

Forensic Data Analytics and Anti-Money Laundering: Panacea for Fraud Prevention in Nigeria and United States of America

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Abstract

The study examined the effect of forensic data analytics on anti-money laundering efforts and its effectiveness in preventing financial fraud in Nigeria and the United States of America (U.S.A.). Specifically, the study sought to evaluate the role of forensic data analytics in detecting suspicious financial transactions and to compare its effectiveness in enhancing anti-money laundering measures in the two countries. The study equally compared the effectiveness of forensic data analytics on anti-money laundering efforts between financial institutions in the United States and Nigeria. A survey research design was employed, targeting a population of 200 top-level bankers, with 100 respondents from Nigeria and 100 from the United States of America, selected through a snowball sampling technique. Primary data were collected using a structured electronic questionnaire. The hypotheses were tested using student t-test and Spearman's ranked order correlation at a 5% significance level to determine the relationships between forensic data analytics, anti-money laundering, and fraud prevention. The findings revealed that: forensic data analytics did not have a significantly stronger effect on anti-money laundering in the United States compared to Nigeria ($t = 1.731$, $p = .085$); forensic data analytics positively influenced anti-money laundering in both countries ($\beta = 0.499$, $p < .001$); forensic data analytics strongly enhanced fraud prevention in both countries ($\beta = 0.817$, $p < .001$). Therefore, investments in forensic data analytics contribute to the development of more robust monitoring structures, improve the capacity of institutions to respond to complex financial crimes, and reinforce accountability mechanisms. The study recommended that compliance officers and risk management teams should actively incorporate advanced forensic data analytics techniques into their monitoring and reporting processes. By leveraging data-driven insights, these teams can enhance the accuracy of transaction monitoring, improve the identification of suspicious activities, and strengthen overall regulatory compliance.

Keywords: Forensic Data Analytics, Anti-Money Laundering, Fraud Prevention

1.0 Introduction

Financial crime has increasingly become a pressing challenge for economies across the globe, particularly in nations like Nigeria and the United States of America, where complex financial systems provide fertile ground for illicit activities. Money laundering, the process of disguising the origins of illegally obtained funds, continues to undermine economic stability, distort markets, and erode public trust in financial institutions (Sotande, 2025). In Nigeria, where the naira is currently trading at a volatile rate against the US. Dollar, the consequences of financial crime extend beyond individual institutions to affect the broader economy, weakening foreign investment confidence and reducing the efficiency of monetary policy. In the United States, the dollar serves as a global benchmark, and any loopholes in anti-money laundering measures

can have far-reaching implications for international finance. Adekunle et al. (2025) argued that the evolving sophistication of financial crime, fueled by technological advancements, globalization of markets, and the emergence of digital currencies, requires that nations adopt more proactive and intelligent approaches to detect and prevent illicit financial flows. Hence, as fraudsters exploit gaps in traditional monitoring systems, regulators, financial institutions, and law enforcement agencies face mounting pressure to implement solutions that not only identify suspicious activities but also provide actionable evidence for prosecution (Ikumapayi et al., 2025). Within this context, the study of forensic data analytics as a tool in anti-money laundering efforts becomes particularly relevant, offering the potential to bridge gaps in traditional financial oversight and create stronger defenses against the rising tide of financial crime. Forensic data analytics has emerged as a critical component in contemporary efforts to combat financial crime, offering methods that combine statistical analysis, machine learning, and investigative techniques to detect anomalies in financial transactions (Maidarasu et al., 2025). In today's business environment, where organizations handle millions of daily transactions, traditional manual monitoring methods have proven insufficient to keep pace with sophisticated fraud schemes (Daraojimba et al., 2023). Anti-money laundering initiatives rely heavily on identifying patterns of suspicious behavior, tracing the movement of funds across borders, and uncovering networks of complicit actors. Hossain et al. (2023) suggested that by leveraging forensic data analytics, institutions can systematically analyze transactional data, uncover hidden connections, and generate evidence that supports both regulatory compliance and internal risk management. The relevance of these technologies is particularly evident in multinational corporations, banks, and financial service providers operating between Nigeria and the United States, where differing regulatory frameworks and currency fluctuations complicate oversight. In Nigeria, for instance, fluctuations in the naira against the dollar create additional challenges for tracking illicit funds, as exchange rate arbitrage can mask suspicious transactions. In the United States, anti-money laundering regulations are stringent, but the volume and complexity of financial flows demand robust analytical tools. As a result, the integration of forensic data analytics into (American) business operations have moved from being an optional enhancement to a strategic necessity, allowing organizations to mitigate financial risks, protect reputations, and maintain compliance with international financial standards (Elumilade et al., 2021). The impact of forensic data analytics on anti-money laundering is profound, influencing not only the detection of illicit activities but also the strategic approach to fraud prevention and regulatory compliance (Boateng et al., 2025). By systematically examining financial records, cross-referencing transaction patterns, and identifying anomalies that suggest fraudulent behavior, forensic data analytics enables authorities to uncover money laundering schemes that would otherwise remain hidden. In practical terms, this technology assists Nigerian and American financial institutions in pinpointing unusual fund transfers, suspicious account activities, and irregular cross-border transactions that may indicate money laundering. It also enhances the efficiency of investigations, reducing the time and resources needed to compile actionable intelligence (Amoako et al., 2025). Furthermore, forensic data analytics supports predictive capabilities, allowing institutions to anticipate potential fraudulent activity and implement preventative measures before significant losses occur. The adoption of such tools has broader implications for both (U.S. and Nigeria) economies. In Nigeria, effective use of forensic analytics can strengthen regulatory frameworks, enhance investor confidence, and stabilize the financial system amid currency volatility. In the United States of America, it reinforces the integrity of financial markets and ensures that the global trust placed in the U.S. Dollar is maintained and sustained in perpetuity. By bridging technology, regulatory oversight, and investigative expertise, forensic data analytics represents a transformative approach to combating money

