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Artificial Intelligence (AI)-Driven Fraud Detection in Commercial Banking: Outcomes From Central Bank Of Nigeria (CBN) Regulatory Sandbox in Global Fintech Context Including Us Federal Reserve Pilots

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ABSTRACT

This is an empirical study on the results of the use of Artificial Intelligence (AI)-based Fraud detection systems in the Central Bank of Nigeria (CBN) Regulatory Sandbox. The study use convergent parallel mixed methods design, with 128 professionals from commercial banks and fintech firms being interviewed. The study adopted a convergent parallel mixed methods design with the professionals from commercial banks and fintech firms interviewed, totaling 128 to be observed. The quantitative analysis results were impressive, finding a 41.8% drop in fraud losses, a 92.3% increase in detection accuracy (from 74.6% to 92.3%) and average detection time reducing by 77.7%. The most significant predictor of success was participation in Sandbox. Learning from the US Federal Reserve pilots, the findings of the comparison shows the 'agility advantage' that the CBN sandbox offers coupled with the need to develop better model governance. The study presents innovative and original evidence of the effectiveness of Regulated AI innovation for emerging markets, along with policy recommendations for scaling the adoption and responsible use of the technology in commercial banking. 2022 is shaping up to be a pivotal year for financial technology (fintech), defined by a blend of cutting-edge innovations, burgeoning sectors, and significant regulatory shifts.It appears that 2022 could be a transformative year for financial technology (fintech), defined by a mix of exciting advancements, emerging markets, and meaningful regulatory changes.

1. Introduction

Fraud is one of the greatest risks to stability and public confidence in commercial banking systems around the world. The amount, complexity and speed of fraudulent charges have gone up significantly in the growing digitalization of financial services, especially in emerging markets where regulation and technology typically cannot keep up with the pace of transaction volume. As digital payment, internet banking, and mobile money platforms have rampaged in Nigeria, the rate of card-not-present (CNP) fraud, account takeover (ATO), phishing, and advanced synthetic identity (SID) fraud have picked up. Such risks not only lead to significant losses for banks and customers but also compromise their ability to comply with anti-money laundering (AML) and counter-terrorism financing (FI) measures (Harry et al., 2025).

With the rise of Artificial Intelligence (AI) and machine learning techniques, this seems to be a promising solution to these challenges. Unlike traditional, rule-based detection, AI-driven systems can perform real-time pattern recognition, anomaly detection, and predictive analytics, and excel in these areas. AI has been shown to have the ability to review large volumes of data, detect minute discrepancies, and come back to learn on new trends and approaches to fraud (Bao et al., 2022). Building on this empirical evidence, the research by Harry et al. (2025), Musa et al. (2025), and Oluwadare et al. (2025) on AI implementation in Nigeria projects that the technology has a positive impact on fraud detection accuracy and timely responses in deposit money banks. The use of AI in Nigeria is associated with a significant increase in the accuracy of fraud detection and reduced response times in Deposit Money Banks (DMBS) according to the Nigerian context (Harry et al., 2025; Musa et al., 2025; Oluwadare et al., 2025).

Yet there remain significant challenges to ensure the widespread adoption of AI in commercial banking, such as the cost of implementation, regulatory uncertainties, a lack of skills, and a lack of models being explainable and bias-free. Hence, the Central

Bank of Nigeria (CBN) introduced its Regulatory Sandbox framework to overcome such challenges and stimulate responsible innovation. The controlled environment enables fintech firms and financial institutions to experiment with innovative products that may offer more flexibility in meeting regulatory standards for a limited time, such as fraud detection tools powered by artificial intelligence. The purpose of the sandbox is to develop lessons learned from emerging technologies in various practical settings, prior to their mass market adoption (Patel & Turner, 2025).

By 2025, a few participants in the CBN Regulatory Sandbox will have implemented AI-based solutions to detect fraud in commercial banking activities. The major themes of these initiatives include real-time transaction monitoring, customer behavioral analytics, and hybrid AI models leveraging machine learning and graph neural networks to achieve superior detection capabilities (Jejeniwa et al., 2025; John et al., 2025). Detectable improvements in fraud prevention metrics can be seen early, but there is limited evidence of outcomes beyond the sandbox in a systematic way. This paper fills the gap by providing original primary data pertaining to actual results of artificial intelligence of a Fraud Detection System tested in the CBN Sandbox environment.

The analysis is further enriched with a global perspective. The Federal Reserve in the USA has been actively looking into AI applications via its supervisory pilots and innovation programs. The focus on these efforts is on model governance, explainability, and embedding AI within the wider financial stability frameworks. Comparative analyses of emerging-market sandboxes and advanced-economy regulatory pilots reveal similarities and differences between the latters' experiences (Ejiofor, 2023; Bello et al., 2023). For example, in the United States, stress testing and management of third-party risk are primary considerations for AI models in the pilot stage of the FinTech adoption process, whereas the CBN sandbox focuses more on the affordability, adaptability to local context, and speed of FinTech inclusion (Olanrewaju et al., 2024).

