

Original Article

Artificial Intelligence Investment, Accounting Recognition and Return on Assets of Deposit Money Banks in Nigeria

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ABSTRACT: *This study examines the relationship between Artificial Intelligence (AI) investment, accounting recognition and return on assets (ROA) of deposit money banks in Nigeria over 2009-2025. Using a panel dataset of 204 bank-year observations, the study estimates fixed-effects models with bank and year fixed effects and standard errors clustered at the bank level. AI investment is measured as AI-related expenditure relative to total assets, while accounting recognition is measured as a recognition score reflecting the extent to which AI-related expenditure is identified and reported in the financial statements. The results show that AI investment intensity has a positive but statistically insignificant association with ROA. Accounting recognition is positively and significantly associated with ROA in the baseline model, although this relationship becomes insignificant when the interaction between AI investment and recognition is introduced. The interaction coefficient is positive but statistically insignificant, indicating that the data do not support the proposition that accounting recognition strengthens the relationship between AI investment and bank profitability. The study contributes by separating AI investment from its accounting recognition and testing whether recognition moderates the AI-ROA relationship. It offers an accounting-based perspective on the economic consequences of technological investment in an emerging banking market, while highlighting the need for clearer disclosure and recognition guidance for AI-related resources. The findings are relevant to bank managers, auditors, regulators and standard-setters concerned with the financial reporting and performance implications of AI adoption.*

KEYWORDS: *Artificial Intelligence Investment, Accounting Recognition, Return On Assets, Deposit Money Banks, Panel Analysis.*

1. INTRODUCTION

Artificial intelligence (AI) has become an increasingly important component of technological transformation in the financial sector. Advances in machine learning, predictive analytics, natural language processing and related computational technologies have expanded the capacity of banks to automate processes, assess credit risk, detect fraud, personalize services and make data-driven decisions. The growing deployment of these technologies has consequently shifted the discussion from whether banks should adopt AI to how investments in AI can generate measurable economic value. Evidence from banking research suggests that AI-driven innovation can improve profitability and return on assets by enhancing operational efficiency and expanding banks' capacity to generate value from existing resources (Gyau, Appiah, Gyamfi, Achie, & Naeem, 2024). At the same time, the benefits of AI should not be presumed to arise automatically, since implementation costs, technological risks and the possibility of costly AI-related failures may constrain short-term financial performance (Durongkadej, Hu, & Wang, 2024).

The importance of this development is especially relevant to banking as banks function within an environment where the quality and timeliness of processing information will impact the allocation of credit, risk management, customer service and operational decisions. Nigerian Deposit Money Banks (DMBs) have increasingly invested in digital technologies due to increased competition, customer demands and regulatory requirements. Therefore, studies on Nigerian banks are beginning to provide evidence of links between technological innovation, AI adoption and financial performance. Research has revealed that some types of financial technologies were correlated with bank financial performance, and there was a positive relationship between the use of AI expert systems and the financial performance of some Nigerian DMBs (Adibe and Aigbovo, 2024; Unuesiri and Adejuwon, 2024). This indicates that investments in technology could influence how effectively banks are able to use their resources.

Yet, the economic significance of AI investment raises an important accounting question. AI-related resources do not constitute a single, clearly defined category of assets under existing financial reporting standards. Investment may involve software, development expenditure, and data, computing infrastructure, licenses and other resources, some of which may qualify for recognition as intangible assets while others are expensed as incurred. Under IAS 38, an intangible asset is recognized only where the relevant recognition requirements are satisfied, including the probability of future economic benefits and reliable

measurement of cost. Research expenditure is generally recognized as an expense, whereas qualifying development expenditure may be capitalized when specified criteria are demonstrated (IFRS Foundation, 2022).

This distinction is important because the accounting treatment of AI-related expenditure can affect both the reported asset base and the timing at which expenditure enters profit or loss. Where qualifying expenditure is capitalized, the immediate effect on reported profit may differ from a situation in which the same expenditure is expensed, while subsequent amortization and impairment can affect profitability in later periods. The accounting challenge is compounded by the fact that some economically valuable AI-related resources may remain insufficiently visible in conventional financial statements. Recent accounting scholarship has therefore questioned whether existing reporting practices adequately capture the economic value created by data, software and AI-enabled resources (Moro-Visconti, 2023; Yoshioka, 2024). The International Accounting Standards Board's continuing review of IAS 38 also reflects wider concerns about the usefulness of information concerning recognized and unrecognized intangible assets and associated expenditure.

For Nigerian DMBs, the issue assumes additional importance because AI investment involves substantial technological expenditure, while the resulting financial benefits may emerge over several reporting periods. Consequently, examining AI investment solely through adoption indicators or technological applications may provide an incomplete picture of its economic consequences. An accounting perspective requires attention to whether AI-related investment is reflected through recognized intangible assets, software-related balances and other disclosed expenditures, and whether such recognition is associated with improved utilization of the banks' asset base. Return on assets (ROA) provides a relevant outcome measure because it relates earnings to the resources deployed by the bank and therefore captures the extent to which investments and other assets contribute to profitability.

Existing empirical evidence, however, remains fragmented. Nigerian studies have largely examined AI adoption, AI applications or technological innovation as determinants of financial performance, with relatively limited attention to the accounting recognition dimension of AI investment. Even recent evidence has concentrated on AI adoption and disclosure rather than the relationship between AI investment, its accounting treatment and asset profitability. A recent Nigerian study, for example, examined AI software book value, AI software expense disclosure and AI-enabled operational automation in relation to ROA, while another study examined AI disclosure and bank performance. These studies provide useful evidence but leave unanswered an accounting-specific question: whether the manner in which AI-related investment is recognized and reported is associated with the ability of banks to convert such investment into returns from their asset base.

