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Adoption of AI Tools and Fraud Detection in Selected Microfinance Banks in Lagos

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***Abstract-** The rapid rise of fraud in financial institutions continues to threaten stability, erode trust, and undermine long-term sustainability. Microfinance banks (MFBs) in Nigeria, designed to provide financial services to low-income earners and small businesses, are particularly vulnerable due to limited collateral requirements, weak technological infrastructure, and reliance on trust-based relationships. This study examined the adoption of Artificial Intelligence (AI) tools for fraud detection in selected microfinance banks in Lagos, Nigeria. Specifically, it investigated the extent of AI adoption, its effectiveness in enhancing fraud detection, the challenges hindering adoption, and strategies for improvement. The study employed a descriptive survey design with a structured questionnaire administered to 45 respondents drawn from staff of selected MFBs. Data were analyzed using descriptive statistics and regression analysis via SPSS. Findings revealed that although AI adoption in Lagos MFBs remains moderate, AI tools significantly enhance fraud detection accuracy, reduce detection time, and minimize financial losses. However, adoption is constrained by financial costs, inadequate expertise, and weak regulatory frameworks. The test of hypotheses confirmed that AI adoption has a significant positive effect on fraud detection, while challenges exert a negative influence. Respondents strongly endorsed strategies such as infrastructure investment, continuous staff training, and supportive government policies as critical enablers of AI adoption. The study concludes that AI tools are not optional innovations but strategic necessities for mitigating fraud risks in microfinance banking. It recommends coordinated efforts by banks, regulators, and FinTech firms to overcome adoption barriers and strengthen fraud prevention systems.*

***Keywords:** artificial intelligence, fraud detection, microfinance banks, adoption challenges*

I. INTRODUCTION

Background of the Study

Fraud in financial institutions has long posed a significant challenge, threatening the integrity, stability, and sustainability of banking systems globally. The banking industry operates largely on trust, and fraudulent practices erode public confidence, weaken financial performance, and destabilize economies (Umoh et al., 2024). Microfinance banks (MFBs), which were established to provide financial services such as microcredit, savings, and micro-insurance to low-income earners, women, and small-scale entrepreneurs, are especially vulnerable. Their client base is broad, often involving individuals with little or no formal credit history, and transactions are frequently carried out with minimal collateral requirements (Taiwo and Benson, 2016).

Consequently, their reliance on trust-based relationships exposes them to a wider spectrum of fraudulent schemes. In Nigeria, fraud in the microfinance sector has manifested in various forms, including loan diversion, falsification of documents, identity theft, cyber-enabled scams, insider manipulation, and misappropriation of deposits (Kanu et al., 2023). According to the Central Bank of Nigeria (CBN), fraud-related losses in microfinance banks increased steadily between 2018 and 2022, undermining profitability and threatening the long-term survival of these institutions. The introduction of Artificial Intelligence (AI) tools into banking operations has opened up new possibilities for fraud detection and prevention. AI encompasses advanced techniques such as machine learning, natural language processing, robotic process automation, and predictive analytics, all of which can be deployed to strengthen fraud detection frameworks (Bello and Komolafe, 2024).

These tools enable banks to process large volumes of transactional data in real time, uncover anomalies, and predict fraudulent activities before they escalate into significant losses (Zainal, 2023). Unlike traditional fraud detection methods, which are typically reactive and dependent on static rules or manual oversight, AI-driven systems leverage adaptive models that continuously evolve with emerging fraud patterns (Oko-Odion, 2025).

This capacity to detect subtle and sophisticated fraud schemes makes AI particularly relevant in Lagos, Nigeria's commercial and financial hub, where microfinance banks grapple with rising cases of fraud perpetrated both internally by staff and externally by cybercriminals. Globally, empirical evidence suggests that AI adoption has yielded substantial improvements in fraud detection and financial risk management. For instance, in India, microfinance institutions integrating AI-based credit scoring and fraud monitoring tools reported a reduction in non-performing loans and better credit risk profiling (Rehman et al., 2025). Similarly, in Europe, commercial banks using AI-enabled fraud detection systems recorded up to 50 percent improvements in identifying suspicious transactions and fraudulent behavior (Christensen, 2021). These examples underscore the transformative potential of AI in safeguarding financial institutions. However, despite the benefits, the adoption of AI tools within Nigerian microfinance banks is still at an early stage (Avula, 2021).

Given these realities, Lagos State presents a critical case for examining AI adoption and fraud detection practices. As Nigeria's financial capital, Lagos hosts the largest concentration of microfinance banks, with diverse client bases and high transaction volumes (Onyeiwu et al., 2021). The city also experiences more frequent fraud incidents relative to other regions, largely due to its status as a hub for financial innovation and cybercrime (Okeke and Onyekachukwu, 2024). Therefore, investigating how microfinance banks in Lagos are adopting AI tools, the challenges they face, and the extent to which these tools are effective in detecting fraud is crucial. The findings of such a study will not only deepen understanding of technology adoption in Nigeria's microfinance sector but also provide evidence-based insights for strengthening financial stability and improving public trust.

Statement of the Problem

Despite the growth of digital banking and technological innovations, fraud remains a persistent challenge for microfinance banks in Lagos. Traditional fraud detection methods in these institutions are largely manual and reactive, making them slow in identifying suspicious activities (Bello et al., 2023b). These methods rely on employee vigilance, customer reporting, and post-transaction auditing, which are insufficient in addressing sophisticated and rapidly evolving fraud schemes. The result has been recurring losses, erosion of customer trust, and, in some cases, the collapse of microfinance banks. Although AI tools present an opportunity for real-time fraud detection and predictive analysis, their adoption in microfinance institutions remains limited. Several barriers contribute to this situation, including inadequate technical expertise, high implementation costs, lack of infrastructural support, and regulatory uncertainty (Farahbakhsh et al., 2024). Moreover, the absence of empirical studies examining the extent to which AI has been adopted in Lagos-based microfinance banks creates a knowledge gap. This gap makes it difficult for policymakers, practitioners, and regulators to design strategies that will strengthen fraud detection mechanisms in the sector. Therefore, there is an urgent need to investigate the adoption of AI tools in microfinance banks and evaluate their impact on fraud detection in Lagos.

