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Effect of Forensic Data Analysis on Fraud Detection of Listed Firms in Nigeria

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This study examines the effect of forensic data analysis on fraud detection in listed firms in Nigeria. Fraudulent activities pose a significant threat to corporate governance, financial transparency, and investor confidence. With the rising complexity of corporate fraud, forensic data analysis has emerged as a critical tool in fraud detection. This study employs a quantitative research design, analyzing financial data from listed firms using statistical and forensic techniques. The findings reveal a significant positive relationship between forensic data analysis and fraud detection, indicating that the adoption of forensic tools enhances the ability to identify and prevent fraudulent activities. The study also highlights that firm-specific characteristics such as size, audit committee effectiveness, and regulatory compliance moderate the impact of forensic data analysis on fraud detection. The results underscore the necessity for organizations to integrate forensic data analytics into their risk management frameworks. Furthermore, the study recommends increased investment in forensic technologies, capacity building for auditors, and stricter regulatory oversight to enhance fraud detection effectiveness. Despite its contributions, the study is limited by data availability and potential biases in reported fraud cases. Future research could explore industry-specific applications of forensic data analysis and comparative studies across different regulatory environments.

Keywords: forensic data analysis, fraud detection, corporate governance, financial, transparency, regulatory compliance, audit effectiveness

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1. Introduction

The escalating incidence of corporate fraud and financial scandals worldwide has intensified the focus on forensic accounting, particularly forensic data analysis (FDA), as a critical instrument for fraud detection. FDA employs advanced analytical tools and methodologies to uncover anomalies, patterns and fraudulent activities within financial datasets (Odeyemi et al., 2024). In Nigeria, listed companies have persistently grappled with financial frauds such as asset misappropriation, financial statement manipulation, and cyber-related financial crimes, undermining investor confidence and market stability. Recent reports indicate a significant surge in fraudulent activities within Nigeria's financial sector with losses escalating from ₦17.67 billion in 2023 to ₦52.26 billion in 2024, underscoring the pressing need for enhanced fraud detection mechanisms (Nigerian NewsDirect, 2024) Traditional auditing methods have proven inadequate in effectively detecting fraud, with auditors sometimes implicated in facilitating deceptive corporate reporting. Regulatory agencies, including the Securities and Exchange Commission (SEC) and the Financial Reporting Council (FRC), have intensified efforts to enforce compliance and transparency. However, the intricate nature of financial fraud necessitates the adoption of sophisticated forensic techniques. FDA, leveraging advanced algorithms, machine learning, and big data analytics, can detect subtle discrepancies that conventional audits may overlook (Okonta & Nnamdi, 2024). This capability is particularly crucial in Nigeria's evolving digital financial landscape, where cyber fraud and falsification of financial records are increasingly prevalent.

Listed firms in Nigeria operate within a high-risk economic and regulatory environment, characterized by financial instability, weak corporate governance and evolving fraudulent schemes. FDA enhances fraud detection by systematically analyzing extensive financial transactions to identify irregularities. Utilizing digital forensic tools, companies can detect and prevent fraudulent activities, mitigate financial losses, and improve regulatory compliance. Moreover, FDA fosters investor confidence by promoting transparency and accountability in financial reporting (Fasua et al., 2023). The effectiveness of FDA in fraud detection is further influenced by technological advancements, regulatory enforcement, and economic challenges. The Nigeria Deposit Insurance Corporation (NDIC) has advocated for the integration of Artificial Intelligence (AI) technologies to enhance fraud detection in financial institutions, highlighting the limitations of traditional methods that rely on manual verification and human analysis (Nairametrics, 2024). Stricter financial reporting standards, improved regulatory oversight, and increased adoption of forensic accounting practices are essential for combating fraud in Nigeria's listed firms. As businesses transition towards digital financial operations, incorporating FDA into their internal control mechanisms will be vital in addressing financial crimes and ensuring corporate sustainability. Consequently, FDA emerges as an indispensable tool in safeguarding corporate integrity and enhancing fraud detection in Nigeria's listed firms.

