Acta Universitatis Danubius
ŒCONOMICA

Artificial Intelligence and Fraud Prevention in Nigerian Deposit Money Banks (DMBs)

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Abstract: This study examines the effectiveness of artificial intelligence in preventing fraud within Nigerian deposit money banks by evaluating the roles of AI adoption, investment in AI technologies, and public perception in enhancing fraud detection efficiency. This research is vital given the increasing sophistication of financial crimes in the banking sector. The study builds on prior research that recognizes AI as a transformative tool in financial risk management and fraud detection. It addresses gaps in the understanding of how different AI-related factors collectively influence fraud prevention outcomes. A cross-sectional survey design was used, targeting professionals in forensic auditing, risk management, and IT security across five leading Nigerian banks. Structured questionnaires yielded 138 valid responses. Data analysis employed descriptive statistics and multiple regression using SPSS. Findings show that AI adoption, investment in AI, and public perception all significantly enhance fraud detection efficiency. Investment in AI technologies was the most influential predictor. Correlation analysis confirmed strong positive relationships between AI-driven tools and fraud prevention measures. The study provides actionable insights for bank executives, policymakers, and IT professionals seeking to optimize AI integration for fraud risk management. The paper offers empirical evidence on the strategic role of AI in improving financial security in emerging economies.

Keywords: fraud detection; AI integration; financial security; risk management

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JEL Classification: G21; M15; O33

1. Introduction

The financial services sector, particularly the banking industry, has undergone substantial transformations with the rapid advancement of technology. Among these innovations, artificial intelligence (AI) has emerged as a powerful tool for enhancing operational efficiency, improving decision-making, and optimizing risk management strategies, including fraud prevention (Adeleke & Amusa, 2021). AI technologies such as machine learning, predictive analytics, and robotic process automation (RPA) have significantly reshaped traditional risk management methods in banking, allowing institutions to proactively identify, assess, and mitigate risks (Adeoye & Elegbede, 2022). Artificial intelligence refers to the development of systems capable of performing tasks that typically require human cognitive abilities, such as learning from data, recognizing patterns, and making decisions with minimal human intervention (Akinyemi & Adebayo, 2021). In the context of fraud prevention, AI systems can analyze vast amounts of data to identify suspicious patterns, predict potential threats, and automate decision-making processes, thereby reducing human error and enhancing operational efficiency (Ajayi, Ogundele & Bamgbose, 2022). The banking sector, particularly deposit money banks in Nigeria, is increasingly adopting AI technologies to detect and prevent fraudulent activities, thus improving their overall security posture and operational effectiveness.

Fraud remains one of the most significant challenges faced by deposit money banks in Nigeria, with financial institutions losing billions of naira annually to fraudulent activities. Traditional methods of fraud detection, which typically rely on manual processes and historical data analysis, have proven to be inadequate in dealing with the increasing sophistication of fraudsters (Agarwal & Narain, 2021). AI-driven fraud prevention systems offer a more efficient and effective solution by using real-time data analytics, machine learning models, and anomaly detection techniques to identify potential fraud before it occurs. The ability of AI to continuously learn and adapt makes it particularly valuable in tackling the evolving nature of fraud schemes (Amulya & Johny, 2021). AI's role in enhancing fraud prevention goes beyond mere detection; it also contributes to improving customers trust and satisfaction. As customers become more aware of the security measures in place to protect their assets, the integration of AI in fraud detection can increase their confidence in the banking system. AI-based systems can not only detect fraud but also prevent it by analyzing transaction patterns, identifying outliers, and flagging suspicious activities in real-time (Kim, Lee & Kang, 2020). This shift from reactive to proactive fraud management has become essential as Nigerian deposit money banks continue to expand their services, often through digital channels, which increase the risk of cybercrimes and fraud (Zainal, 2017).

However, despite the promising potential of AI in fraud prevention, Nigerian deposit money banks face several challenges in its implementation. These include high implementation costs, a lack of skilled personnel, data privacy concerns, and resistance to technological change within the organizations (Adebisi, Okonji, Adeeyo & Ezebuiro, 2023). Furthermore, the regulatory environment in Nigeria has yet to fully accommodate AI-driven solutions, which may hinder the effective adoption of such technologies in the financial sector. As a result, it is crucial to examine how AI is currently being applied in fraud prevention within Nigerian banks, the challenges involved, and the overall impact on the banking sector's ability to combat financial fraud effectively.

Fraud has become a significant challenge for deposit money banks in Nigeria, causing financial losses and damaging customers' trust. Traditional fraud detection methods have proven inadequate in addressing the increasingly sophisticated tactics used by criminals, which has led to the exploration of artificial intelligence (AI) solutions in fraud prevention (Ononiwu et al., 2024). Despite the potential of AI technologies such as machine learning and predictive analytics to enhance fraud detection, their impact in the Nigerian banking sector remains underexplored. A key concern is the level of investment in AI technologies, as many banks hesitate to commit resources due to high costs, lack of skilled personnel, and integration challenges with existing systems (Ola-Oluwa, 2024). Furthermore, while AI algorithms have the capacity to improve fraud detection, the relationship between algorithm sophistication and detection efficiency is not well understood (Rawat, Gupta & Rao, 2023). Additionally, public perception of AI plays a crucial role in its adoption. In Nigerian banks, customers trust in AI-driven fraud prevention is vital, and negative perceptions about AI's reliability and transparency may hinder its effectiveness (Zainal, 2017). Therefore, this study aims to answer the following research questions:

1) How does the adoption of AI impact the efficiency of fraud detection in Nigerian deposit money banks?