Aim and Objectives of the Study

The aim of this study is to examine the adoption of Artificial Intelligence tools and their role in fraud detection in selected microfinance banks in Lagos, Nigeria.

The specific objectives are to:

i. Assess the extent to which machine learning algorithms, rule-based expert systems, and anomaly detection tools are adopted for fraud detection in selected microfinance banks.
ii. Evaluate the effectiveness of machine learning models (such as decision trees and neural networks), data mining techniques, and predictive analytics tools in detecting and preventing fraudulent transactions.
iii. Identify the technical, organisational, and regulatory challenges associated with implementing AI-driven fraud detection tools, including real-time monitoring systems, automated risk scoring models, and behavioural analytics technologies in microfinance banks.
iv. Recommend strategies to enhance the adoption and effective utilisation of AI-based fraud

detection tools, including machine learning systems, automated monitoring platforms, and advanced analytics solutions, within microfinance banks.

Research Questions

This study seeks to answer the following research questions:

i. To what extent have machine learning algorithms, rule-based expert systems, and anomaly detection tools been adopted for fraud detection in selected microfinance banks?
ii. How effective are machine learning models (such as decision trees and neural networks), data mining techniques, and predictive analytics tools in enhancing fraud detection and prevention in microfinance banks?
iii. What technical, organisational, and regulatory challenges hinder the adoption and effective use of AI-driven fraud detection tools, including real-time transaction monitoring systems, automated risk scoring models, and behavioural analytics technologies?
iv. What strategies can be employed to improve the adoption and effective utilisation of AI-based fraud detection tools, such as machine learning systems and advanced analytics platforms, within the microfinance sector??

Research Hypotheses

The study is guided by the following hypotheses:

H01: Machine learning algorithms, rule-based expert systems, and anomaly detection have no significant effect on fraud detection in microfinance banks in Lagos.

H1: Machine learning algorithms, rule-based expert systems, and anomaly detection have a significant effect on fraud detection in microfinance banks in Lagos.

H02: Technical, organisational, and regulatory challenges associated with implementing AI-driven fraud detection tools do not significantly affect fraud detection in microfinance banks.

H2: Technical, organisational, and regulatory challenges associated with implementing AI-driven fraud detection tools significantly affect fraud detection in microfinance banks.

Significance of the Study

This study holds significance for multiple stakeholders. For microfinance banks, the findings will provide insights into the potential of AI tools in enhancing fraud detection systems, thus improving operational efficiency and reducing financial losses. For policymakers and regulators such as the Central Bank of Nigeria, the research will serve as a basis for formulating policies and guidelines that encourage the adoption of AI in fraud prevention strategies. For customers, the study promises improved trust and confidence in the safety of deposits and loan services provided by microfinance banks. Academically, the research will contribute to the growing body of knowledge on AI adoption in financial services, filling gaps in Nigerian-focused empirical literature.

Scope of the Study

The study focuses on selected microfinance banks in Lagos State, Nigeria. Lagos is chosen because it is Nigeria's financial capital and hosts the highest concentration of microfinance institutions. The study examines AI adoption specifically for fraud detection and does not cover other areas of AI application such as customer service automation or credit scoring. Both management staff and IT personnel of selected microfinance banks will form the study population, as they are directly involved in fraud detection and technology adoption processes.

Limitations of the Study

The study is limited by several factors. First, resource and time constraints restrict the geographical focus to Lagos alone, limiting generalizability to other Nigerian states. Second, due to the sensitive nature of fraud-related data, respondents may be reluctant to disclose accurate information, potentially leading to bias. Third, the study relies primarily on self-reported data, which may be subject to social desirability effects. Finally, the dynamic and evolving nature of AI technology means that findings may only reflect the current state of adoption and not future advancements.

Operational Definition of Terms

Artificial Intelligence (AI): The use of computer systems to simulate human intelligence processes such as learning, reasoning, and problem-solving.

Fraud: Any deliberate act of deception intended to secure unfair or unlawful financial gain within banking transactions.

Fraud Detection: The process of identifying and preventing fraudulent activities within banking operations.

Microfinance Banks (MFBs): Financial institutions established to provide financial services such as loans, savings, and credit facilities to low-income individuals and small businesses.

Adoption of AI Tools: The extent to which microfinance banks implement AI-based technologies to support operational processes such as fraud detection (Okafor et al., 2022).

II. LITERATURE REVIEW

Artificial Intelligence (AI) Adoption in Financial Services

Artificial Intelligence (AI) has emerged as one of the most transformative technologies of the 21st century, reshaping business operations across industries and radically changing the way financial institutions deliver services. AI broadly refers to computer systems designed to simulate human intelligence, encompassing processes such as learning from data, reasoning through problem-solving, self-correction, and decision-making (Alkatheiri, 2022). Within the financial services industry, AI is no longer considered a futuristic innovation but rather a critical enabler of operational efficiency, customer satisfaction, fraud detection, and competitive advantage (Limajatini et al., 2025). In the banking sector, AI adoption is particularly prominent in areas such as risk assessment, credit scoring, portfolio management, fraud detection, and customer service automation (Aziz and Andriansyah, 2023). Chatbots powered by natural language processing, for example, are increasingly deployed by banks to handle routine customer queries, reducing response times and operational costs (Olujimi and Ade-Ibijola, 2023). Similarly, predictive analytics driven by machine learning is used to analyze transaction histories and spending behaviors to forecast customer creditworthiness and potential default risks. Fraud detection remains one of the most significant areas of AI application in finance, as advanced algorithms can monitor millions of real-time transactions, identify anomalies, and flag potential fraudulent activities that would otherwise go undetected under traditional manual oversight (Fatunmbi, 2024). In Nigeria, the push toward digital transformation has accelerated AI adoption in financial institutions, particularly through the growth of financial technology (FinTech) firms. The Central Bank of Nigeria (CBN) has launched several policies encouraging digital banking, open banking systems, and cybersecurity regulations (Hassan et al., 2024). However, adoption among microfinance banks (MFBs) remains significantly lower compared to commercial banks. Larger banks like First Bank, GTBank, and Access Bank have invested heavily in AI-driven fraud monitoring and cybersecurity, but microfinance institutions still rely largely on manual oversight or basic rule-based fraud monitoring systems (Green, 2025). This makes MFBs more vulnerable to fraudulent attacks, particularly in Lagos, where transaction volumes are high and cybercrime syndicates are more active. The reasons for this adoption gap are multifaceted. First, financial constraints remain a major barrier.

