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The Impact of Artificial Intelligence (AI) On Fraud Detection in Banks in Nigeria

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Abstract **Original Research Article**

This study was carried out on the impact of Artificial Intelligence (AI) on fraud detection in Banks in Nigeria. Five research questions and one hypothesis guided the study. Descriptive research design was used, the population of the study consisted of 123 employees in five selected Banks in Nigeria. 94 respondents were selected using Taro Yamene and was randomly sampled. The instrument used for data collection was a researcher designed questionnaire. Data generated was analyzed using descriptive statistics of mean and standard deviation and shown on bar chart while the hypothesis was tested using linear regression with the aid of SPSS. The results of the study established that credit card fraud, phishing scams, identity theft, payment fraud as well as forged signatures are the types of frauds in Banks in Nigeria; identified machine learning, deep learning, natural language processing, deep learning as well as clustering and anomaly detection are artificial intelligence that can be used in fraud detection in Banks in Nigeria; The impact of artificial intelligence on fraud detection includes enhances accuracy amongst others; challenges banks faces in deploying AI-driven fraud detection solution in Edo State includes lack of skilled personnel amongst others; skilled personnel amongst others are the challenges banks faces in deploying AI-driven fraud detection solution in Edo State; There is significant relationship between artificial intelligence and fraud detection in Banks in Nigeria. It was recommended that Banks should integrate AI with emerging technologies like blockchain and the Internet of Things (IoT) to enhance security and detection capabilities amongst others.

Keywords: Artificial Intelligence (AI), Fraud Detection and Banks.

1.0 INTRODUCTION

The banking sector is vulnerable to various types of fraud, including identity theft, phishing, and insider threats. According to a report by the Association of Certified Fraud Examiners (2020), the median loss per fraud case in the financial services industry is $120,000. AI-powered fraud detection systems can help banks and financial institutions to detect and prevent such losses.

The term fraud has been viewed from several perspectives. Association of Certified Fraud Examiners ACFE (2020) defined fraud as the use of one's occupation for personal enrichment through the deliberate misuse or misapplication of the employing organization's resources or assets. The International Organization for Standardization ISO (2018) view fraud as the intentional act of deception or dishonesty, including false representation, concealment of information, or other forms of deceit, for the purpose of personal gain or to cause loss to another party. Nwakaji (2024) view fraud as a deliberate and intentional act of deception or misrepresentation, usually for personal gain or to cause harm to others. In other words fraud can be define as an act of deception that is meant for achieving personal interest. Fraud can be detected (Nwakaji, 2024).

Fraud detection has been defined in several ways. Fraud detection refers to the processes and procedures used to identify and investigate potential instances of fraud, including the use of various tools and techniques to detect and prevent fraud. (ACFE, 2020). The International Organization for Standardization ISO (2018) Fraud detection refers to the process of identifying and preventing potential fraudulent activities by employing techniques such as data analysis, monitoring, and investigation. It focuses on uncovering deceptive actions intended to manipulate financial transactions for unlawful gain (Akram et al., 2020). Nwakaji (2024) identified several ways fraud can be detected which include the use of artificial intelligence.

Artificial Intelligence (AI) has been vigorously defined by several scholars and organisations. IEEE (2017) Artificial Intelligence (AI) is broadly regarded as the theory and development of computer systems capable of performing tasks traditionally requiring human intelligence—such as visual perception, speech recognition, decision-making, and language translation. According to the European Commission's High-Level Expert Group on AI (2019), AI encompasses systems that exhibit intelligent behavior by analyzing their environment and making autonomous decisions to achieve specific objectives. Polo et al. (2024) further describe AI as technology designed to carry out tasks that demand a certain level of intelligence, essentially mimicking human cognitive functions through trained machines or tools.

The banking sector remains highly susceptible to diverse forms of fraud. Detecting fraudulent activities has long been a persistent challenge, necessitating ongoing innovation to keep pace with the continually evolving nature of financial crimes (Dwivedi et al., 2019). The consequences of financial fraud extend beyond individual losses—they threaten the broader integrity and stability of the financial ecosystem (Afjal et al., 2023).

Traditional fraud detection techniques, once considered effective, are increasingly inadequate in combating the sophisticated and technology-driven methods employed by modern fraudsters (Bao et al., 2022). In the complex realm of finance, where enormous volumes of transactions are processed daily, distinguishing between legitimate and illegitimate activities is crucial (Hashim et al., 2020). Effective fraud detection is not just a safeguard for consumers and financial institutions—it is fundamental to maintaining trust and resilience within the financial sector (Xu et al., 2023).