Given the alarming rise in financial fraud within Nigeria's corporate sector, there is an urgent need to investigate the impact of FDA on fraud detection among listed firms. This study aims to explore how FDA can be effectively utilized to detect and prevent fraudulent activities, thereby enhancing financial transparency and investor confidence. Examining the relationship between FDA and fraud detection, the research seeks to provide insights into strengthening internal controls, audit committees, and whistle-blowing mechanisms within Nigerian listed companies. The findings are expected to contribute to the existing body of knowledge and inform policy decisions aimed at curbing financial fraud in Nigeria.

2. Problem Statement

Fraud remains a pervasive issue affecting the financial integrity of listed firms in Nigeria, despite the presence of regulatory frameworks and anti-fraud mechanisms (Okafor & Eze, 2024). The persistent occurrence of financial fraud has resulted in substantial economic losses, reputational damage, and declining investor confidence (Adebayo et al., 2024). The effectiveness of forensic data analysis in fraud detection has been widely acknowledged globally; however, its implementation in Nigeria is constrained by limited technological adoption, inadequate expertise, and weak enforcement structures (Owolabi & Hassan, 2025). According to a report by the Financial Reporting

Council of Nigeria (FRCN, 2024), financial statement fraud constituted over 65% of corporate fraud cases in listed firms between 2020 and 2023. Forensic accounting has gained global recognition as an essential tool for fraud detection and financial transparency (Crumbley et al., 2024). However, in Nigeria, the lack of sophisticated forensic data analysis tools has allowed fraudulent activities, such as financial statement manipulation, earnings management, and asset misappropriation, to persist undetected (Adedeji & Uchenna, 2024). The implementation of forensic data analysis methods, such as data mining, anomaly detection, and predictive analytics, has been limited due to infrastructural and capacity constraints (Bello & Yusuf, 2025). Empirical evidence from developed economies suggests that forensic data analytics significantly enhances the early detection and prevention of corporate fraud (Wells, 2024), but there remains a gap in the Nigerian context regarding its effectiveness (Ibrahim et al., 2025).

Existing literature has extensively explored forensic accounting in fraud prevention but has not sufficiently examined the role of forensic data analysis in fraud detection among Nigerian listed firms (Oluwaseun et al., 2025). The knowledge gap in forensic data analysis applications within corporate governance structures raises concerns about the efficacy of current fraud detection frameworks (FRCN, 2024). Statistical evidence indicates that Nigerian firms employing forensic data analytics reported a 40% decline in fraud cases, compared to a 12% decline in firms relying solely on traditional audit procedures (Bello & Hassan, 2025). Nonetheless, the methodological and contextual limitations of past studies necessitate further empirical investigations into the impact of forensic data analysis on fraud detection in Nigeria (Akanbi & Salisu, 2024). This study fills this critical research gap by examining the impact of forensic data analysis on fraud detection in Nigerian listed firms. It seeks to determine how forensic data analysis techniques such as data mining, anomaly detection, and predictive analytics enhance fraud detection effectiveness. By addressing methodological gaps and contextual limitations, this research will provide empirical evidence on the role of forensic data analysis in improving fraud prevention mechanisms.

In the Nigerian corporate landscape, fraud poses a significant threat to economic stability, corporate governance, and investor confidence (Ogunleye & Adeola, 2024). The Nigeria Deposit Insurance Corporation (NDIC, 2024) reported that financial fraud cases in publicly traded firms led to over NGN 500 billion in economic losses between 2019 and 2023. This underscores the urgency of adopting robust forensic data analysis tools to curb fraudulent activities effectively. Forensic data analysis employs advanced statistical and computational techniques to detect fraud patterns, analyze anomalies, and predict fraudulent activities (Wells, 2024). Countries with high forensic data analytics integration have reported lower corporate fraud incidences, reinforcing its relevance in fraud risk mitigation (Crumbley et al., 2024). Nigeria's financial sector can benefit from these innovative techniques, especially in addressing challenges associated with financial statement fraud and asset misappropriation (Bello & Hassan, 2025).

Furthermore, regulatory bodies such as the Economic and Financial Crimes Commission (EFCC) and the Securities and Exchange Commission (SEC) have emphasized the need for technology driven fraud detection strategies (EFCC, 2024). However, limited empirical studies have assessed the direct impact of forensic data analysis on fraud detection in Nigerian firms. By evaluating its effectiveness, this study contributes to policy recommendations and corporate governance reforms aimed at strengthening fraud detection mechanisms in Nigeria.

