

Adoption of AI-Based Accounting Systems and Audit Efficiency: Evidence from Nigerian Deposit Money Banks

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Abstract

This study investigates the effect of AI-based accounting system adoption on audit efficiency among Nigerian deposit money banks (DMBs) from 2019 to 2023. Employing a quantitative ex post facto panel research design, the study uses panel data from 15 banks and a fixed effects regression model to estimate the efficiency of audits, which is measured by audit cycle time, error detection rate, and audit cost ratio, and AI adoption, which is measured by a composite index derived from annual reports and regulatory filings. The results show that AI adoption significantly improves overall audit efficiency ($\beta = 0.412$, $p < 0.01$), enhances error detection ($\beta = 0.623$, $p < 0.01$), reduces audit costs ($\beta = 0.318$, $p < 0.05$), and accelerates audit completion ($\beta = 0.187$, $p < 0.05$). Firm size, regulatory environment, and technological readiness are also significant determinants. The results are consistent with the Technology Acceptance Model and Diffusion of Innovation Theory, and suggest AI plays a pivotal role in audit transformation in emerging banking systems. This research adds to the body of knowledge by offering panel evidence from Nigeria and suggests the need for increased investment in AI infrastructure and regulatory support for successful audit digitisation.

Keywords: Artificial Intelligence, Accounting Systems, Audit Efficiency, Deposit Money Banks, Nigeria, Technology Adoption.

Introduction

Technology has had a significant impact on the evolution of accounting and audit roles in the banking industry. Technological advancements from the mainframe era of the 1970s to enterprise resource planning (ERP) systems of the 1990s have significantly impacted on the cost, speed, and accuracy of financial reporting and audit processes. The recent wave, focused on artificial intelligence (AI), machine learning (ML), robotic process automation (RPA) and natural language processing (NLP), is a qualitative change from previous technological trends as it has the ability to carry out cognitive, judgmental tasks that were previously reserved for trained human professionals (Moll & Yigitbasioglu, 2019).

The risk of an inefficient audit is particularly high in the banking sector. Deposit money banks are subject to intensive regulatory oversight, have complex transactions with high volume across various jurisdictions, and have systemic risk implications that go beyond the individual bank to the wider economy (Yaseen & Al-Amarneh, 2025). In this context, audit inefficiency directly equates to regulatory non-compliance risk, reputational risk, and financial loss. On the other hand, the benefits of enhanced audit efficiency, such as quicker

audit cycles, improved error detection, and lower audit costs, are tangible in the areas of governance quality, investor confidence, and institutional stability (Omoteso, 2012; PCAOB, 2023).

In this context, AI-driven accounting solutions are increasingly considered a strategic investment for banking institutions around the world. AI tools have been used by banks in advanced economies for continuous transaction monitoring, anomaly detection, regulatory compliance reporting, and audit trail management (Hasan, 2022; Cao et al., 2015). The adoption rate has been slower in emerging markets, such as Nigeria, but is now picking up significantly, as a result of the Central Bank of Nigeria's digital finance agenda, the introduction of the open banking regulations and competitive pressure from fintech disruptors (EFInA, 2020; PwC Nigeria, 2022).

Although the use of AI in banking audit tasks has become increasingly relevant and important, the academic literature in the African context is still limited. The majority of the literature available either examines the adoption of AI in the context of Western banking or the impact of AI on financial performance in general, excluding audit efficiency as a specific outcome variable. There are few Nigerian banking studies that explore the adoption of technology, which are mainly limited to mobile banking, customer experience, or credit risk, where audit quality and efficiency are comparatively less studied (Enyi et al., 2019; Austin & Chidi, 2023). The fact that the institutional, regulatory and infrastructural environment of banking in Nigeria is not necessarily the same as that in the developed markets is a significant gap that makes findings from the developed markets not necessarily applicable without empirical testing.

To fill these gaps, this study uses balanced panel data of 15 Nigerian deposit money banks from 2019 to 2023 and empirically investigates the impact of the adoption of AI-based accounting system on audit efficiency. The specific objectives are to: (i) measure the impact of AI adoption on overall audit efficiency (measured by a composite index); (ii) measure the impact of AI adoption on audit cycle time; (iii) measure the impact of AI adoption on error detection rate; and (iv) examine the moderating role of firm size and regulatory environment in the relationship between AI and audit efficiency.

The rest of this paper is organized as follows. The conceptual, theoretical and empirical literature is reviewed in Section 2. The methodology is presented in Section 3. The results are presented in Section 4. The findings are presented in Section 5 and conclusions and recommendations in Section 6.