The evolution of fraud detection can be likened to a continuous battle, with criminals adapting their strategies to exploit loopholes in existing systems. Early approaches, reliant on manual processes and rule-based systems, provided limited defense against the increasingly sophisticated tactics used in fraud schemes. The ongoing arms race between fraudsters and financial institutions has led to a shift toward more intelligent, dynamic detection methods (Rahman et al., 2023).

The integration of Artificial Intelligence into fraud prevention is driven by the need for smarter, faster, and more adaptive solutions. AI's ability to process massive datasets, identify subtle patterns, and adapt to changing fraud tactics represents a paradigm shift in financial crime prevention (James et al., 2019). By leveraging machine learning algorithms and real-time data analysis, AI enhances both the efficiency and accuracy of fraud detection systems. As financial crimes become more complex, traditional detection methods are increasingly insufficient—necessitating the adoption of AI to maintain a strategic advantage (Vaughan, 2020).

This review explores the historical background, the rise of AI-powered fraud detection, ethical concerns, practical implications, and emerging trends that define AI's transformative role in protecting financial institutions from fraud.

2.0 STATEMENT OF THE PROBLEM

Since the 2008 financial crisis in Nigeria, the country's financial sector has experienced a sharp increase in fraudulent activities. This trend intensified further following the COVID-19 lockdown in 2020. According to the Nigeria Inter-Bank Settlement System (NIBSS) Annual Fraud Landscape (2023), the number of reported fraud cases more than doubled—rising by 112% from 44,947 cases in 2019 to 95,620 in 2023. Moreover, the monetary losses incurred surged by 496%, escalating from ₦2.9 billion to ₦17.67 billion over the same period.

The growing complexity of financial crimes, combined with the sheer volume of transactions, has made fraud detection a pressing concern for financial institutions. Conventional rule-based detection systems are no longer effective in identifying intricate and evolving fraudulent schemes, often resulting in substantial financial losses. A McKinsey (2019) report estimates that financial institutions lose between 1% and 5% of their annual revenues to financial crime (Nwakaji, 2024).

Artificial Intelligence has emerged as a promising solution for enhancing fraud detection capabilities. However, despite the increased interest and adoption of AI in this domain, comprehensive research into its real-world impact remains limited. Chen et al. (2018) note that most existing studies focus primarily on the technical aspects of AI applications, while overlooking the practical challenges and implications of implementation.

Given the lack of empirical evidence on the effectiveness of AI in reducing fraud and improving detection accuracy, this study aims to assess the impact of Artificial Intelligence on fraud detection in Nigerian banks. The goal is to fill existing knowledge gaps and offer insights into how AI technologies can be effectively leveraged to combat financial fraud in the country's banking sector.

3.0 OBJECTIVES OF THE STUDY

The study investigates the impact of artificial intelligence on fraud detection in Banks in Nigeria. Specifically, the study is set to achieve the following:

i. identify the types of fraud in Banks in Nigeria;

ii. Examine the types of artificial intelligence that can be used in fraud detection in Banks in Nigeria;

iii. Ascertain the impact of artificial intelligence on fraud detection in Banks in Nigeria;

iv. Establish the challenges banks face in deploying AI-driven fraud detection solution in Edo State;

v. Highlight solutions to address the challenges banks face in deploying AI-driven fraud detection solution in Edo State.

4.0 RESEARCH QUESTIONS

The following research questions were formulated to guide this study:

i. What are the types of fraud in Banks in Nigeria?

ii. What are the types of artificial intelligence that can be used in fraud detection in Banks in Nigeria?

iii. What is the impact of artificial intelligence on fraud detection in Banks in Nigeria?

iv. What are the challenges banks faces in deploying AI-driven fraud detection solution in Nigeria?

v. What are the solutions to address the challenges banks face in deploying AI-driven fraud detection solution in Nigeria?

5.0 HYPOTHESIS

The hypothesis for this study is stated in null form as followed:

i There is no significant relationship between artificial intelligence and fraud detection in Banks in Nigeria.