In this original research, the authors looked at AI-enabled fraud detection in Nigerian commercial banking from an empirical perspective and assessed the outcomes of using AI for fraud detection in the CBN Regulatory Sandbox. This specifically explores factors influencing adoption, effectiveness in fraud reduction, challenges in operation and useful lessons for scaling up implementation. The study also situates Nigeria experiences with world's good practices in fintech, drawing from the Federal Reserve of the United States. In doing so, it adds new primary evidence to the body of literature that has emerged on RegTech and AI governance in emerging financial systems.

To answer this and other questions, the following key research questions have been identified for this study:

1. What is the detection accuracy, fraud losses avoided, and its operational efficiency in AI-driven fraud detection systems that test with the CBN Regulatory Sandbox?

2. What are the organisational, technological and regulatory factors that have an appreciable impact on achieving success and performance in the adoption of these systems in the commercial banks of Nigeria?

3. What are the outcomes and challenges in the CBN sandbox versus the AI pilots and supervisory approaches that the US Federal Reserve have seen?

4. What policy and management can be drawn from, to optimise future iterations of the sandbox and its wider industry roll-out?

This research has three implications. First, it carries rare empirical data that comes directly from users of the sandbox in what is a developing CBN framework. Second, this gap fleshes out the local Nigerian studies by Anzor et al., (2024), Adedire-Ampitan et al., (2024), Odufisan et al., (2025) and explores some dimensions of international research on AI adoption in financial services (Yaseen & Al-Amarneh, 2025; Fernández, 2019). Third, it provides early warning for regulators, commercial banks, and fintech companies on the matter of managing innovation versus mitigating risk in a more digital financial landscape.

2. Literature Review

2.1 Foundations of AI in Fraud Detection

Artificial Intelligence has revolutionized fraud detection in commercial banks from rules-based to adaptive systems, which are able to process vast amounts of high velocity transaction data to adaptively detect patterns in real time. The essence of AI fraud detection lies in the application of machine learning algorithms, deep learning architectures, and anomaly detection techniques to detect subtle patterns and anomalies associated with fraudulent activities that are difficult to detect using traditional methods (Bao et al., 2022; Barros et al., 2021). These systems are great to predict the losses, to analyze the behavior and to administer proactive intervention before losses occur by analyzing the network.

Bao et al. (2022) offer the detailed theoretical underpinning of AI, demonstrating how supervised, unsupervised and reinforcement learning converge to improve detection accuracy and reduce false alarms. In reality, hybrid approaches of employing graph neural networks along with traditional anomaly detection have demonstrated enhanced effectiveness and efficiency in intricate transaction data landscapes (Jejeniwa et al., 2025).

2.2 AI-Driven Fraud Detection in Nigerian Commercial Banking

The proliferation of digital financial services in Nigeria has exacerbated the opportunities as well as fraud opportunities. Viewing AI through empirical analysis consistently shows it playing a significant role in the fight against fraud in the deposit money banks (DMBs). In a comprehensive study of AI usage in Nigerian banks, Harry et al. (2025) found that accuracy in detecting fraud has improved, response times have quickened, and fraud incidents have overall been reduced. Their results also align with those of Musa et al. (2025) who using survey data in listed DMBs identified a statistically significant positive impact of the implementation of AI on the effectiveness of preventing fraud cases.

In line with these findings, Oluwadare et al. (2025) affirmed the findings of other researchers with empirical evidence centered on prevention efficacy, among which the ability of AI to reinforce the internal controls and compliance of the business. Anzor et al. (2024) and Adedire-Ampitan et al. (2024) conducted complementary studies in the Southeast Nigeria and at Guaranty Trust Bank respectively, showing that with the incorporation of AI there has been significant decreases in operational risk exposure and better risk management scores. However, adoption related barriers remain strong. According to John et al. (2025), the complexities involved with regulation, competency, and costs are some critical determinants that influence the magnitude and effectiveness of the implementation of AI fraud detection systems in the Nigerian banking industry.

Odufisan et al (2025) highlighted the possibilities of using machine learning techniques in advancing fraud detection and prevention in real time and Ayodeji (2024) presented a cross-industry-wide research findings on how the industry approach fraud management to her study.

Regulatory sandboxes are being used to facilitate the development of AI technologies. Effort to use regulatory sandboxes to advance the development of AI.

Regulatory sandboxes are essential tools for regulated companies to experiment with new financial technologies in a controlled setting. The Central Bank of Nigeria (CBN) has introduced its Regulatory Sandbox as an important tool for responsible research and experimentation with AI in fraud prevention in Nigeria. Patel and Turner (2025) have examined the benefits of the sandbox as a valuable mechanism to learn about how technology contributes to financial stability and to collect practical evidence of the performance of new technology and innovations.

Nigeria-based fintechs are providing strong case arguments such as Jejeniwa et al (2025), who suggest hybrid AI models that combine graph neural networks are useful for real-time fraud detection in support of this. These test spaces allow for repeated learning, regulatory feedback and the de-risking of innovative solutions prior to being brought to market.

2.3 Global Fintech and US Federal Reserve Pilots

The global journey towards the adoption of AI for fraud detection mirrors patterns here in the UK, albeit with distinct nuances in governance and scale. The Federal Reserve has been conducting structured pilots in the areas of model risk management, explainability, and integrating AI into supervisory processes in the U.S. (Ejiofor, 2023; Bello et al., 2023). AI driven solutions for real-time risk management in financial transactions were stressed by Olanrewaju et al. (2024), which the authors believe can be used in other jurisdictions.