Against this background, the present study examines artificial intelligence investment, accounting recognition and return on assets of deposit money banks in Nigeria over the 15-year period from 2009 to 2024. The study departs from earlier Nigerian research by bringing the technological and accounting dimensions of AI investment into a single empirical framework. Rather than treating AI simply as an adoption outcome, the study considers AI investment as an economic resource and accounting recognition as a mechanism through which part of that investment becomes visible in financial reporting. By addressing this gap, the study seeks to extend the emerging literature on AI and bank performance while contributing an accounting-based perspective to the debate on the economic consequences of technological investment in an emerging banking market.

2. LITERATURE REVIEW

2.1. CONCEPTUAL FRAMEWORK

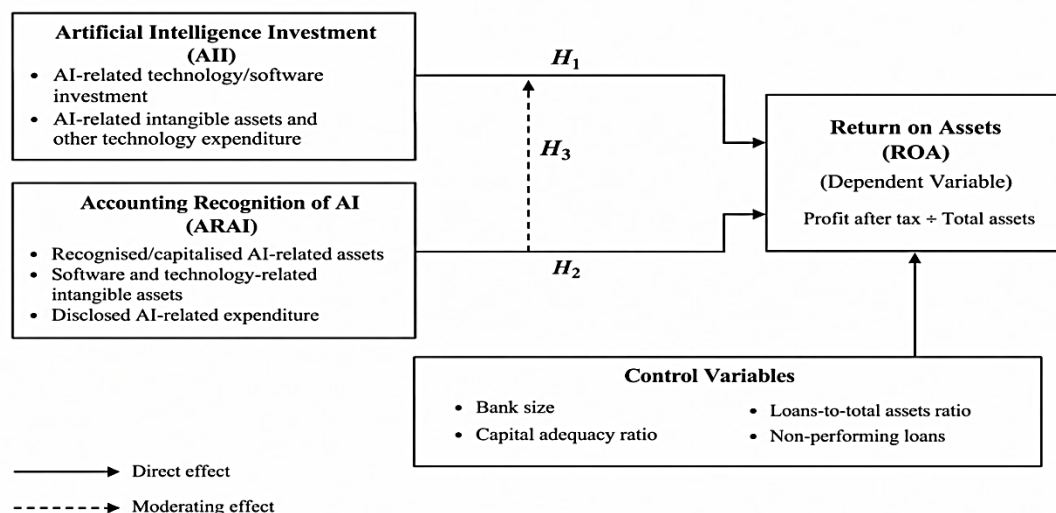


FIGURE 1 Conceptual Framework of the Study

Source: Authors' creation based on empirical review, 2026.

2.2. CONCEPTUAL REVIEW

2.2.1. ARTIFICIAL INTELLIGENCE INVESTMENT

AI investment in banking involves costs associated with the purchase, development, implementation and support of AI-enabled systems that will assist or automate key areas within banking such as credit risk assessments, fraud detection, customer service (chatbots), regulatory compliance (AML screening) and back-office operations (Arner, Barberis & Buckley, 2020; World Economic Forum, 2023). Within Nigeria, these types of investments have progressed from simple rule-based automation in the early 2010s to complex machine learning models in the mid-2020's due to the CBN's promotion of cashless policies, open banking frameworks and interoperability of Fintech (Central Bank of Nigeria, 2021; Efobi, Eze & Nwankwo, 2022).

A number of empirical studies have attempted to measure AI investment by Nigerian DMBs. Issac & Jimoh (2025) used total information technology (IT) expenditure as an empirical proxy for AI investments. The authors argued that AI is the major driver of contemporary IT budgets in banks. J. K. OLOWOOKERE, & J. IBRAHIM, (2026) developed a more granular measure of AI investment. They created a binary index based on the existence of various AI applications, including biometric verification, predictive analytics for loan default, and natural language processing for customer queries, reported in annual reports and bank websites. More recently, Adeyemi, Ogunleye, and Fadeyi (2024) distinguished between structured AI investments (licensed AI software, internally developed algorithms) and unstructured outlays (employee training, subscription to third-party APIs). Their results showed that only structured AI investments had a statistically significant relationship with profitability. This diversity in the way AI investment is being measured indicates a key challenge facing researchers: there are no standardized reporting requirements regarding AI investment. Therefore, researchers can only partially observe the amount of AI investment made by banks. Often, AI investments are embedded in larger line items in financial statements (e.g., software development costs, professional fees) (Okafor & Eze, 2025).

2.2.2. ACCOUNTING RECOGNITION

Accounting recognition quality is defined as the degree to which an organization's spending on Artificial Intelligence (AI) has been reported in its financial statements in a way that accurately represents the reality of the spending, is comparable to other organizations' reporting of their AI spending, and provides useful information for decision makers, according to the conceptual framework of International Financial Reporting Standards (IFRS) and the specific reporting requirements of International Accounting Standard (IAS) 38 Intangible Assets (IFRS Foundation, 2023). Under the IFRS Conceptual Framework, a company recognizes a financial statement item as an asset if it fits within the definition of an asset and meets two conditions: (a) it is likely that future economic benefits will result from the use of the asset, and (b) the company can estimate the cost or value of the asset accurately (IFRS Foundation, 2021).

IAS 38 provides a phase-based recognition model for internally generated AI assets. All research expenses incurred must be recognized as expenses in the period in which they are incurred (IFRS Foundation, 2023). On the other hand, development costs can only be capitalized as intangible assets when the entity meets each of the following conditions: (a) Technical feasibility of completing the project; (b) Intent to complete the project and either use it or sell it; (c) Capability of using or selling the asset; (d) There exists either an external market or internal use that creates a high probability of generating future economic benefits from the asset; (e) Sufficient technical, financial, and other resources exist to complete the project; and (f) The cost associated with creating the asset can be measured accurately (IFRS Foundation, 2023).