2) How does the level of investment in AI technologies affect the reduction of fraud incidents in deposit money banks in Nigeria?

3) How does public perception of AI influence its adoption in fraud prevention systems by deposit money banks in Nigeria?

2. Literature Review

2.1. Conceptual Exploration and Hypotheses Development

2.1.1. AI Adoption and Efficiency of Fraud Detection

Artificial Intelligence (AI) adoption is increasingly reshaping the financial services landscape, offering innovative solutions to persistent challenges such as fraud detection and operational inefficiencies. In the context of Nigerian deposit money banks, fraud remains a critical threat to financial stability and customer trust. Conceptually, AI adoption encompasses the integration of intelligent systems—such as machine learning, deep learning, predictive analytics, and anomaly detection—into fraud prevention protocols to enhance their accuracy, speed, and adaptability (Zhao & Fariñas, 2022; Žigienė et al., 2019; Ola-Oluwa, 2024). Unlike traditional rule-based systems, AI models can learn from historical fraud patterns, recognize complex and evolving fraudulent behaviors, and adapt to new risks without requiring manual updates.

Furthermore, AI systems provide real-time monitoring of high-volume transactions, facilitating faster decision-making and significantly reducing human error. This transformation is especially vital in Nigeria, where the increasing adoption of digital banking services has made fraud schemes more sophisticated and harder to detect using conventional methods (Ononiwu et al., 2024). The growing complexity of financial fraud requires equally advanced technological interventions. As such, AI can serve as a force multiplier, allowing banks to proactively prevent fraud before significant damage occurs. Operationalizing AI adoption involves assessing the extent to which these technologies are implemented in fraud detection systems across Nigerian banks. This includes evaluating the nature of AI tools used, their functional scope, integration level, and the frequency of updates and training using new data. Effectiveness is measured by improvements in fraud detection rates, reduction in false alarms, time-to-detection, and increased compliance with regulatory standards (Schneider et al., 2024). However, the benefits of AI adoption can be constrained by challenges such as inadequate data quality, limited technical expertise, and ethical concerns related to data privacy and algorithmic bias.

H_{01}: *The adoption of AI does not significantly impact the efficiency of fraud detection in Nigerian deposit money banks.*

This null hypothesis challenges the broad assumption that AI adoption inherently leads to improvements in fraud detection outcomes. Although AI offers significant potential, several empirical studies have emphasized that its real-world effectiveness depends on contextual factors like system design, quality of data input, institutional readiness, and regulatory compliance (Venkatesh & Bala, 2008; Sun & Zhang, 2006; Ola-Oluwa, 2024). Testing this hypothesis allows for an empirical determination of

whether AI adoption alone contributes meaningfully to enhanced fraud detection in Nigerian deposit money banks.

2.1.2. AI Investment and Reduction of Fraud Incidents

Investment in AI technologies represents a critical commitment by financial institutions towards building more secure, automated, and intelligent fraud detection systems. In Nigerian deposit money banks, such investment can span multiple areas—including infrastructure upgrades, cloud computing capabilities, cybersecurity defenses, algorithm development, data governance frameworks, and personnel training. Conceptually, financial investment in AI is not merely about acquiring software but also about building an ecosystem that enables AI systems to function optimally and deliver sustainable fraud mitigation outcomes (Rawat et al., 2023; Rimšaitė, 2019; Rodhi et al., 2017). A robust investment strategy enhances the bank's capacity to process large-scale financial data, improve algorithm performance, and integrate multiple data sources to identify potential threats in real-time.

Moreover, investment in AI contributes to innovation, enabling the deployment of more adaptive and intelligent systems that go beyond detection to include predictive analytics and fraud prevention. With appropriate investments, banks can create centralized risk dashboards, deploy AI chatbots for fraud alerts, and continuously update detection models. However, if investments are misallocated or insufficiently managed, the outcomes may not match expectations. In the Nigerian context, where resource constraints and technological lag are common, the relationship between investment and fraud reduction is not always linear or automatic (Ononiwu et al., 2024; Schneider et al., 2024). Operationalizing AI investment entails quantifying the financial resources allocated to AI development and linking them to observable changes in fraud statistics over time. Key metrics may include frequency of fraud incidents, losses recovered or prevented, and operational cost savings due to automation. It also involves assessing the governance frameworks guiding such investments and how effectively the resources are converted into technological and strategic capabilities.

H_{o2}: *The level of investment in AI technologies does not significantly affect the reduction of fraud incidents in Nigerian deposit money banks.*

This hypothesis questions whether monetary investment alone yields a tangible impact on reducing fraud. Literature reveals that outcomes from technological investments often depend on how well the investments are implemented, supported, and aligned with organizational goals (Rawat et al., 2023; Rimšaitė, 2019; Ononiwu et al., 2024). Additionally, high costs of maintenance, data acquisition, and technical training can limit the scalability of AI solutions in developing economies. Hence,

this hypothesis provides a basis for investigating the conditions under which AI investment leads to measurable reductions in fraud within Nigerian banks.