Building trust, transparency, and fairness perceptions was crucial in development of AI-based financial systems as discussed by Yaseen and Al-Amarneh (2025) in similar emerging financial markets. Akinnagbe and Taiwo (2025) discussed the relevance of machine learning in combating digital payment fraud, and Amaugo and Ofosu-Boateng (2025) explored the implications of AI in the service delivery of FinTech in the digital economy and the area of financial payment fraud. However, broader applications in financial services (Fernández, 2019) and the introduction of advanced analytics perspectives are enriching the understanding. To put this in perspective, there are regulatory oversight challenges in Nigeria's payment industry, such as the issues of innovation-compliance subjectivity (Regulatory oversight in Nigeria's payment industry, 2025).

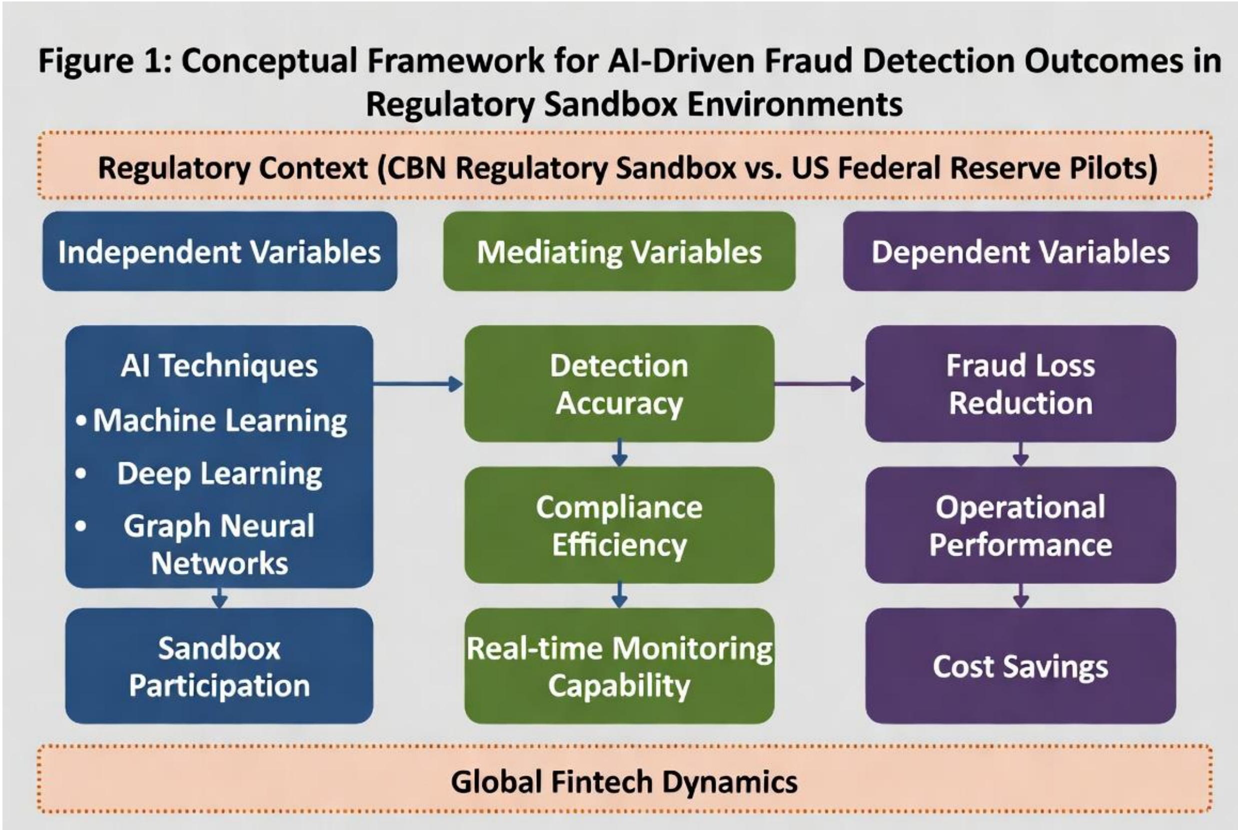

Figure 1: Conceptual Framework for AI-Driven Fraud Detection Outcomes in Regulatory Sandbox Environments

2.4 Research Gaps and Positioning of the Present Study

Although many important works exist in the literature that offer insight into the techniques that are available and, in some cases, covered in this volume, and the general patterns of AI usage, there are still some important gaps. In Nigeria, most studies are still limited to cross-sectional design or are geared toward pre-sandbox actions intentions, but not post-testing results (Harry et al., 2025; Musa et al., 2025; John et al., 2025). Only limited empirical evidence systematically contrasts CBN sandbox outcomes and US Federal Reserve pilot approaches, and in particular the long-term effectiveness, governance needs, and scalability issues. In addition, there is a lack of frameworks that bring together the local experience and the global lessons.