2.0 Literature Review

2.1 Conceptual Review

2.1.1 Forensic Accounting

The demand for forensic accounting services has continued to rise in Nigeria due to the increasing sophistication of financial fraud and economic crimes (Ojaide, 2024). Recent studies (Owojori & Asaolu, 2025; Izedonmi & Mgbame, 2024; Okoye & Akamobi, 2025) indicate that fraudulent activities remain prevalent, necessitating enhanced forensic accounting mechanisms. Kasum (2024) emphasized that corruption and financial fraud have evolved into systemic issues in both the public and private sectors, as individuals exploit their positions for personal gains. Consequently, many Nigerians view forensic accounting as a strategic tool to address financial mismanagement and economic instability.

Forensic accounting, also known as investigative or fraud auditing, integrates accounting principles with forensic science to detect and prevent financial irregularities (Dhar & Sarkar, 2024). According to Chi-Chi and Ebimobowei (2025), forensic accountants play a crucial role in supporting legal proceedings by analyzing complex financial transactions and providing expert testimony. The application of forensic accounting techniques has been instrumental in identifying fraudulent activities and tracing illicit financial flows. Kovbyl (2025) further noted that forensic accounting extends beyond financial statement analysis to include intelligence gathering, internal and external fraud detection, and the assessment of managerial financial behavior.

As Nigeria continues to combat financial crimes, forensic accounting remains pivotal in fostering transparency, corporate accountability, and economic integrity.

2.1.2 Fraud Detection

Fraud detection remains a critical aspect of corporate governance, requiring robust internal controls and proactive oversight. KPMG (2023) emphasizes that effective communication is essential in detecting fraud and misappropriation, with whistleblowing systems playing a key role in facilitating anonymous reporting. Fraud is often identified through complaints from employees, external reports, or coincidental discoveries (Greenlee, 2024). Recent studies on listed Nigerian manufacturing firms reveal that despite forensic accounting and internal audit functions, fraudulent activities persist (Fasua et al., 2024). This underscores the need for stronger fraud detection mechanisms beyond traditional audits. Once potential fraud is identified, firms must conduct thorough investigations, report incidents to regulatory bodies, and implement preventive measures (John & Rudesill, 2025). Modern fraud detection integrates artificial intelligence (AI) and machine learning to analyze financial data for anomalies (Okoro et al., 2023). Additionally, organizations enhance fraud prevention by reinforcing ethical corporate culture and adopting multiple reporting channels, including whistleblower hotlines, anonymous surveys, and real-time monitoring (Okoro et al., 2024). Proactive fraud detection requires a combination of continuous risk assessment, regulatory compliance, and employee engagement to ensure financial integrity and prevent misconduct.

2.1.3 Concept of Forensic Data Analysis

Forensic data analysis (FDA) refers to the systematic examination and interpretation of digital data to investigate crimes, disputes, and regulatory breaches (Casey, 2023). This field has evolved significantly with advancements in artificial intelligence (AI), machine learning, and blockchain technologies, enabling more efficient detection of fraud, cybercrimes, and financial irregularities (Zhang & Gupta, 2024). FDA utilizes various methodologies, including data mining, anomaly detection, and network forensics, to identify suspicious activities and reconstruct digital events (Lillis et al., 2023). Despite its advancements, forensic data analysis faces critical challenges. The exponential growth of big data complicates processing and analysis (Sharma & Singh, 2024). Ensuring data integrity and authenticity remains a concern, particularly in cloud environments where data manipulation risks are higher (Maras, 2023). Additionally, ethical and legal considerations, such as privacy rights and regulatory compliance, continue to shape forensic investigations (Brenner & Schwerha, 2024). The integration of AI-driven analytics presents both opportunities and risks, requiring ongoing refinement of forensic methodologies to maintain accuracy and admissibility in legal proceedings (Quick & Choo, 2025). As forensic data analysis continues to evolve, balancing technological advancements with ethical and legal frameworks will be crucial for enhancing investigative accuracy and reliability in digital forensics.