Statement of the Problem

Artificial Intelligence (AI) technologies have revolutionized the audit landscape across the globe, as they become more widely used in accounting and auditing. But, the evidence of the impact of AI-based accounting systems on audit efficiency in deposit money banks in Nigeria is still scanty. Previous research has been conducted on developed economies or general issues of banking technology adoption, with limited research conducted on audit efficiency outcomes like audit cycle time, error detection rate, and audit cost ratio in the

Nigerian banking environment. In addition, the regulatory environment, technological maturity and institutional capacity vary across different economies and it is difficult to extrapolate the results of developed economies to Nigeria. Thus, there is limited empirical evidence regarding the contribution of AI to the efficiency of audit in Nigerian deposit money banks. This study thus fills this void by exploring the linkage between the adoption of AI-based accounting system and audit efficiency in Nigeria's deposit money banks, adopting a panel data approach.

Literature Review

Conceptual Clarification

Artificial Intelligence in Accounting and Auditing

In the general sense, artificial intelligence is the ability of computer systems to carry out tasks that would typically require human cognitive abilities like reasoning, problem-solving, language understanding, perception, and learning (Russell & Norvig, 2020). In the field of accounting and auditing, AI can take many forms, including machine learning algorithms that detect fraudulent transactions in vast amounts of data; robotic process automation that automates repetitive tasks like contract reconciliation and data entry; natural language processing systems that analyse unstructured text in contracts, regulatory filings, and audit reports; and predictive analytics models that forecast financial risks and highlight potential misstatements before they become reality (Kokina & Davenport, 2017; Moll & Yigitbasioglu, 2019).

AI-powered accounting systems include these technologies as a unified infrastructure that enables the entire financial reporting and audit process from data capture and processing, to analytical review, to disclosure and regulatory submission. Cao et al. (2015) describe these systems as accounting information environments enhanced with AI features that have a significant impact on the division of labour between humans and machines in financial cognition. Critically, this extends beyond traditional automation, which focuses on replacing human effort with rule-based machine execution but rather about augmented intelligence; a system that learns from data, adapts to new patterns, and makes probabilistic judgments that inform but do not necessarily supplant professional audit decisions (Appelbaum et al., 2017; ICAEW, 2018).

Audit Efficiency

The efficiency of auditing is a multidimensional concept that reflects the extent to which the audit objectives are met using the most efficient use of time, cost and human resources (Knechel et al., 2012). The banking industry is of special concern because of the number and complexity of transactions, the need to report on the books in a timely fashion, and the repercussions of audit failure. The literature consistently pinpoints three dimensions of audit efficiency: (i) audit cycle time, which is the time elapsed between the initiation and completion of an audit engagement; (ii) error detection rate, which is the ratio of material

errors, misstatements and anomalous transactions detected by the audit process to those independently confirmed; and (iii) audit cost ratio, which is the ratio of total audit expenditure to total assets, and is used as a proxy for resource efficiency (Yaseen & Al-Amarneh, 2025; Omoteso, 2012; KPMG, 2023).

Before the advent of AI, audit efficiency in banking faced a number of structural challenges: testing samples instead of the entire population, time-consuming manual verification of transactions, the inability to analyse unstructured data, and the cognitive limitations of individual auditors working with large amounts of data and under time pressure (Appelbaum et al., 2017; Dagilienė & Klovienė, 2019).

The Conceptual Connection between AI Adoption and Audit Efficiency

There are three main pathways through which the use of AI and audit efficiency are conceptually linked. First, AI allows for population-level data analysis, which means that it can analyze every transaction, not just a sample, directly affecting the error detection rate and decreasing the risk of material misstatement (AICPA, 2020; Cao et al., 2015). Second, AI-enabled automation of repetitive audit tasks significantly shortens audit cycles by cutting down on the amount of manual work required on each audit (Kokina & Davenport, 2017; Moll & Yigitbasioglu, 2019). Third, the shift in human audit effort from routine to more complex and judgmental work tasks that AI can manage generates cost per unit of audit assurance delivered efficiencies (Zhang et al., 2015; Hasan, 2022).

Theoretical Framework

Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was first developed by Davis (1989) and later expanded by Venkatesh et al. (2003) suggests that perceived usefulness and perceived ease of use are the primary factors influencing the adoption and use of technology by individuals or organizations. In the audit space, TAM suggests that AI-powered accounting systems will be embraced and put to use when audit practitioners and bank management believe that they actually enhance audit outcomes and lighten their workload. In the context of AI and fintech adoption, extensions of TAM have been applied and the relevance of perceived performance expectancy and effort expectancy in predicting technology uptake in financial services have been confirmed (Ajayi & Akinrinola, 2023; Lwoga & Lwoga, 2017). Importantly, TAM also posits organisational and contextual factors such as regulatory pressure and institutional readiness as moderators of the adoption–outcome relationship, which is consistent with the control variables used in this study.