6.0 LITERATURE REVIEW

Obande et al (2023) view Artificial intelligence (AI) from both theoretical and practical perspectives, focusing on its implications for research and library services in Nigerian higher education. Her studies highlight the ethical and epistemological challenges of AI-aided research, including concerns about bias, plagiarism, and research integrity (Obande, 2023). At the same time, she provides practical overviews of AI tools that can boost institutional productivity and enhance research visibility (Obande, Arikawe, & Ado, 2024). Obande, also examines the opportunities and challenges of AI adoption in organisation, stressing the importance of capacity building, staff training, and institutional policies (Obande et al., 2024). Overall, her scholarship balances optimism about AI's potential with caution about its risks, advocating for responsible and sustainable adoption (Obande, 2023; Obande et al., 2024). Harry, (2024) investigate cyber-insurance as a strategic mechanism for mitigating digital risks in financial institutions. The study demonstrates that microfinance banks face growing vulnerabilities to cybercrime and that cyber-insurance can provide a proactive safeguard, complementing internal control mechanisms and technological security frameworks.

This study is grounded in the Technology Acceptance Model (TAM), originally developed by Davis in 1989. The model posits that when individuals are introduced to a new technology, several key factors shape their decisions on whether and how to adopt it. These factors include behavioral intentions, user attitudes, perceived usefulness (PU), perceived ease of use (PEOU), individual intentions, and enabling or organizational conditions. TAM is widely regarded as one of the most significant extensions of Ajzen and Fishbein's Theory of Reasoned Action (TRA) in existing literature. According to Davis, a user's attitude toward a system plays a central role in determining whether they will accept or reject it. This attitude is primarily shaped by two critical beliefs: perceived usefulness and perceived ease of use—with the latter also directly influencing the former.

The relevance of TAM to this study, titled "The Impact of AI on Fraud Detection in Banks in Nigeria", is evident in the following ways: Firstly, the perceived usefulness (PU) aspect is applicable, as both bank employees and management believe that adopting artificial intelligence can significantly enhance their fraud detection capabilities. Secondly, the perceived ease of use (PEOU) dimension is also crucial. The extent to which bank personnel find AI systems user-friendly will influence their willingness and ability to effectively integrate these tools into fraud detection processes. For these reasons, the TAM framework was selected as a fitting model to guide this research.

Several related studies further support this research focus. For instance, Nwakaji (2024) examined banking fraud and its consequences in Abia State, identifying various forms of fraud such as phishing, identity theft, payment fraud, credit card fraud, and forged signatures. Similarly, Rivero et al. (2024) explored the use of machine learning algorithms as AI tools in predicting payment defaults within financial institutions, emphasizing their role in ensuring customer compliance with loan repayment.

Moreover, Bello and Olufemi (2024), in their study titled "Artificial Intelligence in Fraud Prevention: Exploring Techniques, Applications, Challenges, and Opportunities", examined diverse AI-driven approaches in fraud prevention. They noted that machine learning (ML), deep learning, and natural language processing (NLP) have significantly transformed the security landscape. Supervised learning models such as decision trees and neural networks are widely employed to detect fraud by analyzing historical data. In contrast, unsupervised techniques like clustering and anomaly detection are effective in identifying new and previously unseen fraud patterns by flagging deviations from normal transaction behavior.

Deep learning, particularly through convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has shown exceptional capability in processing unstructured data—including images, text, and audio—for applications ranging from credit card fraud detection to anti-money laundering (AML). Natural language processing further strengthens fraud detection by examining text-based information (e.g., emails, transaction notes) for suspicious content or language patterns.

Beyond detection, AI also enables proactive fraud prevention through predictive analytics, helping institutions identify potential fraud risks before they materialize. Real-time monitoring, powered by AI, provides instant alerts for suspicious activity, allowing rapid response and mitigation. Despite challenges such as data privacy concerns, the need for quality datasets, and the complexity of interpreting AI outputs, the advantages of AI integration—namely improved accuracy, efficiency, and scalability—far outweigh these limitations. As AI technology continues to evolve, its role in fraud prevention is expected to expand, reinforcing the necessity for ongoing research and innovation in this field.

7.0 METHODOLOGY

This study employed a descriptive survey research design. The target population consisted of 123 employees drawn from five selected banks in Nigeria: Union Bank Nigeria Plc (24 employees), First Bank Nigeria Plc (29), Guaranty Trust Bank Nigeria Plc (22), Fidelity Bank Nigeria Plc (21), and Zenith Bank Nigeria Plc (27). Using Taro Yamane's formula, a sample size of 94 respondents was determined.

