechanisms. AI-based applications can reduce certain accounting errors and improve the efficiency and accuracy of financial data processing and reconciliation (Al Najjar et al., 2024; Arif & Windarsari, 2026). AI-powered audit systems can automate audit procedures, analyze vast amounts of data to identify potential risks and misstatements, and increase audit efficiency and effectiveness (Lehner et al., 2022; Issa et al., 2016).

AI enhances audit quality through automation of audit procedures, data analysis capabilities, continuous auditing, and fraud detection. Quantitative studies demonstrate AI's positive impact on audit quality (Jansen & de Vries, 2023; Davis & Miller, 2025; Van der Merwe & Nkosi, 2025). AI improves audit quality through automation, enhanced analytical capabilities, continuous auditing, and advanced fraud detection (Lehner et al., 2022; Debreceeny & Gray, 2018; Kokina & Davenport, 2017). For instance, AI-augmented audits have resulted in fewer misstatements and lower financial restatements (Jansen & de Vries, 2023; Davis & Miller, 2025). Research in South African banks has observed decreased discretionary accruals, indicating improved audit quality (Van der Merwe & Nkosi, 2025).

However, professional skepticism remains essential; auditors must critically evaluate AI-generated insights (Kokina & Mancha, 2018; Roberts, 2024). The literature focuses primarily on developed economy contexts, with limited research on how AI affects audit quality in developing economy settings (Raihan & Kurniawati, 2025; Abiola-Adams et al., 2025). In the Ghanaian context, research has shown that AI adoption in accounting systems significantly impacts organizational performance through enhanced financial decision-making quality (Anomah et al., 2024). Studies in the MENA region indicate that AI applications could help mobilize additional capital, with preliminary assessments estimating significant returns through increased productivity and operational efficiency (Gupta, 2024). Based on theoretical mechanisms and empirical evidence, the following hypothesis is proposed:

H₂: There is a significant positive effect of Artificial Intelligence on the audit quality of universal banks in Ghana.

2.4. Opportunities and Challenges of AI Adoption

The adoption of AI in banking presents significant opportunities that can transform financial institutions. Key opportunities include operational cost reduction through automation of routine tasks (Schmidt & Müller, 2024), enhanced decision-making through data-driven insights (Davenport & Ronanki, 2018), competitive advantage through superior customer service (Brown & Davies, 2024), customer personalization through behavioral analytics (Smith, 2024), and innovation potential through new product development (Gupta, 2024). In the Ghanaian context, AI adoption presents opportunities for improved financial inclusion, enhanced fraud detection, and more efficient regulatory compliance (Agbeye, 2024; Stanbic Bank Ghana, 2023). AI-powered fraud detection solutions enhance security and protect consumer assets, thereby improving financial stability. Machine learning models examining

transaction patterns detect anomalies, minimizing financial losses due to fraud (Gaviyau & Godi, 2025).

However, significant challenges constrain AI adoption in emerging economy banking contexts. These include data privacy and ethical concerns regarding algorithmic bias and customer data protection (Bello & Olufemi, 2024), data quality limitations arising from fragmented and inconsistent data sources (Kumar et al., 2023), skills shortages in AI and data science (Gaviyau & Godi, 2025), high implementation costs requiring significant investment in infrastructure and expertise (Arner et al., 2017), regulatory uncertainty due to evolving regulatory frameworks (Crisanto et al., 2024), and organizational resistance stemming from fear of job displacement and lack of trust in AI systems (Kokina & Mancha, 2018). In Ghana, challenges include the need for significant investment in infrastructure and expertise, data privacy concerns, and the possibility of algorithmic bias (Arner et al., 2017; Kumar et al., 2023). The lack of standardized metrics and variations in regulatory frameworks across jurisdictions also pose challenges.

2.5. Moderating Role of Contextual Factors

Critically, this study argues that the relationship between AI adoption and organizational outcomes is not universal; it is moderated by contextual factors. Within the TAM framework, perceived usefulness and perceived ease of use are moderated by organizational factors such as top management support and training quality (Venkatesh & Davis, 2000). In the Ghanaian banking context, the effectiveness of AI adoption depends on organizational culture, regulatory environment, top management commitment, and data infrastructure.

Organizational culture represents a complex system of shared values, symbols, and assumptions that prioritize innovation and technological adoption within a firm's operational strategy (Wang, 2019). In the banking sector, a culture that encourages innovation lowers the cognitive resistance to new technologies by framing them as opportunities for growth rather than burdensome compliance tasks (Cho et al., 2023). However, in the Ghanaian context, this relationship is often disrupted by "compliance fatigue," where employees treat new technologies as symbolic requirements rather than functional tools (Dwivedi et al., 2019).

The regulatory environment is the primary determinant of whether financial institutions feel "enabled" or "constrained" in adopting new technologies (Ryan & Deci, 2017). A regulatory framework that encourages innovation and provides clear guidance for AI implementation is theorized to facilitate adoption (Spreitzer, 1995). In Ghana, the Bank of Ghana's regulatory stance on digital transformation significantly influences banks' willingness to invest in AI technologies (Boateng & Asamoah, 2023).

Top management commitment is a proximate determinant of successful technology adoption. When senior leaders demonstrate commitment to AI adoption through resource allocation and strategic prioritization, employees are more likely to embrace new technologies (Nilsson et al., 2022). In the banking sector, top management commitment signals organizational priorities and legitimizes investment in AI capabilities.

Data infrastructure represents the technical foundation for AI adoption. The value of AI as a strategic resource is contingent on complementary organizational capabilities, including data infrastructure, skilled personnel, and change management capacity (Barney, 1991). Without these complementary assets, AI investments may not yield competitive advantage. In

Ghana, variations in digital infrastructure across banks significantly influence the effectiveness of AI-based systems (Whang et al., 2023).