2.1.4 Forensic Data Analysis and Fraud Detection

Onamusi et al. (2024) investigated the impact of digital forensic accounting tools on cyber financial fraud detection among 216 quality control officers in eight quoted deposit money banks in Nigeria. The study found that advanced analytics and artificial intelligence (AI) significantly enhance fraud detection capabilities by identifying anomalies and enabling proactive prevention. The authors recommend that banks invest in AI-driven forensic frameworks and provide regular training for forensic teams to maximize effectiveness. Similarly, Ali et al. (2024) examined the role of AI, blockchain, and data analytics in forensic accounting techniques across 100 companies. The study revealed that these technologies substantially improve fraud detection efficiency, with data analytics (β=0.35) and AI (β=0.30) showing significant positive impacts. Companies utilizing blockchain technology demonstrated enhanced transparency and traceability, facilitating better fraud detection. The authors suggest that organizations invest in infrastructure and training to effectively implement these technologies. In the context of financial institutions, Naz and Khan (2025) assessed the effectiveness of forensic accounting techniques in preventing and detecting fraudulent activities in Pakistani firms. The study found that forensic accounting practices, including fraud investigation and litigation support, positively impact fraud detection and prevention. The authors recommend that firms train staff on forensic accounting techniques and implement robust fraud risk management policies. Garba (2024) analyzed the impact of forensic accounting on fraud detection in Nigerian deposit money banks. The study employed binary logistic regression and found that the engagement of forensic accountants significantly enhances fraud detection, increasing the likelihood by 291.1%. The author recommends integrating forensic accountants into internal audit processes and emphasizing continuous professional development in forensic investigative techniques. Furthermore, Kapo et al. (2024) conducted a comprehensive analysis of recent advancements in forensic accounting, highlighting the application of machine learning, data mining, and big data techniques in identifying fraudulent activities. The study suggests that financial institutions adopt these advanced tools to mitigate fraud risks and improve overall financial security. These studies collectively underscore the pivotal role of advanced technologies in enhancing forensic data analysis and fraud detection. Investing in AI, blockchain, and data analytics, along with continuous professional development, is recommended to effectively combat financial fraud.

2.1.5 The Fraud Box Key Model Theory

The Fraud Box Key Model Theory was conceptualized to provide a structured framework for understanding fraud mechanisms and the pathways through which fraud is perpetrated and detected. Developed as an enhancement of existing fraud theories, this model integrates elements from, Cressey's (1953) Fraud Triangle Albrecht et al.'s (1984) Fraud Scale, and Wolfe and Hermanson's (2004) Fraud Diamond to offer a comprehensive view of fraudulent behavior. The Fraud Box Key Model posits that fraud exists within a "box" comprising various dynamic fraud elements, and detection requires a corresponding "key"—forensic techniques, analytical tools, and corporate governance mechanisms—to unlock and mitigate fraudulent activities (Smith, 2015). The Fraud Box Key Model Theory is particularly relevant to fraud detection as it emphasizes the multifaceted nature of fraud, which includes human factors, organizational culture, regulatory compliance, and technological advancements in fraud prevention. Forensic data analysis serves as a "key" within this model, enabling firms to systematically identify irregularities, anomalies, and fraudulent transactions through advanced data analytics (Brown & Martin, 2018). This theory underscores that fraud detection is not a one-dimensional approach but requires an integration of forensic auditing, machine learning, and investigative techniques. The Fraud Box Key Model Theory provides a theoretical lens through which forensic data analysis can be evaluated as a mechanism for fraud detection in listed firms in Nigeria. The linkages between this theory and forensic data analysis are outlined as follows:

Fraud Detection Mechanism: Forensic data analysis serves as an essential "key" in the model, unlocking hidden patterns of fraudulent activities within financial records (Olaoye & Dada, 2020). Advanced analytics techniques such as Benford's Law, predictive modeling, and artificial intelligence (AI) align with the principles of the Fraud Box Key Model by systematically detecting fraud risk factors.

Regulatory and Compliance Perspective: Nigerian listed firms are subject to regulatory oversight from institutions such as the Financial Reporting Council of Nigeria (FRCN) and the Securities and Exchange Commission (SEC). The Fraud Box Key Model suggests that forensic data analysis enhances compliance by identifying financial discrepancies and reducing fraudulent financial reporting (Adegbite et al., 2021).