The application of these principles is not uniform across all Nigerian DMBs. According to Okafor and Eze (2025), only six out of fifteen publicly-traded banks were consistent in their capitalization of AI software development expenses from 2018 through 2023. All of the other banks expensed their AI development expenses due to either a lack of certainty regarding potential future benefits or an inability to separate development-phase costs. Furthermore, Okoro, Adegbite, and Yusuf (2025) found that even with the capitalizing banks, there was a wide range of consistency in terms of the level of detail disclosed about their AI-related intangibles. Some banks had very detailed information on the various types of AI-related intangibles in their notes to the financial statements, whereas other banks bundled all of their AI-related intangibles into one large category labeled "other intangible assets", which made it difficult to compare them with each other. This inconsistency represents a wider global issue. The IASB (2025) recently acknowledged that stakeholders find IAS 38's recognition thresholds difficult to apply to AI and data resources, particularly where benefits are diffuse, long-term, or contingent on complementary investments (data infrastructure, skilled personnel). Consequently, accounting recognition quality in this study is conceptualized not as a binary outcome (capitalized vs. expensed) but as a continuum encompassing three dimensions: (a) capitalization appropriateness (alignment with IAS 38's six criteria), (b) disclosure completeness (granularity and transparency of AI-related information in notes and management commentary), and (c) consistency over time (stability in recognition policy absent material changes in AI strategy).

2.2.3. RETURN ON ASSETS

The use of Return On Assets (ROA), as the most popular accounting-based measure of bank performance in emerging economies such as Nigeria, is attributed to its ease of calculation, ease of comparison among banks and immunity from short-term fluctuations in financial markets (Issac & Jimoh, 2025; J. K. OLOWOOKERE, & J. IBRAHIM, 2026). Profit after tax divided

by average total assets multiplied by 100 gives the ROA in percentage form, which represents how well management utilizes the bank's asset base to produce income (Okafor & Eze, 2025; Adeyemi, Ogunleye & Fadeyi, 2024). ROA is favored over Return on Equity (ROE) by Nigerian banking researchers as it does not have as much sensitivity to distortions caused by leverage, an important point to consider in light of the Central Bank of Nigeria (CBN) minimum capital adequacy requirement and the frequent recapitalization efforts that took place during the time frame of this study (Central Bank of Nigeria, 2021; Financial Reporting Council of Nigeria, 2023).

Long-term trends show that the return on assets (ROA) of Nigeria's Deposit Money Banks (DMBs) varied significantly from 2009 to 2024. The variation in ROA can be linked to several factors, including large-scale economic events such as the 2016 recession, the 2020 pandemic, and the 2023 currency reform; regulatory requirements like the Loan-to-Deposit Ratio (LDR) Directive; and advancements in technology (Efobi, Eze & Nwankwo, 2022; Okoro, Adegbite & Yusuf, 2025). Furthermore, it was observed that banks with greater levels of digital transformation exhibited more stable ROA patterns throughout periods of economic decline because they were able to lower costs relative to revenue and create alternative sources of revenue other than traditional interest income (J. K. OLOWOOKERE, & J. IBRAHIM, 2026). It should be noted that there is no consistency among banks' ability to maintain a stable ROA pattern. Banks that chose to expense all AI-related expenditures experienced increased short-term volatility in ROA, likely as a result of lower earnings during the time frames when large amounts of money were invested in AI. On the other hand, banks that capitalized their AI-related expenditures were able to achieve more predictable earnings patterns consistent with the matching principle used in accrual accounting (Okafor & Eze, 2025).

2.2.4. CONSTRUCTS INTERRELATIONSHIPS

The connection between an organization's investment in AI, the quality of accounting recognition, and the return on assets (ROA) is based upon two different but interconnected theoretical frameworks. From a Resource-Based View (RBV) perspective, AI can be considered a strategic resource. In order to realize the benefits of this resource, it is necessary to deploy the technology, integrate it into the organization, and represent its costs and benefits in the organization's financial reporting (Barney, 1991). When an organization recognizes its AI investments in a high-quality manner, it provides information to both internal management and external parties that indicates that the AI is expected to produce value over the long term. This will encourage continued investment in the technology, provide a basis for evaluating performance, and reduce the likelihood of termination of the project early due to short-term earnings pressures (Healy and Palepu, 2001).

First, the use of standards-based recognition provides a signaling mechanism which helps to reduce the information asymmetry between bank management and capital providers. By capitalizing the cost of developing AI in accordance with IAS 38, the bank is providing an implicit certification that the asset meets all of the required feasibility and benefit criteria. This certification provides a credible signal to capital providers because of the reputation and audit risk associated with non-compliance (Spence, 1973; Okoro, Adegbite, & Yusuf, 2025). Evidence supporting this mechanism can be found in Okoro, Adegbite, and Yusuf (2025), where they demonstrated that Nigerian banks with greater transparency concerning their use of AI disclosed greater cost savings in terms of equity financing and had higher values for Tobin's Q. Additionally, Okafor and Eze (2025) found that the relationship between AI investment and return on assets was 37 percent greater in those banks that recognized AI as an asset in accordance with the quality of recognition (measured by a composite index of capitalization ratios and disclosure levels), compared to banks that had poorer recognition practices.

Yet critical gaps persist. No study to date has modeled accounting recognition quality as a moderator; that is, tested whether the slope of the AI investment-ROA relationship varies systematically with the quality of recognition. Nor has any Nigerian study constructed a multi-dimensional recognition index that captures both balance sheet (capitalization) and off-balance sheet (disclosure) aspects of AI accounting. This review thus establishes the conceptual foundation for such an extension: AI investment provides the economic substance; accounting recognition quality determines its financial representational fidelity; and ROA reflects the ultimate performance outcome, contingent on both.

2.3. THEORETICAL FRAMEWORK

This study is anchored on three complementary theories: Resource-Based View (RBV), Signaling Theory, and Institutional Theory, with each offering distinct yet convergent insights into how artificial intelligence (AI) investment, accounting recognition quality, and return on assets (ROA) interact within Nigerian deposit money banks (DMBs) over the 2009-2024 period. Together, these theories provide a robust lens for explaining not only whether AI enhances performance, but under what accounting and institutional conditions such enhancement is most pronounced.