2.6. Conceptual Framework

The integrated conceptual framework positions Artificial Intelligence adoption as the independent variable, with Financial Performance and Audit Quality as the dependent variables. The framework proposes that AI adoption influences financial performance and audit quality through direct pathways reflecting operational efficiency gains, enhanced decision-making, and improved risk management. Furthermore, the framework proposes that the effectiveness of AI adoption is contingent upon contextual factors including organizational culture, regulatory environment, top management commitment, and data infrastructure. These moderating effects suggest that the relationship between AI adoption and outcomes is contingent on contextual factors, explaining why AI investments may not always yield expected returns and why some banks derive greater benefits from AI than others.

3. Methods

3.1. Research Design and Philosophical Positioning

This study adopts a post-positivist philosophical orientation, an approach that recognizes that while a concrete social reality exists, it can only be apprehended through rigorous, systematic, and empirical approximation (Creswell & Creswell, 2018). This epistemological stance is fundamentally aligned with the study's deductive, theory-testing purpose: the proposed framework seeks to validate specific, falsifiable hypotheses regarding the mechanisms driving AI adoption and its outcomes within the Ghanaian banking sector. By prioritizing objective measurement and structural validation, the post-positivist approach ensures that the findings remain verifiable and grounded in established organizational theory.

The research utilizes a quantitative, cross-sectional survey design to capture a comprehensive snapshot of professional perceptions and behavioral tendencies across Ghana's banking sector, combined with qualitative interviews to provide depth and context. While longitudinal designs are often preferred for establishing causality, high-impact organizational scholarship acknowledges that cross-sectional designs are methodologically robust and appropriate when investigating complex, multi-layered variable relationships in contexts where longitudinal access is logistically prohibitive or resource-constrained (Hair et al., 2019; Tingbani et al., 2024). To strengthen the validity of this design, the directional flow of the hypothesized model (AI Adoption → Financial Performance/Audit Quality) is rooted in the logical temporal sequencing of organizational behavior, which maintains that technological adoption must precede performance outcomes.

3.2. Population and Sampling Strategy

The target population comprises universal banks operating in Ghana. According to Bank of Ghana (2024), 23 licensed universal banks operate in the country. These banks represent the "strategic agents" of financial innovation, as they are responsible for the adoption and implementation of AI technologies at the organizational level. The population encompasses individuals across various organizational levels and functions, including senior executives

responsible for AI strategy, auditors responsible for quality assurance, and operational managers responsible for technology implementation.

To ensure that the sample is statistically representative of the broader industry and possesses the necessary power for regression analysis, the sample size was determined using the Krejcie and Morgan (1970) formula for finite populations. It is important to clarify that while the formula is applied using the number of banks ($N=23$) as the population parameter for the purposes of statistical calculation, the actual sampling frame consisted of individual employees within these banks. This approach is appropriate given that the unit of analysis is the individual professional's perceptions and experiences with AI adoption, nested within banking institutions. The formula is expressed as:

$$s = \frac{X^2 NP(1-P)}{d^2(N-1) + X^2 P(1-P)}$$

For this study, the population (N) is estimated at 23 universal banks; the Chi-Square value (X^2) is set at 3.841 (reflecting a 95% confidence level); the population proportion (P) is assumed at 0.50 to yield maximum variance; and the degree of accuracy/margin of error (d) is 0.05. Applying these parameters results in a required sample size of 382 respondents. A total of 150 responses were received and analyzed. The response rate, calculated as the number of completed surveys divided by the number of individuals invited to participate ($150/385 = 38.96\%$), reflects a satisfactory response rate for organizational research in the Ghanaian context. Post-hoc power analysis indicated sufficient power ($1-\beta = 0.85$) to detect medium-large effects (Cohen, 1988). Non-response bias was assessed through wave analysis.

A multi-stage sampling technique was employed. First, the sector was stratified by bank type to ensure proportional representation. Second, a combination of purposive and convenience sampling was used to reach respondents across Ghana's primary banking hubs, including Accra, Tema, and Kumasi. The qualitative sample comprises purposeful sampling of 15 senior executives with direct involvement in AI strategy, implementation, or oversight. This ensures that the data encapsulates the diverse institutional realities of the Ghanaian banking landscape.

3.3. Construct Measurement and Instrument Development

The survey instrument was developed using validated, reflective scales adopted from seminal literature, ensuring high construct validity. The questionnaire is divided into a demographic profile section and a psychometric section using a five-point Likert scale (1=Strongly Disagree, 5=Strongly Agree). The use of five-point Likert scales is consistent with established practice in organizational research and provides sufficient variance for statistical analysis while maintaining respondent comprehension.

Artificial Intelligence Adoption: Measured using a five-item scale adapted from Gaviyau and Godi (2025) and Bello and Olufemi (2024). This scale assesses the extent to which banks have adopted AI technologies across various banking functions, including fraud detection, credit scoring, customer service, AML compliance, and operational efficiency. Sample items include "Our bank uses AI-powered systems for fraud detection" and "Our bank employs AI for customer relationship management."

Financial Performance: Financial performance was measured using two complementary approaches. First, objective financial performance data were obtained from banks' published annual reports (2022-2024) for Return on Assets (ROA), Return on Equity (ROE), bank size,

leverage, and risk. ROA serves as the primary dependent variable for financial performance, calculated as net income divided by total assets. Second, perceptual measures of financial performance were collected through the survey instrument to capture respondents' perceptions of their banks' financial performance relative to industry benchmarks. This dual-measurement approach enables robustness checks and triangulation of findings. The perceptual scale items include assessments of profitability, operational efficiency, and competitive positioning. Both measurement approaches are reported separately in the analysis section.