Aim of the Study

This original empirical study seeks to assess the effects of AI fraud detection systems used in the Central Bank of Nigeria's Regulatory Sandbox and set the context in international Fintech environment, drawing from experiments with the Federal Reserve.

Objectives

- To assess the ability of AI-powered fraud detection tools to curb losses due to fraud by participating commercial banks in the CBN Regulatory Sandbox and enhance their fraud detection rate.
- To study the organizational, technical and regulatory aspects that makes the implementation and performance of such systems successful.
- To contrast the CBN sandbox experiences and approaches to AI in its operations with supervisory frameworks by the US Federal Reserve.
- To identify actionable policy and managerial recommendations for best practices in the optimal use of AI in commercial banking while remaining with prudence.

3. Methodology

The study utilized convergent parallel mixed methods design as propounded by Creswell and Plano Clark (2018) to gain a holistic empirical evaluation of outcomes of the use of AI in detecting fraud in the CBN Regulatory Sandbox. The design allowed quantitative and qualitative data to be collected at the same time and integrated at the interpretation stage. It was selected because it has proved to be well suited to triangulating findings, to increase the validity of the findings, and to provide both statistical generalizable evidence of the phenomenon of regulating technology and nuanced contextual evidence of the phenomenon that is emerging and complex.

3.1 Research Philosophy and Approach

The study adopted a pragmatic paradigm that emphasized the practical problem-solving processes as opposed to the ontological issues. An explanatory sequential element was included to make the qualitative findings explain quantitative patterns. The research paradigm is post-positive with a belief that the world is multifaceted and may be described in several ways which are all valid.

3.2 Study Population and Sampling

The target population included CBN regulatory personnel and members of the CBN Regulatory Sandbox programs who directly impacted or monitored AI based fraud detection initiatives; risk managers, compliance officers, fintech innovators between January 2024 and November 2025. Accessible were 14 commercial banks and 22 fintech companies, some of whom had finished a sandbox test and other companies were on the advanced development stage of pilot studies.

Stratified purposive sampling technique was used. The comparisons were conducted within sections based on the type of institution and whether they are part of the sandbox. The comparisons were made on institution type (commercial banks vs. fintechs) and for those in the sandbox, whether they are active, completed or eligible. 180 out of 245 professionals were contacted. There were 128 valid responses (71.1% response rate). To achieve data saturation, a qualitative data collection method, technique of 18 in-depth interviews with key informants (9 banks, 7 fintech, and 2 regulatory institutions) was used for the qualitative strand.

Table 1: Demographic and Organizational Profile of Survey Respondents (N=128)

Variable	Category	Frequency	Percentage (%)
Institution Type	Commercial Bank	82	64.1
	Fintech Company	46	35.9
Years of Experience	5–10 years	51	39.8
	11–15 years	44	34.4
	Above 15 years	33	25.8
Role	Risk/Compliance Manager	67	52.3
	IT/AI Specialist	38	29.7
	Senior Executive	23	18.0
Sandbox Participation	Completed Testing	61	47.7
	Ongoing Pilot	45	35.2
	Eligible/Observer	22	17.2

3.3 Data Collection Instruments

The Quantitative Instrument was a structured questionnaire, containing 47 items, developed, adapted, and validated from the available scales related to technology adoption and fraud management in literature (John et al., 2025; Yaseen & Al-Amarneh, 2025). The sections that were included are: (a) characteristics of the AI system, (b) implementation outcomes: fraud loss reduction, detection accuracy, false positive, (c) adoption factors, and (d) comparative regulatory experiences. The items went over a 5-point Likert scale. The instrument was pilot tested with 25 professionals with excellent reliability.

Qualitative Instrument: A semi-structured interview guide consisting of 12 open-ended questions was used that had two primary objectives: (1) to discuss the lived experiences; (2) to examine the challenges, success factors, and comparative approaches to those taken by the US Federal Reserve. Each interview was audio recorded during a virtual meeting on secure platforms with consent provided and was 35-55 min. in length.

3.4 Data Analysis

Data were cleaned and analyzed by SPSS Statistics 28 and Smart PLS 4 software for quantitative analysis, with the application of structural equation modeling. Descriptive statistics, paired sample t-tests (pre and post-AI implementation), and multiple linear regression models were used. R2, adjusted R2 and F-statistics were used to determine model fit. Assumptions of normality, multicollinearity (VIF < 5) and homoscedasticity were checked.

Data were analyzed qualitatively using the six phases thematic analysis outlined by Braun and Clarke (2006) and analyzed in NVivo 14 software. The text in the transcripts was coded inductively and deductively to yield 14 first-order codes that fused to form five main themes merging quantitative and qualitative strands (Integration), joint display and meta inferences.