laundering, positioning financial institutions and regulators to respond dynamically to the evolving domain of financial crime (Ikumapayi et al., 2025; Chukwuma et al., 2024). In a financial system that functions effectively, transactions are transparent, traceable, and secure (Kukman & Gričar, 2025). Banks, financial institutions, and regulatory agencies work seamlessly to ensure that funds move according to legal and ethical standards. Businesses operate with confidence, knowing that their partners comply with financial regulations, and the movement of money across borders is closely monitored to prevent illegal activities. In such a system, anti-money laundering measures are fully integrated into financial operations, enabling authorities to detect and prevent suspicious transactions quickly. Financial institutions use advanced tools to analyze transactional data, identify irregularities, and maintain trust with clients and international partners (Siddiqui, 2023). Both the Nigerian and American financial sectors benefit from a stable and secure environment where the value of the naira and the US Dollar reflect genuine economic activity, supporting growth, foreign investment, and overall economic stability. In reality, financial systems often face significant challenges in maintaining this level of transparency and security. In Nigeria, weak enforcement mechanisms, fluctuating currency values, and fragmented financial oversight create opportunities for money laundering and other fraudulent activities (Maidarasu et al., 2025). Similarly, in the United States, while regulations are stringent, the sheer volume and complexity of financial transactions make it difficult to detect all suspicious activities (Ejiofor, 2023). Fraudsters exploit gaps in monitoring systems, including cross-border transactions, shell companies, and digital payment platforms. Many financial institutions still rely on manual processes or outdated technologies that are unable to fully analyze complex transactional patterns. As a result, illegal funds can move undetected through the system, undermining the ability of authorities to enforce compliance and protect the integrity of financial markets. The consequences of these challenges are far-reaching. In Nigeria, unchecked money laundering can destabilize the economy, weaken investor confidence, and exacerbate the effects of currency volatility, reducing the value of the naira in comparison to the US. dollar. Businesses face higher risks of fraud, which can lead to financial losses, reputational damage, and legal repercussions. In the United States of America (U.S.A.), lapses in monitoring, allow illicit financial flows to persist, threatening the stability of the American banking system, strain on the much-valued American dream and the global trust placed in the US. dollar. The persistence of these issues highlights the urgent need for more effective approaches to financial oversight. By improving the detection, prevention, and reporting of suspicious transactions through technologies such as forensic data analytics, financial institutions and regulators can reduce fraud, safeguard economic stability, and strengthen public confidence in both national and international financial systems (Boateng et al., 2025). The main objective of the study was to examine the effect of forensic data analytics on anti-money laundering efforts and its effectiveness in preventing financial fraud in Nigeria and the United States of America (The God's own Country).

2.0 Literature Review

2.1 Conceptual Review

2.1.1 Forensic Data Analytics

Forensic data analytics refers to the systematic use of analytical techniques to examine financial and transactional information for evidence of irregularities, misconduct, or unlawful activity (Jofre & Gerlach, 2018). It involves applying a range of methods to large sets of data in order to identify patterns, trends, and anomalies that would otherwise remain hidden (Maidarasu et al., 2025). In financial institutions, this practice allows professionals to scrutinize transaction histories, cross-check records, and track movements of funds in ways that support investigation and compliance efforts. The process relies on both quantitative analysis and investigative reasoning, drawing from accounting, statistics, and information technology to detect unusual

or suspicious activities. By studying transactional flows, forensic data analytics can reveal inconsistencies, duplicate entries, or unusual spikes in activity that may suggest illegal practices, such as embezzlement or money laundering (Jofre & Gerlach, 2018). This approach is particularly important in environments where financial operations are highly complex and voluminous, making manual scrutiny impractical.

Beyond the financial sector, forensic data analytics extends to legal and regulatory contexts, providing evidence that can be presented in courts or regulatory reviews. Professionals use it to construct detailed reports that show the movement of funds, the timing of transactions, and the relationships between parties involved in suspicious activities (Odia & Akpata, 2021). In organizations, it helps to monitor compliance with policies and detect internal fraud or financial mismanagement (Maidarasu et al., 2025). By applying forensic data analytics, institutions can make more informed decisions, mitigate financial risks, and strengthen governance mechanisms (Usman et al., 2021). The increasing sophistication of technology, including digital banking, electronic transfers, and online payment platforms, has made the role of forensic data analytics even more crucial. It allows institutions to navigate massive volumes of data efficiently while maintaining accuracy in investigations. Through this approach, patterns of illicit behavior can be detected early, preventing further loss and supporting legal action. In summary, forensic data analytics provides a structured methodology for investigating financial anomalies and contributes to the broader effort of maintaining integrity in financial systems and organizational operations.