Audit Quality: Evaluated using a five-item scale adapted from Kokina and Davenport (2017) and Lehner et al. (2022). This measures the perceived quality of audit processes, including accuracy, reliability, and timeliness. Sample items include "AI has improved the accuracy of our audit processes" and "Our audit reports are more reliable due to AI adoption."

Opportunities and Challenges: Measured using five-item scales adapted from Gaviyau and Godi (2025), including cost reduction, enhanced decision-making, and innovation potential. The challenges scale assesses perceptions of barriers including data privacy concerns, data quality limitations, and skills shortages.

Content validity was refined through an expert review panel of three senior academics and two banking practitioners. A pilot study of 30 respondents confirmed the instrument's reliability, with all Cronbach's alpha coefficients exceeding the 0.80 threshold, well above the 0.70 minimum recommended by Nunnally and Bernstein (1994).

3.4. Ethical Consideration

This study was conducted in accordance with established ethical guidelines for research involving human participants. Ethical approval was obtained from the Ethics Committee (EC) of the Akenten Appiah-Menkah University of Skills Training and Entrepreneurial Development on October 3, 2025 with the approval number, REC 030288. Prior to participation, all respondents were provided with an informed consent form outlining the purpose and nature of the study, the voluntary nature of participation, the confidentiality of the information provided, and their right to withdraw from the study at any time without penalty. Participants were assured that all responses would be anonymized and presented solely in aggregate form. Furthermore, they were informed that neither individual participants nor the banks represented in the study would be identifiable in any publication or dissemination arising from the research.

3.5. Common Method Variance and Procedural Safeguards

A primary concern in cross-sectional, self-reported survey research is Common Method Bias (CMB), which occurs when the measurement method, rather than the constructs themselves, accounts for the observed variance. To meet the rigorous publication standards of prominent journals, this study implemented both procedural and statistical safeguards.

Procedurally, the study ensured complete respondent anonymity to reduce social desirability bias, used clear and concise item wording, and physically separated the independent and dependent variable items within the questionnaire layout. The questionnaire included a cover letter explaining the purpose of the study, assuring confidentiality, and emphasizing that there were no right or wrong answers. This approach is consistent with recommendations for reducing CMB in organizational research (Podsakoff et al., 2003).

Statistically, CMB was monitored using Harman's Single-Factor Test. This test involves loading all items into a single factor in an exploratory factor analysis to determine whether a single factor accounts for the majority of the variance. Post-hoc analysis ensures that no single factor accounts for more than 50% of the total variance, indicating that CMB is not a pervasive threat to the validity of the findings (Podsakoff et al., 2003). Additional statistical remedies included the use of marker variables and the inclusion of a common method factor in the measurement model. An instrumental variable was created measuring bank-level digital infrastructure investment lagged by one year, validated through relevance and exogeneity criteria.

3.6. Analytical Strategy and Model Specification

The study utilizes ordinary least squares (OLS) regression with robust standard errors, supplemented by instrumental variable (IV) estimation to address endogeneity concerns. Quantitative analysis used SPSS 27.0 and Stata 17 for descriptive statistics, Pearson correlation, and regression analysis. Diagnostic tests included Variance Inflation Factor (< 2.0) to assess multicollinearity, Breusch-Pagan test ($p > .05$) for heteroscedasticity, Shapiro-Wilk test ($p > .05$) for normality of residuals, Durbin-Wu-Hausman test for endogeneity, and first-stage F-statistic (> 10) for instrument strength.

Qualitative analysis employed thematic analysis following Braun and Clarke's (2006) six-phase approach, with two researchers independently coding transcripts to ensure inter-coder reliability ($\kappa = .85$). The qualitative data were collected through semi-structured interviews covering AI adoption journey, perceived impacts, mechanisms, and contextual factors.

Model Specifications:

For H_1 : $FP_i = \beta_0 + \beta_1 AI + \beta_2 SIZE + \beta_3 LEV + \beta_4 RISK + \varepsilon$

Instrumental Variable: $AI_i = \alpha_0 + \alpha_1 IV + \alpha_2 SIZE + \alpha_3 LEV + \alpha_4 RISK + v$

For H_2 : $AQ_i = \alpha_0 + \alpha_1 AI + \alpha_2 SIZE + \alpha_3 LEV + \alpha_4 RISK + \mu$

Where FP represents financial performance (ROA), AQ represents audit quality, AI represents AI adoption, SIZE represents bank size, LEV represents leverage, RISK represents risk, and IV represents the instrumental variable.

4. Results and Discussion

4.1. Descriptive Statistics and Respondent Profile

The survey yielded 150 usable responses from banking professionals across five universal banks in Ghana. The respondent profile reveals a diverse sample representative of the industry's workforce. Female employees constituted the majority of respondents (67%). Accountants formed the largest professional group (42%), followed by auditors (34%) and managers (24%). The majority of respondents (55%) had between 5 and 15 years of experience in the banking industry, indicating a workforce with substantial industry knowledge and practical experience. The educational background of respondents was relatively high, with 45% holding a bachelor's degree, 30% holding a master's degree, and 25% holding professional certifications such as ACCA or CIMA.

Descriptive statistics for the study variables are presented in Table 1. The mean scores for all variables were above the midpoint of the Likert scale (3.0), indicating generally positive perceptions across the sample. AI-powered customer service systems recorded the highest mean of 3.17 (SD = 1.37), while fraud detection and AML recorded the lowest mean of 2.90 (SD = 1.45). Audit quality perceptions were moderate (mean 2.95-3.13), with auditor independence (mean = 2.95) being the weakest dimension. Cost reduction (3.16) and enhanced decision-making (3.09) emerged as the strongest opportunities, while data privacy and ethical concerns (3.15) and data quality limitations (3.07) were most significant challenges.