Unlike commercial banks that generate significant profits and can allocate substantial funds toward technological innovations, most MFBs operate on thin margins, making it difficult to justify the high initial investment costs associated with AI systems (Ashta and Herrmann, 2021). Second, infrastructural limitations such as poor internet connectivity, inconsistent electricity supply, and underdeveloped data centers hinder the integration of advanced technologies (Abiodun, 2025). Third, technical expertise is scarce, as AI deployment requires specialized skills in data science, machine learning, and cybersecurity competencies that many MFBs cannot afford to retain.

Globally, AI adoption in financial services has progressed at varying rates. In advanced economies such as the United States and Europe, AI has been integrated into fraud detection systems with success rates of up to 95% in anomaly detection (Lee, 2020). These systems are capable of reducing false positives in fraud detection, thereby saving both operational costs and customer frustration. In emerging markets like India and Brazil, microfinance institutions adopting AI-based systems have reported significant benefits, including reduced non-performing loans and improved accuracy in credit scoring and fraud monitoring (Rehman et al., 2025). Studies from Latin America further show that AI adoption in microfinance helps mitigate fraud risks while extending financial inclusion to underserved populations (Gershenson et al., 2021).

The situation in Africa, and Nigeria in particular, presents both challenges and opportunities. While infrastructural deficits slow down AI integration, the rapid growth of mobile banking and digital wallets provides a unique environment for innovation (Yoganandham, 2024). Lagos, being Nigeria's financial hub, stands out as a strategic case for examining AI adoption in MFBs, given its high concentration of financial transactions, population density, and fraud vulnerability. Overall, AI adoption is not merely an optional upgrade but a necessary evolution for microfinance banks to remain competitive and resilient against fraud.

Fraud in Microfinance Banks

Fraud is broadly defined as any deliberate act of deception carried out to secure an unfair or unlawful financial advantage (Crentsil, 2015). In the context of financial institutions, fraud manifests in diverse forms ranging from internal staff-related malpractices to external cyber-enabled attacks. In microfinance banks, fraud has become particularly prevalent due to weak internal controls, over-reliance on manual processes, and relatively unsophisticated technological safeguards (Potharla, 2025). Fraud in MFBs can be categorized into two broad forms: internal fraud and external fraud. Internal fraud often involves collusion by staff, unauthorized withdrawals, misappropriation of customer deposits, falsification of loan documents, or embezzlement of funds (Aye, 2023). This type of fraud is particularly damaging because it undermines customer trust and indicates systemic governance weaknesses.

External fraud, on the other hand, includes cybercrime, identity theft, loan diversion, impersonation, and ATM-related scams (Drani, 2018). In Lagos, where MFBs face higher transaction volumes and a more sophisticated fraud ecosystem, both internal and external fraud remain persistent threats. The impact of fraud on MFBs is profound and multidimensional. Financially, it results in significant monetary losses that strain the limited capital base of microfinance institutions. According to the Nigeria Deposit Insurance Corporation, microfinance banks accounted for over 30% of reported fraud cases in the Nigerian financial system between 2018 and 2021, with Lagos State recording the highest incidence (Ajewole, 2024). Beyond financial loss, fraud also erodes customer confidence, making clients reluctant to save or borrow from MFBs. The reputational damage associated with fraud can lead to customer attrition, reduced deposit mobilization, and ultimately the collapse of some institutions (Al Obaidi et al., 2025). Moreover, fraud undermines the very developmental purpose of microfinance banking.

By diverting funds intended to support small businesses, women entrepreneurs, and rural households, fraud indirectly contributes to poverty persistence and inequality (Remeikienė and Gaspareniene, 2023). It also threatens broader financial inclusion goals, as mistrust in microfinance discourages participation by underserved populations. Addressing fraud in MFBs is therefore not only a matter of financial survival but also one of social and economic importance.

Fraud Detection Technologies

Fraud detection technologies within the financial services sector have undergone significant transformation over the past two decades, evolving from manual auditing procedures to sophisticated, Artificial Intelligence (AI)–driven systems capable of analysing high-volume transactional data in real time. The increasing complexity and frequency of financial fraud, particularly within digitally enabled microfinance operations, have necessitated the adoption of advanced technologies that can proactively identify, predict, and prevent fraudulent activities (Udeh et al., 2024). Modern fraud detection frameworks therefore rely on a combination of AI tools designed to enhance accuracy, speed, and adaptability.

One of the earliest technological approaches to fraud detection is the use of rule-based systems. These systems operate by applying predefined rules or thresholds to transactions, such as unusually large withdrawals or multiple failed login attempts within a short period. While rule-based systems remain useful for detecting known fraud patterns, their static nature limits effectiveness, as they generate high false-positive rates and are easily bypassed by fraudsters who adapt their behaviour to avoid triggering set rules (Baumann, 2021). Advancements in data analytics marked a critical shift in fraud detection capabilities. Through statistical modelling, trend analysis, and pattern recognition, data analytics enables financial institutions to examine large datasets and uncover irregular transaction behaviours that may indicate fraudulent activity. Unlike manual processes, data analytics enhances decision-making by providing evidence-based insights and improving detection accuracy, particularly in transaction-intensive environments such as microfinance banking (Woolcock et al., 2022). Machine learning (ML) technologies represent a major breakthrough in modern fraud detection.