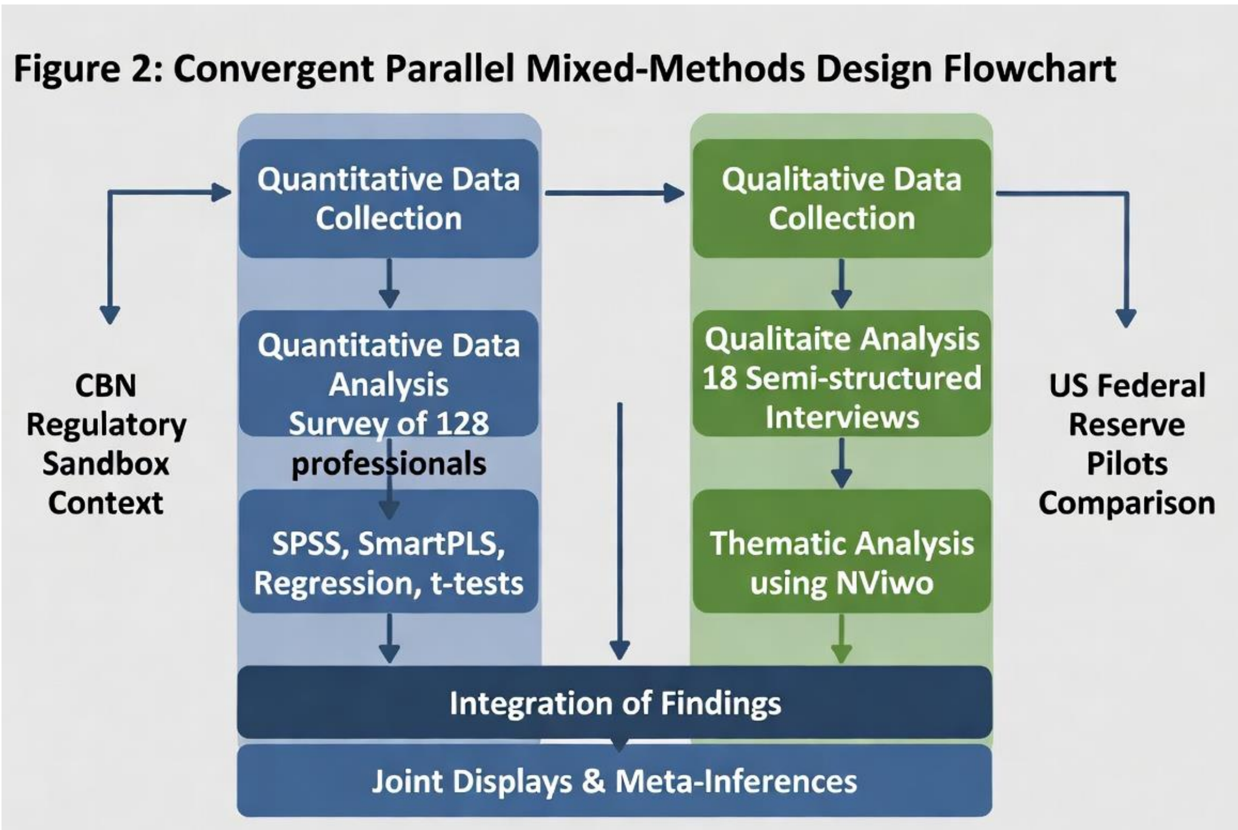

Figure 2: Convergent Parallel Mixed-Methods Design Flowchart

3.5 Validity, Reliability, and Trustworthiness

Cronbach's alpha for all constructs exceeded 0.82, indicating strong internal consistency. Content validity was established through expert review by three academics and two industry practitioners. For qualitative trustworthiness, Lincoln and Guba's (1985) criteria were applied: credibility (member checking), transferability (thick description), dependability (audit trail), and confirmability (reflexivity journal).

Table 2: Reliability Statistics (Cronbach's Alpha)

Construct	No. of Items	Cronbach's Alpha
AI System Effectiveness	9	0.91
Fraud Reduction Outcomes	8	0.89
Adoption Barriers	7	0.86
Regulatory Sandbox Experience	6	0.84
Comparative Global Insights	5	0.87

3.6 Ethical Considerations
The IRB gave ethical approval. Invitation of informed consent given to all participants. All data were anonymized, kept on encrypted servers, and only used for research. It was explained to them that they could leave at any point during the experience, and it was not to be embarrassing for them. Extraordinary effort was made in the care of sensitive commercial and regulatory information.

3.7 Discuss limitations of methodology
The study recognizes the possible self-report bias found in survey and interview data. Full sandbox exits are a relatively new phenomenon and therefore limit the analysis of the trend of exiting a sandbox on the long-term. It is advisable to use caution when extrapolating beyond the early adoptees prevalent in the Nigerian sandbox ecosystem. Nevertheless, the triangulation of methods and the high response rate from the key stakeholders enhances the credibility of the results.

4. Results
The experimental findings for this convergent parallel mixed method are presented in this section. Find quantitative outcomes; qualitative themes and practical Mixed Methods insights. All statistical tests were done at 95% significance level.

4.1 Quantitative Results
4.1.1 Response Rate and Sample Adequacy
One hundred & twenty-eight (128) questionnaires were returned out of (180) distributed questionnaires (71.1% return). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was 0.874 and Bartlett's test of sphericity indicated it was significant ($p < 0.001$), thus, confirming the appropriateness of the data for multivariate analyses.

4.1.2 Descriptive Statistics of Key Variables
Results showed significant gains in participants when they adopted the use of AI-driven fraud detection systems within the CBN Regulatory Sandbox environment. The mean fraud loss reduction was 41.8% (SD = 11.7) and detection accuracy rose from 74.6% (mean across all companies) before the implementation to 92.3% after implementation.