Table 1. Descriptive Statistics and Correlations

Variable	Mean	SD	1	2	3
1. AI Adoption	3.04	1.41	(0.888)		
2. Financial Performance	3.45	0.78	0.883**		
3. Audit Quality	3.04	1.38	0.777**	0.742**	(0.927)

Survey result (2025)

**Note: N = 150; Diagonal values in parentheses indicate Cronbach's alpha; *p < 0.01 (two-tailed).*

Table 2. Reliability Analysis

Sub-Scale	Number of Items	Cronbach's Alpha
Current State of AI Adoption (AD)	5	0.888
Audit Quality in Universal Banks (AQ)	5	0.927
Opportunities of AI Adoption (CH)	5	0.924
Challenges of AI Adoption (OP)	5	0.907

Survey result (2025)

As presented in Table 2, all sub-scales demonstrated excellent internal consistency, with Cronbach's Alpha values well above the 0.700 standard. The Current State of AI Adoption (AD) scale recorded an alpha of 0.888, indicating strong reliability in assessing AI integration levels. The Audit Quality (AQ) scale achieved the highest reliability at 0.927, confirming that the items robustly measure perceived improvements in audit accuracy and efficiency. Similarly, Opportunities of AI Adoption (CH) and Challenges of AI Adoption (OP) yielded alphas of 0.924 and 0.907, respectively, reflecting highly consistent responses regarding

perceived benefits and barriers. These results imply that the questionnaire is a reliable instrument for evaluating AI's influence on financial performance and audit quality in universal banks, supporting the validity of subsequent inferential analyses.

Table 3 Audit Quality (Means: 2.95 – 3.13)

Rank	Item	Mean	SD	Interpretation
1	AQ4 – Rigorous and comprehensive audit procedures	3.13	1.37	Highest confidence; audit methodologies are seen as thorough and well-executed.
2	AQ2 – Auditor professional competence and expertise	3.11	1.43	Auditors are viewed as skilled and knowledgeable, though with some variation.
3	AQ1 – Financial statements give a true and fair view	3.03	1.39	Neutral- positive; financial reporting quality is acceptable but not outstanding.
4	AQ5 – Timely and actionable audit reports	3.00	1.45	Exactly neutral; report usefulness and timeliness are areas of mixed opinion.
5	AQ3 – Auditor independence and objectivity	2.95	1.42	Lowest score; concern that auditors may be influenced by management.

Survey result (2025)

The findings as seen in table 3 suggest that technical audit quality is reasonably strong- processes are rigorous, and auditors are competent; however, the governance dimension (independence) lags, which is a critical red flag. Independence is the bedrock of audit credibility; if respondents perceive undue management influence, the reliability of audit outcomes may be called into question, even if the procedures are technically sound. The moderate score for timeliness (AQ5) also hints at possible bottlenecks in reporting cycles, which could delay decision making. Overall, audit quality appears satisfactory but not exemplary, with governance and communication requiring targeted improvement.

Table. 4 AI Opportunities (Means: 2.92 – 3.16)

Rank	Item	Mean	SD	Interpretation
1	OP1 – Reducing long-term operational costs	3.16	1.40	Most recognized benefit; efficiency gains are the primary expected outcome.
2	OP3 – Enhancing strategic decision-making through predictive insights	3.09	1.41	Strong appreciation for AI's role in data-driven leadership.
3	OP4 – Gaining competitive advantage in the Ghanaian market	3.05	1.39	Moderately seen as a differentiator, though not overwhelmingly so.
4	OP2 – Deepening customer relationships via hyper-personalization	2.98	1.44	Neutral; personalization benefits are not yet clearly visible to respondents.
5	OP5 – Entering new markets or creating innovative products	2.92	1.46	Lowest and most variable; innovation and market expansion

are viewed with greatest uncertainty.

Survey result (2025)

From table 4. respondents clearly see AI as a tool for efficiency and internal improvement rather than a catalyst for customer centric transformation or market disruption. The top three opportunities all relate to internal operational or strategic gains, while the bottom two involve external, customer facing or innovative outcomes. This suggests a conservative, risk-averse mindset among banking professionals: they embrace AI where it promises clear, measurable cost savings but are less convinced of its ability to fundamentally reshape customer relationships or open entirely new revenue streams. The highest SD for OP5 indicates that opinions on AI's innovative potential are deeply divided, possibly reflecting differing levels of digital maturity across banks.

4.2. Correlation Analysis

Pearson correlation analysis was conducted to examine the relationships between AI adoption and the dependent variables. The results revealed a strong positive correlation between AI adoption and financial performance ($r = 0.883$, $p < 0.01$), indicating that banks with higher levels of AI adoption tend to have better financial performance. Similarly, a strong positive correlation was found between AI adoption and audit quality ($r = 0.777$, $p < 0.01$), suggesting that AI adoption is associated with enhanced audit quality. These preliminary findings provide initial support for the hypothesized relationships.

4.3. Regression Analysis

The OLS regression model for H_1 explained 78.3% of the variance in ROA ($R^2 = 0.783$, $\beta = 0.885$, $p < 0.001$). IV estimation confirmed this relationship ($\beta = 0.801$, $p < 0.001$), with the Durbin-Wu-Hausman test (4.27, $p = 0.039$) indicating significant endogeneity. The finding that OLS overestimates AI's effect is consistent with expectations-banks with better financial performance may be more likely to invest in AI (reverse causality). The IV estimation addresses this concern by using the lagged digital infrastructure investment as an instrument for AI adoption, providing more robust causal inference.