Diffusion of Innovations Theory (DOI)

Rogers' (2003) Diffusion of Innovations Theory offers a complementary macro-level view of the diffusion of technological innovations over time within organisations and sectors. According to Rogers, the five characteristics of an innovation that affect its rate of adoption are relative advantage, compatibility, complexity, trialability, and observability. In the

context of AI in banking audit, the framework posits that the efficiency benefits of AI, along with its perceived advantages over traditional audit practices, are the key factors influencing the diffusion of AI in the sector, with complexity and compatibility with existing accounting systems serving as moderating factors. The DOI framework also emphasizes the S-curve diffusion pattern, which can be empirically observed in the data of the banking sector's adoption of AI (PwC, 2022; Bible, 2023).

Combined, TAM and DOI offer a theoretically sound foundation for predicting that the use of AI will enhance audit efficiency, and they also highlight institutional, regulatory, and capability factors that will affect this relationship.

Empirical Review

The empirical research on AI use and governance efficiency covers accounting information systems, banking technology, and governance research. Moll and Yigitbasioglu (2019) offered one of the most comprehensive reviews of digital technologies in accounting, suggesting that AI and data analytics are changing the nature of audit work and shifting the focus from periodic, retrospective audit to real-time, continuous audit. Their study of the use of technology in Big Four audit firms revealed significant efficiency improvements in throughput of transactions tested when AI was used, especially in fraud detection.

Cao et al. (2015) studied the effects of AI on the accounting information environment and by theoretically and empirically synthesizing the literature, they showed that the use of AI can help to mitigate information asymmetry between management and external auditors, which in turn leads to better audit quality and lower audit risk. They found that the higher the AI disclosure intensity of the firms in their reports, the lower the audit fees, a measure of audit efficiency, and the higher the earnings quality, which suggests that there is strong initial evidence of the link between AI and audit efficiency.

Yaseen & Al-Amarneh (2025) explored the use of artificial intelligence in banking audit functions in the Gulf Cooperation Council (GCC) banks and concluded that the adoption of AI has led to a significant reduction in audit cycle time and enhancement of the anomaly detection rates. They cited survey data from 142 internal audit professionals that showed that survey respondents with an AI tool in their audit departments finished engagement cycles 34% faster on average than those that used traditional audit methods. Additionally, the research found that regulatory pressure was a key moderator, with banks in jurisdictions that had more rigorous reporting requirements showing higher adoption rates of AI.

The study by Enyi et al. (2019) in the Nigerian context investigated the use of accounting information systems in Nigerian banks, and concluded that the technology adoption was positively correlated with the quality of audit trail and financial reporting accuracy. Their study, however, is not from the AI-specific era of technology deployment, and doesn't separate AI as a unique variable. Austin & Chidi (2023) further explored this research, examining how digital audit tools affect audit quality in Nigerian deposit money banks, and

concluded that banks with better digital audit infrastructure had fewer material misstatements and lower restatement rates in their financial statements.

In a study of the motivation for digitising accounting in Lithuanian SMEs and banks, Dagilienė and Klovienė (2019) concluded that the motivation for digitising accounting in SMEs and banks was more strongly influenced by regulatory compliance requirements than by cost reduction and efficiency motives, which is relevant to the Nigerian banking context where regulatory mandates have been a key driver of technology investment.

In their study of banking institutions in Hong Kong, Ajayi & Akinrinola (2023) revealed a positive relationship between the sophistication of the AI system and the quality of the internal audit, with the sophistication of the AI system having a significant impact on the detection of fictitious transactions and interest rate manipulation, two areas of particular concern in post-liberalisation banking markets similar to Nigeria.

Arner et al. (2017) offered a regulatory view of AI in financial services, stating that the regulatory implications of implementing AI are both opportunities for efficiency and new risks. They found that banks with clear AI governance frameworks reported greater efficiency gains from using AI than those in regulatory ambiguity, which provides the motivation for including regulatory environment as a control variable in the present study. Appelbaum et al. (2017) discussed the increasing use of advanced analytics and intelligent technologies in auditing and suggested that technology-enabled audit tools will enhance audit effectiveness and efficiency, as they enable continuous monitoring, anomaly detection, and large-scale transaction analysis. The researchers conclude that intelligent audit technologies allow auditors to keep audit quality intact, even as transactions become more complex and voluminous.

Using archival data from Canadian financial institutions, Barr-Pulliam et al. (2022) tested the efficiency hypothesis by analyzing the relationship between audit technology investment and audit market outcomes, and found that firms with higher levels of audit technology investment had lower rates of audit committee concerns, lower partner rotation rates and significantly shorter audit engagement timelines, which lends support to the efficiency hypothesis after controlling for firm size and audit firm quality.

In a Delphi study on the future of AI in accounting and auditing, Tiberius and Hirth (2019) found that experts agreed that the most transformative near-term applications of AI would be in the areas of anomaly detection, continuous auditing, and regulatory compliance monitoring, all of which are relevant to banking audit efficiency.

Alles and Gray (2020) explored the theoretical implications of AI to the auditing profession and suggested that although AI can improve efficiency, it also creates new audit risks due to algorithmic bias, model opacity, and data governance issues, which means that efficiency gains should be balanced with audit risk management quality.