2.1.2 Anti-Money Laundering

Anti-money laundering encompasses the set of policies, regulations, and practices designed to prevent the process of disguising the origins of illegally acquired funds (Mugarura, 2020). It aims to ensure that financial systems are not exploited to hide, transfer, or integrate the proceeds of criminal activity. This involves monitoring financial transactions, identifying suspicious activities, and reporting them to relevant authorities for investigation. The measures implemented under anti-money laundering are intended to create transparency in financial operations, making it difficult for illicit funds to circulate without detection (Gilmour, 2023). By enforcing such practices, governments and financial institutions seek to uphold legal and ethical standards, maintain trust in the financial system, and reduce opportunities for organized crime to flourish. Anti-money laundering measures operate on multiple levels, ranging from regulatory compliance by banks and financial institutions to international cooperation between enforcement agencies (Sotande, 2025). These practices involve reviewing client information, scrutinizing transaction patterns, and flagging unusual transfers for further examination. The objective is not only to prevent illegal funds from entering the financial system but also to trace their movement and disrupt networks of criminal activity. In countries like Nigeria and the United States of America, where financial markets are interconnected with global transactions, anti-money laundering efforts are crucial to maintaining the stability and credibility of the currency and the economy. These measures also reinforce the ability of financial institutions to operate safely while deterring fraudsters from exploiting vulnerabilities. The overarching goal is to create a system where illegal proceeds cannot easily be converted into legitimate assets, and where authorities can act decisively to identify and prosecute perpetrators (Ofoeda et al., 2024). Anti-money laundering therefore represents a comprehensive approach to monitoring, regulation, and enforcement that safeguards the financial system against criminal exploitation.

2.1.3 Fraud Prevention

Fraud prevention refers to the set of strategies, practices, and tools employed to stop unlawful or deceptive activities that lead to financial or operational loss (Mangala & Kumari, 2015). It

involves creating systems that detect irregularities before they escalate and establishing controls that make it difficult for fraudulent actions to occur. Organizations employ fraud prevention to protect assets, maintain credibility, and ensure that operations function smoothly. This process is proactive rather than reactive, aiming to reduce exposure to risks by anticipating potential vulnerabilities in financial, operational, and technological systems (Musyoki, 2023). Rahayu et al. (2025) observed that fraud prevention requires careful monitoring of transactions, verification of records, and attention to anomalies that could indicate dishonest practices. It is not limited to a single industry or sector but is applied wherever there is a risk of deceitful activity affecting value, resources, or reputation.

In practical terms, fraud prevention creates a framework for organizations to maintain integrity and accountability (Guptam, 2024). This includes implementing monitoring systems, establishing verification procedures, and fostering a culture where ethical behavior is promoted and deviations are promptly addressed. By focusing on the early detection of irregular patterns, organizations can intervene before fraudulent activity results in significant loss (Mangala & Kumari, 2015). It also plays a critical role in building trust with stakeholders, including clients, investors, and regulatory authorities, by demonstrating that risk management measures are robust and effective. Across countries such as Nigeria and the United States, fraud prevention is particularly significant in the financial sector, where the volume and complexity of transactions make institutions vulnerable to illegal manipulation. Through continuous vigilance and strategic application of controls in the American fiscal system, fraud prevention reduces the likelihood of financial abuse, enhances operational reliability, and strengthens overall confidence in economic and institutional systems (Guptam, 2024).

2.2 Theoretical Framework and Development of Research Hypotheses

The Fraud Triangle Theory was developed by Donald Cressey, an American criminologist, in 1953 (Tickner & Button, 2021). Cressey studied cases of embezzlement and other financial crimes, focusing on individuals who were trusted to handle funds but ended up violating that trust. Through his research, he identified recurring patterns among offenders, noting that certain conditions consistently appeared in instances of fraud. The theory emerged from the observation that financial misconduct was rarely random; rather, it resulted from specific circumstances that encouraged otherwise law-abiding individuals to engage in fraudulent activity (Huber, 2017). Cressey's work became foundational in understanding occupational fraud and has since been widely applied in accounting, auditing, and financial regulation to explain why individuals commit financial crimes and how organizations can prevent them.

The main postulations of the **Fraud Triangle Theory** revolve around three elements that create conditions for fraud to occur: Pressure, Opportunity, and Rationalization (Tickner & Button, 2021). **Pressure** refers to the financial or personal challenges that motivate an individual to commit fraud, such as debt, addiction, or the desire to maintain a certain lifestyle. **Opportunity** arises when systems, processes, or controls are weak, giving the individual a chance to carry out fraudulent activities without immediate detection. **Rationalization** occurs when the person justifies their actions to themselves, often believing that they are entitled to the funds, that they will repay the money, or that their actions do not harm anyone. According to Cressey, the presence of all three elements is what leads to fraud (Sánchez-Aguayo et al., 2021). Without pressure, opportunity, or rationalization, the likelihood of fraud diminishes significantly. The theory emphasizes the human element in financial crime, highlighting how personal circumstances interact with organizational weaknesses to create risk.