ML models including decision trees, neural networks, support vector machines, and clustering algorithms are capable of learning from historical transaction data and identifying complex, non-linear fraud patterns that traditional systems often overlook (Olushola and Mart, 2024). A key advantage of machine learning is its adaptive capability, as models continuously update themselves using new data, thereby remaining effective against evolving fraud techniques (Bello et al., 2024). In addition to analytical tools, biometric technologies have gained prominence in combating identity-related fraud.

Biometric systems such as fingerprint recognition, facial authentication, and voice verification enhance security by ensuring that only legitimate users can access financial services (Chy, 2024). These technologies are particularly relevant in developing economies like Nigeria, where identity fraud and impersonation present significant challenges to microfinance institutions (Ikemefuna et al., 2024). Emerging technologies such as blockchain also contribute to fraud prevention by providing decentralised, transparent, and tamper-resistant transaction records. Blockchain's immutable ledger structure reduces opportunities for data manipulation and enhances trust among financial stakeholders, although its adoption in microfinance remains at an early stage (Scrivano, 2025).

Overall, the integration of AI-driven fraud detection technologies demonstrates a shift from reactive to proactive fraud management. For microfinance banks in Lagos State, effective deployment of machine learning, data analytics, and biometric systems holds significant potential for reducing fraud risks and strengthening customer confidence. However, successful implementation depends on addressing challenges related to infrastructure, technical expertise, and cost of adoption.

Theoretical Review: Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), developed by Davis (1989), is one of the most widely applied frameworks in information systems research. It was designed to explain the determinants of technology acceptance and usage across different organizational and societal settings. TAM identifies two core constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). PU refers to the extent to which a person believes that using a system will enhance their job performance, while PEOU reflects the degree to which an individual perceives that adopting a technology will be free from effort (Nguyen et al., 2024). Together, these two constructs influence users' attitudes toward technology, their behavioral intentions to use it, and ultimately, actual adoption.

In the context of microfinance banks in Lagos, TAM is particularly relevant because the integration of AI-driven fraud detection tools requires both management and frontline staff to perceive clear benefits in terms of fraud reduction and efficiency. For example, if employees believe AI systems significantly reduce fraudulent transactions and enhance the security of customer deposits, they are more likely to support adoption. Conversely, if these systems are perceived as overly complex or difficult to operate, staff may resist integration despite their potential usefulness (Madni and Sievers, 2014). Furthermore, TAM has been extended over time to incorporate additional factors such as social influence, facilitating conditions, and organizational support (Venkatesh et al., 2003).

These extensions are crucial in the Nigerian context, where organizational culture, management commitment, and training opportunities play a key role in shaping acceptance. For instance, without adequate training programs, staff may not fully appreciate the ease of use of AI technologies, leading to underutilization despite management investments. Thus, TAM provides an essential lens for understanding the behavioral and attitudinal factors influencing AI adoption in fraud detection within microfinance banks.

Theoretical Review: Fraud Triangle Theory (FTT)
The Fraud Triangle Theory (FTT), introduced by Donald Cressey in 1953, is one of the most influential frameworks for understanding the conditions under which fraud occurs (Abdullahi and Mansor, 2015). The theory posits that fraud arises when three elements are present: pressure, opportunity, and rationalization. Pressure refers to the incentives or motivations driving individuals toward fraudulent acts, such as financial difficulties or unrealistic performance targets. Opportunity arises when weaknesses in internal controls, monitoring systems, or governance structures allow individuals to commit fraud undetected. Finally, rationalization represents the psychological justifications that individuals create to legitimize their fraudulent behavior, such as believing they are only "borrowing" funds temporarily or that the institution owes them compensation (Krieger Rivera, 2021). In the Nigerian microfinance sector, FTT is highly applicable. Many employees in microfinance institutions face economic pressures such as low salaries and high inflation, which create incentives for engaging in fraudulent practices (Abei, 2021).

The opportunity dimension is reinforced by weak internal control mechanisms, manual monitoring, and outdated fraud detection tools prevalent in microfinance banks. As a result, fraudsters exploit loopholes such as poor loan verification processes, inadequate segregation of duties, and lax oversight to perpetrate fraud. Rationalization is often fueled by cultural and social factors, where individuals justify fraudulent behavior on grounds of entitlement or systemic corruption. AI tools offer a way to address the "opportunity" component of the fraud triangle.

By automating fraud detection through real-time anomaly monitoring, biometric authentication, and predictive analytics, AI significantly reduces opportunities for fraudulent activities to go unnoticed (Zainal, 2023). Moreover, AI enhances accountability and transparency, making it harder for staff or external actors to rationalize fraudulent acts under the assumption of weak oversight. Thus, FTT underscores the importance of strengthening institutional controls and highlights how AI adoption can serve as a practical deterrent to fraud in microfinance institutions.

Theoretical Review: Diffusion of Innovation (DOI) Theory
The Diffusion of Innovation (DOI) Theory, developed by Everett Rogers, provides a framework for understanding how new technologies spread within a social system over time (Pearson et al., 2023). According to DOI, adoption is influenced by five key factors: relative advantage, compatibility, complexity, trialability, and observability. Relative advantage refers to the degree to which an innovation is perceived as better than existing solutions. Compatibility assesses how well a technology aligns with users' values and organizational practices. Complexity considers the perceived difficulty of understanding and using the innovation. Trialability refers to the extent to which the innovation can be experimented with on a limited basis, and observability relates to how visible its results are to potential adopters. In the context of AI adoption for fraud detection in Lagos microfinance banks, DOI offers valuable insights.