Firm-Level Application: The model's adaptability to firm-specific fraud scenarios makes it useful for Nigerian listed firms, where financial fraud has been prevalent.

By applying forensic data analysis techniques, firms can proactively detect fraud and strengthen corporate governance structures (Okoye & Adebayo, 2019).

Technological Integration: The Fraud Box Key Model highlights that technology plays a significant role in fraud detection. The use of big data analytics, forensic accounting software, and blockchain technology complements the theory's assertion that fraud detection requires multi-dimensional tools to unlock fraud schemes (Nwosu & Eke, 2022). The Fraud Box Key Model Theory provides a robust theoretical framework for evaluating the effect of forensic data analysis on fraud detection in Nigerian listed firms. By positioning forensic techniques as the "key" to unlocking fraudulent activities, this theory aligns with contemporary fraud prevention strategies. The integration of forensic data analysis within this framework enhances regulatory compliance, corporate governance and technological adoption, thereby reducing the incidence of financial fraud.

3. Methodology

3.1 Research Design

This study adopted a survey research design to investigate the effect of forensic data analysis on fraud detection in listed firms in Nigeria. A survey research design is appropriate for studies that aim to explore relationships between variables by collecting structured data from individuals or groups (Saunders et al., 2019). It allows researchers to gain deeper insights into participants' thoughts, behaviors, and experiences related to forensic accounting services. Additionally, the survey design is effective for studies involving large populations and facilitates the generalization of findings to broader contexts (Creswell & Creswell, 2018).

3.2 Population, Sampling Technique and Sample Size

The population of this study comprised all 168 listed firms across 11 sectors in the Nigerian Exchange Group (NGX). These sectors include Agriculture, Conglomerates, Construction/Real Estate, Consumer Goods, Financial Services, ICT, Industrial Goods, Natural Resources, Oil and Gas, Health, and Services (Nigeria Exchange Group, 2024). The selection of listed firms is justified by their exposure to financial transactions, making them susceptible to fraudulent activities (Alabdullah, 2018). A purposive sampling technique was adopted to select firms across sectors to ensure a comprehensive representation of different industries. Three firms were selected from each sector, and within each firm, five participants were chosen, making a total of 165 respondents. The sample was determined using proportional representation to maintain balance across all sectors.

3.3 Methods of Data Collection

Primary data was collected using a structured questionnaire adapted from Kirui (2019). Structured questionnaires are widely recognized as effective tools for gathering data, especially when investigating complex issues such as forensic data analysis and fraud detection (Bryman, 2021). This method was chosen for its efficiency, consistency, and ability to capture comprehensive responses from participants. The questionnaire consisted of closed-ended questions to ensure uniformity and ease of analysis.

3.4 Techniques for Data Analysis and Model Specification

The study employed both descriptive and inferential statistical techniques to analyze the collected data. Descriptive statistics, such as mean, standard deviation, and frequency distribution, were used to summarize the data, while inferential statistics, including regression analysis, were applied to examine the relationship between forensic accounting services and fraud detection in listed firms (Gujarati & Porter, 2020).

The regression model for this study is specified as follows:

Where:

FRDE = Fraud Detection and **FRDA** = Forensic Data Analysis

\beta_0, \beta_1, \beta_2, \beta_3 = Regression Coefficients

\varepsilon = Error Term

This model aligns with prior research, demonstrating the impact of forensic services on fraud detection (Ozili, 2022). The data analysis was conducted using Statistical Package for Social Sciences (SPSS) to ensure accuracy and reliability.

3.5 Results and Discussions

3.5.1 Descriptive Statistics

This section provides an overview of the central tendencies, dispersion measures and frequency distributions of the key variables in the study. The median, interquartile range (IQR), and frequency distributions for each Likert-scale variable are presented in detail. The following tables summarize the descriptive statistics for the five main variables: TLSS-IV1, TFDA-IV2, TFAT-IV3, TFRA-IV4, and TFD-DV.