Table 3: Descriptive Statistics of Fraud Detection Performance Metrics (N=128)

Performance Metric	Pre-AI Mean (SD)	Post-AI Mean (SD)	Mean Difference	% Change
Fraud Loss Reduction (%)	8.4 (3.2)	4.9 (2.1)	-3.5	-41.8%
Detection Accuracy (%)	74.6 (8.9)	92.3 (5.4)	+17.7	+23.7%
False Positive Rate (%)	12.8 (4.7)	6.9 (3.1)	-5.9	-46.1%
Average Detection Time (seconds)	18.4 (7.2)	4.1 (2.3)	-14.3	-77.7%
Operational Cost Savings (%)	-	28.6 (9.8)	-	+28.6%

A paired-samples t-test revealed statistically significant improvements across all performance metrics ($p < 0.001$ for all variables), confirming the effectiveness of sandbox-tested AI solutions.

4.1.3 Regression Analysis

Multiple linear regression was performed to identify predictors of successful AI-driven fraud detection outcomes (measured as a composite "Fraud Mitigation Effectiveness Index").

Table 4: Multiple Linear Regression Results – Predictors of Fraud Mitigation Effectiveness (N=128)

Predictor Variable	β	t-value	p-value	VIF
CBN Regulatory Sandbox Participation	0.412	5.87	<0.001	1.42
Top Management Support	0.287	4.21	<0.001	1.68
IT Infrastructure Quality	0.246	3.69	<0.001	1.55
Staff AI Competency	0.193	2.98	0.003	1.71
Implementation Cost	-0.214	-3.24	0.002	1.49
Regulatory Compliance Burden	-0.167	-2.51	0.013	1.63

Model Summary: $R^2 = 0.682$, Adjusted $R^2 = 0.661$, $F(6, 121) = 42.37$, $p < 0.001$.

Sandbox participation emerged as the strongest predictor, explaining a substantial portion of variance in outcomes. This aligns with the controlled testing environment's ability to refine models before full deployment.