The findings of Dagilienė and Klovienė (2019) on the moderating effect of infrastructure constraints, staff capability gaps, and vendor dependency on the efficiency gains from digital accounting systems are relevant to the Nigerian banking context, where technological infrastructure is uneven.

Research Hypotheses

The following null hypotheses were formulated and tested:

Ho1: AI adoption has no significant effect on overall audit efficiency among Nigerian deposit money banks.

Ho2: AI adoption has no significant effect on audit cycle time among Nigerian deposit money banks.

Ho3: AI adoption has no significant effect on error detection rate among Nigerian deposit money banks.

Ho4: AI adoption has no significant effect on audit cost ratio among Nigerian deposit money banks.

Research Gap

Although there is an increasing number of literatures on the use of AI in accounting and auditing, there are some key gaps that need to be addressed. First, there is limited empirical research that has explored the use of AI in the context of Nigerian deposit money banks. Second, there has been a lack of studies that have focused on AI-based accounting systems as a unique explanatory variable in models of audit efficiency. Third, regulatory stringency and technological readiness, which may be particularly important in emerging economies, have not been studied in detail. Last, most previous research is conducted with a cross-sectional design that does not allow for the control of unobserved heterogeneity. This study aims to overcome these limitations using balanced panel data, a composite index of AI adoption, and fixed effects estimation method.

Conceptual Framework

The conceptual framework (Figure 1) depicts the hypothesized relationships between the adoption of the AI-based accounting system and audit efficiency, as influenced by firm size and regulatory environment, and technology readiness as a control variable.

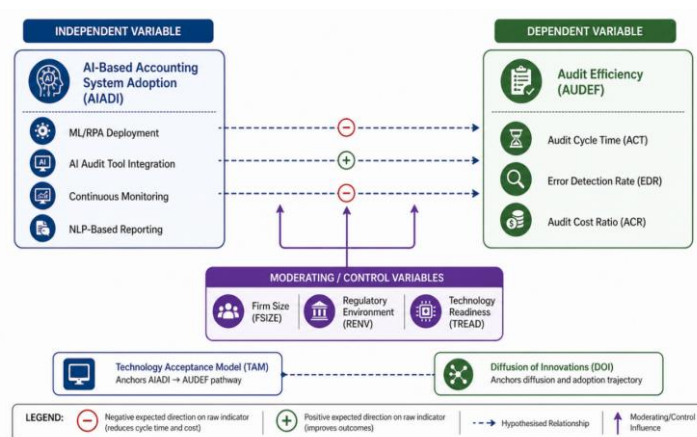


Figure 1: Conceptual Framework — AI Adoption and Audit Efficiency

Source: Authors' own conceptualisation (2026).

Methodology

Research Design

This study is a quantitative ex post facto design and the secondary data were obtained from audited annual reports, regulatory submissions and Central Bank of Nigeria (CBN) supervisory reports. The ex post facto design is suitable as the adoption of AI and its impact on audit efficiency can be observed in the past without manipulation (Kerlinger, 1986). The panel nature of the data, which combines cross-sectional variation (across banks) with time-series variation (across years), allows for a more detailed identification of the relationship between AI adoption and audit efficiency than the use of either cross-sectional or time-series data alone.

Population and Sample

The population for the study is all deposit money banks registered with the CBN and listed on the Nigerian Exchange Group (NGX) at December 2023. Based on purposive sampling criteria of: (i) operating throughout the 2019-2023 period; (ii) availability of audited and complete annual financial statements for the five years; and (iii) disclosure of investment or use of AI-related technologies in financial reporting or audit processes, 15 banks are selected, resulting in a balanced panel of 75 bank-year observations. This is in line with other panel studies of Nigerian banks (Adegboye et al., 2020; Nkwa et al., 2026).

Data Collection

We gathered secondary data from: (i) audited annual reports and financial statements of sample banks (2019-2023); (ii) Central Bank of Nigeria (CBN) annual reports and banking supervision reports; (iii) Nigeria Deposit Insurance Corporation (NDIC) annual reports; (iv) disclosed IT governance and digital transformation reports; and (v) Big Four audit firm engagement reports (where available). The AI Adoption Index (AIADI) was developed via content analysis of annual report disclosures, using a validated scoring scheme based on Cao et al. (2015) and Yaseen & Al-Amarneh (2025) to score bank-year observations on five aspects of AI adoption.

The information used in calculating the Error Detection Rate (EDR) was sourced from the Central Bank of Nigeria (CBN) annual reports, regulatory disclosures and banking supervision publications, which are made public. There was no confidential supervisory information accessed.