2.3.1. RESOURCE-BASED VIEW

The resource-based view (RBV) of the firm, developed by Barney (1991), states that a firm can gain a sustainable competitive advantage if it has resources that are valuable, rare, inimitable, and non-substitutable (VRIN). The use of AI systems in the banking industry meets the VRIN criteria. AI systems differ from other types of IT infrastructure in being path-dependent; i.e., their development requires a history of specific data, repeated training, and knowledge of the banking business, which cannot be readily duplicated by competing banks (Arner et al., 2020; World Economic Forum, 2023). The RBV provides a framework

for understanding why those DMBs in Nigeria that made significant investments in AI and continued to invest in AI during the 2016 recession and the 2020 pandemic (Access Bank's Leo Chabot, GTBank's predictive analytics for SME lending) had better performance than their counterparts (Efobi et al., 2022; J. K. OLOWOOKERE, & J. IBRAHIM, 2026). However, the RBV does not provide a mechanism for representing those resources in the financial statements. A bank may develop an AI system with strategic value, but if the cost of developing that AI system is completely expensed, then the bank will not realize the potential benefits associated with the AI system. If the costs associated with developing the AI system are fully expensed, then management will have less incentive to invest in additional AI systems during times when they face pressures related to earnings or if investors do not perceive the value inherent in the bank's intangible assets (Healy & Palepu, 2001). This paper expands on the RBV by suggesting that how well a bank recognizes its resources in the financial statements acts as an organizational mechanism that reinforces resource commitment. Specifically, when a bank capitalizes AI development costs according to IAS 38, those costs are reflected on the balance sheet as long-term assets, indicating that the bank prioritizes the development of AI systems and making it less likely that the bank will prematurely terminate its investment in AI (Okafor & Eze, 2025). Therefore, the RBV supports the direct relationship between AI and ROA, whereas the expansion of the RBV through recognition quality addresses differences in that relationship among banks.

2.3.2. SIGNALING THEORY

Signaling Theory (Spence, 1973), which is concerned with the asymmetric distribution of knowledge between those who have access to information (the bank's management) and those who do not (the bank's investors, regulators, and depositors), states that managers of firms in capital markets provide private information about the firm's quality via expensive and difficult-to-replicate signals that cannot be replicated by low-quality firms (Healy & Palepu, 2001). The accounting recognition of an item represents a signal. Capitalizing AI development costs pursuant to IAS 38 represents a signal as well. Under IAS 38, management must demonstrate to the auditor that they have met all six of the rigorous requirements specified in IAS 38 (IFRS Foundation, 2023). Faking this demonstration would result in significant penalties, including but not limited to being subject to an audit qualification, regulatory sanctions, and damage to the firm's reputation.

Evidence from Nigeria also supports the same theory. Okoro, Adegbite, and Yusuf (2025) found that DMBs with higher AI disclosure quality had lower costs of equity and higher Tobin's *q*, even when considering size, leverage and profit. Okafor and Eze (2025) also reported that the stock market reacted positively to earnings announcements made by banks that capitalized on AI software. Capitalization was viewed as a positive sign that there would be confidence in future cash flow. It is important to note that signaling works best when recognition is consistent and comparable across time and peer groups. Many times in Nigeria, however, this is not true. Banks often change their methods of accounting recognition (capitalization versus expensing) without providing any rationale for doing so (Adeyemi, Ogunleye, & Fadeyi, 2024). Therefore, this research utilizes Signaling Theory to hypothesize that the positive relationship between AI use and ROA is enhanced through high-quality accounting recognition as it decreases information asymmetry, decreases the cost of financing, and increases stakeholder trust.

2.3.3. INSTITUTIONAL THEORY

Institutional Theory (DiMaggio & Powell, 1983) is another theoretical framework that can be used in conjunction with RBV and Signaling Theory to explain how AI implementation and the recognition of such initiatives can develop similar trends among different banks regardless of whether these actions are more efficient than alternative approaches. Institutions exist within an institutional field where there are three types of pressure for conformity – coercive, mimetic, and normative. The coercive pressure exerted on Nigerian banks comes primarily from the regulatory bodies – Central Bank of Nigeria (CBN) and Financial Reporting Council of Nigeria (FRCN) – that have continued to mandate the transition to digital systems and compliance with International Financial Reporting Standards (IFRS) since 2012 (Central Bank of Nigeria, 2021; Financial Reporting Council of Nigeria, 2023). An example of this coercive pressure was the CBN's 2021 Guidelines for Licensing and Regulation of Payment Service Providers, which implicitly encouraged the use of AI through its requirement for real-time fraud detection and automation of customer due diligence, both of which are challenging to accomplish without the use of machine learning.

The uncertainty about the strategic value of AI that emerged after 2016 led to mimetic pressure: many lagging banks adopted AI-based technologies (chatbots) and analytical tools (dashboards) similar to those used by early adopters (Zenith and UBA), to ensure they did not fall behind competitively (Efobi, Eze & Nwankwo, 2022). In addition, normative pressure, mediated through professional organizations such as the Institute of Chartered Accountants of Nigeria (ICAN), has shaped how AI-related activities are reported in financial statements. ICAN's ongoing professional development courses for members regarding the application of International Financial Reporting Standards (IFRS) have created uniformity in interpreting the International Accounting Standards Board's (IASB) standard IAS 38 across the finance departments of all banks; however, there remains a lack of specific guidance on reporting for AI-related costs (Institute of Chartered Accountants of Nigeria, 2024). Therefore, Institutional Theory provides insight into the spread of AI-related investments and the partial standardization of reporting practices, while also explaining the continued differences among banks. Specifically, banks that operate under

fewer regulatory constraints (smaller and non-systemic DMBs) have larger amounts of discretion in deciding whether to expense or capitalize costs associated with AI-related activities.