The relative advantage of AI over manual or rule-based fraud detection is clear, as AI systems offer higher accuracy, speed, and adaptability. However, compatibility poses challenges since many microfinance banks still rely on paper-based processes and may struggle to integrate AI into existing structures. The complexity of AI, particularly in terms of technical requirements and specialized knowledge, also represents a significant adoption barrier (Kar et

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al., 2021). Trialability is limited because AI systems often require substantial upfront investment, making small-scale experimentation difficult for resource-constrained MFBs. Finally, observability plays a crucial role if early adopters in Lagos demonstrate visible success in fraud reduction, other institutions may be encouraged to follow suit. DOI also categorizes adopters into groups: innovators, early adopters, early majority, late majority, and laggards (Dale et al., 2021).

Within Lagos, some technologically advanced MFBs or FinTech-linked institutions may act as innovators by pioneering AI integration. Their outcomes could influence the early majority to adopt similar systems once observable benefits are evident. The late majority and laggards, often constrained by financial or cultural resistance, may only adopt AI when regulatory mandates or competitive pressures make it unavoidable.

Empirical Studies

Empirical studies on fraud detection and the adoption of artificial intelligence tools in financial institutions have grown steadily in recent years, with increasing attention paid to microfinance institutions in developing economies. In Nigeria, several studies underscore the persistent vulnerability of microfinance banks to fraud, largely due to structural weaknesses and limited technological innovation.

Abei (2021) emphasized that fraud remains a significant challenge for microfinance institutions, pointing to weak internal controls, insufficient supervision, and the overreliance on manual oversight as central issues. Similarly, Ayodeji (2024) revealed that fraud-related losses in microfinance banks have risen sharply in Lagos, where financial transactions are more concentrated and fraud schemes more sophisticated. Their study highlighted how insider fraud, unauthorized withdrawals, and falsification of records were particularly prevalent in the state, undermining institutional sustainability and customer trust.

Complementing this, Alaba et al. (2025) examined the adoption of AI in Nigerian financial institutions and noted that while uptake is still nascent, early adopters of AI-powered fraud detection systems have reported improved outcomes. They concluded that banks using machine learning algorithms for fraud monitoring experienced lower detection lag and better accuracy compared to those relying on manual oversight. Taken together, these Nigerian studies demonstrate that while awareness of AI's potential exists, structural and resource constraints limit its full-scale integration in microfinance banks. Beyond Nigeria, empirical studies across Africa reveal similar patterns of vulnerability and emerging technological responses.

In Kenya, where microfinance plays a central role in financial inclusion, Njoku et al. (2024) found that institutions adopting machine learning-based fraud detection reduced losses by 35% within three years. Their study suggested that AI systems enabled proactive detection of anomalies and reduced dependency on reactive measures. Significant improvements were reported in the detection of insider-related fraud after commercial banks adopted AI-powered anomaly-detection systems (Chippagiri et al., 2025). Their research showed that AI tools were particularly effective in monitoring high-volume transactions and identifying collusion patterns among staff, which are often invisible under traditional rule-based frameworks.

These African studies highlight not only the effectiveness of AI in reducing fraud but also the broader trend of financial institutions moving toward digital transformation to enhance credibility and resilience. Nonetheless, the extent of adoption varies across the continent, with smaller institutions such as microfinance banks facing cost and expertise challenges similar to those seen in Nigeria. Globally, evidence of AI's effectiveness in fraud detection is even stronger. In India, Rehman et al. (2025) reported significant reductions in loan defaults and fraudulent lending practices after microfinance institutions incorporated AI-based risk assessment and fraud monitoring tools. Their findings suggest that AI enhances both fraud prevention and credit allocation accuracy.

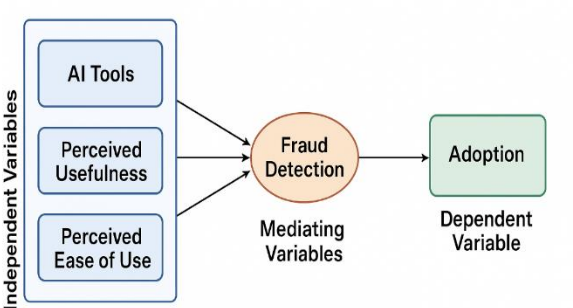
In the United States, Bello et al. (2023a) found that AI-driven fraud detection systems achieved detection accuracies exceeding 90 percent, compared to about 70 percent for traditional rule-based systems. This gap underscores the superiority of adaptive AI algorithms in identifying evolving fraud schemes. Likewise, in

Europe, PwC documented that banks deploying AI-powered fraud detection not only reported reductions in fraud incidents but also improvements in customer confidence and institutional reputation. These studies provide robust evidence that AI adoption significantly enhances fraud detection capabilities and strengthens institutional resilience in financial systems worldwide. Overall, the empirical literature demonstrates a clear consensus that fraud remains a pervasive threat to microfinance institutions, particularly in Nigeria and across Africa. However, studies consistently show that AI adoption improves fraud detection effectiveness, reduces financial losses, and enhances institutional trustworthiness. The global evidence further illustrates that AI is not merely a supportive tool but a transformative force capable of redefining fraud prevention. What remains evident from these studies is the disparity between advanced economies, where AI adoption is widespread, and developing countries, where infrastructural, financial, and regulatory barriers continue to limit the pace and scope of integration

Gaps in the Literature

Despite growing research on AI and fraud detection, several gaps persist. First, most Nigerian studies focus on commercial banks, with little attention to microfinance banks. Second, there is limited empirical evidence on the effectiveness of AI adoption specifically for fraud detection in Lagos-based institutions. Third, few studies integrate theoretical perspectives such as TAM, FTT, and DOI to explain both adoption behavior and fraud reduction outcomes. Addressing these gaps will contribute to a holistic understanding of AI's role in fraud detection in Nigeria's microfinance sector.