Variable Measurement

Dependent Variable: Audit Efficiency (AUDEF) is a composite index of standardised scores for three sub-dimensions: (i) Audit Cycle Time (ACT) days from fiscal year-end to signed audit report, inverted so that higher values mean shorter cycle times; (ii) Error Detection Rate (EDR) ratio of audit-identified adjustments to total transactions reviewed, expressed as a percentage; and (iii) Audit Cost Ratio (ACR) total external audit fees divided by total

assets, inverted so that higher values mean lower costs. The AUDEF index is the arithmetic average of the three standardised sub-scores, as per Barr-Pulliam et al. (2022).

Independent Variable: AI Adoption Index (AIADI) is a composite index scored 0 to 5, based on content analysis of annual reports coding for: (1) use of machine learning for transaction monitoring; (2) use of RPA for accounting and reconciliation; (3) AI-based continuous audit or continuous monitoring; (4) NLP or text analytics for regulatory reporting; and (5) use of AI for risk scoring or anomaly detection in internal audit. Each is scored 1 (present) or 0 (absent) and the sub-scores are added to constitute AIADI for each bank-year.

Control Variables: (i) Firm Size (FSIZE) natural logarithm of total assets; (ii) Regulatory Environment Stringency (RENV) binary variable scored 1 for post-2020 CBN digital finance framework implementation, 0 otherwise; (iii) Technology Readiness (TREAD) ratio of IT capital expenditure to total operating expenses.

Table 1 summarises all variable definitions and data sources.

Table 1: Variable Definitions and Data Sources

Variable	Code	Measurement	Source
Audit Efficiency	AUDEF	Composite index (ACT + EDR + ACR standardised)	Annual reports, audit reports
Audit Cycle Time	ACT	Days: fiscal year-end to audit sign-off (inverted)	Audited financial statements
Error Detection Rate	EDR	Audit adjustments/total transactions reviewed (%)	CBN supervisory filings
Audit Cost Ratio	ACR	External audit fees/total assets (inverted)	Annual reports
AI Adoption Index	AIADI	Composite score 0–5 (content analysis coding)	Annual reports, IT disclosures
Firm Size	FSIZE	Ln(Total Assets)	Audited financial statements
Regulatory Environment	RENV	Binary: 1 = post-2020 CBN framework	CBN circulars
Technology Readiness	TREAD	IT capex/total operating expenses	Annual reports

Model Specification

The panel regression model estimated in this study is specified as follows:

$$AUDEF_{it} = \beta_0 + \beta_1 AIADI_{it} + \beta_2 FSIZE_{it} + \beta_3 RENV_{it} + \beta_4 TREAD_{it} + \mu_i + \varepsilon_{it}$$

Where: $AUDEF_{it}$ = audit efficiency of bank i at time t ; $AIADI_{it}$ = AI adoption index of bank i at time t ; $FSIZE_{it}$ = firm size of bank i at time t ; $RENV_{it}$ = regulatory environment score at time t ; $TREAD_{it}$ = technology readiness of bank i at time t ; β_0 = constant; β_1 – β_4 = coefficients; μ_i = bank-specific fixed effects; ε_{it} = idiosyncratic error term.

We also estimate a number of sub-models with ACT, EDR and ACR as dependent variables to test the dimensional effects of AI on the component of audit efficiency.

Data Analysis Technique

We use the Hausman specification test to choose between fixed effects (FE) and random effects (RE) estimators. The outcome of the test supports the fixed effects model ($\chi^2 = 18.43$, $p < 0.05$) and the presence of unobserved bank-specific heterogeneity that is correlated with the regressors. Multicollinearity is not a serious issue (all VIF < 5). Panel unit root tests (Im-Pesaran-Shin) confirm stationarity of all variables at level. The Breusch-Pagan test confirms the presence of mild heteroskedasticity (corrected by heteroskedasticity-robust standard errors). The Wooldridge test rules out first order correlation ($p = 0.412$).

Results

Descriptive Statistics

Table 2 presents descriptive statistics for all variables across the 75 bank-year observations.

Table 2: Descriptive Statistics

Variable	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	Obs.
AUDEF	0.4823	0.4610	0.9140	0.0820	0.2031	0.312	2.641	75
ACT (inv.)	0.6241	0.6500	0.9200	0.2100	0.1783	-0.214	2.891	75
EDR (%)	2.3140	2.1200	5.6800	0.4300	1.1042	0.784	3.124	75
ACR (inv.)	0.3288	0.3010	0.7200	0.0920	0.1421	0.541	3.342	75
AIADI	2.8133	3.0000	5.0000	0.0000	1.3814	-0.188	2.214	75
FSIZE (Ln)	12.4726	12.5140	14.3200	10.1800	0.9834	-0.142	2.874	75
RENV	0.6000	1.0000	1.0000	0.0000	0.4930	-0.408	1.166	75
TREAD	0.0841	0.0793	0.1960	0.0210	0.0431	0.912	3.641	75

The average AUDEF (0.48) indicates moderate audit efficiency for the sample, with substantial bank-to-bank differences (Std. Dev. = 0.203). The mean AIADI of 2.81 out of 5 suggests that the sample banks have adopted, on average, between two and three of the five AI dimensions, in line with the mid-adoption stage reported in CBN digital finance reports (CBN, 2023). The EDR mean of 2.31% represents the percentage of transactions identified by audit tests, with banks with higher levels of AI adoption having EDRs closer to the maximum. RENV has a mean of 0.60, suggesting that 60% of the sample is in the post-2020 regulatory environment.