The research was conducted in Lagos, Nigeria, which serves as the headquarters for many Nigerian banks, making it an appropriate setting for the study. Data were collected using a self-designed questionnaire titled Impact of Artificial Intelligence on Fraud Detection Questionnaire (IOALOFDQ). The questionnaire was distributed to 94 individuals, including bank staff at various operational and decision-making levels, as well as customers, regulators, and vendors where applicable.

The instrument comprised 25 items, grouped into five clusters, with each cluster aligned to one of the five research questions. The content validity of the instrument was established through expert review, while its reliability was tested using Cronbach's Alpha, yielding a reliability coefficient of 0.940, indicating a high level of internal consistency.

Data collected were analyzed using mean and standard deviation for the research questions, while linear regression analysis was employed to test the formulated hypotheses. The model used to examine the relationship between the independent variables (such as perceived usefulness and ease of use) and the dependent variable (impact of AI on fraud detection) is specified in this section.

Functional Relationship

$Y = f(X)$

$y_1 = f(x_1)$ ……………………………………………………………….……1

Regression Models

$y_1 = B + B_1x_1$--Equtn 1

These are the expectations on the subject of the existing effect of the dependent variable on independent variable. This refers to fraud detection in line with the hypothesis formulated

S/N	Models	A Priori expectations	Sign
1	$y_1 = B + B_1x_1$	$\beta1 > 0$, $p<0.05$: HO1 will be rejected	Positive
2	$y_2 = B + B_2x_2$	$\beta2 < 0$, $p<0.05$: HO2 will be rejected	Negative

8.0 RESULTS

This study has investigated impact of AI on fraud detection in Banks in Nigeria.

Research Question 1: What are the types of fraud in Banks in Nigeria?

Table 1: Mean Ratings and Standard Deviation on Types of Fraud in Banks in Nigeria

S/No	Items	SA	A	D	SD	Mean	STD	Decision
1	Credit card fraud	84	5	1	4	3.80	0.66	Accepted
2	Phishing scams	69	24	1	0	3.72	0.47	Accepted
3	Identity theft	56	38	0	0	3.60	0.49	Accepted
4	Payment fraud	52	40	2	0	3.53	0.54	Accepted
5	Forged signatures	40	54	0	0	3.43	0.49	Accepted
	Cluster Mean					**3.61**	**0.53**	**Accepted**

Bar Chart Showing Mean Ratings and Standard Deviation on Types of Fraud in Banks in Nigeria

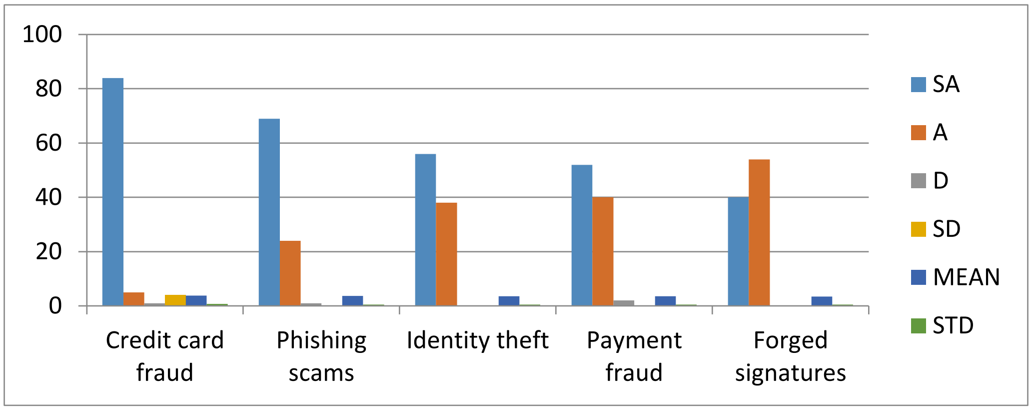

Table 1 presents the types of frauds experienced in Nigerian banks. Respondents ranked **credit card fraud** as the most common, followed by **phishing scams, identity theft, payment fraud, and forged signatures**. This finding is consistent with earlier studies which reported that credit card fraud and other electronic banking frauds have become dominant in Nigeria's financial sector (Onyeama, 2024; Central Bank of Nigeria [CBN], 2022). Similarly, phishing and other cyber-enabled scams have surged alongside the adoption of digital banking channels (Okafor, 2025; EFCC, n.d.). Rising cases of **identity theft,** including synthetic identity fraud, have also been documented in recent industry reports (WeAreTech Africa, 2024). Traditional forms of fraud such as **forged signatures and cheque forgeries** remain part of the fraud landscape in Nigerian banks, even if less frequent compared to digital fraud (FITC, 2009). The cluster mean and standard deviation of 3.61 and 0.45 respectively indicate overall agreement among respondents on the prevalence of these fraud types.