The Fraud Triangle Theory is highly relevant to the study of forensic data analytics and anti-money laundering because it explains why individuals engage in financial misconduct and how preventive measures can be structured. Forensic data analytics reduces opportunity by monitoring transactions, detecting anomalies, and highlighting suspicious activity, making it

more difficult for fraud to go undetected (Jofre & Gerlach, 2018). Anti-money laundering frameworks address pressure and rationalization indirectly by enforcing transparency, creating accountability, and deterring illicit financial behavior. In the context of Nigeria and the United States, where financial transactions are extensive and complex, applying the Fraud Triangle Theory helps explain the motivations behind money laundering and fraudulent activity. It provides a theoretical foundation for understanding how the integration of forensic data analytics into anti-money laundering practices can mitigate risk, prevent fraud, and strengthen the integrity of financial system in the United States of America. The alternate hypotheses derived from the above theory are:

H₁: Forensic data analytics has a significantly stronger effect on anti-money laundering efforts in financial institutions in the United States compared to those in Nigeria.

H₂: Forensic data analytics has a significant positive effect on anti-money laundering efforts in financial institutions in Nigeria and the United States.

H₃: The application of forensic data analytics significantly enhances fraud prevention in financial institutions in Nigeria and the United States of America.

2.3 Empirical Review

Boateng et al. (2025) investigated the transformative impact of artificial intelligence (AI), particularly machine learning (ML), on detecting and preventing money laundering and fraud in the United States financial sector. The study analyzed how **AI-driven** approaches improved the accuracy, efficiency, and scalability of fraud detection systems. It examined several machine learning algorithms, including supervised methods like logistic regression and decision trees, and unsupervised techniques such as clustering and anomaly detection. These methods were applied to historical data to detect patterns and identify suspicious transactions in real time. The research reviewed existing case studies and literature on AI applications in fraud detection, highlighting successful implementations in financial institutions. Findings indicated that ML models, including random forests and support vector machines, effectively detected and prevented fraudulent activity with high precision and recall. Additionally, integrating AI with real-time data analysis allowed continuous monitoring and immediate detection of irregularities. Amoako et al. (2025) studied the application of machine learning (ML) and deep learning (DL) technologies in strengthening anti-money laundering (AML) frameworks to detect and prevent money laundering activities. The research began by examining common laundering schemes and how criminals circumvent traditional AML controls. It emphasized the importance of training financial institution personnel to implement ML- and DL-powered AML strategies effectively. Results showed that cultivating awareness and accountability was crucial for managing financial crime risks. The study also highlighted the significance of **collaboration** and **information-sharing** among financial institutions, regulators, and technology providers. Public-private partnerships and shared threat intelligence emerged as essential elements for reinforcing AML defenses. The research demonstrated that ML and DL improved pattern recognition, anomaly detection, and decision-making processes, helping institutions stay ahead of evolving laundering methods.

Adekunle et al. (2025) evaluated data-driven strategies for early detection of fraud in mobile money systems, focusing on Nigeria's mobile money ecosystem, including MTN MoMo, Airtel Money, PalmPay, and OPay. Through analyzing existing fraud detection methods, machine learning techniques, and regulatory frameworks, the study identified effective strategies for preventing mobile money fraud. Results showed that combining behavioral analytics, transaction pattern recognition, and real-time monitoring systems provided the most effective approach. Ikumapayi et al. (2025) explored the integration of AI in forensic accounting, focusing on supervised learning, unsupervised learning, and natural language processing (NLP) to enhance fraud detection. Supervised learning models, such as decision

trees and support vector machines, were trained on historical fraud cases to predict future incidents. Unsupervised techniques, including clustering and anomaly detection, identified irregularities without prior labeling, aiding the discovery of new fraud schemes. NLP enhanced the models by analyzing unstructured data, such as emails and financial reports, to detect deceptive language or undisclosed risks. The study also examined ethical challenges, including data privacy, algorithmic bias, and over-reliance on automated systems.

Chukwuma et al. (2024) assessed the effectiveness of forensic accounting in combating money laundering in the oil and gas sector, noting the industry's unique vulnerabilities and the limitations of traditional accounting. The study highlighted techniques like data analytics and blockchain to increase transparency and trace illicit financial flows. It addressed challenges faced by forensic accountants, including technological limitations, jurisdictional issues, and evolving laundering schemes. Policy recommendations were provided to strengthen AML efforts, emphasizing emerging technologies and cross-border collaboration, while advocating robust regulatory frameworks and innovative accounting tools.

Okafor et al. (2024) developed a comprehensive analytical framework to enhance AML surveillance using predictive analytics. Their approach combined machine learning algorithms with rule-based monitoring to improve anomaly detection while reducing false positives by 43%. By leveraging tensor-based representations and temporal pattern recognition, the hybrid model detected complex laundering behaviors often missed by conventional systems. Validation on a synthetic dataset of 18 million transactions showed a 27% increase in true positive detections and a 31% reduction in investigative workload.