For H_2 , the OLS model explained 60.4% of the variance in audit quality ($R^2 = 0.604$, $\beta = 0.777$, $p < 0.001$). IV estimation confirmed this relationship ($\beta = 0.702$, $p < 0.001$), with the Durbin-Wu-Hausman test (3.11, $p = 0.078$) suggesting endogeneity concerns are less pronounced for the audit quality relationship. Diagnostic tests confirmed no multicollinearity ($VIF < 2.0$), homoscedasticity (Breusch-Pagan test $p > 0.05$), and normal residuals (Shapiro-Wilk test $p > 0.05$).

Table 5 Hypothesis Testing Results

Hypothesis	Path	β (OLS)	β (IV)	SE	p-value	R^2	Decision
H_1	AI $\rightarrow$ FP	0.885	0.801	0.058	<0.001	0.783	Supported
H_2	AI $\rightarrow$ AQ	0.777	0.702	0.062	<0.001	0.604	Supported

Survey result (2025)

As can be seen from table 5, the R^2 values obtained in this study (0.783 for financial performance, 0.604 for audit quality) are notably high compared to prior empirical research in this domain. Studies by Schmidt and Müller (2024) in European banking contexts reported R^2

values ranging from 0.31 to 0.45 for similar models, while Davis and Miller (2025) found R^2 values between 0.28 and 0.42 in US banking contexts. The higher explanatory power in the present study may be attributed to several factors: (1) the use of perceptual measures that may capture both objective and subjective aspects of performance, (2) the inclusion of qualitative insights that informed model specification, (3) the relatively early stage of AI adoption in Ghanaian banking, where the marginal impact of initial adoption may be greater than in more mature markets, and (4) the potential influence of common method bias, despite procedural and statistical safeguards. The subsequent discussion contextualizes these effect sizes within the broader literature and addresses the implications of the high explanatory power.

4.4. Qualitative Findings

Thematic analysis of the 15 semi-structured interviews with senior banking executives revealed five key themes that elaborate and contextualize the quantitative findings.

Mechanisms Linking AI to Financial Performance: Executives identified four primary mechanisms through which AI enhances financial performance. Operational efficiency gains were described as the most direct mechanism: "AI has enabled us to automate 30% of our routine operations, resulting in a significant reduction in operational costs." Enhanced decision-making was highlighted as another key mechanism: "Our ROA improvement is largely attributable to better decision-making through AI-powered analytics." Improved risk management was emphasized by risk officers: "AI has been instrumental in reducing our non-performing loans significantly by improving our credit assessment capabilities." Customer experience enhancement was also identified: "AI-powered personalization has increased our cross-selling by 25%."

AI Enhancement of Audit Quality: Executives described how AI improves audit quality through automation and efficiency: "AI automates 80% of our routine audit tasks, allowing auditors to focus on complex judgment areas." Anomaly detection was highlighted: "AI algorithms flag suspicious transactions that human auditors might miss." Continuous auditing was described as transformative: "We now have real-time monitoring of transactions, enabling immediate detection of irregularities." Enhanced evidence evaluation was also noted: "AI provides more robust audit reports with comprehensive data analysis."

Moderating Role of Contextual Factors: Four contextual moderators were identified by executives. Organizational culture emerged as the most significant barrier: "The biggest barrier isn't technology; it's culture. Getting people to trust AI and change their work habits is the real challenge." The regulatory environment was seen as crucial: "Clear regulatory guidance gives us confidence to invest in AI. Regulatory uncertainty creates hesitation." Top management commitment was emphasized: "Leadership commitment is crucial. Without board-level support, AI initiatives fail." Data infrastructure was identified as foundational: "Garbage in, garbage out. Without quality data, AI is useless."

Implementation Challenges: Executives identified several key challenges in AI implementation. Skills shortages were cited as a major constraint: "Finding qualified data scientists and AI specialists in Ghana is extremely difficult." Cost constraints were mentioned: "The initial investment is substantial, and returns take time to materialize." Regulatory uncertainty was highlighted: "Regulations are evolving, making it difficult to plan long-term

AI investments." Legacy systems were described as a barrier: "Our legacy systems are not compatible with modern AI technologies, requiring expensive upgrades."

Success Factors: Executives identified factors that contribute to successful AI implementation. Phased implementation was recommended: "Start small with pilot projects, learn from them, and gradually scale up." Stakeholder engagement was emphasized: "Involving employees early in the process reduces resistance and builds buy-in." Partnerships were seen as valuable: "Partnering with fintech companies and technology providers accelerates AI adoption." Continuous learning was highlighted: "AI is evolving rapidly; we need to continuously update our skills and systems."

4.5. Triangulation

Triangulation of quantitative and qualitative findings revealed convergence on several key points. Both methods confirmed the positive AI-outcome relationships, with quantitative analysis establishing effect sizes and qualitative findings explaining underlying mechanisms. Cost reduction and enhanced decision-making emerged as key benefits in both the quantitative survey (mean scores 3.16 and 3.09) and qualitative interviews. Data quality and skills were identified as major challenges in both data sources. Complementarity emerged as qualitative findings explained mechanisms underlying quantitative relationships; for example, the qualitative finding that AI enables continuous auditing explains the quantitative relationship between AI adoption and audit quality. The qualitative findings also identified contextual moderators, including organizational culture, regulatory environment, top management commitment, and data infrastructure, which were not captured in the quantitative analysis but are critical for understanding the conditions under which AI adoption yields optimal outcomes.

4.6. Impact of Artificial Intelligence on Financial Performance

The findings provide robust evidence supporting H₁: AI adoption significantly and positively impacts financial performance. Both OLS ($\beta = 0.885$, $p < 0.001$) and IV ($\beta = 0.801$, $p < 0.001$) models confirm this relationship. The finding that OLS overestimates AI's effect is consistent with expectations: banks with better financial performance may be more likely to invest in AI (reverse causality). This finding aligns with TAM (Davis, 1989), where perceived usefulness drives adoption by enhancing job performance. RBV (Barney, 1991) further supports this; AI qualifies as a valuable and potentially rare resource enabling competitive advantage. The qualitative findings elaborate the mechanisms: operational efficiency gains, enhanced decision-making, improved risk management, and customer experience enhancement.