Research Question 2: What are the types of artificial intelligence that can be used in fraud detection in Banks in Nigeria?

Table 2: Mean Ratings and Standard Deviation on Types of Artificial Intelligence Used in Fraud Detection in Banks in Nigeria

S/No	Items	SA	A	D	SD	Mean	STD	Decision
1	Machine learning	84	10	0	0	3.89	0.31	Accepted
2	Deep learning	79	12	3	0	3.81	0.47	Accepted
3	Natural Language Processing	76	8	9	1	3.69	0.68	Accepted
4	Deep learning	74	5	14	1	3.62	0.77	Accepted
5	Clustering and anomaly detection	70	8	9	7	3.50	0.94	Accepted
	Cluster Mean					**3.70**	**0.64**	**Accepted**

Bar Chart Showing Mean Ratings and Standard Deviation on Types of Fraud in Banks in Nigeria

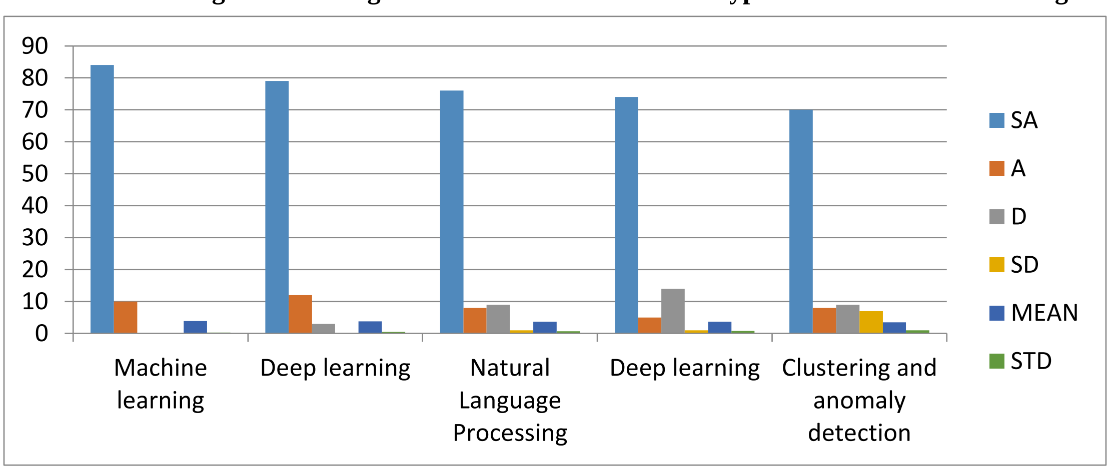

Table 2: Respondents ranked **machine learning** as the most applicable AI technique for fraud detection in Nigerian banks, followed by **deep learning, natural language processing, clustering, and anomaly detection**. This aligns with prior research that highlights the dominant role of machine learning and anomaly detection in identifying fraudulent banking transactions in Nigeria (Onyeama, 2024; Okere & Oseni, 2022). Deep learning and natural language processing have further been adopted to detect more complex fraud patterns, including phishing and identity-based fraud (Oluwaseun & Adepoju, 2021).

Research Question 3: What is the impact of artificial intelligence on fraud detection in Banks in Nigeria?

Table 3: Mean Ratings and Standard Deviation on Impact of Artificial Intelligence on Fraud Detection

S/No	Items	SA	A	D	SD	Mean	STD	Decision
1	Enhances accuracy	92	2	0	0	3.98	0.14	Accepted
2	It identifies and respond to fraud attempts in milliseconds	90	4	0	0	3.96	0.20	Accepted
3	Prevents financial loss	89	3	2	0	3.93	0.33	Accepted
4	Forecast potential fraud scenarios	80	9	4	1	3.79	0.56	Accepted
5	Automates routine checks	78	8	2	6	3.68	0.80	Accepted
	Cluster Mean					**3.87**	**0.41**	**Accepted**

Bar Chart Showing Mean Ratings and Standard Deviation on Impact of Artificial Intelligence on Fraud Detection