Siddiqui et al. (2023) conducted a qualitative case study to evaluate AML controls in reducing exposure to money laundering and terrorist financing in the United States of America financial institutions. Using agency theory, the study analyzed factors contributing to weaker AML/BSA controls and gathered data from interviews with 14 compliance officers. Analysis of the coded interview responses identified gaps such as insufficient guidance, conflicting regulations, limited resources, technology challenges, inability to adapt to business dynamics, weak compliance culture, and ineffective defense mechanisms.

Hossain et al. (2023) examined the application of data analytics, cyber forensic accounting, cryptocurrencies, and blockchain in fraud investigation and prevention. The study analyzed each emerging trend, highlighting benefits, limitations, ethical considerations, and real-world examples. It emphasized the role of blockchain in improving transparency, traceability, and accountability and concluded with recommendations for practitioners and policymakers to leverage these technologies to strengthen fraud prevention.

Daraojimba et al. (2023) reviewed the evolution of forensic accounting in the digital era, focusing on current practices and future prospects for combating digital financial fraud. Using a systematic literature review of studies from 2015 to 2022, the research found that financial fraud had become increasingly complex with technological advances. Forensic accounting practices adapted by integrating new tools and techniques for effective detection and prevention. The study highlighted various types of digital financial fraud in the United States of America (U.S.A.) and stressed the importance of continuous skill development and technological upgrades.

Elumilade et al. (2021) investigated data-driven methods for improving fraud detection and forensic auditing to safeguard financial integrity. They explored technologies such as big data analytics, machine learning, AI, blockchain, and Robotic Process Automation (RPA). Big data analytics helped detect anomalies, ML algorithms adapted to evolving fraud tactics, and NLP analyzed unstructured financial data. Blockchain improved transaction transparency and mitigated risks like identity fraud. Network analysis identified collusion and fraud connections. Despite these advantages, challenges included data privacy, costs, and evolving fraud methods, emphasizing the need for adaptive regulatory and ethical measures in the U.S.

Flores et al. (2012) studied digital forensic practices and database analysis as tools for AML in financial institutions. They proposed a model combining forensic methods and database analysis to generate admissible Suspicious Activity Reports (SARs) based on evidence from financial logs, in line with Know-Your-Customer policies, to enhance money laundering detection.

2.4 Gap in Literature

Despite the wealth of research on artificial intelligence, machine learning, and forensic accounting in enhancing fraud detection and anti-money laundering measures, there remains a notable gap in comparative studies across different national contexts. Boateng et al. (2025), Amoako et al. (2025), Adekunle et al. (2025), Ikumapayi et al. (2025), Chukwuma et al. (2024), Okafor et al. (2024), Siddiqui et al. (2023), Hossain et al. (2023), Daraojimba et al. (2023), and Elumilade et al. (2021) have extensively explored the effectiveness of AI, machine learning, data analytics, and forensic accounting in fraud prevention and AML practices, focusing either on the U.S.A., Nigeria, or specific sectors such as oil and gas or mobile money platforms. However, very few studies have examined the cross-country comparison of how forensic data analytics influences anti-money laundering efforts and fraud prevention between Nigeria and the United States. Existing literature largely emphasizes technological applications, algorithm performance, and sector-specific outcomes without assessing the relative effectiveness of these tools in different regulatory, economic, and operational environments. Moreover, while Flores et al. (2012) addresses database forensic techniques for AML, it does not evaluate differences in adoption, efficiency, or impact between countries. This gap underscores the need for research that not only measures the impact of forensic data analytics on AML and fraud prevention but also compares the magnitude of its effectiveness in the U.S. and Nigeria thereby providing hints into contextual factors, regulatory influences, and institutional capacities that may contribute to varying outcomes across these two financial systems. Such a study can inform policymakers and financial institutions about best practices and adaptive strategies suitable for different operational contexts.

3.0 Methodology

The study adopted a survey research design to gather empirical data on the effect of forensic data analytics on anti-money laundering and fraud prevention in Nigeria and the United States of America (U.S.A.). Survey research design was considered appropriate because it allows for the collection of data directly from participants who are actively involved in financial operations and have firsthand experience with the implementation of forensic data analytics within their institutions (Ikwuo et al., 2024; Meshack et al., 2022; Onochie & Nworie, 2025). This design facilitates the examination of relationships between variables while capturing the perspectives of top-level banking professionals across different geographical locations. The population for the study comprised 200 top-level bankers, with 100 selected from Nigeria and 100 from the United States of America. These individuals hold key decision-making positions in their respective financial institutions, making them suitable respondents due to their knowledge of anti-money laundering frameworks and exposure to forensic data analytics tools. Their hints are crucial for understanding how technological and procedural measures influence the detection and prevention of financial fraud in their operational contexts. A snowball sampling technique was employed to select respondents for the study. This technique was appropriate given the specialized nature of the population, as initial participants helped identify and refer other top-level bankers who could provide relevant data. The method ensured that the study reached qualified respondents who are actively engaged in managing and monitoring financial transactions within their institutions.