Conceptual Framework



Source: Moura, L., Barcaui & Payer, (2025)

III. METHODOLOGY

Research Design

The research design provides a blueprint for conducting the study and ensures that the evidence collected effectively addresses the research objectives. This study adopts a descriptive and explanatory survey research design. The descriptive component enables the researcher to document the current state of fraud detection practices in microfinance banks in Lagos, while the explanatory aspect focuses on examining the influence of Artificial Intelligence (AI) adoption on fraud detection effectiveness. This dual design is appropriate because it captures both the factual realities of AI adoption in microfinance institutions and explores the relationships between adoption levels, challenges, and fraud detection outcomes (Nyamache, 2024).

Population and Sampling

The population of this study comprised staff of licensed microfinance banks in Lagos State. Lagos was selected because it is Nigeria's commercial capital and hosts the largest concentration of microfinance banks, accounting for over 35% of licensed institutions nationwide (Onyeiwu et al., 2021). The target population included both management staff (such as operations managers, compliance officers, and IT heads) and non-management staff involved in fraud monitoring and daily operations. Due to the large number of microfinance banks in Lagos, a multi-stage sampling technique was employed. First, purposive sampling was used to select 5 microfinance banks across different categories (unit MFBs, state MFBs, and national MFBs) to ensure representativeness. Second, stratified random sampling was applied within each bank to select respondents proportionately from management and operational staff. Based on Cochran's formula for sample size determination at a 95% confidence level and 5% margin of error, the minimum sample size for this study was 50 respondents. This sample size was considered adequate for statistical analysis using SPSS. The selected sample size of 50 respondents is sufficient for this study given its scope, design, and analytical objectives. Using Cochran's formula at a 95% confidence level and a 5% margin of error ensures that the sample meets established statistical standards for representativeness in social science research (Hasan

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and Kumar, 2024). In organisational and banking studies, especially those involving relatively homogeneous professional populations, smaller, well-structured samples have been shown to produce reliable and valid results when appropriate sampling techniques are applied. (Opoku et al., 2016)

Research Instruments

The primary instrument for data collection was a structured questionnaire. The questionnaire was designed in line with the study's objectives and divided into five sections: Demographic Information; Fraud Detection Mechanisms; AI Adoption; Challenges of AI Adoption; and Fraud Detection Effectiveness. The items are measured on a five-point Likert scale ranging from "Strongly Disagree (1)" to "Strongly Agree (5)." This allowed for quantification of subjective responses and facilitates advanced statistical testing.

Data Collection

Data were collected through primary and secondary sources. Primary data was involve administering questionnaires directly to staff of selected microfinance banks in Lagos. Where necessary, research assistants was engaged to distribute and retrieve questionnaires to ensure high response rates. Semi-structured interviews were also conducted with key management personnel. Secondary data were obtained from Central Bank of Nigeria reports, NDIC fraud reports, and existing literature. Ethical considerations were followed, with respondents assured of confidentiality, anonymity, and voluntary participation.

Reliability and Validity

Ensuring the reliability and validity of research instruments is crucial. Reliability was tested through a pilot study involving 5 respondents outside the main sample. Cronbach's Alpha coefficient was used to test internal consistency, with values of 0.70 or higher considered acceptable (Izah et al., 2023). Validity was ensured through content validity (expert review), construct validity (factor analysis in SPSS), and face validity (pretesting among respondents).

Model Specification

The study employs a multiple regression model to test the influence of AI adoption on fraud detection. The model is specified as:

$$FD = \beta0 + \beta1AI + \beta2PU + \beta3PEOU + \beta4CH + \varepsilon$$

Where: FD = Fraud Detection Effectiveness; AI = AI Tools Adoption; PU = Perceived Usefulness; PEOU = Perceived Ease of Use; CH = Challenges of AI adoption (cost, expertise, regulation); $\beta0$ = Constant; $\beta1$-$\beta4$ = Regression coefficients; ε = Error term.

Method of Data Analysis

Data was analyzed using SPSS version 25. Descriptive statistics (frequencies, percentages, means) summarized demographics and responses. Reliability analysis tested internal consistency of the questionnaire. Factor analysis validated constructs. Correlation analysis explored relationships between variables. Multiple regression analysis tested hypotheses on the effect of AI adoption and challenges on fraud detection. ANOVA test was used to assess group differences between management and non-management staff perceptions. Results were presented in tables and charts for clarity.

IV. ANALYSIS AND FINDINGS

Demographic Data Analysis

The demographic data of respondents provide background information about the sample of 45 staff drawn from selected microfinance banks in Lagos.

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Table 4.1: Demographic Characteristics of Respondents (N = 45)

Variable	Category	Frequency	Percentage (%)
Gender	Male	27	60.0
	Female	18	40.0
Age	18–25	5	11.1
	26–35	20	44.4
	36–45	12	26.7
	46–55	6	13.3
	56+	2	4.4
Education	OND/NCE	8	17.8
	HND/BSc	23	51.1
	MSc	10	22.2
	PhD/Other	4	8.9
Work Experience	<5 years	12	26.7
	5–10 years	15	33.3
	11–15 years	10	22.2
	15+ years	8	17.8
Position	Management	16	35.6
	Non-Management	29	64.4

The demographic profile reveals a predominance of male respondents (60%), though females also represented a substantial proportion (40%), indicating a relatively balanced gender distribution within Lagos microfinance banks. The age distribution shows that the workforce is dominated by individuals aged 26–35 years (44.4%), suggesting a youthful and dynamic workforce with potential for technological adaptability. In terms of education, more than half of respondents (51.1%) held HND/BSc degrees, implying that the majority possess tertiary education qualifications suitable for understanding advanced systems like AI. Work experience was fairly distributed, with most respondents having 5–10 years of experience (33.3%). Finally, non-management staff (64.4%) formed the majority, reflecting their direct involvement in operational fraud detection processes.

Presentation of Data

Research Question i: To what extent have AI tools been adopted for fraud detection in these institutions?