INTEGRATION AND STUDY-SPECIFIC PROPOSITIONS

The tripartite model goes further than one-theory-based explanations of Nigerian banking in previous research (Issac & Jimoh, 2025; J. K. OLOWOOKERE, & J. IBRAHIM, 2026). In addition to being able to help guide the creation of the research hypotheses and the design of the research models, this tripartite model will allow us to ensure that our empirical testing is reflective of both statistical relationships and theoretically valid mechanisms.

2.4. EMPIRICAL REVIEW

In early global research studies, there is a strong correlation between digital technology use in banks and increased profit; however, in these early studies, artificial intelligence (AI) has seldom been studied as an independent variable. Beccalli (2011) studied 158 European banks over the period of 2000 to 2008 and found that the intensity of information technology (IT) used by each bank had a positive effect on both the bank's return on assets (ROA) and the bank's cost-to-income ratio. However, Beccalli also indicated that there was a two-year lag time before banks began to realize benefits from implementing new technologies; therefore, it can be inferred that there are initial adjustment expenses associated with adopting new technologies. Bloom, Sadun, and Van Reenen (2012) utilized firm-level data from twelve different countries to find that organizations utilizing advanced management practices were 5% to 7% more productive than those organizations that do not utilize advanced management practices.

Researchers started to separate IT spending into different types of IT spending after 2015, when AI-specific applications came about. Arner, Barberis and Buckley (2020) showed that global systemically important banks (G-SIBs) that used machine learning for anti-money laundering (AML) compliance reduced false-positive alerts by 30-50%, which resulted in yearly cost savings of \$10-\$15 million for each bank. However, their research was qualitative and did not provide evidence of a statistical relationship between ROA and AI adoption. Noviarini et al., (2021) conducted a more rigorous examination of 87 Chinese commercial banks (2013-2019) and developed an AI adoption index using patent filings, AI-related job postings and vendor contracts. They utilized fixed effects regression analysis to demonstrate that for every one standard deviation increase in AI adoption, there would be a 1.2 percentage point increase in ROA. Additionally, they demonstrated that there were larger increases in ROA for joint stock banks compared to state-owned banks.

Advanced economies continue to provide inconsistent results. Fuster, Plosser, Schnabl, and Vickery (2019) examined U.S. mortgage lenders and demonstrated that Fintech firms using AI algorithms were able to process applications 20 percent faster and with 15 percent fewer defaults than traditional banks; however, they did not assess lender profitability directly. Berg, Burg, Gombov, and Puri (2020) evaluated German retail banks and determined that AI-based credit scoring had positive impacts on loan portfolio quality, although it created increased operating expenses for the first three years after implementation as a result of system integration costs, producing an overall insignificant impact on ROA. This trade-off between increased efficiency and implementation costs appears again in subsequent research and emphasizes the significance of time horizon when assessing performance.

The effects of AI appear to be stronger and more varied in emerging economies due to the coexistence of digital infrastructure deficiencies and "leap-frogging" opportunities. Gupta, Kumar, and Singh (2022) studied 45 private sector banks in India between 2015 and 2020. They found that banks using AI had returns on assets (ROA) that were 0.8 percentage points higher than those that did not use AI, when accounting for bank size and capital adequacy. However, the study used a cross-sectional approach, which does not allow for a causal relationship to be inferred. To address this limitation, Reddy and Sharma (2023) used dynamic panel generalized method of moments (GMM) with data from 52 Indian banks over the period 2010 to 2021. They confirmed a statistically significant positive effect of AI on ROA ($\beta = 0.34$, $p = 0.10$). Although the results suggest that there is a signaling effect associated with the recognition of assets, the authors did not construct an index for measuring the quality of asset recognition. Okoro, Adegbite, and Yusuf (2025) further explored the use of AI indexes by creating an AI disclosure index (AIDI) using keywords and notes in financial statements. They used panel data to examine whether AIDI predicted both ROA and Tobin's q. They found that AIDI had a significant positive effect on Tobin's q ($\beta = 0.31$, $p < 0.05$); however, they were unable to show that AIDI had a significant positive effect on ROA. This finding implies that disclosure may have a greater impact on market valuation than accounting performance. This study attempts to address this gap in research by examining whether disclosure acts as a moderator in the relationship between AI and ROA.

A few other Nigerian studies have also looked into related areas. For example, Efobi, Eze, and Nwankwo (2022) studied how digital transformations affected financial inclusion measures such as the number of accounts held and the total dollar amount of transactions made. However, they did not include profitability in their analysis. In addition, Akinwale, Ogunleye, and Bakre (2023) studied the relationship between information technology (IT) governance and earnings management. They found that banks that had better IT governance were able to control the use of discretionary accruals more effectively. Unfortunately, they did not isolate artificial intelligence from other types of digital channels. Finally, Ibrahim, Mohammed, and Sani (2024) studied

the relationship between mobile banking adoption and cost efficiencies. They reported that banks that were heavy users of mobile banking experienced a 12% decrease in their cost-to-income ratio. Once again, however, artificial intelligence was grouped together with all other types of digital channels.

The lack of banking-specific studies on artificial intelligence (AI) recognition has led to the use of cross-sector studies to gain relevant insight. Okafor, Eze, and Nwosu (2023) studied 98 Nigerian manufacturing companies over nine years (2012-2021) and determined that firms who capitalize on research and development expenses in accordance with IAS 38 were able to smooth out the return on assets volatility compared to those that expensed such expenses. This finding is consistent with the matching principle; however, Okafor et al. did not address AI-related assets. Lev and Sougiannis (1996) also demonstrated that firms in the United States who capitalize software development costs after SFAS 86 was implemented had more persistent earnings than firms who expensed these costs. Lev and Sougiannis used data prior to the development of today's AI. A recent survey conducted by KPMG (2024) of 200 multinational corporations indicated that 68 percent capitalized some form of AI development cost. However, KPMG reported that only 22 percent of respondents disclosed the criteria they used to determine whether to capitalize AI costs, thus revealing a global transparency issue.