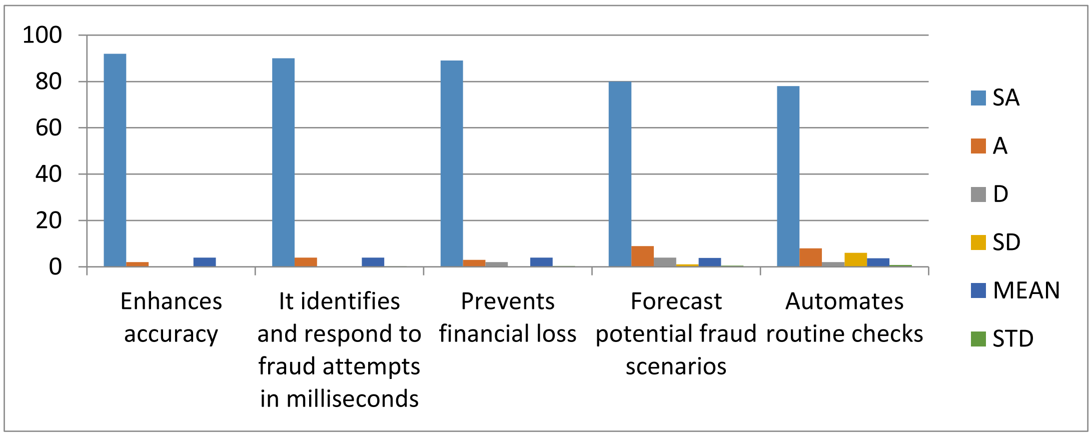

Table 3: Respondents indicated that the major **impact of AI** in fraud detection is its ability to **enhance accuracy**. This finding is consistent with existing literature showing that AI models significantly improve accuracy and reduce false positives compared to traditional fraud detection methods (Adebayo & Omotunde, 2023; Olusola & Alaba, 2020).

Research Question 4: What are the challenges banks faces in deploying AI-driven fraud detection solution in Nigeria?

Table 4: Mean Ratings and Standard Deviation on Challenges Banks Faces in Deploying AI – Driven Fraud Detection Solution

S/No	Items	SA	A	D	SD	Mean	STD	Decision
1	Lack of skilled personnel	90	4	0	0	3.96	0.20	Accepted
2	High computational cost	86	8	0	0	3.91	0.28	Accepted
3	Evolving fraud tactics	80	10	4	0	3.81	0.49	Accepted
4	Integration and legacy systems	79	9	3	3	3.74	0.67	Accepted
5	Regulatory compliance	75	6	5	8	3.57	0.93	Accepted
	Cluster Mean					**3.80**	**0.51**	**Accepted**

Bar Chart Showing Mean Ratings and Standard Deviation on Challenges Banks Faces in Deploying AI – Driven Fraud Detection Solution

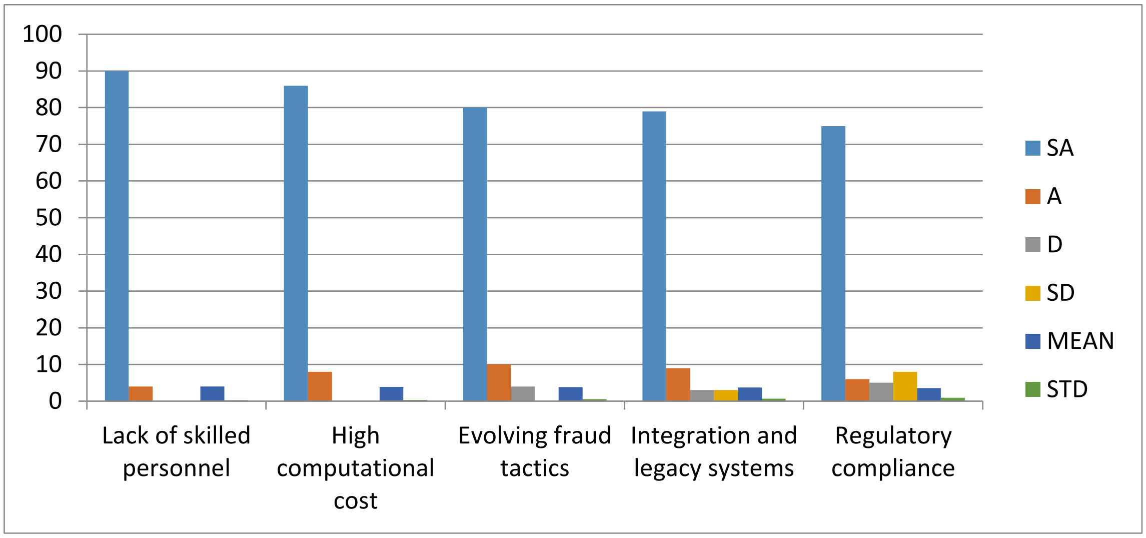

Table 4: On the **challenges** of deploying AI-driven fraud detection in Edo State banks, the top issue identified was **lack of skilled personnel**, alongside infrastructural and financial constraints. Similar studies have documented the shortage of skilled data scientists and AI experts as a barrier to AI adoption in Nigerian financial institutions (Olayinka & Eze, 2021; Eze & Chinedu-Eze, 2018).