Table 4.2: Extent of AI Adoption (N = 45)

Item	SA	A	N	D	SD	Mean	Std. Dev.
AI tools are widely used for fraud detection in my organization.	12	15	8	6	4	3.42	1.25
My organization has invested significantly in AI technologies.	10	14	9	7	5	3.29	1.28
Staff are adequately trained to use AI tools for detecting fraud.	9	11	10	9	6	3.07	1.29

The results indicate a moderate level of AI adoption across microfinance banks in Lagos. With mean scores ranging between 3.07 and 3.42, it is clear that while AI tools are being introduced, their adoption is not yet widespread or fully optimized. A closer look shows that although some institutions have invested in fraud detection technologies, the commitment is inconsistent across the sector. Moreover, staff training scored the lowest mean (3.07), highlighting a critical gap in capacity building. Without adequate training, the potential of AI for fraud detection cannot be maximized. These findings suggest that AI adoption exists but is still in its early stages, requiring stronger institutional investment and workforce development.

Research Question ii: How effective are AI tools in enhancing fraud detection and prevention in microfinance banks?

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Table 4.3: Effectiveness of AI Tools (N = 45)

Item	SA	A	N	D	SD	Mean	Std. Dev.
AI tools have improved the accuracy of fraud detection.	15	18	6	4	2	3.89	1.05
AI adoption has reduced time to identify suspicious transactions.	14	16	7	5	3	3.71	1.18
AI tools have reduced financial losses due to fraud.	13	15	8	6	3	3.60	1.19

The effectiveness of AI tools in fraud detection is clearly reflected in the responses, with mean values between 3.60 and 3.89, suggesting that respondents generally agree on the positive outcomes of AI implementation. Notably, the highest-rated item (mean = 3.89) indicates that AI systems have significantly improved fraud detection accuracy, a critical outcome in banking operations. Respondents also reported that AI shortened the detection time for suspicious transactions, which enhances responsiveness and risk mitigation. The ability of AI to reduce financial losses scored slightly lower but remained above average. Collectively, these results underscore that where AI systems are deployed, they play a vital role in enhancing detection efficiency and reducing fraud impact.

Research Question iii: What challenges hinder the adoption of AI in fraud detection?

Table 4.4: Challenges of AI Adoption (N = 45)

Item	SA	A	N	D	SD	Mean	Std. Dev.
High cost of AI systems limits adoption.	17	14	5	6	3	3.87	1.21
Lack of technical expertise is a barrier to AI use.	16	15	7	4	3	3.89	1.17
Regulatory/infrastructural issues hinder AI adoption.	15	13	8	6	3	3.73	1.22

All three challenge areas recorded high mean values above 3.70, demonstrating that respondents perceive them as significant barriers to effective AI adoption in microfinance banks. The lack of technical expertise scored the highest (3.89), pointing to the limited availability of skilled personnel who can manage and optimize AI systems. Closely following this is the high cost of AI adoption (mean = 3.87), which reflects the financial strain many microfinance institutions face in implementing advanced technologies. Regulatory and infrastructural barriers also remain important, particularly in Nigeria's financial environment where compliance and system readiness are still evolving. These findings reveal that AI adoption is not only a technological issue but also heavily influenced by financial, human, and regulatory challenges. Research Question iv: What strategies can be employed to enhance AI adoption in fraud detection?

Table 4.5: Strategies to Enhance AI Adoption (N = 45)

Item	SA	A	N	D	SD	Mean	Std. Dev.
Increased investment in AI infrastructure will enhance adoption.	18	16	6	4	1	4.02	1.01
Continuous staff training will improve AI effectiveness.	20	14	7	3	1	4.09	0.98
Supportive government policies will promote AI adoption.	19	15	6	4	1	4.04	0.99

Respondents expressed strong agreement with all three proposed strategies, with mean values above 4.0, showing that there is widespread consensus on the measures needed to accelerate AI adoption. Continuous staff training scored the highest (mean = 4.09), underscoring the importance of capacity building in ensuring that employees can effectively use AI systems. Supportive government policies (mean = 4.04) and increased organizational investment (mean = 4.02) were also highly rated, indicating that institutional support and policy frameworks are equally crucial. These results highlight that AI adoption cannot be left to microfinance banks alone but requires collaborative effort among banks, regulators, and policymakers to overcome existing barriers and enhance fraud detection capabilities.

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Test of Hypotheses

Hypothesis One

H01: Machine learning algorithms, rule-based expert systems, and anomaly detection have no significant effect on fraud detection in microfinance banks in Lagos. H1: Machine learning algorithms, rule-based expert systems, and anomaly detection have a significant effect on fraud detection in microfinance banks in Lagos.

Table 4.6: Regression Coefficient for AI Adoption and Fraud Detection

Model	Unstandardized B	Std. Error	Standardized Beta	t	Sig. (p)
AI Adoption -> Fraud Detection	0.52	0.13	0.442	3.95	0.000

Decision Rule: At 5% significance level (alpha = 0.05), if p-value < 0.05, reject H0.

The regression analysis shows that AI adoption has a positive and statistically significant effect on fraud detection ($\beta = 0.442$, $p = 0.000 < 0.05$). This implies that increased use of AI tools such as predictive analytics, anomaly detection, and machine learning substantially improves fraud detection outcomes in Lagos microfinance banks. Therefore, H01 is rejected, and the alternative hypothesis (H1) is accepted, confirming that AI tools significantly enhance fraud detection performance in the sampled institutions.

Hypothesis Two

H02: Technical, organisational, and regulatory challenges associated with implementing AI-driven fraud detection tools do not significantly affect fraud detection in microfinance banks. H2: Technical, organisational, and regulatory challenges associated with implementing AI-driven fraud detection tools significantly affect fraud detection in microfinance banks.