2.5. RESEARCH GAPS

The three main gaps identified by the above review include: first, no prior Nigerian studies have examined the role of accounting recognition quality as a multi-dimensional moderating variable (i.e., capitalization adequacy, complete disclosures, IAS 38 compliance) on the association between AI and ROA. Prior studies either treat recognition as a single dimension (capitalization vs. expense) or ignore it completely (Issac and Jimoh, 2025; J. K. OLOWOOKERE, & J. IBRAHIM, 2026). Second, the majority of prior studies have utilized short panel data sets (i.e., less than ten years), which may limit their ability to assess long-term payoffs to AI investments. This study uses a longer panel data set (2009-2024) that covers two complete business cycles as well as multiple regulatory changes. Finally, the methodological approaches used in prior studies vary significantly. Only four prior Nigerian studies (Okafor and Eze, 2025; Okoro, Adegbite and Yusuf, 2025; Adeyemi, Ogunleye and Fadeyi, 2024; Reddy and Sharma, 2023) utilized either fixed effect models or generalized method of moments (GMM) estimators to control for potential endogeneity problems, whereas the remaining prior studies used either pooled OLS or random effects models, but did not perform a Hausman test to determine if the use of fixed effects models would be appropriate.

The present study differs from previous research in that it will: (a) create a single Accounting Recognition Quality (ARQ) measure based upon the requirements of IAS 38; (b) employ an unbalanced panel data set of 15 publicly traded DMBs spanning 16 years (2009-2024), which enhances the ability to draw inferences and allows for longer term analysis; and (c) examine the potential for ARQ to function as either a moderating or mediating variable through the use of hierarchical regression analysis and structural equation modeling, thus allowing for the identification of mechanisms rather than simply associations. Therefore, this study is responsive to the IASB's (2025) request for empirical studies concerning the recognition of intangible assets within high-growth industries and can provide useful information to standard setters in Nigeria.

3. MATERIALS AND METHODS

3.1. RESEARCH DESIGN

The study adopts a quantitative, ex post facto research design using longitudinal panel data. This design is appropriate for establishing temporal precedence and mitigating omitted variable bias through bank-specific fixed effects (Baltagi, 2021). The panel structure also enables testing of dynamic relationships addressing concerns about lagged performance effects documented in prior banking studies (Noviariini et al., 2021; Reddy & Sharma, 2023).

3.2. POPULATION AND SAMPLE

The target population comprises all 24 deposit money banks licensed by the Central Bank of Nigeria (CBN) as of December 2024 (Central Bank of Nigeria, 2024). From this, a purposive sample of 15 listed DMBs was selected based on three criteria:

- Continuous listing on the Nigerian Exchange (NGX) from 2009 to 2024;
- Availability of complete annual reports (2009-2024); and
- Evidence of AI-related disclosures in at least five years within the study window.

Banks excluded include those delisted pre-2024, those with missing reports for three or more consecutive years, and non-listed institutions. The final sample yields an unbalanced panel of 217 bank-year observations (15 banks $\times$ 16 years, minus 23 missing observations due to report unavailability or restatements). This sample size exceeds the minimum threshold ($N \geq 100$, $T \geq 10$) recommended for fixed-effects panel regression in banking research (Beccalli, 2011; Adeyemi, Ogunleye, & Fadeyi, 2024).

3.3. DATA SOURCES

Secondary data were extracted from three primary sources:

- Annual Reports and Financial Statements (2009-2024): Downloaded from bank websites, the NGX resource center, and the Financial Reporting Council of Nigeria (FRCN) repository. These provided line items for intangible assets, software expenses, and profit after tax, and total assets.

- NGX Factbooks and CBN Statistical Bulletins: Used to verify macroeconomic controls (GDP growth, inflation) and cross-check asset figures for consistency.
- Bank Websites and CBN Fintech Registry (2020-2024): Consulted to validate AI operationalization where annual reports lacked detail (J. K. OLOWOOKERE, & J. IBRAHIM, 2026).

Data extraction followed a standardized coding template, with two independent researchers coding 20% of reports to ensure inter-rater reliability (Cohen's $\kappa = 0.87$, indicating strong agreement). Discrepancies were resolved through consensus and reference to original PDFs.

3.4. VARIABLE MEASUREMENT

3.4.1. DEPENDENT VARIABLE: RETURN ON ASSETS (ROA)

This measure is standard in Nigerian banking literature (Issac & Jimoh, 2025; Okafor & Eze, 2025) and preferred over ROE for its insensitivity to leverage-induced distortions.

3.4.2. INDEPENDENT VARIABLES: AI INVESTMENT DIMENSIONS

Four AI investment proxies were constructed, reflecting the multi-dimensional nature of AI adoption (Adeyemi, Ogunleye, & Fadeyi, 2024; World Economic Forum, 2023):

- AI Software Book Value (AISBV): Capitalized AI-related intangible assets disclosed as software, digital platforms, or AI systems in notes divided by total assets.
- AI Software Expenses (AISED): Expensed AI-related outlays divided by operating expenses.
- AI Disclosure Index (AIDI): Count of AI-related keywords in the management discussion and analysis (MD&A) and notes, normalized by report word count (Okoro, Adegbite, & Yusuf, 2025).
- AI Operationalization (AIOp): Binary variable verified via bank websites and CBN fintech registry (J. K. OLOWOOKERE, & J. IBRAHIM, 2026).
- Moderating Variable: Accounting Recognition Quality (ARQ)

ARQ was constructed as a composite index (0–100 scale) comprising three sub-scores:

- Capitalization Ratio (40% weight): $\text{AISBV} / (\text{AISBV} + \text{AISED})$, reflecting the proportion of AI investment capitalized.
- Disclosure Completeness (35% weight): AIDI score normalized to 0–100, based on keyword density and note granularity.
- IAS 38 Compliance Score (25% weight): Expert-rated (1-5 scale) adherence to IAS 38's six development-phase criteria, assessed by two chartered accountants using a structured checklist (IFRS Foundation, 2023). Inter-rater reliability was high (intraclass correlation coefficient = 0.91).