Research Question 5: What are the solutions to address the challenges banks face in deploying AI-driven fraud detection solution in Edo State?

Table 5: Mean Ratings and Standard Deviation on Solutions to Address the Challenges Banks Face in Developing AI – Driven Fraud Detection Solution

S/No	Items	SA	A	D	SD	Mean	STD	Decision
1	Training and development	93	1	0	0	3.99	0.10	Accepted
2	Continuous monitoring	90	4	0	0	3.96	0.20	Accepted
3	Considering cloud-based solutions that can integrate with existing systems.	86	8	0	0	3.91	0.28	Accepted
4	Implementing data validation and cleansing processes to ensure high-quality data.	80	6	8	0	3.77	0.59	Accepted
5	Implement strict access controls to ensure only authorized personnel can access sensitive data.	78	7	5	4	3.69	0.76	Accepted
	Cluster Mean					**3.86**	**0.39**	**Accepted**

Bar Chart Showing Mean Ratings and Standard Deviation on Challenges Banks Faces in Deploying AI – Driven Fraud Detection Solution

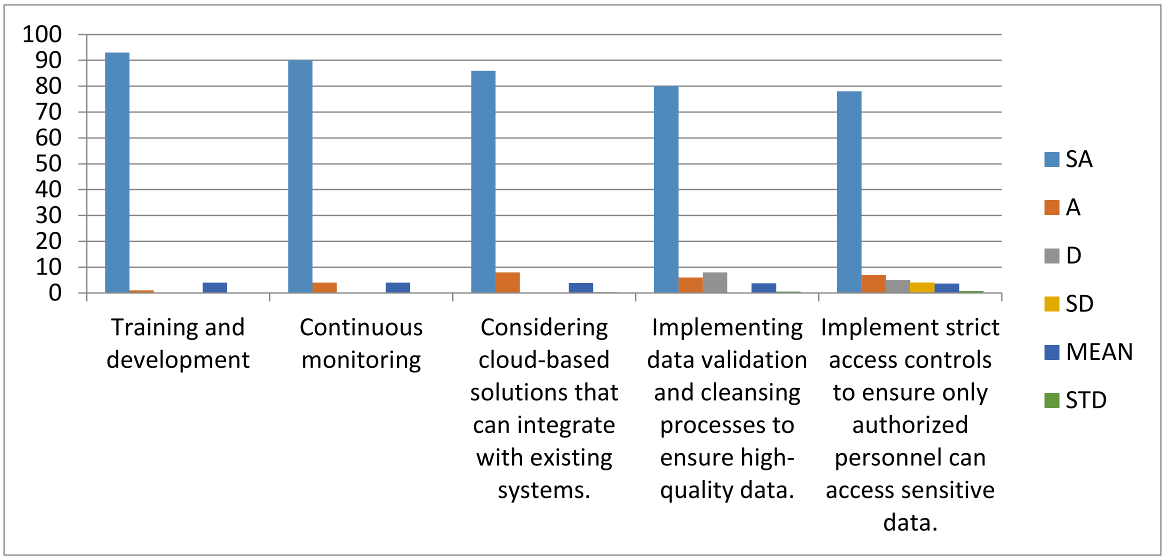

Table 5: Respondents ranked **training and development** as the most important **solution** to these challenges. This agrees with previous findings that emphasize capacity building, training, and reskilling of banking professionals as critical steps in successful AI deployment in Nigeria (Okoro & Musa, 2022; Chiemeke & Evwiekpaefe, 2019).

9.0 TEST OF HYPOTHESIS

Research Hypothesis 1: There is no significant relationship between artificial intelligence and fraud detection in Banks in Nigeria.