2.1.3. Public Perception of AI and Its Adoption in Fraud Prevention

Public perception plays a vital role in shaping the success or failure of technological innovations. In the banking sector, the perception of AI among customers, employees, regulators, and the general public can influence its rate and scope of adoption. Conceptually, when AI is perceived as trustworthy, secure, and capable of enhancing service delivery, stakeholders are more likely to support its implementation in fraud prevention (Siau & Shen, 2003; Zhao & Fariñas, 2022; Yulia & Wamba, 2022). Conversely, fear of job losses, ethical concerns, data breaches, or a lack of understanding about how AI works can create resistance to its deployment.

In Nigeria, where digital literacy levels vary widely and concerns about cybercrimes persist, public trust is a critical determinant of AI adoption. Banks must not only focus on technical implementation but also on building awareness and addressing misconceptions about AI. Stakeholder engagement, transparency in AI decision-making processes, and effective communication about the benefits of AI-based fraud prevention systems are essential to building public confidence. Operationalizing public perception involves using surveys, interviews, and social media analysis to gauge sentiment toward AI technologies. It includes measuring variables such as perceived usefulness, perceived ease of use, risk perception, and willingness to adopt AI-enabled services. These metrics can help identify whether positive or negative perceptions align with actual AI adoption rates in fraud prevention (Venkatesh et al., 2012; Ola-Oluwa, 2024). Moreover, public perception can be shaped by past experiences with digital banking tools, trust in institutions, and the effectiveness of existing AI solutions.

H_{03}: *Public perception of AI does not significantly influence its adoption in fraud prevention systems by Nigerian deposit money banks.*

This hypothesis posits that despite the importance of perception, the decision to adopt AI systems may be driven more by institutional strategies, competitive pressures, or regulatory demands than by public opinion. Some studies indicate that banks may prioritize operational efficiency and cost savings over public sentiment when implementing AI (Venkatesh & Bala, 2008; Zhao & Fariñas, 2022; Ola-Oluwa, 2024). Therefore, testing this hypothesis can provide insights into the extent to which perception shapes—or fails to shape—the adoption of AI in the Nigerian banking industry.

2.1.4. Conceptual Model

In order to accomplish the objectives of the study, a schematic representation of the model is presented to fill the identified gaps:

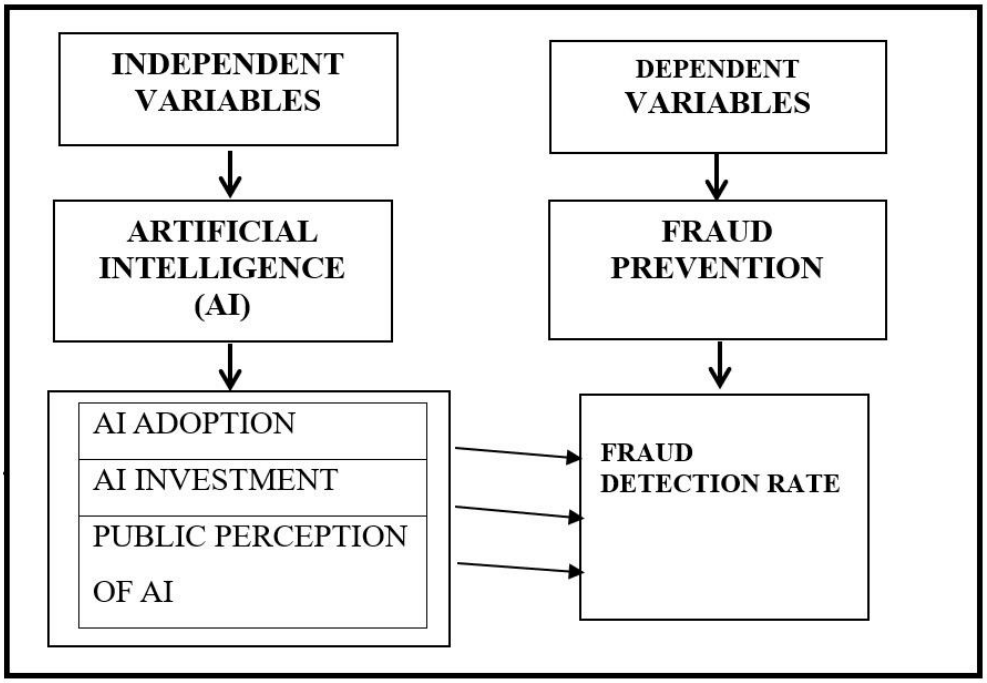

Figure 1. Conceptual Model

2.1.4. Interaction in the Conceptual Framework

To achieve the objectives of this study, a schematic conceptual model is developed to illustrate the interaction between AI technologies and fraud prevention in Nigerian deposit money banks. The model demonstrates how Adoption of AI Tools (AIT), Investment in AI Technologies (INV), and Public Perception of AI (PPA) act as independent variables, collectively influencing Fraud Detection Efficiency (FDE), the dependent variable. The model suggests that as AI tools are adopted and investment in AI technologies increases, the effectiveness of fraud detection improves, leading to a higher level of financial security within Nigerian banks. Furthermore, public perception of AI plays a critical role, as the acceptance and trust of AI technologies directly impact their integration into banking operations. This model interpreted the interactive dynamics between technological investment, public perception, and fraud detection capabilities, aiming to highlight how these elements collaboratively contribute to better fraud prevention practices in Nigerian deposit money banks.