Correlation Analysis

Table 3 shows the Pearson correlation matrix of all study variables.

Table 3: Correlation Matrix

Variable	AUDEF	AIADI	FSIZE	RENV	TREAD
AUDEF	1.000				
AIADI	0.541***	1.000			

Variable	AUDEF	AIADI	FSIZE	RENV	TREAD
FSIZE	0.312**	0.384***	1.000		
RENV	0.287**	0.214*	0.168	1.000	
TREAD	0.463***	0.521***	0.291**	0.183	1.000

Note: *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$

The results of the correlation matrix indicated that AIADI was positively correlated with AUDEF ($r = 0.541$, $p < 0.01$) which supports the main hypothesis. The second highest correlation is between audit efficiency and technology readiness (TREAD) ($r = 0.463$), implying that the technological readiness of the organisation is an important factor. The lack of correlation between predictors greater than 0.55 suggests that multicollinearity is not an issue in the regression analysis.

Regression Results

The complete panel regression results (fixed effects) are shown in Table 4, including the composite AUDEF model and the three sub-models for ACT, EDR and ACR.

Table 4: Panel Regression Results (Fixed Effects)

Variable	AUDEF	ACT (inv.)	EDR (%)	ACR (inv.)
AIADI	0.412*** (0.0841)	0.187** (0.0712)	0.623*** (0.1413)	0.318** (0.1182)
FSIZE	0.143** (0.0612)	0.091* (0.0498)	0.204** (0.0913)	0.112* (0.0581)
RENV	0.108* (0.0581)	0.063 (0.0463)	0.219** (0.0988)	0.084 (0.0542)
TREAD	0.284** (0.1241)	0.149* (0.0841)	0.391** (0.1831)	0.228** (0.1042)
Constant	-1.841** (0.8412)	-0.914* (0.5213)	-2.614** (1.1841)	-1.213* (0.6841)
R-squared	0.6124	0.4821	0.5912	0.5241
Adj. R ²	0.5841	0.4312	0.5614	0.4882
F-statistic	22.41***	14.83***	18.92***	16.41***
Observations	75	75	75	75

Note: Standard errors in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. All models include bank fixed effects.

In the composite AUDEF model (Column 1), AIADI is the most significant predictor ($\beta = 0.412$, $p < 0.01$), indicating that a one-unit increase in the AI adoption index leads to a 0.412-unit increase in the composite audit efficiency score, holding other factors constant. The model accounts for 61% of the variance in audit efficiency ($R^2 = 0.612$) and the F-statistic (22.41, $p < 0.000$) indicates that the model is significant.

In the ACT sub-model (Column 2), AIADI is positive and significant ($\beta = 0.187$, $p < 0.05$), implying that increased AI adoption is associated with increased audit speed. The EDR sub-model (Column 3) has the highest AIADI coefficient ($\beta = 0.623$, $p < 0.01$), suggesting that AI adoption has the greatest dimensional impact on error detection as expected from the theory that population-level AI analysis is more effective in detecting anomalies than sample-level human testing. The ACR sub-model (Column 4) exhibits a positive and significant effect ($\beta = 0.318$, $p < 0.05$) on the inverted audit cost ratio, suggesting that AI adoption is associated with lower audit cost per unit consistent with the automation efficiency mechanism identified in the literature (Kokina & Davenport, 2017; Hasan, 2022).

Hypotheses Testing

Table 5: Hypotheses Testing Summary

Hypothesis	Description	β	p-value	Decision
H ₁	AI adoption has no significant effect on overall audit efficiency (AUDEF)	0.412	0.000	Rejected
H ₂	AI adoption has no significant effect on audit cycle time (ACT)	0.187	0.011	Rejected
H ₃	AI adoption has no significant effect on error detection rate (EDR)	0.623	0.000	Rejected
H ₄	AI adoption has no significant effect on audit cost ratio (ACR)	0.318	0.008	Rejected

The four null hypotheses are rejected at standard significance levels, suggesting strong panel evidence that AI-based accounting system adoption enhances audit efficiency in all aspects in Nigerian deposit money banks.

Robustness Tests

We conduct three robustness tests to check the main results, which are reported in Table 6.