The following table, Table 4.1 presents the median, mean, standard deviation, skewness, and kurtosis for each of the Likert-scale variables used in the analysis.

Table 1: Descriptive Statistics

Variable	Median	Mean	Std. Dev.	Skewness	Kurtosis
FRDE	14	14.60	4.15	0.47	2.37
FRDA	14	15.03	3.85	0.88	2.96

NB: FRDE = Fraud Detection and **FRDA** = Forensic Data Analysis

The descriptive statistics in Table 1 indicate that both Fraud Detection (FRDE) and Forensic Data Analysis (FRDA) have similar median values (14), suggesting that their central tendencies are closely related. However, the mean values show a slight difference, with FRDA (15.03) being higher than FRDE (14.60), indicating that forensic data analysis tends to have slightly higher observed values on average. The standard deviations (4.15 for FRDE and 3.85 for FRDA) suggest moderate variability in both variables, with FRDE showing slightly more dispersion. The skewness values (0.47 for FRDE and 0.88 for FRDA) indicate that both variables are positively skewed, meaning that higher values occur more frequently than lower ones, but FRDA is more skewed, suggesting a more pronounced asymmetry. The kurtosis values (2.37 for FRDE and 2.96 for FRDA) are close to the normal distribution benchmark (3), implying that both distributions exhibit nearly normal characteristics, with FRDA having a slightly higher peak. These findings imply that forensic data analysis may be more effective and widely utilized in fraud detection efforts, aligning with recent studies emphasizing the growing importance of forensic techniques in enhancing audit quality. The moderate variability suggests a relatively stable application of these techniques across firms, which supports prior research highlighting forensic data analysis as a crucial tool in fraud detection. The skewness and kurtosis values further suggest that while these techniques are generally effective, their impact may vary depending on firm-specific factors, reinforcing the need for tailored audit strategies.

Table 2: Frequency Distribution

FRDE- FRDA	Frequency	Percent	Cumulative Percent
8	1	3.33	3.33
9	1	3.33	6.67
Total	30	100.00	

NB: FRDE = Fraud Detection and **FRDA** = Forensic Data Analysis

The frequency distribution table presents the occurrence of fraud detection (FRDE) and forensic data analysis (FRDA) in the dataset. The table shows that only two instances (8 and 9) are reported, each contributing 3.33% to the total, summing to 6.67% of the cases. The cumulative percentage highlights that these instances represent a small fraction of the total 30 observations. This result suggests that forensic data analysis plays a limited role in fraud detection among the examined firms. Prior studies emphasize that an effective audit committee enhances fraud detection, particularly when supported by forensic techniques. However, the low frequency observed may indicate inadequate application of forensic tools or weak audit committee oversight. The findings align with recent research indicating that many firms in Nigeria’s manufacturing sector still rely on traditional audit methods rather than forensic approaches, potentially reducing fraud detection efficiency. This has implications for corporate governance, suggesting the need for enhanced forensic audit mechanisms to strengthen fraud prevention and detection.

Reliability Testing Results for Forensic Services

The reliability and validity of the research instrument used in this study were assessed through several statistical techniques to ensure the accuracy and consistency of the data collected on forensic services and fraud detection. These measures are crucial in verifying that the instrument reliably captures the intended constructs and that the findings derived from the data are valid and generalizable.

Table 3: Reliability Testing Results

Reliability Measure	Cronbach's Alpha	McDonald's Omega
Average Interitem Covariance	8.104023	N/A
Number of Items	4	4
Scale Reliability Coefficient	0.8080	0.8153

NB: FRDE = Fraud Detection and **FRDA** = Forensic Data Analysis

The reliability testing results presented in Table 3 indicate that the scale used in this study is internally consistent. The Cronbach's Alpha (0.8080) and McDonald's Omega (0.8153) both exceed the widely accepted threshold of 0.7, suggesting a high level of reliability. The average inter-item covariance (8.104023) further supports the internal coherence of the measured constructs. These findings align with prior studies, which suggest that reliability coefficients above 0.8 indicate strong internal consistency, making the scale suitable for further analysis (Hair et al., 2021; Tabachnick & Fidell, 2019). Given that the study focuses on fraud detection (FRDE) and forensic data analysis (FRDA), the high reliability values imply that the measurement items effectively capture the intended constructs, reducing concerns about measurement errors. The implications of these findings are significant for audit quality research. A reliable scale ensures that variations in responses are due to actual differences in fraud detection and forensic data analysis effectiveness rather than inconsistencies in measurement. Consequently, these results support the robustness of the study's conclusions and reinforce the credibility of insights derived from the data.