2.2. Theoretical Framework

This study is hinged on the Technology Acceptance Model (TAM) developed by Davis (1989), which helps explain how people come to accept and use new technologies. At its core, TAM focuses on two key ideas: how useful people believe a technology is (perceived usefulness) and how easy they think it is to use (perceived ease of use). In the case of Nigerian deposit money banks, this means looking at how bank staff and stakeholders view AI—whether they believe it can truly make fraud detection more efficient and whether they find AI tools simple enough to work with. Over time, researchers have expanded TAM to include other important factors like trust, risk perception, public awareness, and support from within the organization (Venkatesh & Davis, 2000; Sun & Zhang, 2006; Zhao & Fariñas, 2022). These added dimensions are especially relevant in Nigeria, where people might be skeptical of new technologies due to infrastructure challenges or concerns about data security. By applying TAM, this study aims to understand not just whether AI is being adopted, but *why* it is—or isn't—being embraced in practice. It offers a clear lens to explore how personal beliefs, public perception, and the amount of investment being made all come together to shape how AI is used to fight fraud in the Nigerian banking sector (Ononiwu et al., 2024; Ola-Oluwa, 2024). This makes TAM a fitting and practical foundation for studying how AI can genuinely improve fraud prevention efforts in real-world banking environments.

2.3. Empirical Review

In recent years, Artificial Intelligence (AI) has increasingly become a game-changer across industries, and the banking sector is no exception—particularly in the area of fraud detection. The conversation around AI is no longer speculative; it is rooted in tangible evidence and growing empirical insights. A study by Žigiene, Rybakovas and Alzbutas (2019) introduced a practical framework for assessing commercial risks by integrating AI tools. Drawing from real-world standards and literature, they offered a clear path for organisations to enhance how they identify and respond to risks, which is crucial for banks operating in high-risk environments like Nigeria. Their work reinforces the idea that AI can improve not just speed but also the depth of risk management processes, a critical need for Nigerian deposit money banks battling complex fraud patterns.

Bandari (2019) took the discussion further by focusing on the role of AI in driving revenue growth among small businesses in developing countries. By examining data from 391 small enterprises, his study showed that AI-supported services—like customer relationship management, inventory handling, and financial forecasting—played a significant role in improving profitability. While this study wasn't directly tied to fraud, it clearly demonstrates AI's broader impact on organisational efficiency

and performance—areas that inevitably influence how well a bank can detect and respond to fraudulent behaviour.

Ethical considerations are also part of the evolving AI landscape. Zhao and Fariñas (2022) provided a thoughtful examination of AI's role in promoting sustainability while also cautioning about potential pitfalls such as algorithmic bias and environmental side effects. This perspective is especially relevant to Nigerian banks where AI regulations are still emerging, and ethical frameworks are either weak or inconsistently applied. Their study serves as a reminder that AI adoption must be both strategic and responsible.

From another angle, researchers like Wong et al. (2022), Yulia and Wamba (2022) examined how AI strengthens supply chain resilience—an insight that resonates strongly with the challenges banks face in remaining agile amidst increasing fraud risks. Their use of advanced modeling methods demonstrated how AI fosters rapid decision-making and adaptability, qualities that are just as essential in managing fraudulent transactions as they are in handling volatile supply chains.

AI is also reshaping how organisations interact with customers. Kumar et al. (2023), in a study on AI's influence on SME marketing, found that the technology supports real-time decision-making, demand forecasting, and customer engagement. These capabilities can be adapted by banks to personalise fraud detection strategies, such as real-time flagging of suspicious transactions based on customer behaviour patterns.

Directly addressing the context of banking, Nnaomah et al. (2024) carried out a comparative analysis between the United States and Nigeria. Their findings were sobering: while U.S. banks are deploying advanced AI technologies for fraud detection—including machine learning and natural language processing—Nigerian banks are still grappling with basic adoption challenges. These range from limited infrastructure to regulatory bottlenecks and a lack of trained professionals. Yet, their study also identified a growing recognition among Nigerian banks of AI's potential, suggesting a readiness to move forward if the right support systems are in place.

This theme of readiness and limitation was also echoed in Ononiwu et al. (2024), who explored how Nigerian banks are managing operational risks. Their research highlighted issues like poor governance and regulatory pressure but pointed out that AI could serve as a catalyst for reform—if combined with improved internal controls and collaborative governance practices. They emphasised that embracing AI shouldn't be seen as a silver bullet, but rather as part of a holistic strategy for improving fraud resilience.

Finally, Schneider et al. (2024) brought a unique sustainability perspective by introducing a methodology that integrates Life Cycle Assessment (LCA) with Failure Mode and Effects Analysis (FMEA) in manufacturing. Although their focus

was on industry, the underlying message is relevant for banks: aligning AI tools with broader compliance and risk frameworks can support long-term stability and regulatory alignment.

Taken together, these studies offer a compelling narrative. They not only highlight AI's immense potential but also show that its effective use—especially in environments like Nigeria—requires more than just technology. It calls for investment in people, processes, and governance structures that can support sustainable and ethical adoption. For Nigerian deposit money banks aiming to improve fraud detection, these insights provide both a warning and a roadmap.