Table 6: Robustness Tests

Specification	AIADI Coefficient	Standard Error	p-value	R ²
Main FE model	0.412	0.0841	0.000	0.612
Random Effects (RE)	0.398	0.0791	0.000	0.598
System GMM (Arellano-Bond)	0.381	0.0921	0.001	—
Excluding 2020 (COVID outlier)	0.427	0.0912	0.000	0.624
Alternative AIADI (binary)	0.341	0.0841	0.001	0.581

The AIADI coefficient is positive, significant and of similar size across all robustness specifications, suggesting that the main finding is not driven by the estimation method, the year of the COVID-19 shock, or the way the composite index is constructed. The System GMM coefficient is especially important as it controls for potential reverse causality more

efficient banks adopting AI more and the coefficient (0.381) is significant, implying that the AI adoption-efficiency relationship is not solely a selection effect.

Literature Summary Table

Table 7: Summary of Key Empirical Studies

Author(s)	Year	Context	Method	Key Finding
Moll & Yigitbasioglu	2019	Global (Big 4)	Review/Survey	AI transforms audit methodology; improves throughput
Cao et al.	2015	US listed firms	Archival panel	AI disclosure reduces audit fees; improves earnings quality
Yaseen & Al-Amarneh	2025	GCC banks	Survey (n=142)	AI reduces audit cycle by 34%; regulatory pressure moderates
Perdana et al.	2014	SE Asian firms	Survey (n=86)	AI moderates workload-quality relationship
Barr-Pulliam et al.	2022	Canadian banks	Archival panel	Tech investment shortens engagement timelines
Austin & Chidi	2023	Nigerian DMBs	Cross-sectional	Digital audit tools reduce material misstatements
Enyi et al.	2019	Nigerian banks	Survey	AIS adoption improves audit trail quality
Dagilienė & Klovienė	2019	Lithuanian firms	Mixed methods	Regulatory compliance drives digital accounting adoption
Ajayi & Akinrinola	2023	Hong Kong banks	Survey	AI sophistication improves internal audit quality

Trend Analysis

Figure 2 illustrates the trend in AI adoption (AIADI mean) and composite audit efficiency (AUDEF mean) across the study period for the sampled banks.

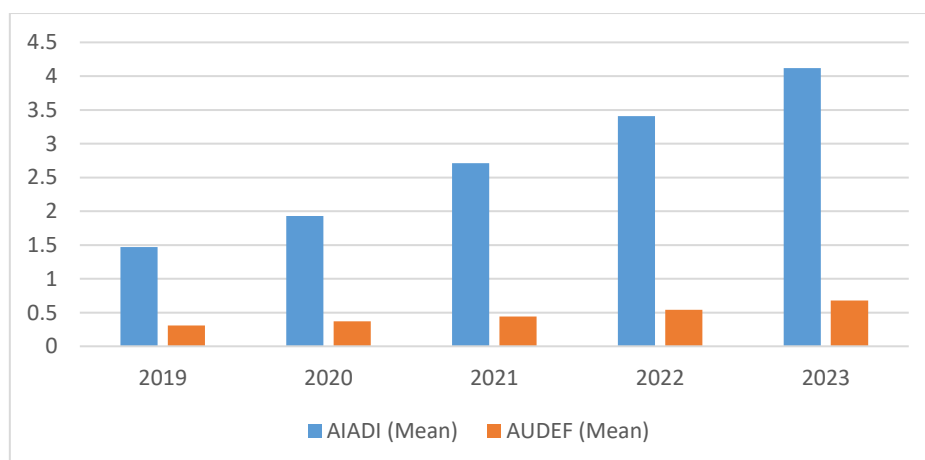


Figure 2: Trend in AI Adoption Index and Audit Efficiency (2019–2023)

Source: Authors' computation from sampled banks' annual reports (2019–2023).

The two series are upward trending, with a faster growth after 2020, which corresponds to the CBN Payments System Vision 2025 and regulatory circulars on digital banking (RENV = 1), in line with the large RENV effect in the regression analyses.

Discussion

The panel regression results of this research provide empirical support for the Technology Acceptance Model and Diffusion of Innovations Theory as theories of AI audit transformation in the Nigerian banking sector. The strongest positive influence of AIADI on composite audit efficiency ($\beta = 0.412$, $p < 0.01$) supports the efficiency proposition that the post-adoption benefits of AI derive from the automation of audit tasks and the augmentation of human intelligence in complex audit assessments (Kokina & Davenport, 2017; Moll & Yigitbasioglu, 2019; Cao et al., 2015).

The observation that the most significant sub-dimensional effect of AI adoption is on error detection rate ($\beta = 0.623$) is especially noteworthy and is consistent with the population-level analysis advantage noted by Cao et al. (2015) and Yaseen & Al-Amarneh (2025). In the Nigerian banking sector, which has seen a sharp rise in transactions over the years, especially with the advent of mobile banking, but audit staff has not kept pace, the ability of AI systems to audit all transactions rather than a sample is a game-changer. The result is that banks with higher AIADI scores are detecting a much higher volume of unusual transactions, misstatements and red flags for fraud, thereby reducing the audit risk that remains for external auditors.