The magnitude of the effect ($R^2 = 0.783$) warrants contextualized interpretation. While this explanatory power exceeds that reported in comparable studies in developed economy contexts (Schmidt & Müller, 2024; Davis & Miller, 2025), several factors may explain this difference. First, the Ghanaian banking sector is in an earlier stage of AI adoption, where the initial impact of technology investments may be more pronounced than in saturated markets. Second, the study's perceptual measures capture both objective performance and subjective assessments, potentially accounting for variance beyond purely objective indicators. Third, the qualitative insights that informed model specification may have resulted in more precise operationalization of relevant constructs. Fourth, despite procedural safeguards, common

method variance may partially inflate observed relationships. Future research should employ objective performance data and longitudinal designs to further validate these findings.

The significant direct effect confirms that AI adoption provides the operational foundation for improved financial performance. Banks that adopt AI technologies can automate routine tasks, reduce operational costs, improve decision-making through data-driven insights, and enhance customer experience through personalization. This is particularly important in the banking sector, where operational efficiency and customer satisfaction are key drivers of financial performance. The finding also has implications for understanding the conditions under which technology investments yield financial returns. Previous research has emphasized the role of external factors such as market conditions and regulatory pressures in driving financial performance (Osei-Assibey Bonsu, 2024). While these factors are undoubtedly important, the current findings suggest that internal technological capabilities, specifically AI adoption, play a crucial role in enabling banks to capitalize on market opportunities.

The finding that the IV estimate is lower than the OLS estimate suggests that endogeneity is a significant concern in the AI-financial performance relationship. Banks with better financial performance may be more likely to invest in AI, creating a reverse causality problem. The IV estimation addresses this concern by using lagged digital infrastructure investment as an instrument, providing more robust causal inference. This methodological contribution is important for the literature, as most previous studies have not addressed endogeneity concerns, potentially overestimating the impact of AI on financial performance.

4.7. Effect of Artificial Intelligence on Audit Quality

The findings provide robust evidence supporting H₂: AI adoption significantly and positively affects audit quality. Both OLS ($\beta = 0.777, p < 0.001$) and IV ($\beta = 0.702, p < 0.001$) models confirm this relationship. This agrees with DOI Theory (Rogers, 2003), particularly relative advantage; AI's anomaly detection and data processing capabilities offer superior audit outcomes. TAM (Davis, 1989) complements this through perceived usefulness in accuracy and efficiency. The qualitative findings elaborate the mechanisms: automation of routine tasks, enhanced data analysis, continuous auditing, and advanced fraud detection.

The significant effect of AI on audit quality has important implications for the banking sector. Audit quality is critical for maintaining stakeholder trust, regulatory compliance, and financial stability. AI enhances audit quality by automating routine audit procedures, enabling more comprehensive data analysis, facilitating continuous auditing, and improving fraud detection. Banks that adopt AI technologies are able to conduct more accurate, timely, and reliable audits, reducing the risk of financial misstatements and fraud.

The finding that the IV estimate is close to the OLS estimate suggests that endogeneity concerns are less pronounced for the AI-audit quality relationship. This may be because audit quality is less directly linked to financial performance, reducing the reverse causality concern. However, the qualitative findings suggest that banks with stronger audit functions may be more likely to invest in AI, creating some endogeneity.

The descriptive findings show moderate audit quality perceptions, with auditor independence being the weakest dimension. This suggests that while AI enhances audit procedures, human oversight and professional skepticism remain essential (Kokina & Mancha, 2018). Auditors must critically evaluate AI-generated insights and maintain independence in

their judgment. This is particularly important in the Ghanaian context, where regulatory oversight is evolving, and professional audit standards are being strengthened.

4.8. Opportunities and Challenges of AI Adoption

The findings validate the opportunities and challenges identified in the literature. The most prominent opportunity was cost reduction (mean = 3.16), followed by enhanced decision-making (mean = 3.09). The lower mean score for AI's potential to create innovative financial products (mean = 2.92) suggests banks may not yet be fully leveraging AI for product innovation. The most significant challenge was concerns regarding data privacy, algorithmic bias, and ethical AI use (mean = 3.15). Data quality limitations (mean = 3.07), high implementation costs (mean = 3.00), skills shortages (mean = 2.93), and organizational resistance (mean = 2.96) further constrain adoption.

The finding that cost reduction is the most prominent opportunity reflects the immediate operational benefits of AI. Banks can automate routine tasks, reducing labor costs and improving efficiency. However, the lower scores for innovation potential suggest that banks may be using AI primarily for efficiency gains rather than strategic transformation. This is consistent with the qualitative finding that banks are in the early stages of AI adoption, focusing on pilot projects and incremental improvements rather than radical innovation.

The finding that data privacy and ethical concerns are the most significant challenges reflects growing awareness of AI risks. Algorithmic bias, data protection violations, and lack of transparency are significant concerns for banks and their customers. The Ghanaian banking sector, like many emerging economies, lacks comprehensive regulatory frameworks for AI, creating uncertainty and risk. The finding that skills shortages are also a significant challenge reflects the difficulty of finding qualified AI professionals in Ghana, where the supply of data scientists and AI specialists is limited.

4.9. Moderating Role of Contextual Factors

The qualitative findings extend the theoretical framework by identifying four key moderators: organizational culture, top management commitment, regulatory environment, and data infrastructure. These moderating effects suggest that the relationship between AI adoption and outcomes is contingent on contextual factors, explaining why AI investments may not always yield expected returns and why some banks derive greater benefits from AI than others.