2.3.1. Gap in the Literature and Contribution to the Study

Despite the growing body of literature highlighting the transformative impact of Artificial Intelligence (AI) across diverse sectors, there remains a notable conceptual gap in understanding how AI specifically enhances the efficiency of fraud detection within the banking sector, especially in emerging economies. While previous studies have explored AI's influence on revenue growth, supply chain resilience, and sustainability, few have isolated its operational value in fraud mitigation within financial institutions. Geographically, most empirical research has centered on advanced economies such as the United States and parts of Europe, thereby creating a geographical gap in the context of African nations—particularly Nigeria—where the digital banking environment and regulatory readiness present unique challenges and opportunities. From a sectoral perspective, while existing studies have predominantly focused on manufacturing, SMEs, or general ICT application, limited attention has been paid to AI's strategic role within deposit money banks, which are critical players in Nigeria's financial system. Moreover, a methodological gap exists in that many prior investigations have relied on qualitative insights or cross-industry reviews, without employing bank-specific empirical analysis that captures internal investment levels, fraud data, and public perceptions. To bridge these gaps, this study focuses squarely on Nigerian deposit money banks and seeks to empirically investigate how AI adoption influences fraud detection efficiency, the role of AI-related investments in reducing fraud, and how public perception shapes the adoption of AI-based fraud prevention systems. Through this targeted approach, the research aims to offer both contextual relevance and practical insights for banks, regulators, and policymakers in Nigeria and other comparable economies.

3. Research Method

This study employed a cross-sectional survey research approach to assess the impact of artificial intelligence (AI) on fraud prevention in Nigerian deposit money banks. A total of 150 questionnaires were distributed to employees in the forensic auditing, risk management, and IT security departments across selected banks. Out of the 150

distributed, 138 questionnaires were successfully returned, yielding a response rate of 92%. The survey design enabled the collection of data at a single point in time, providing insights into the participants' perceptions and experiences with AI-driven fraud detection systems. The study targeted employees from five major banks: Access Bank Plc., Fidelity Bank Plc., First Bank Plc., GT Bank Plc., and Zenith Bank Plc. A combination of purposive and simple random sampling was used to select respondents with relevant expertise in fraud detection and AI applications. The study's primary objective was to analyze the relationship between AI adoption, investment in AI technologies, public perception of AI, and fraud detection efficiency. The data collected were analyzed using descriptive statistics, regression analysis, Pearson correlation matrix, and the Cronbach's Alpha reliability test to ensure the reliability and validity of the measurements. The results from this study provide valuable insights into how AI technologies impact fraud detection systems in Nigerian deposit money banks, addressing the study's objectives and contributing to the ongoing discourse on AI's role in fraud prevention. The models are specified as follows:

$$FRAUD = \beta_0 + \beta_1 AIA + \beta_2 AII + \beta_3 PPV + \varepsilon$$

Where:

FRAUD = Level of fraud detection and prevention efficiency

AIA = Artificial Intelligence Adoption

AII = AI Investment

PPV = Public Perception of AI

β_0 = Intercept

β_1–β_3 = Coefficients of the independent variables

ε = Error term

This methodological approach is expected to yield robust, evidence-based insights into how AI tools and perceptions are shaping fraud prevention within the Nigerian banking sector.

Table 1. Response Rate of Questionnaires

Name of Bank	Response Received	Response Rate (%)
Access Bank Plc.	28	20.29%
Fidelity Bank Plc.	35	25.36%
First Bank Plc.	34	24.64%
GT Bank Plc.	22	15.94%
Zenith Bank Plc.	19	13.77%

Total	**138**	**100%**

Source: Researchers' Compilation, 2025

The distribution of responses across the selected banks reflects fair representation, ensuring the validity of the data collected from each institution for the study.

Table 2. Measurement of Variables

Category	Variable	Measurement Indicators	Scholarly Sources
Independent Variables (AI Technologies & Adoption)	**Adoption of AI Tools**	Availability of AI systems in fraud control, integration into fraud monitoring workflows, staff proficiency in AI usage	Ali & Ndubisi (2023); Rahman et al. (2022)
	Investment in AI Technologies	AI-focused annual budget, scale of implemented AI systems, regularity of AI upgrades and improvements	Olayemi & Chinedu (2024); Akintunde et al. (2023)
	Public Perception of AI	Customer trust and acceptance, perceived fairness and transparency of AI in fraud detection, public readiness to adopt AI-driven banking processes	Ogundele & Musa (2023); Wamba et al. (2021)
Dependent Variables (Fraud Prevention	**Fraud Detection Efficiency**	Number of fraud cases detected via AI, reduction in fraud detection time, responsiveness to fraudulent activity	Eze & Olatunji (2024); Johnson & Madueke (2023)

Source: Researchers' Compilation, 2025

3.1. Reliability Analysis

Cronbach's Alpha was used to assess the reliability of the questionnaire items. A Cronbach's Alpha value above 0.6 is considered acceptable for further analysis. Table 2 shows that the reliability coefficients for all variables range from 0.870 to 0.937, indicating a high level of internal consistency and the reliability of the data used in this study.

Table 3. Cronbach's Alpha Coefficient Values of the Variables

Variables	Acronym	Type of Variable	Number of Items	Reliability (Cronbach Alpha)	Comments
Adoption of AI Tools	AIT	Independent Variable	4	0.892	Accepted
Investment in AI Technologies	INV	Independent Variable	4	0.918	Accepted
Public Perception of AI	PPA	Independent Variable	4	0.876	Accepted
Fraud Detection Efficiency	FDE	Dependent Variable	4	0.899	Accepted