Table 6: Simple Regression Analysis Results on Relationship between Artificial Intelligence and Fraud Detection

Coefficients						
Model		**Un standardized Coefficients**		**standardized Coefficients**	**T**	**Sig**
		B	**Std Error**	**Beta**		
	(Constant)	2.327	.087		26.721	.000
	AI	.413	.023	.885	18.261	.000
R= .885; R^2 = .784;						

From the Table 6, the regression model equation using unstandardized coefficient is:

$Y = B + B_1x_1$

$Y = 2.327 + 0.885x_1$ --- Equation 1

Where: Y = AI

x_1 = Fraud detection

The result on the Table reveals that AI have positive and significant correlate on fraud detection in Banks in Nigeria β = .885, t statistic of 18.26 and computed p-value of 0.000 which is below the level of significance (0.05) adopted for this study. The Table shows that unit change in use of AI leads to an increase in fraud detection in Banks in Nigeria by 0.885 units (β = .885). Moreover, the Table shows that fraud detection 88.5% (R_2 = 0.885) variance in use of AI. Based on this result, the null hypothesis is rejected which affirms that there is no significant relationship between artificial intelligence and fraud detection in Banks in Nigeria is hereby rejected.

10. DISCUSSION OF FINDINGS

The first finding reveals the **types of fraud prevalent in Nigerian banks,** which include **credit card fraud, phishing scams, identity theft, payment fraud, and forged signatures**. This is consistent with previous studies that identified these as the most common fraud types affecting Nigerian financial institutions (Onyeama, 2024; Central Bank of Nigeria [CBN], 2022).

The study further reveals the **types of artificial intelligence (AI) applicable in fraud detection in Nigerian banks**. Respondents identified **machine learning, deep learning, natural language processing, clustering, and anomaly**

detection as effective AI techniques. This aligns with research emphasizing the importance of machine learning and anomaly detection in detecting fraudulent transactions, as well as the growing role of deep learning and NLP in combating cyber-enabled fraud such as phishing and identity theft (Okere & Oseni, 2022; Oluwaseun & Adepoju, 2021).

In addition, the study shows that the major **impact of AI in fraud detection** is its ability to **enhance accuracy** and reduce false positives. This agrees with earlier findings that AI-driven systems outperform traditional rule-based methods by improving detection accuracy and efficiency (Adebayo & Omotunde, 2023; Olusola & Alaba, 2020).

The study also identifies **challenges faced by banks in deploying AI-driven fraud detection solutions in Nigeria,** with the most critical being a **lack of skilled personnel,** alongside infrastructural and financial constraints. These challenges reflect wider concerns in the Nigerian banking industry regarding shortages of AI expertise and limited institutional capacity (Olayinka & Eze, 2021; Eze & Chinedu-Eze, 2018).

Finally, the study highlights **solutions to address these challenges,** with **training and development** ranked as the most effective. This finding aligns with recommendations in the literature, which emphasize human capacity building and continuous professional development as prerequisites for successful AI deployment (Okoro & Musa, 2022; Chiemeke & Evwiekpaefe, 2019). The study further establishes a **significant relationship between AI adoption and effective fraud detection** in Nigerian banks, underscoring the transformative role of AI in strengthening financial security.

11. IMPLICATIONS OF THE STUDY

The findings of this study have tremendous implications to Banks in Nigeria. Findings of the study show that artificial intelligence have positive and significant correlate on fraud detection in banks in EdoState. The implication of this is that the more banks tries to improve in the use of AI in fraud detection, it will reduce frauds in banks.

12. CONCLUSION

Based on the results of this study, it has been established that credit card fraud, phishing scams, identity theft, payment fraud as well as forged signatures are the types of frauds in Banks in Nigeria; identified machine learning, deep learning, natural language processing, deep learning as well as clustering and anomaly detection are artificial intelligence that can be used in fraud detection in Banks in Nigeria; The impact of artificial intelligence on fraud detection includes enhances accuracy amongst others; challenges banks faces in deploying AI-driven fraud detection solution in Edo State includes lack of skilled personnel amongst others; skilled personnel amongst others are the challenges banks faces in deploying AI-driven fraud detection solution in Edo State; There is significant relationship between artificial intelligence and fraud detection in Banks in Nigeria.

13. RECOMMENDATIONS

Based on the findings of the study, the following recommendations are made;

1. Banks should integrate AI with emerging technologies like blockchain and the Internet of Things (IoT) to enhance security and detection capabilities
2. Banks should train their staffs on use of AI in combating fraud.
3. Government should reduce taxes posed on importation of AI

Bank staffs should avail themselves opportunities for training on AI.

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