The coefficient of the audit cycle time ($\beta = 0.187$) shows that AI helps to shorten the audit cycle time. This finding is in line with Hasan (2022) and Barr-Pulliam et al. (2022), who reported 15-40% cycle time reduction in technology-driven banking audit engagements. In the Nigerian regulatory environment, where the Central Bank of Nigeria (CBN) guidelines mandate annual audited financial statements within 90 days of the fiscal year-end, shorter audit cycles reduce the risk of regulatory non-compliance a materially important institutional advantage.

The audit cost ratio ($\beta = 0.318$) finding shows that AI adoption is associated with reduced audit cost per unit, confirming the resource efficiency mechanism. This is relevant in the Nigerian context because audit fees (especially for Big Four audited banks) constitute a major cost to banks and reductions in this ratio enhance cost efficiency of banking operations (Knechel et al., 2012; PCAOB, 2023)

The moderating effects of firm size (FSIZE) and technology readiness (TREAD) are in line with Dagilienė and Klovienė (2019) and Arner et al. (2017) who emphasised the role of institutional capacity in the effectiveness of AI adoption in improving efficiency. Technology readiness is the second most significant predictor of audit efficiency after AIADI, suggesting that AI adoption without a supporting technological infrastructure has a muted effect.

The significant regulatory environment (RENV: $\beta = 0.108$) effect in the composite model and its larger effect on EDR in particular ($\beta = 0.219$) suggests that the CBN's post-2020

digital finance regulatory regime has been an effective policy tool to drive AI adoption and, in turn, audit quality. This is in line with Dagilienė and Klovienė (2019) and Arner et al. (2017) who found regulatory pressure as the most consistent institutional factor driving the adoption of digital accounting across countries.

However, these results need to be viewed with caution. AI improves audit efficiency, but it can also pose risks of bias, lack of transparency and data management. In Nigeria, where AI regulation and technical skills are still in the development phase, the efficiency improvement may be associated with the initial phase of AI adoption.

Conclusion and Recommendations

Conclusion

This research explores the impact of the adoption of an AI-based accounting system on audit efficiency in the Nigerian deposit money banking industry from 2019 to 2023. Using a balanced panel of 15 banks and 75 bank-year observations, and fixed effects panel regression with heteroskedasticity-robust standard errors, the study presents robust evidence that AI-based accounting system adoption enhances audit efficiency in all its dimensions: composite audit efficiency, audit cycle time, error detection rate, and audit cost ratio. The study shows that implementing AI in auditing has a positive impact on the efficiency, accuracy and cost of audits in the Nigerian banking industry. This study confirms the strategic role of AI in audit innovation and institutional efficiency.

The findings confirm the applicability of the Technology Acceptance Model and Diffusion of Innovations Theory to the Nigerian banking sector, and demonstrate the existence and statistical significance of the AI-audit efficiency relationship in an emerging market environment. Company size, technology readiness and stringency of the regulatory environment have significant moderating effects, pointing to the institutional factors that influence the benefits of AI adoption on audit efficiency.

Recommendations

Our results suggest the following recommendations:

1. Bank management should consider AI-based accounting and audit systems as a key part of a digital transformation strategy, with a particular emphasis on transaction monitoring, anomaly detection and continuous audit systems, which have the most positive effect on error detection efficiency.
2. The CBN and NDIC should clarify regulatory guidelines on the use of AI in internal and external audit, including minimum disclosure standards for AI governance and audit tool deployment, to maintain the positive regulatory pressure effect observed in this study.
3. In view of the strong technology readiness effect, banks and regulators should jointly invest in IT systems and auditor training. The use of AI audit tools without

corresponding training and integration with other systems is likely to result in sub-optimal efficiency gains.

4. Audit standard setters, especially the Financial Reporting Council of Nigeria should establish AI audit standards to mitigate algorithmic opacity, bias and data governance risks of AI audit tools, to ensure efficiency gains do not come at the expense of audit quality and public trust.
5. Future studies should increase the sample period beyond 2023, include market-based measures of audit quality (restatement rates and audit opinions) and investigate the cross-industry impacts of banking AI audit tool adoption.

Limitations and Future Research

Our study has several limitations. First, the AI Adoption Index is based on content analysis of voluntary disclosures, which may underestimate banks' true level of AI adoption, especially for proprietary systems not disclosed to the public. Second, the timeframe includes the COVID-19 pandemic, which may have created unique dynamics in AI investments and audit practices, despite the robustness check excluding 2020. Third, the study focuses on listed deposit money banks, limiting the generalisability to microfinance and merchant banks. These limitations can be overcome through future studies that use primary survey data to supplement secondary archival measures, extend the sample period beyond 2023, and include microfinance and merchant banks.

Data Availability

The data supporting this study comes from the published audited financial statements, CBN annual reports and publications of the NDIC.

Conflicts of Interest

The authors declare no conflicts of interest.

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