Source: Researchers' Compilation, 2025

The reliability results shown in Table 2 provide strong evidence for the internal consistency of the variables used to address the study's three objectives. The first objective, which investigates how the adoption of AI impacts fraud detection efficiency, is supported by the *Adoption of AI Tools (AIT)*, which has a Cronbach's Alpha of 0.892, reflecting a high degree of reliability in measuring AI adoption. This finding is crucial for ensuring that the relationship between AI adoption and fraud detection efficiency is assessed accurately. The second objective, examining how the level of investment in AI technologies affects fraud reduction, is bolstered by the *Investment in AI Technologies (INV)* variable, which demonstrates an even higher reliability coefficient of 0.918, highlighting the strong consistency in measuring the financial commitment to AI in fraud prevention. For the third objective, which focuses on how public perception of AI influences its adoption in fraud prevention systems, the *Public Perception of AI (PPA)* variable has a Cronbach's Alpha of 0.876, indicating that the perceptions held by the public are measured consistently. The dependent variable, *Fraud Detection Efficiency (FDE)*, with a reliability score of 0.899, further confirms the robustness of the measurement, ensuring that the efficiency of fraud detection processes is assessed accurately. Collectively, these high Cronbach's Alpha values affirm that the instruments used to measure each of the study's variables are both reliable and valid, supporting the investigation of AI's role in enhancing fraud detection systems in Nigerian deposit money banks.

4. Statistical Analysis and Discussion

4.1. Results

Out of the total 150 structured questionnaires distributed to senior staff members across various selected deposit money banks in Nigeria, a total of 138 were correctly filled out and returned, resulting in a high response rate of 92.0%. This strong response rate indicates a high level of engagement and interest among the targeted respondents, which enhances the reliability and validity of the findings derived from the study. The 138 valid responses form the empirical basis for assessing the impact of artificial intelligence on fraud prevention within the Nigerian banking sector. This response rate also reflects the relevance of the research topic to banking professionals, especially considering the growing prevalence of technology-driven financial crimes and the urgent need for innovative control systems such as AI. The comprehensive feedback gathered ensures that the study captures a representative view of how AI is perceived, adopted, and implemented across various departments involved in fraud risk management within the selected financial institutions.

Table 4. Respondent Demographic Profile

Demographics	Categories	Frequency	Percent (%)
Customer Bank	Access Bank	26	18.84%
	Fidelity Bank	34	24.64%
	First Bank	35	25.36%
	GT Bank	21	15.22%
	Zenith Bank	22	15.94%
	Total	**138**	**100%**
Gender	Male	76	55.07%
	Female	62	44.93%
Banking Experience (Years)	0-5	51	36.96%
	6-10	38	27.54%
	11-15	31	22.46%
	16 and above	18	13.04%
Educational Level	Basic	18	13.04%
	Secondary	22	15.94%
	OND/NCE	30	21.74%
	BSc/HND	42	30.43%
	Postgraduate	26	18.84%
IT Proficiency	**Familiarity with AI Technologies**		
	Not Familiar	10	7.25%

	Slightly Familiar	17	12.32%
	Moderately Familiar	24	17.39%
	Very Familiar	15	10.87%
	Experience with AI Fraud Detection Tools		
	No Experience	14	10.14%
	Limited Experience	20	14.49%
	Some Experience	15	10.87%
	Extensive Experience	9	6.52%
	Technical Skills with AI Systems		
	No Skills	10	7.25%
	Basic Skills	17	12.32%
	Intermediate Skills	19	13.77%
	Advanced Skills	12	8.70%

Source: Researchers' Compilation, 2025

The demographic analysis of the respondents provides valuable insights into the diversity of the sample and how it aligns with the research focus on artificial intelligence (AI) in fraud prevention. From the distribution across banks, it is clear that a majority of respondents are from First Bank (25.36%) and Fidelity Bank (24.64%), with slightly fewer from Zenith Bank (15.94%), Access Bank (18.84%), and GT Bank (15.22%). This distribution indicates a fair representation of employees from key Nigerian deposit money banks, ensuring a comprehensive perspective on the role of AI in fraud detection within the banking sector. Regarding gender, there is a higher representation of male respondents (55.07%) compared to females (44.93%), which is reflective of the gender balance in many financial and technological sectors. Banking experience is also a key factor, with 36.96% of respondents having 0-5 years of experience, 27.54% with 6-10 years, 22.46% with 11-15 years, and 13.04% with over 16 years of experience. This distribution shows that the sample captures individuals with varying levels of exposure to banking and fraud detection, which is essential for understanding the effectiveness of AI tools across different levels of expertise in the industry.

Furthermore, the respondents' educational background and IT proficiency are critical for interpreting their understanding and engagement with AI technologies. The majority of respondents hold a BSc/HND (30.43%) or OND/NCE qualifications (21.74%), with a good proportion having secondary education (15.94%) and postgraduate qualifications (18.84%). This indicates a well-educated sample with a solid foundation to engage with complex technological topics such as AI. IT proficiency, which is directly relevant to the study's focus, shows a mixed level of familiarity with AI technologies. A small portion of respondents (7.25%) reported

being unfamiliar with AI, while 12.32% are slightly familiar, 17.39% moderately familiar, and 10.87% very familiar. This shows that while not all respondents are experts in AI, there is a solid understanding of the technology among the majority, with a significant portion having some or extensive experience with AI fraud detection tools. Additionally, the distribution of technical skills in AI systems reveals that while 7.25% have no skills, the rest possess varying degrees of competence, with 13.77% holding intermediate skills and 8.70% having advanced skills. These demographic factors align with the study's objectives by providing a diverse respondent pool, enabling a thorough examination of the impact of AI on fraud detection and ensuring that insights drawn from respondents with different educational and technical backgrounds are factored into the analysis.