Organizational culture emerged as the most significant moderator. Banks with a culture that values innovation, risk-taking, and continuous learning are better able to leverage AI for performance improvement. This is consistent with the literature on organizational culture and innovation (Wang, 2019; Cho et al., 2023). Banks with bureaucratic, risk-averse cultures may struggle to adopt AI effectively, even with significant investment.

Top management commitment was also identified as a crucial moderator. Banks with committed leadership that allocates resources, champions AI initiatives, and models AI adoption are more likely to succeed. This is consistent with the TAM framework (Venkatesh & Davis, 2000), which emphasizes the role of organizational support in technology adoption.

The regulatory environment emerged as a significant moderator. Banks operating in a clear, supportive regulatory environment are more confident in investing in AI. Regulatory uncertainty creates hesitation and limits investment. This finding has implications for policymakers, who should provide clear guidance on AI adoption in the banking sector.

Data infrastructure was identified as a foundational moderator. Banks with robust data infrastructure, including data quality, integration, and governance, are better able to leverage AI effectively. This is consistent with the RBV framework (Barney, 1991), which emphasizes the importance of complementary assets for value creation.

4.10. Theoretical Implications

This study makes several theoretical contributions to the literature on AI adoption in emerging economy banking contexts. First, it extends the Technology Acceptance Model by incorporating contextual moderators specific to developing economies. The findings demonstrate that perceived usefulness and perceived ease of use are moderated by organizational factors such as top management support and organizational culture, and by environmental factors such as regulatory readiness. This extension addresses the gap in TAM research, which has primarily focused on individual-level factors without adequately considering the organizational and environmental context.

Second, the study extends the Resource-Based View by identifying the complementary capabilities necessary for AI to create competitive advantage. The findings demonstrate that AI is not a standalone strategic resource; its value depends on complementary organizational capabilities, including data infrastructure, skilled personnel, and change management capacity. Without these complementary assets, AI investments may not yield competitive advantage. This extension addresses the critique that RBV has been applied primarily to static resources rather than dynamic capabilities.

Third, the study extends Diffusion of Innovation theory by incorporating institutional factors that influence adoption decisions in developing economies. The findings demonstrate that adoption decisions are influenced not only by the technology's inherent advantages but also by the institutional environment's readiness for AI implementation. This extension addresses the gap in DOI research, which has primarily focused on the technology itself without adequately considering the institutional context.

Fourth, the study contributes to the growing literature on AI in finance by providing empirical evidence from a Sub-Saharan African context. Most AI research has focused on developed economies, with limited attention to emerging economies. The findings demonstrate that AI can have significant positive impacts on financial performance and audit quality in developing economy banking contexts, but these impacts are contingent on contextual factors.

4.11. Practical Implications

The findings have important practical implications for banking practitioners, regulators, and policymakers in Ghana and similar emerging economy contexts.

For universal banks, the findings suggest that AI adoption should be a strategic priority. Banks should invest in AI infrastructure and skills, recognizing that AI qualifies as a valuable resource enabling competitive advantage. However, investments should be targeted and phased, starting with customer-facing applications where adoption levels are currently highest. Banks should integrate AI into audit and risk management functions, as these areas show significant benefits from AI adoption. Banks should also implement robust data governance frameworks to address data quality limitations and data privacy concerns. Finally, banks should engage stakeholders and manage change to overcome organizational resistance.

For managers, the findings highlight the importance of fostering an organizational culture that supports innovation. Banks should develop a culture that values risk-taking, continuous learning, and technological adoption. This includes leadership commitment to AI, integration of AI into organizational strategy, and recognition and reward systems that reinforce AI adoption. Managers should also invest in training and development that enhances employee skills and confidence in using AI technologies.

For regulators, particularly the Bank of Ghana, the findings suggest that regulatory frameworks should be updated to address AI adoption in the banking sector. Regulators should develop AI-specific regulatory guidelines that provide clear guidance on AI adoption, data protection, and algorithmic accountability. This would reduce regulatory uncertainty and give banks confidence to invest in AI. Regulators should also establish regulatory sandboxes that allow banks to test AI applications in a controlled environment. Additionally, regulators should promote capacity building through training programs and partnerships with academic institutions.

For policymakers, the findings suggest that AI adoption in the banking sector should be supported through enabling policies. Policymakers should facilitate data sharing and infrastructure development to address data quality limitations. They should also invest in education and training to address skills shortages in AI and data science. International mandates should be supported by capacity-building programs that help banks develop the capabilities needed to implement AI effectively.

4.12. Limitations and Future Research

This study has several limitations that should be acknowledged. First, the cross-sectional design limits the ability to establish causal relationships. While the hypothesized model is grounded in theoretical reasoning and instrumental variable estimation provides more robust causal inference, longitudinal research is needed to confirm the causal direction of the relationships. Future research should employ longitudinal designs to track how AI adoption influences financial performance and audit quality over time.

Second, the reliance on self-reported data raises concerns about common method bias. Although procedural and statistical safeguards were implemented, future research should incorporate objective measures of AI adoption, such as actual technology expenditure or the number of AI applications deployed, to complement self-reported perceptions. Multi-source data, such as supervisor ratings or regulatory assessments, could also strengthen the findings.

Third, the study focused on the banking sector in Ghana, which may limit the generalizability of the findings to other sectors or countries. The banking industry has unique characteristics, including its role in the national economy, its regulatory environment, and its traditional organizational structures. Future research should examine whether the findings replicate in other financial sectors, such as insurance or asset management, and in other developing country contexts.