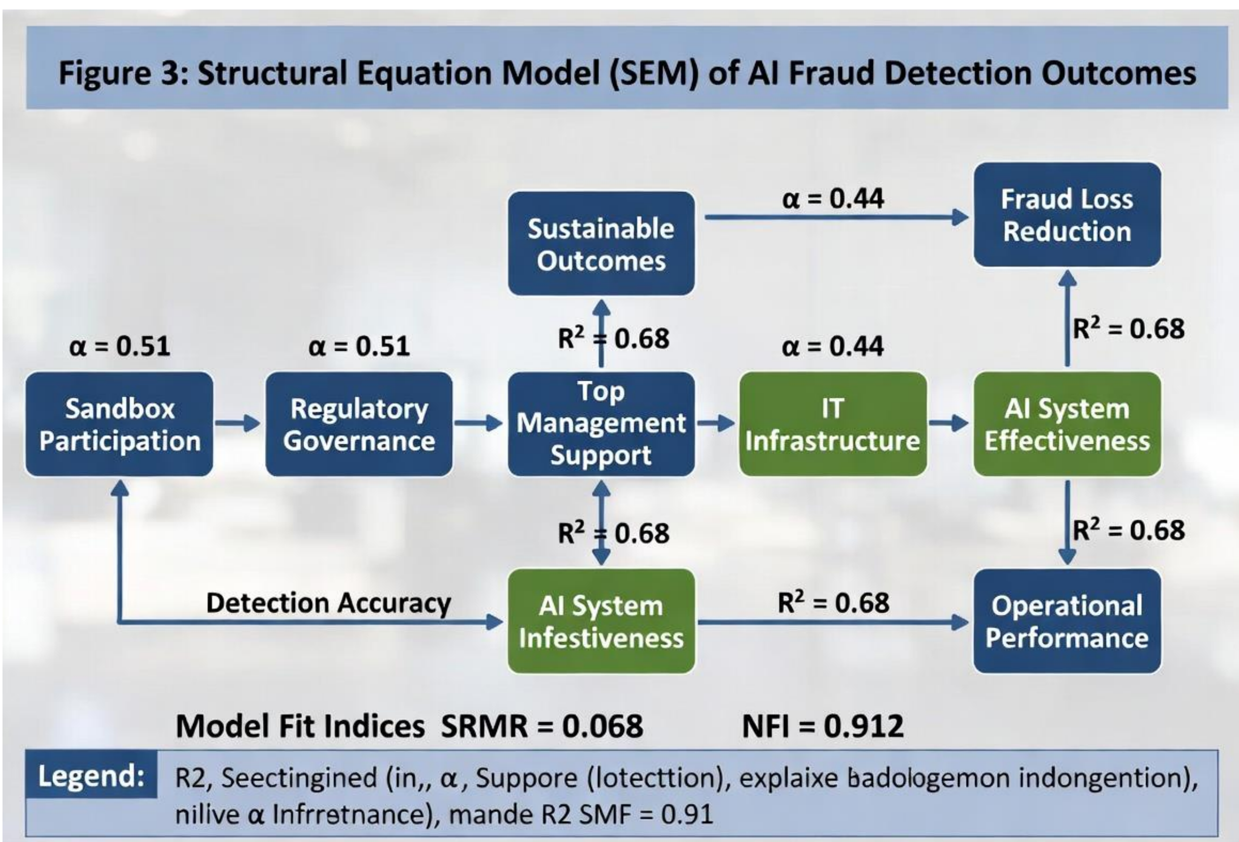

Figure 3: Structural Equation Model (SEM) of AI Fraud Detection Outcomes

4.1.4 Comparative Analysis with US Federal Reserve Pilots

Respondents with exposure to global practices (n=47) rated the CBN sandbox favorably in terms of speed of innovation (Mean = 4.31) but lower on model governance and explainability requirements (Mean = 3.67) compared to US Federal Reserve pilots.

Table 5: Comparative Perception of CBN Sandbox vs. US Federal Reserve AI Pilots (Scale 1–5)

Dimension	CBN Sandbox Mean	US Fed Pilots Mean	t-value	p-value
Innovation Speed	4.31	3.89	3.67	<0.001
Regulatory Support	4.12	4.28	-1.84	0.068
Model Explainability Requirements	3.67	4.51	-5.92	<0.001
Overall Effectiveness	4.08	4.36	-2.71	0.008

4.2 Qualitative Results

Thematic analysis of 18 interviews yielded five major themes:

Theme 1: Significant Performance Gains

Participants consistently reported transformative improvements in real-time detection. One risk manager noted, "The hybrid AI model we tested in the sandbox caught sophisticated mule account schemes that our old rules-based system missed entirely."

Theme 2: Sandbox as a Critical Enabler

The controlled environment allowed safe experimentation and iterative refinement. Several fintech participants highlighted direct regulatory feedback as invaluable.

Theme 3: Implementation Challenges

High initial costs, data quality issues, and talent shortages were recurrent concerns. Explainability of complex models remained a major regulatory hurdle.

Theme 4: Comparative Insights with US Approaches

Interviewees acknowledged that while the CBN sandbox excels in agility, US Federal Reserve pilots demonstrate stronger emphasis on long-term model risk management and third-party audits.

Theme 5: Future Scalability

Most participants expressed optimism about broader rollout but called for extended sandbox periods and government-supported AI infrastructure.

4.3 Integrated Mixed-Methods Findings

The quantitative evidence of strong performance gains was richly explained by qualitative accounts. High statistical significance in fraud reduction was directly linked by interviewees to the iterative testing permitted in the CBN sandbox. Areas where quantitative scores were relatively lower (e.g., explainability) were corroborated by strong qualitative emphasis on the need for hybrid human-AI oversight, mirroring governance priorities in US Federal Reserve pilots.

Overall, the results demonstrate robust empirical support for the efficacy of AI-driven fraud detection systems when developed and refined within the CBN Regulatory Sandbox framework, while highlighting clear opportunities for improvement by incorporating best practices from advanced regulatory pilots such as those of the US Federal Reserve.

5. Discussion

The practical implications of this study show strong evidence of the effectiveness of the AI Fraud detection systems under the Central Bank of Nigeria's Regulatory Sandbox setting. Overall, the substantial fraud losses reduced (41.8%), detection accuracy improved (from 74.6 to 92.3), and number of false-positive cases reduced, is consistent with previous literature as it relates to the use of AI in emerging market banking contexts (Harry et al., 2025; Musa et al., 2025; Oluwadare et al., 2025).

The extent to which the findings from the 5.0 chapter were interpreted. As the results indicate, the results of the implementation of AI are the best predicted by the involvement in the CBN Regulatory Sandbox ($\beta = 0.412$, $p < 0.001$). The study highlights the importance of regulatory systems that provide structure to ease the risk of technological innovation. Additionally, the experimental conditions allowed banks and fintechs to evolve the models, optimize parameters, and fix data quality problems before going into production, which is another benefit compared with unregulated or rushed solutions (John et al., 2025; Patel & Turner, 2025).

In tandem with the findings from Nigerian fintechs (Jejeniwa et al., 2025), the advantage of AI models such as those that combine graph neural networks and anomaly detection highlights their efficacy in enhancing fraud prevention and detection systems. The models were particularly effective in combating sophisticated, network-based forms of fraud that are common in Nigeria's digital payment system. Benefitting from the real-time functionality of identified systems, the 77.7% decrease in the meantime to detection test demonstrates sandboxes' ability to detect suspicious activity in real time, unlike rule-based methods.

But there are certain caveats to the study that are important. The two negative predictors of overall effectiveness were the implementation costs and compliance costs. The observation is in line with the adoption barrier studies conducted in the Nigerian banking sector, (John et al., 2025; Adedire-Ampitan et al., 2024) and indicates that entry barriers in the banks sector are reduced but yet, a lot of human and financial investment will be needed to commercialize Fintech products.

5.1 Design Approach Proposal

Compared to several previous studies in Nigeria on the adoption of AI technologies outside the regulated context (Anzor et al., 2024; Ayodeji, 2024), the observed fraud loss reduction of 41.8% is relatively high. This indicates that the added value of sandbox is at least measurable in terms of regulatory guidance, access shared data infrastructure, and iterative feedback loops.