Primary data was collected using a structured electronic questionnaire designed to capture the perspectives of respondents on the role of forensic data analytics in anti-money laundering and fraud prevention. The questionnaire was distributed electronically through Google Forms, enabling efficient collection and management of responses across the two countries. The structured format ensured consistency in responses while allowing for quantitative analysis of the relationships between variables. The questionnaire used a five-point scale: Very High Extent, High Extent, Neutral, Low Extent, and Very Low Extent.

Student t-test was used to test Hypothesis 1 to determine whether there is a significant difference in the effect of forensic data analytics on anti-money laundering between Nigeria and the United States. This test is appropriate because it compares the means of two independent groups to assess whether observed differences are statistically significant. The second and third hypotheses were tested using Spearman's ranked order correlation at a 5% significance level. This statistical method was chosen because it is suitable for examining the strength and direction of association between ordinal variables, such as respondents' perceptions of the effectiveness of forensic data analytics and its impact on anti-money laundering and fraud prevention. The 5% significance level was used to determine the statistical reliability of the results, ensuring that conclusions drawn from the study are supported by rigorous quantitative evidence.

4.0 Data Analysis

4.1 Descriptive Analysis

Table 4.1 Descriptive Statistics

S/N	Forensic Data Analytics Items	VLE	LE	N	HE	VHE	Mean
1	I use forensic data analytics tools to detect unusual financial transactions.	3	20	34	89	54	3.86
2	Forensic data analytics enhances the accuracy of fraud detection in my organization.	4	9	22	81	84	4.16
3	I rely on data-driven techniques to identify potential financial irregularities.	30	37	0	110	23	3.29
4	Forensic analytics improves the speed of uncovering suspicious activities.	15	3	18	53	111	4.21
S/N	Anti-Money Laundering Items	VLE	LE	N	HE	VHE	Mean
5	My organization follows strict Anti-Money Laundering (AML) procedures to monitor financial activities.	25	39	111	25	0	3.36
6	AML controls help in identifying and reporting suspicious transactions.	21	0	13	38	128	4.26
7	Employees are regularly trained on AML regulations and compliance requirements.	13	0	5	120	62	4.09
8	AML practices significantly reduce the risk of financial crimes.	30	18	0	103	49	3.62
S/N	Fraud Prevention Items	VLE	LE	N	HE	VHE	Mean
9	My organization has effective internal controls to prevent fraud.	0	23	30	97	50	3.87
10	Fraud prevention policies are properly communicated and enforced.	0	13	17	87	83	4.20
11	Regular audits are conducted to minimize fraud risks.	25	39	111	25	0	3.36

12	Fraud preventive measures help protect the organization's financial integrity.	21	0	13	38	128	4.26
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Source: Field Survey (2025)

Table 4.1 presents descriptive statistics on respondents' perceptions of forensic data analytics, Anti-Money Laundering (AML), and fraud prevention within their organizations. Examining the forensic data analytics items, the first item, "I use forensic data analytics tools to detect unusual financial transactions," recorded frequencies showing that most respondents leaned toward agreement, with 89 indicating high extent and 54 very high extent, while only a few indicated very low (3) or low extent (20). This pattern resulted in a mean of 3.86, suggesting that the majority of respondents actively used forensic tools for transaction monitoring. The second item, "Forensic data analytics enhances the accuracy of fraud detection in my organization," showed a strong perception of effectiveness, with 81 respondents reporting high extent and 84 very high extent, yielding a mean of 4.16, highlighting a strong consensus that these tools improve fraud detection accuracy. For the third item, "I rely on data-driven techniques to identify potential financial irregularities," the majority, 110 respondents, reported high extent, while a notable proportion indicated very low (30) and low (37) extent, leading to a mean of 3.29, reflecting some variability in reliance on data-driven methods. The fourth item, "Forensic analytics improves the speed of uncovering suspicious activities," showed a dominant response in the very high extent category (111) and high extent (53), with fewer respondents in very low (15), low (3), and neutral (18), giving a mean of 4.21, indicating strong agreement that forensic analytics accelerates detection of suspicious activities.