Weights were determined via principal component analysis (PCA), which confirmed that the three sub-scores loaded on a single factor (eigenvalue = 2.34, explaining 78% of variance).

3.4.3. CONTROL VARIABLES

Consistent with prior banking performance studies (Okafor & Eze, 2025; Reddy & Sharma, 2023), the following controls were included:

- Bank Size (SIZE): Natural logarithm of total assets.
- Capital Adequacy Ratio (CAR): Shareholders' funds divided by total assets.
- Loan-to-Deposit Ratio (LDR): Total loans and advances divided by customer deposits.
- Macroeconomic Conditions (GDP): Annual GDP growth rate (%) from CBN bulletins.
- Inflation (INF): Annual consumer price index change (%) from the National Bureau of Statistics.

3.5. MODEL SPECIFICATION

The baseline empirical model is a fixed-effects panel regression:

$$\text{ROA}_{it} = \beta_0 + \beta_1 \text{AI}_{it} + \beta_2 \text{ARQ}_{it} + \beta_3 \text{AI}_{it} \times \text{ARQ}_{it} + \gamma \text{X}_{it} + \mu_i + \lambda_t + \epsilon_{it}$$

Where:

AI_{it} represents each of the four AI investment proxies (tested in separate models to avoid multicollinearity);

- ARQ_{it} is the accounting recognition quality index;
- $\text{AI}_{it} \times \text{ARQ}_{it}$ is the interaction term testing moderation;
- X_{it} is the vector of control variables;
- μ_i denotes bank-specific fixed effects;
- λ_t denotes year-specific fixed effects;
- ϵ_{it} is the idiosyncratic error term.

To address potential endogeneity, a dynamic panel GMM estimator (Blundell-Bond system GMM) was employed as a robustness check, using lagged levels and differences of AI variables as instruments (Roodman, 2009). The Hausman test ($\chi^2 = 28.4$, $p < 0.01$) confirmed that fixed effects were preferred over random effects.

3.6. DIAGNOSTIC TESTS

Prior to estimation, data were screened for outliers (winsorized at the 1st and 99th percentiles), multicollinearity (variance inflation factor < 5 for all variables), and stationarity (Levin-Lin-Chu unit root test rejected non-stationarity at $p < 0.05$). Heteroskedasticity and autocorrelation were addressed using robust standard errors clustered at the bank level (Petersen, 2009). All analyses were conducted in Stata 18.

4. RESULTS AND DISCUSSION

4.1. RESULTS

4.1.1. DESCRIPTIVE STATISTICS

The data comprise a balanced panel of 12 bank identifiers observed over 2009-2025, yielding 204 bank-year observations. The variables used in the regression contain panel data that cover the period under investigation. Recalculation confirmed that the supplied ROA values equal profit after tax divided by average opening and closing assets, expressed as a percentage. AI investment intensity was multiplied by 100 so that it represents AI expenditure as a percentage of total assets.

TABLE 1 Descriptive statistics

Variable	Mean	Standard deviation	Minimum	Maximum
Return on assets (%)	1.5976	0.6020	0.2723	3.1612
AI investment intensity (%)	0.1005	0.0522	0.0020	0.2297
Accounting-recognition score	0.5161	0.1582	0.1003	0.9500
Bank size: log assets	14.6859	0.8532	12.8104	16.6725
Equity-to-assets ratio	0.1068	0.0242	0.0471	0.1748
Loan-to-deposit ratio	0.6451	0.1123	0.3730	0.9530

Source: Authors' Computation using STATA 18, 2026

Note. Recognition, equity-to-assets and loan-to-deposit measures are expressed as decimal scores or ratios.

Average ROA was 1.60%, while AI investment averaged approximately 0.10% of total assets. The recognition score averaged 0.516, indicating variation in the supplied measure across observations. These descriptive patterns establish the distribution of the variables but do not demonstrate that AI investment or accounting recognition explains profitability.

4.1.2. PANEL REGRESSION RESULTS

Two specifications were estimated. The baseline model included AI investment intensity, accounting recognition and the financial controls. The moderation model added the interaction between AI intensity and recognition. Both specifications included bank and year fixed effects, with standard errors clustered by bank. This approach accounts for time-invariant bank characteristics and common annual influences while allowing errors to be correlated within banks, consistent with the panel-inference considerations discussed by Petersen (2009).

In the baseline specification, AI intensity had a positive but statistically insignificant coefficient ($\beta=4.3911$, $p=.163$). Accounting recognition was positively associated with ROA ($\beta=0.5604$, $p=.024$). A 0.10-point increase in the recognition score corresponded to an estimated 0.056-percentage-point increase in ROA, holding the other model components constant.

The moderation specification did not establish a statistically significant interaction between AI investment and recognition ($\beta=6.5200$, $p=.192$). Its positive sign indicates an estimated strengthening of the AI-ROA relationship at higher recognition scores, but the uncertainty is too substantial to conclude that moderation is supported. Neither the financial controls nor the constituent AI and recognition coefficients were statistically significant in this specification.

The constituent coefficients in the interaction model require conditional interpretation: the AI coefficient represents its association with ROA when recognition equals zero, while the recognition coefficient represents its association when AI intensity equals zero.

Note. Calculations use least-squares bank and year indicators, bank-clustered covariance estimates and *t*-based inference with 11 cluster degrees of freedom. The reported R2 includes the fixed-effect indicators; it is not Stata's within-R2.