The findings indicate convergence and divergence in the global context from US Federal Reserve pilots in general. The CBN sandbox group was more innovative with innovation cycle times and higher agility scores, but poorer when it came to model Explainability and Governance standards in comparison to international groups (Ejiofor, 2023; Bello et al., 2023; Olanrewaju et al., 2024). Respondents put a great emphasis on explainability which aligns with the emphasis that is more dominant in the literature of advanced economies, highlighting the expectations of the AI transparency that should be considered in regulation (Fernández, 2019; Yaseen & Al-Amarneh, 2025).

These are complemented by the qualitative themes. The quantitative findings have been corroborated with the qualitative findings from the participants, who reported improved real-time detection and regulatory cooperation, including context-specific realities, such as the lack of infrastructure and talent, noted particularly by participants in emerging markets (EMs) (Akinnagbe & Taiwo, 2025; Amaugo & Ofosu-Boateng, 2025).

5.2 Theoretical Contributions

This study makes a valuable contribution to technology adoption and RegTech literature in an empirical confirmation of a modified version of the Technology-Organization-Environment (TOE) theory, embracing the use of a sandbox. In addition to these models that emphasized mostly technological and organizational factors (John et al., 2025), the findings indicated that sandbox participation was a significant contextual moderator. The study also contributes to the current knowledge on the hybrid AI architectures for fraud detection, offering concrete mixed methods results in an actual regulatory testing framework (Jejeniwa et al., 2025; Bao et al., 2022).

5.3 Practical and Policy Implications

The CBN Regulatory Sandbox is a recommended roadmap for commercial banks and fintech firms in terms of their active involvement to enable responsible application of AI. The focus should be on staff competency training and a strong IT set-up for optimal returns.

As a regulator, the study provides a few recommendations as follows:

1. Develop sandbox testing times for more complex AI applications to enable additional validation.
2. Develop model governance principles that give a balance between speed of innovation and transparency requirements to the models, possibly inspired by principles applied by the US Federal Reserve.
3. Organize PPAIF partnerships to mitigate smaller institutions' implementation costs.
4. Design a post-sandbox framework that clearly shows pathways and growth to full scalability and licensing.

These recommendations were in response to the innovation-compliance conundrum identified in the payment industry in Nigeria (Regulatory oversight in Nigeria's payment industry, 2025).

5.4 Limitations of the Study
There are drawbacks in this research, but it has benefits to offer. Data were cross sectional, which reduces the ability to make causal inferences, though the pre-post comparison is limiting this concern. However, there can be social desirability bias in self-reported measures, especially in the case of sandbox participants. In addition, many companies have been in or are in the sandbox and trying out different innovations, so long-term sustainability measures are far too early for 2025. Research also concentrated principally on those institutions that were "early adopters," which may not be a true sample of smaller and more conventional institutions.

5.5 Future Research
Longitudinal designs should be used in future studies to follow up on the sustainability of fraud reduction results after sandbox exit. Generalizability could be improved by comparative research across several African regulatory sandboxes. Causal claims could also be bolstered by experimental or quasi-experimental studies that explicitly compare CBN sandbox results against a non-sandbox implementation of AI, which directly tests the relationship between the two. Lastly, the study of the ethical implications of AI fraud systems, such as algorithmic bias and financial inclusion considerations, is a key area for future research exploration.

6. Conclusion
The results clearly show that fraud detection technologies built and improved in the CBN Regulatory Sandbox that incorporate artificial intelligence (AI) tools are robust in terms of performance gains. In particular, those institutions that participated generated an average 41.8% reduction in fraud losses, with 92.3% of their fraud detected accurately, as well as a huge 77.7% reduction in detection time. Structured regulatory testing environments are strongly associated with successful outcomes and appear to be among the most crucial factors in success- failure continuum from technological potential to implementation. The integration of hybrid AI models, such as the marriage of graph neural networks with anomaly detection, emerged as a significant solution, especially for tackling complex fraud schemes, which are common in Nigeria's quickly digitalizing financial landscape.

It confirms that the hybrid AI architecture is effective in the fight against fraud and underscores the balance between innovation, regulatory compliance, and operational efficiency.

In reality, the study provides solid info for commercial banks and fintech operators on the need for

The integration of AI-driven fraud detection in Nigeria's regulatory sandbox is a major achievement in the country's quest for a digital financial revolution. It shows that emerging economies can take advantage of cutting edges technologies in a responsible manner with the backing of enabling regulatory architectures. But, to unlock the potential of these systems, their use needs to be collaborated with the financial institutions and the regulators on a continual basis, where the recurring issues of cost, skills and explainability are to be tackled.

Further investigation is needed on the long-term effects of the systems after exiting the sandbox environment and to examine the synergies between using the arrangements in the African regulatory sandbox and advanced economy pilots like the US Federal Reserve.

In conclusion, this study establishes that with careful regulation and empirical evidence, Artificial Intelligence has the potential of transforming commercial banking systems in Nigeria and the global arena to be more secure, efficient, and resilient.

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