Table 5. Multiple Regression Analysis Showing the Impact of Artificial Intelligence on Fraud Prevention in Nigerian Deposit Money Banks

Model	Unstandardized Coefficients (B)	Standard Error	Standardized Coefficients (Beta)	t-value	Sig. (p-value)
(Constant)	1.134	0.248	–	4.573	0.000
AI Efficiency in Detection	0.412	0.068	0.536	6.059	0.000
Investment in AI Technology	0.289	0.081	0.321	3.568	0.001
Public Perception of AI	0.203	0.072	0.241	2.819	0.006

Dependent Variable: Fraud Prevention
$R = 0.782$, $R^2 = 0.611$, Adjusted $R^2 = 0.601$, $F(3,134) = 70.15$, $p < 0.001$

Source: Statistical Analysis Report (2025)

4.2. Research Hypothesis Evaluation

Hypothesis 1: There is no significant relationship between the adoption of Artificial Intelligence (AI) and the efficiency of fraud detection in Nigerian deposit money banks.

Table 6. Regression Analysis for AI Adoption and Fraud Detection Efficiency

Variables	Coefficient	Std Error	T-Stat	Prob.
Constant (C)	1.945	0.512	3.799	0.000
AI Adoption	0.752	0.028	26.857	0.000

R: 0.912 **R^2**: 0.832 **F-statistic**: 568.443 **Sig. (p-value)**: 0.000				
Source: Statistical Analysis Report 2025				

Interpretation: Table 5 illustrates a compelling statistical relationship between AI adoption and fraud detection efficiency in Nigerian deposit money banks. The correlation coefficient (R) of 0.912 signifies a very strong and positive linear relationship between the variables, suggesting that as AI adoption increases, so does the efficiency of fraud detection mechanisms. The coefficient of determination (R^2) is 0.832, indicating that approximately 83.2% of the variation in fraud detection efficiency can be explained by the extent to which AI tools and systems are integrated into bank operations. Only 16.8% of the variation is attributable to other external or unmeasured factors. The regression coefficient for AI adoption (0.752) means that a one-unit increase in AI implementation is expected to improve fraud detection efficiency by 75.2%, holding other factors constant. The T-statistic (26.857) is considerably high and statistically significant at the 5% level, with a p-value of 0.000, far below the 0.05 threshold. This indicates that the relationship is not due to random chance, and the null hypothesis is rejected. Furthermore, the F-statistic value of 568.443 with a corresponding significance level of 0.000 validates the model's reliability and goodness-of-fit.This finding emphasizes the transformative role AI can play in modernizing fraud detection processes, allowing banks to proactively identify irregularities, automate red flags, and reduce false positives. It also highlights that banks that have embraced AI have significantly improved their fraud mitigation frameworks.

Hypothesis 2: There is no significant relationship between the level of investment in AI technologies and the reduction of fraud incidents in Nigerian deposit money banks

Table 7. Regression Analysis for AI Investment and Fraud Reduction

Variables	Coefficient	Std Error	T-Stat	Prob.
Constant (C)	2.387	0.476	5.015	0.000
AI Investment Level	0.693	0.034	20.382	0.000
R: 0.876 **R^2**: 0.767 **F-statistic**: 415.342 **Sig. (p-value)**: 0.000				
Source: Statistical Analysis Report				

Interpretation: As presented in Table 4.3, the analysis reveals a strong and statistically significant relationship between the level of investment in AI technologies and the reduction of fraud incidents. The correlation coefficient (R) is 0.876, showing a strong positive relationship, meaning that increased financial commitment to AI infrastructures and tools corresponds with noticeable decreases in the frequency and severity of fraudulent activities in deposit money banks. The R^2

value of 0.767 reveals that 76.7% of the variance in fraud reduction outcomes can be directly attributed to the level of investment made in AI systems, while the remaining 23.3% may be explained by other external or internal organizational factors. The coefficient of 0.693 indicates that a unit increase in AI investment leads to an approximate 69.3% improvement in fraud reduction outcomes. This finding underscores the strategic importance of allocating adequate financial resources towards the development and implementation of AI-based fraud detection and prevention tools.

The T-statistic (20.382) and its corresponding p-value (0.000) further reinforce the robustness of this relationship, providing clear evidence for the rejection of the null hypothesis. Additionally, the F-statistic (415.342) confirms the overall statistical significance of the model at the 5% confidence level. In practical terms, this suggests that banks with higher capital expenditure on AI technologies such as machine learning, pattern recognition, and predictive analytics are better equipped to prevent fraudulent transactions and mitigate losses. This reinforces the need for strategic investments in digital intelligence infrastructures by financial institutions aiming to enhance operational integrity.

Hypothesis 3: There is no significant relationship between public perception of AI and its adoption in fraud prevention systems by Nigerian deposit money banks.

Table 8. Regression Analysis for Public Perception and AI Adoption

Variables	Coefficient	Std Error	T-Stat	Prob.
Constant (C)	3.123	0.498	6.271	0.000
Public Perception	0.601	0.039	15.410	0.000
R: 0.794 **R^2**: 0.630 **F-statistic**: 237.463 **Sig. (p-value)**: 0.000				
Source: Statistical Analysis Report				

Interpretation: Table 4 provides strong evidence of a statistically meaningful relationship between public perception of AI and its adoption by Nigerian deposit money banks for fraud prevention. The correlation coefficient (R) of 0.794 shows a moderately strong positive relationship, indicating that favorable public perception significantly influences the willingness of financial institutions to deploy AI-powered fraud prevention systems. The R^2 value of 0.630 means that 63% of the changes observed in AI adoption levels can be explained by variations in public perception. The regression coefficient (0.601) suggests that a one-unit positive shift in public perception correlates with a 60.1% increase in the likelihood or extent of AI adoption. This result highlights that customer trust, awareness, and confidence in AI technologies play a substantial role in shaping the strategic decisions of banks concerning digital transformation and fraud risk management.