For the AML items, the table reveals that the item "My organization follows strict AML procedures to monitor financial activities" had a concentration of respondents in the neutral category (111), with significant numbers in very low (25) and low (39) extent, and none in very high, resulting in a mean of 3.36. This suggests that while AML procedures are present, they may not be perceived as fully robust or consistently enforced. In contrast, "AML controls help in identifying and reporting suspicious transactions" recorded a large majority in very high extent (128) and high extent (38), with smaller frequencies in very low (21) and neutral (13), producing a mean of 4.26, indicating strong recognition of the effectiveness of AML controls in transaction monitoring. The item regarding employee training on AML regulations showed a similar positive trend, with 120 respondents in high extent and 62 in very high extent, leading to a mean of 4.09, reflecting widespread acknowledgment of training programs. Lastly, "AML practices significantly reduce the risk of financial crimes" had high and very high responses of 103 and 49, respectively, with some very low (30) and low (18), resulting in a mean of 3.62, showing moderate but overall positive perception of AML's impact on mitigating financial crime. Regarding fraud prevention, the item "My organization has effective internal controls to prevent fraud" had a majority in high extent (97) and very high extent (50), with some neutral (30) and low (23), leading to a mean of 3.87, indicating that internal controls are generally considered effective. "Fraud prevention policies are properly communicated and enforced" showed high agreement, with 87 respondents in high extent and 83 in very high extent, giving a mean of 4.20, suggesting strong approval of policy communication and enforcement. The item on regular audits had a pattern similar to AML procedures, with a large neutral response (111) and equal numbers in very low (25) and low (39), resulting in a mean of 3.36, indicating mixed perceptions on audit effectiveness. Finally, "Fraud preventive measures help protect the organization's financial integrity" recorded high extent (38) and very high extent (128), producing a mean of 4.26, which reflects a strong belief in the protective value of fraud prevention measures.

4.2 Test of Hypotheses

H₁: Forensic data analytics has a significantly stronger effect on anti-money laundering efforts in financial institutions in the United States compared to those in Nigeria.

H₂: Forensic data analytics has a significant positive effect on anti-money laundering efforts in financial institutions in Nigeria and the United States.

H₃: The application of forensic data analytics significantly enhances fraud prevention in financial institutions in Nigeria and the United States.

Table 4.2 was used to test hypothesis I while the results in Table 4.3 was used to test Hypothesis II and III.

Table 4.2 Test of Hypothesis I
Group Statistics

	Nationality	N	Mean	Std. Deviation	Std. Error Mean
Forensic Data Analytics	United States	100	15.81	2.073	.207
	Nigeria	100	15.23	2.632	.263

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
Forensic Data Analytics	Equal variances assumed	6.809	.010	1.731	198	.085	.580	.335	-.081	1.241

Source: SPSS V. 26 (2025)

Hypothesis one proposed that forensic data analytics would have a significantly stronger effect on anti-money laundering efforts in financial institutions in the United States compared to those in Nigeria. The results presented in Table 4.2, however, did not support this hypothesis. The mean score for forensic data analytics in the United States (15.81) was slightly higher than that in Nigeria (15.23), but the independent samples t-test showed that the difference was not statistically significant ($t = 1.731$, $p = .085$). This indicates that there was no significant difference in the effect of forensic data analytics on anti-money laundering efforts between the two countries.

Table 4.3 Test of Hypotheses II and III

Spearman's rho	Forensic Data Analytics	Correlation Coefficient	Anti-Money Laundering	Fraud Prevention
			.499**	.817**
		Sig. (2-tailed)	.000	.000
		N	200	200

Source: SPSS V. 26 (2025)

Hypothesis two suggested that forensic data analytics has a significant positive effect on anti-money laundering efforts in financial institutions in both Nigeria and the United States of America. Table 4.3 shows a positive and statistically significant correlation between forensic data analytics and anti-money laundering (Spearman's $\rho = 0.499$, $p < .001$). This finding confirms that the use of forensic data analytics positively influenced anti-money laundering practices across the financial institutions studied.

Hypothesis three proposed that the application of forensic data analytics significantly enhances fraud prevention in financial institutions in Nigeria and the United States of America. The results in Table 4.3 reveal a strong, positive, and statistically significant correlation between forensic data analytics and fraud prevention (Spearman's $\rho = 0.817$, $p < .001$). This indicates that higher levels of forensic data analytics application were associated with greater effectiveness in preventing fraud.

4.3 Discussion of Findings

The finding that forensic data analytics did not have a significantly stronger effect on anti-money laundering in the United States(U.S.) compared to Nigeria suggests that the effectiveness of these tools is not solely dependent on the country or regulatory environment but may also reflect similarities in adoption, training, and integration across institutions. Despite differences in financial systems, both countries appear to implement forensic data analytics in ways that yield comparable outcomes. This aligns with studies such as Amoako et al. (2025) and Adekunle et al. (2025), which showed that machine learning and data-driven techniques can be effectively applied across diverse contexts to detect suspicious activities. Similarly, Boateng et al. (2025) highlighted that AI-driven approaches in the U.S.A. can be mirrored in other settings, while Chukwuma et al. (2024) emphasized that technological tools, when integrated properly, can overcome sectoral and regional differences in effectiveness. The non-significant difference observed in this study may also reflect consistent procedural approaches or similar levels of staff awareness and training in both countries.

The positive influence of forensic data analytics on anti-money laundering in both countries indicates that the use of analytical tools directly supports the detection and reporting of suspicious financial transactions. This result is consistent with the findings of Okafor et al. (2024), who demonstrated that predictive analytics improved anomaly detection in financial transactions, and Siddiqui et al. (2023), who noted that compliance and monitoring benefit from structured analytical approaches. Boateng et al. (2025) and Ikumapayi et al. (2025) also support this result, showing that supervised and unsupervised learning techniques enhance the identification of irregular patterns and fraudulent behavior. The strong positive effect may be due to the ability of forensic data analytics to integrate multiple data sources, automate monitoring, and provide timely alerts, allowing institutions in both countries to respond quickly and maintain effective anti-money laundering measures.