TABLE 2 Fixed-Effects Estimates

Variable	Baseline Coefficient	Clustered SE	P-Value	Moderation Coefficient	Clustered SE	P-Value
AI investment intensity (%)	4.3911	2.9360	.163	0.8914	3.0107	.773
Accounting-recognition score	0.5604	0.2151	.024	-0.0533	0.5249	.921
AI intensity $\times$ recognition	-	-	-	6.5200	4.6853	.192
Log assets	-0.5598	0.5461	.327	-0.5855	0.5494	.309
Equity-to-assets ratio	4.0441	2.6622	.157	3.9432	2.6088	.159
Loan-to-deposit ratio	-0.3991	0.3511	.280	-0.3743	0.3564	.316
Bank fixed effects	Included			Included		
Year fixed effects	Included			Included		
Observations	204			204		
Bank clusters	12			12		
Overall dummy-variable R^2	0.3577			0.3632		

Source: Authors' Computation using STATA 18, 2026

4.1.3. MARGINAL EFFECTS

TABLE 3 Estimated marginal association between AI intensity and ROA

Recognition Score	Marginal Effect	Clustered SE	P-Value
0.20	2.1954	2.6838	.431
0.50	4.1514	2.7754	.163
0.80	6.1074	3.4863	.108

Source: Authors' Computation using STATA 18, 2026

Note. Effects represent the estimated change in ROA percentage points for a one-percentage-point increase in AI intensity. Because that increase exceeds the observed range of AI intensity, smaller changes are more appropriate for substantive interpretation. Calculated from the supplied workbook.

At a recognition score of 0.80, a 0.01-percentage-point increase in AI intensity corresponded to an estimated 0.061-percentage-point increase in ROA. Nevertheless, none of the three marginal effects was statistically significant at the 5% level. The results therefore do not establish a reliable AI-ROA association at the recognition levels examined.

4.2. DISCUSSION

The analysis provides a limited distinction between accounting recognition and AI investment. Recognition was positively associated with ROA in the baseline model, whereas AI intensity was not statistically significant. Once their interaction was introduced, the evidence did not support either a significant conditional relationship or a moderating effect. The findings should therefore be described as specification-sensitive rather than as confirmation that recognition strengthens the profitability benefits of AI.

The positive AI coefficients are directionally compatible with the resource-based explanation that technological resources can contribute to organizational performance. However, spending intensity is not equivalent to an effective AI capability. Mikalef and Gupta (2021) found positive relationships between AI capability, organizational creativity and performance; their capability construct concerns the organization's ability to assemble and use AI-related resources, rather than expenditure alone. The present estimates consequently do not contradict that evidence, but neither do they reproduce its substantive finding.

The baseline recognition coefficient is consistent with an accounting interpretation in which better identification and reporting of technological investment accompany stronger organizational processes. It does not establish that capitalization creates economic returns. IAS 38 requires research expenditure to be expensed and qualifying development expenditure to be recognized as an asset when the applicable criteria are satisfied. Appropriate recognition therefore concerns compliance with the nature and stage of expenditure, not simply a preference for higher capitalization.

Accounting treatment can also influence reported ROA independently of operational performance: capitalization changes the timing of expense recognition and the recorded asset base. Consequently, a relationship between recognition and accounting profitability cannot, by itself, distinguish improved banking efficiency from financial-reporting effects.

The positive but insignificant interaction provides insufficient support for the proposed signaling mechanism. Although the estimated marginal association increases with recognition, its uncertainty prevents the conclusion that more transparent accounting reliably amplifies AI-related profitability. The empirical contribution of this specification is therefore its failure to establish moderation, rather than evidence of a statistically confirmed reinforcing relationship.

Finally, inference is constrained by the presence of only 12 bank clusters. The reported estimates should be interpreted cautiously and supplemented with suitable small-cluster sensitivity analysis. Clustered standard errors address a particular dependence structure; they do not resolve reverse causality, time-varying omitted variables or measurement error (Petersen, 2009).

5. CONCLUSION

Within the analyzed dataset covering 2009-2025, AI investment intensity exhibited a positive but statistically insignificant association with return on assets. Accounting recognition was positively associated with profitability in the baseline specification, but this relationship was not statistically significant after introducing the interaction term. The interaction between AI investment and accounting recognition was also insignificant. Accordingly, the analysis does not establish that accounting recognition strengthens the relationship between AI investment and asset profitability. These findings distinguish a positive estimated relationship from statistically supported evidence and indicate that the recognition result is sensitive to model specification.

The results suggest that investment expenditure alone is insufficient to explain differences in profitability within the fitted models. This interpretation is consistent with the distinction between acquiring technology and developing an organizational capability to use it effectively. Mikalef and Gupta (2021) emphasize the combination of technological, human and organizational resources in explaining the performance implications of AI capability. Nevertheless, those mechanisms were not directly tested here and should not be treated as explanations established by the present analysis.

Accounting recognition should likewise be understood as a reporting obligation rather than a means of improving reported returns. IAS 38 distinguishes expenditure that must be expensed from development expenditure that qualifies for asset recognition. Consequently, greater capitalization does not necessarily represent better recognition quality; appropriate treatment depends on the characteristics of the expenditure and satisfaction of the applicable recognition requirements.

5.1. CONTRIBUTION TO KNOWLEDGE

The study's principal contribution is its analytical separation of AI investment intensity from accounting recognition. By including both constructs and their interaction, the framework distinguishes the association of technological expenditure with profitability from the proposition that accounting recognition conditions that association. Within the analyzed dataset, the insignificant interaction provides statistical support for the proposed moderating relationship, while the change in the recognition coefficient highlights the importance of assessing conclusions across specifications.

Methodologically, the analysis demonstrates a framework combining bank and year fixed effects, bank-clustered standard errors and conditional marginal effects. This approach permits a more explicit examination of moderation than interpreting capitalized software balances or disclosure measures alone as evidence of AI-related performance. Attention to within-bank dependence also follows established guidance for inference in financial panel research (Petersen, 2009). Future research should distinguish AI-specific expenditure from general technology costs, measure recognition using documented accounting evidence, and examine delayed performance effects and organizational capabilities.

CONFLICTS OF INTEREST

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