Fourth, the study examined AI adoption at the organizational level but did not examine individual-level factors that may influence adoption and outcomes. Future research could employ multi-level modeling to examine how individual-level factors, such as perceived usefulness and perceived ease of use, interact with organizational-level factors, such as top management commitment and organizational culture.

Fifth, the study focused on financial performance and audit quality as outcomes but did not examine other potential outcomes, such as customer satisfaction, employee engagement, or innovation. Future research should examine a broader range of outcomes to provide a more comprehensive understanding of AI's impact on banking operations.

Sixth, the study did not examine the specific AI technologies that banks are adopting. Different AI technologies, such as machine learning, natural language processing, and robotic process automation, may have different impacts on financial performance and audit quality. Future research should examine the differential impacts of specific AI technologies.

5. Conclusion

5.1. Summary of Findings

This mixed-methods study investigated AI adoption effects on financial performance and audit quality among universal banks in Ghana. The key findings are as follows: AI adoption has a strongly significant positive impact on financial performance ($\beta = 0.885$, $p < 0.001$, $R^2 = 0.783$), confirmed by IV estimation ($\beta = 0.801$, $p < 0.001$). AI adoption significantly enhances audit quality ($\beta = 0.777$, $p < 0.001$, $R^2 = 0.604$), confirmed by IV estimation ($\beta = 0.702$, $p < 0.001$). The opportunities of AI adoption include cost reduction (mean = 3.16) and enhanced decision-making (mean = 3.09). The challenges include data privacy and ethical concerns (mean = 3.15), data quality limitations (mean = 3.07), implementation costs (mean = 3.00), skills shortages (mean = 2.93), and organizational resistance (mean = 2.96). Organizational culture, top management commitment, regulatory environment, and data infrastructure moderate AI-outcome relationships.

AI adoption is a transformative factor in Ghana's banking system with major implications for financial performance and audit quality. Despite being in early stages compared to developed economies, AI integration has demonstrated substantial improvements in profitability, operational efficiency, and audit accuracy. The mixed-methods approach provides a comprehensive understanding; quantitative findings establish relationships and effect sizes; qualitative findings explain mechanisms, identify contextual moderators, and provide practical insights. The study confirms that technological innovation, particularly AI adoption, has become a cornerstone of sustainable banking operations in Ghana.

The findings challenge top-down innovation theories that assume a direct pathway from technology adoption to performance outcomes. Instead, the findings support a more nuanced understanding in which AI adoption influences performance through multiple mechanisms: operational efficiency gains, enhanced decision-making, improved risk management, and customer experience enhancement, with contextual factors serving as critical moderators. This integrated framework, combining TAM, RBV, and DOI with context-specific moderators, provides a comprehensive theoretical foundation for understanding AI adoption in developing economy banking contexts.

The study also highlights the importance of addressing challenges such as data privacy concerns, skills shortages, and regulatory uncertainty to fully realize AI's potential in the banking sector. Banks that successfully navigate these challenges will be better positioned to leverage AI for competitive advantage. Regulators and policymakers play a crucial role in

creating the enabling environment for AI adoption through clear regulatory frameworks, capacity-building programs, and infrastructure development.

5.2. Implications for Practice

For Universal Banks: The findings suggest that AI adoption should be a strategic priority. Banks should invest in AI infrastructure and skills, recognizing that AI qualifies as a valuable and potentially rare resource enabling competitive advantage. Implementation should be phased, starting with customer-facing applications where adoption levels are currently highest. Banks should integrate AI into audit and risk management functions, as these areas show significant benefits from AI adoption. Robust data governance frameworks should be implemented to address data quality limitations and data privacy concerns. Stakeholder engagement and change management are essential to overcome organizational resistance.

For Regulators: The Bank of Ghana should develop AI-specific regulatory guidelines that provide clear guidance on AI adoption, data protection, and algorithmic accountability. Regulatory sandboxes should be established to allow banks to test AI applications in a controlled environment. Capacity building should be promoted through training programs and partnerships with academic institutions. Data sharing and infrastructure development should be facilitated to address data quality limitations.

For Policymakers: AI adoption in the banking sector should be supported through enabling policies. Investments in education and training are needed to address skills shortages in AI and data science. International mandates should be supported by capacity-building programs that help banks develop the capabilities needed to implement AI effectively. Collaboration between government, industry, and academia should be encouraged to foster AI innovation in the banking sector.

5.3. Future Research Directions

Future research should build on this study's findings in several directions. Longitudinal research is needed to confirm the causal relationships identified in this cross-sectional study. Multi-level research could examine how organizational-level factors interact with individual-level factors to influence AI adoption and outcomes. Comparative research across developing economies could examine the generalizability of the findings. Research on specific AI technologies could examine the differential impacts of machine learning, natural language processing, and robotic process automation. Research on other outcomes, such as customer satisfaction and innovation, could provide a more comprehensive understanding of AI's impact on banking operations. Finally, intervention research could evaluate the effectiveness of programs designed to enhance AI adoption in the banking sector.

5.4. Declarations

Ethics Approval and Consent to Participate: This study was conducted in accordance with established ethical guidelines for research involving human participants. Ethical approval was obtained from the Ethics Committee (EC) of the Akenten Appiah-Menkah University of Skills Training and Entrepreneurial Development on October 3, 2025 with the approval number, REC 030288. Prior to participation, all respondents were provided with an informed consent form outlining the purpose and nature of the study, the voluntary nature of participation, the confidentiality of the information provided, and their right to withdraw from

the study at any time without penalty. Participants were assured that all responses would be anonymized and presented solely in aggregate form. Furthermore, they were informed that neither individual participants nor the banks represented in the study would be identifiable in any publication or dissemination arising from the research.

Data Availability: The datasets generated and/or analyzed during the current study are available from the corresponding author upon reasonable request. The data are not publicly available due to confidentiality agreements with participating banks.

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