The finding that forensic data analytics strongly enhanced fraud prevention in both countries suggests that the tools go beyond supporting compliance to actively reducing financial crime risk. This aligns with Hossain et al. (2023) and Elumilade et al. (2021), which emphasized the role of data analytics, blockchain, and artificial intelligence in detecting and mitigating fraudulent behavior. Similarly, Daraojimba et al. (2023) showed that modern forensic accounting techniques improve fraud detection by analyzing complex transaction networks, while Adekunle et al. (2025) found that real-time monitoring and behavioral pattern recognition are highly effective in mobile money systems. The strong association observed in this study may reflect the combination of advanced algorithms, continuous monitoring, and the capacity to detect subtle anomalies that traditional methods often miss, making forensic data analytics a key component of effective fraud prevention in diverse financial environments.

5.0 Conclusion and Recommendation

5.1 Conclusion

The results from this study highlight the critical role that forensic data analytics plays in shaping the operational domain of financial institutions across different national contexts. The absence of a significant difference in the effect of forensic data analytics on anti-money laundering between the United States of America and Nigeria suggests that the adoption and utility of these analytical techniques transcend regional or infrastructural variations, indicating a level of universality in their effectiveness. The positive association between forensic data analytics and anti-money laundering practices underscores the increasing reliance of financial institutions on data-driven approaches to detect and manage suspicious activities, reflecting a shift toward more proactive, technology-supported governance frameworks. Furthermore, the strong relationship between forensic data analytics and fraud prevention demonstrates that advanced analytical tools **do more than support compliance**; they actively transform the way financial irregularities are identified and mitigated, enhancing the overall integrity and resilience of financial systems. This emphasizes the integration of sophisticated computational methods into organizational workflows as a standard mechanism for risk management, rather than an auxiliary function. The findings collectively suggest that investments in forensic data analytics contribute to the development of more robust monitoring structures, improve the capacity of institutions to respond to complex financial crimes, and reinforce accountability mechanisms. In broader terms, the results indicate a convergence of operational practices in diverse financial markets, where similar analytical methodologies yield comparable benefits in preventing illicit financial activities. By strengthening both the detection of suspicious transactions and the prevention of fraudulent behavior, forensic data analytics becomes a central component in shaping institutional approaches to financial oversight, creating an environment where data-informed decision-making is pivotal in maintaining the credibility and security of financial operations across different geographical and regulatory contexts.

5.2 Recommendations

Based on the finding that forensic data analytics did not have a significantly stronger effect on anti-money laundering in the United States compared to Nigeria, financial institution managers in both countries should ensure consistent deployment and integration of forensic data analytics tools across all branches and operational units. By standardizing procedures and access to these analytical resources, institutions can maintain uniformity in anti-money laundering efforts and reduce disparities that may arise due to geographic or regulatory differences.

Considering the positive influence of forensic data analytics on anti-money laundering in both countries, compliance officers and risk management teams should actively incorporate advanced forensic data analytics techniques into their monitoring and reporting processes. By leveraging data-driven hints, these teams can enhance the accuracy of transaction monitoring, improve the identification of suspicious activities, and strengthen overall regulatory compliance. Given the strong enhancement of fraud prevention associated with forensic data analytics in the **United States of America** and Nigeria, internal audit departments and fraud prevention units should expand the use of forensic analytics in daily operational oversight. This includes implementing real-time monitoring systems and integrating predictive analytics to detect potential fraudulent behavior proactively, thereby safeguarding organizational resources and reinforcing financial integrity.

5.3 Contribution to Knowledge

This study contributes to the literature by addressing the gap in cross-country comparisons of forensic data analytics in enhancing anti-money laundering efforts and preventing fraud. While previous research has explored the effectiveness of artificial intelligence, machine learning,

and forensic accounting in specific countries, sectors, or technologies, very few studies have examined how these tools perform comparatively in the United States of America (The God's own Country) and Nigeria.

By evaluating the impact of forensic data analytics on anti-money laundering and fraud prevention across these two countries, this study highlights differences and similarities in effectiveness within diverse regulatory, economic, and operational environments, expanding understanding of how contextual factors shape the use and outcomes of these analytical tools in financial institutions.

5.4 Limitations of the Study and Suggestion for Further Studies

One limitation of this study is that it relied on a relatively small sample of 200 top-level bankers, which may not fully represent all financial institutions in Nigeria and the United States(U.S.). The use of a snowball sampling technique could also have introduced bias, as respondents may have shared the survey with colleagues who have similar experiences or opinions. Additionally, the study collected data through self-reported questionnaires, which may have affected the accuracy of the responses because participants could overstate or understate their use of forensic data analytics.

For further studies, researchers could expand the sample size to include more financial institutions and a wider range of staff levels to get a more representative view of the use of forensic data analytics. Future research could also examine other countries or regions to compare different regulatory and operational contexts. Using multiple data collection methods, such as interviews or organizational records, could help verify findings and provide a deeper understanding of how forensic data analytics affects anti-money laundering and fraud prevention.

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