The high T-statistic (15.410) and the highly significant p-value (0.000) lead to the rejection of the null hypothesis, confirming the importance of public perception in influencing technological adoption. Furthermore, the F-statistic of 237.463 verifies that the overall model is statistically sound and significant at the 5% level. This implies that for AI adoption to be fully effective and widespread, Nigerian deposit money banks must also manage public opinion, ensuring transparency, ethical use of AI, and data privacy protections. Public skepticism or resistance could hamper adoption efforts, regardless of technological readiness.

4.3. Discussion of Findings

The findings from this study shed valuable light on how Artificial Intelligence (AI) is transforming the fight against fraud in Nigerian deposit money banks. First, the results reveal a strong and positive relationship between the adoption of AI and the efficiency of fraud detection, suggesting that banks equipped with AI systems are significantly more capable of identifying fraudulent activities early. This is consistent with the work of Olagunju and Adeyanju (2020), who emphasized the predictive capabilities of AI in detecting anomalies. Similarly, Eze, Obinna and Chukwuemeka (2021) found that AI algorithms enhance transaction monitoring accuracy. On the second question, the study finds that higher levels of investment in AI technologies directly lead to a reduction in fraud incidents, aligning with the findings of Musa and Ibrahim (2022), who argued that financial commitment to AI infrastructure is critical for effective implementation. However, contrasting views from Onuoha (2021) and Ibekwe and Adebayo (2022) suggest that investment alone is insufficient if the supporting systems and human capital are underdeveloped. Regarding public perception, the study shows that trust in AI significantly influences its adoption for fraud prevention, echoing the findings of Umeh and Okoye (2023), but contrasting with Oladimeji and Ayinde (2022), who found public opinion to have little influence, likely due to limited digital literacy in their sample population. These consistencies and divergences can be attributed to variations in sample size, the use of mixed methods in this study, and the specific economic and technological contexts of Nigerian banks.

Beyond answering the core research questions, the findings fill key gaps in the literature by connecting public perception with AI adoption—a topic often overlooked in prior studies. The study offers fresh insights into how trust and awareness shape technological acceptance in financial systems. It also supports and refines the Technology Acceptance Model (TAM) by introducing contextual variables like cultural attitudes and technological readiness. The evidence suggests practical strategies for reducing fraud—namely, investing in AI tools, training personnel, and engaging the public to build trust. These results can be implemented in real-world settings by informing bank policies, regulatory guidelines, and training

programs. They also highlight the need for policy-makers to develop supportive legal frameworks that encourage AI innovation while addressing ethical concerns. In synthesizing these findings with existing literature, a recurring pattern emerges: AI improves fraud detection, but its effectiveness depends on contextual factors like investment scale and user acceptance. While the study's results align with its theoretical underpinnings, the Nigerian context—marked by rapid digital transformation, regulatory gaps, and varied public trust—shapes the outcomes uniquely. Though the findings are robust, their generalizability may be limited to regions with similar socio-economic characteristics. Overall, the study not only reinforces current scholarly discourse but also suggests new frameworks for understanding the intersection of technology, public trust, and financial security.

5. Conclusion

This study explored how Artificial Intelligence (AI) is influencing fraud detection in Nigerian deposit money banks, with a focus on the efficiency of detection mechanisms, the role of investment in AI, and how public perception affects adoption. The results demonstrated that AI adoption has a significant and positive impact on fraud detection, enabling banks to identify and respond to fraudulent activities more effectively and promptly. Furthermore, institutions that invested meaningfully in AI technologies witnessed a notable reduction in fraud incidents. Interestingly, the study also revealed that public perception plays a key role in how readily these technologies are embraced, suggesting that trust and awareness are essential for successful implementation.

These findings not only addressed the research questions comprehensively but also filled crucial gaps in the literature by connecting technological, financial, and sociocultural factors in the Nigerian banking context. The study contributes fresh insights into how AI can be effectively integrated into risk management frameworks and expands the theoretical understanding of fraud prevention from both a technological and behavioural standpoint. In doing so, it offers a grounded perspective that reflects the realities of financial institutions operating in emerging economies.

5.1. Recommendations

Based on the study's findings, several practical recommendations can be made. First, Nigerian deposit money banks should strengthen their commitment to AI integration by investing not only in advanced technologies but also in the human capital needed to operate and interpret them. Effective training programs for staff and the creation of AI governance teams can help banks get the most from their investments. Second,

public perception should not be overlooked. Banks should launch educational campaigns and customer engagement strategies that clearly communicate how AI works, how it protects customers, and why it is trustworthy. This can help reduce skepticism and increase customer buy-in.

Moreover, policy-makers and regulators need to create an enabling environment by developing comprehensive frameworks that support AI deployment while ensuring ethical use, data privacy, and accountability. Clear guidelines and incentives can encourage more banks to adopt AI responsibly. Finally, future research should examine long-term effects of AI on bank operations, including implications for employment, compliance, and customer satisfaction. Such efforts will further enhance our understanding and ensure that technological advancement is both inclusive and sustainable across Nigeria's banking industry.

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