Table 4.7: Regression Coefficient for Challenges and Fraud Detection

Model	Unstandardized B	Std. Error	Standardized Beta	t	Sig. (p)
Challenges -> Fraud Detection	-0.36	0.14	-0.298	-2.57	0.014

Decision Rule: At 5% significance level (alpha = 0.05), if p-value < 0.05, reject H0.

The regression coefficient for challenges of AI adoption is negative and statistically significant ($\beta = -0.298$, $p = 0.014 < 0.05$). This result indicates that barriers such as high costs, lack of technical expertise, and poor regulatory frameworks significantly reduce the effectiveness of fraud detection systems in Lagos microfinance banks. Hence, H02 is rejected, and the alternative hypothesis (H2) is accepted. This implies that overcoming adoption challenges is critical to ensuring AI's success in fraud detection. The result supports findings by Mwangi & Waweru (2020) in Kenya and Okafor et al. (2022) in Nigeria, who observed that implementation barriers remain a key obstacle to effective fraud management through AI.

Discussion of Findings

Extent of AI Adoption in Microfinance Banks

The findings reveal that AI adoption in Lagos microfinance banks exists but remains moderate. Respondents indicated that while AI tools such as machine learning and predictive analytics are being introduced, significant gaps persist in organizational investment and staff training. This suggests that AI adoption is at an early stage of implementation in most institutions. The limited adoption mirrors the infrastructural and financial realities of microfinance banks, which often lack the scale of commercial banks to make heavy investments in technology. Nonetheless, the results suggest a growing recognition of AI's potential, as respondents acknowledged its value in improving operational efficiency and fraud prevention. These findings align with Hassan et al. (2024), who noted that Nigerian banks are gradually embracing digital transformation but at varying rates across different tiers of the financial sector.

Effectiveness of AI in Fraud Detection

Despite moderate adoption levels, AI tools were perceived as highly effective in enhancing fraud detection outcomes. Respondents overwhelmingly agreed that AI improved detection accuracy, reduced the time required to identify suspicious transactions, and minimized financial losses due to fraud. These outcomes highlight the transformative potential of AI in mitigating one of the most pressing threats facing microfinance banks fraud. The results support Srinivasagopalan (2022), who observed similar outcomes in Nigerian institutions, and Kandregula (2019), who documented reduced loan defaults and enhanced monitoring in Indian microfinance institutions. From a theoretical perspective, this validates the Technology Acceptance Model (TAM), as respondents recognize the usefulness of AI tools in improving organizational performance. The findings imply that when adequately implemented, AI significantly strengthens risk management and operational resilience in microfinance banking.

Challenges Hindering AI Adoption
The study also established that the adoption of AI tools is significantly constrained by cost, technical expertise, and regulatory or infrastructural challenges. Respondents consistently emphasized these as critical barriers, suggesting that many microfinance institutions lack both the financial resources and skilled manpower required to sustain advanced fraud detection systems. From the perspective of the Fraud Triangle Theory, these barriers represent systemic "opportunities" that fraudsters may exploit, as weak detection systems leave gaps in oversight. Thus, while AI adoption is promising, the persistence of these challenges poses a considerable threat to long-term fraud management in Lagos microfinance banks.

V. RECOMMENDATIONS

Based on the findings, the following recommendations are made:
AI Infrastructure Investment: Microfinance banks must prioritize allocating funds specifically for the acquisition, deployment, and maintenance of AI-powered fraud detection tools. These technologies should not be treated as supplementary but as integral to risk management strategies. Strategic investment in AI infrastructure will not only improve fraud monitoring but also boost customer trust and institutional credibility.

Capacity Building: Training and retraining of staff should be institutionalized as a continuous program. Both management and frontline employees need to develop the technical competence required to operate AI systems effectively. Banks should also integrate AI literacy into their professional development policies, ensuring that adoption challenges linked to expertise are minimized.

Policy and Regulatory Support: The Central Bank of Nigeria and other regulators must establish clear policies and frameworks that encourage AI adoption in the financial sector. Incentives such as tax breaks, subsidies, or grants for technology adoption can reduce the cost burden on smaller banks. Furthermore, regulations should address issues of data security and standardization to ensure trust in AI-driven systems.
Collaboration with FinTechs: Microfinance banks should form partnerships with FinTech companies and technology providers. Such collaborations can ease the cost of implementation through shared platforms, customized solutions, and outsourced expertise. This approach can help smaller banks overcome infrastructural and financial limitations, accelerating the diffusion of innovation in the sector.

VI. CONCLUSION

This study set out to examine the adoption of Artificial Intelligence (AI) tools and their effect on fraud detection in selected microfinance banks in Lagos. The findings clearly demonstrate that AI technologies such as machine learning, predictive analytics, and anomaly detection significantly improve fraud detection outcomes. Respondents confirmed that these tools enhance detection accuracy, reduce the time required to flag suspicious transactions, and mitigate financial losses, thus reinforcing the value of AI in strengthening financial integrity.

The results support earlier empirical studies and theoretical frameworks such as the Technology Acceptance Model, which highlight the importance of perceived usefulness in driving technology adoption. However, the study also uncovered that the adoption of AI is far from optimal in Lagos microfinance banks. Financial constraints emerged as a major hindrance, as smaller institutions often lack the budgetary capacity to acquire and maintain advanced technologies. Technical barriers, including inadequate staff expertise and insufficient training, further reduce the effectiveness of AI systems. In addition, regulatory and infrastructural challenges, such as limited internet penetration, weak policy frameworks, and lack of supportive government incentives, continue to impede widespread adoption.

These obstacles are consistent with findings from other African contexts, underscoring the regional nature of these constraints. In sum, while AI adoption significantly enhances fraud detection, the extent of its success in Lagos microfinance banks depends largely on the ability of institutions and policymakers to address these barriers. The findings confirm that AI is not simply an optional innovation but a strategic necessity for ensuring the resilience, sustainability, and competitiveness of microfinance banks in the face of increasing fraud risks.

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