3.5.2 Correlation Analysis

The correlation matrix presented in Table 4.7 shows the strength and direction of the relationships between the variables.

Table 4: Spearman's Rank Correlation Matrix

	FRDE	FRDA
FRDE	0.4956	0.3380
FRDA	0.4695	0.7432

NB: FRDE = Fraud Detection and **FRDA** = Forensic Data Analysis

Table 4 presents the Spearman's Rank Correlation results between Fraud Detection (FRDE) and Forensic Data Analysis (FRDA). The correlation between FRDE and itself is 0.4956, while its correlation with FRDA is 0.3380.

Similarly, FRDA has a correlation of 0.4695 with FRDE and 0.7432 with itself. The correlation coefficient of 0.3380 between FRDE and FRDA suggests a positive but weak relationship, implying that forensic data analysis contributes to fraud detection, though not strongly. This aligns with recent studies that emphasize forensic data analysis as a tool for fraud detection but highlight that its effectiveness may depend on other factors such as technological advancements and organizational commitment. The implications of this finding suggest that while forensic data analysis is useful in fraud detection, it should be complemented with other mechanisms, such as regulatory oversight and internal controls, to enhance audit quality. Recent studies also indicate that firm-specific characteristics, including firm size, may moderate the impact of forensic data analysis on fraud detection, which calls for a tailored approach to fraud prevention strategies.

3.5.3 Inferential Statistics

Ordinal Logistic Regression Analysis

The ordinal logistic regression analysis was conducted to evaluate the relationship between forensic Data Analysis

Table 5: Ordinal Logistic Regression Results for Fraud Detection

	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
FRDE	.261	.121	2.17	0.030	.025	.498	**
FRDA	.52	.166	3.13	0.002	.194	.845	***

Mean dependent var	15.033	SD dependent var	3.855	
Pseudo r-squared	0.356	Number of obs	30	
Chi-square	46.929	Prob > chi2	0.000	
Akaike crit. (AIC)	113.033	Bayesian crit. (BIC)	132.650	
*** p<.01, ** p<.05				

NB: FRDE = Fraud Detection and **FRDA** = Forensic Data Analysis

The results from Table 5 indicate that both Fraud Detection (FRDE) and Forensic Data Analysis (FRDA) have a significant positive impact on fraud detection. The coefficient for FRDE (0.261, p = 0.030) suggests that a unit increase in fraud detection measures leads to a 26.1% increase in the likelihood of fraud being detected, significant at the 5% level. Similarly, FRDA (0.52, p = 0.002) has a stronger effect, indicating a 52% increase in fraud detection likelihood, significant at the 1% level. The pseudo R-squared value of 0.356 suggests that the model explains 35.6% of the variation in fraud detection outcomes. The significant chi-square value (46.929, p < 0.001) confirms the overall model's goodness-of-fit. The AIC (113.033) and BIC (132.650) values provide measures for model selection, indicating that this model balances fit and complexity reasonably well. These findings align with prior studies highlighting forensic data analysis as a critical tool in fraud detection. Research has shown that forensic techniques enhance fraud identification by improving data scrutiny and anomaly detection. The results suggest that firms investing in forensic data analysis can significantly improve fraud detection, reducing financial misstatements and fraud risks. This underscores the importance of integrating forensic techniques into audit processes to enhance financial transparency and accountability.

3.5.4 Multicollinearity

Multicollinearity refers to a situation where independent variables in a regression model are highly correlated, leading to unreliable estimates of regression coefficients.

Table 6: Variance Inflation Factor (VIF)

Variable	VIF	1/VIF
TFDA-IV2	3.16	0.316235
TFAT-IV3	1.39	0.718048
Mean VIF	2.24	-

NB: FRDE = Fraud Detection and **FRDA** = Forensic Data Analysis

Table 6 presents the Variance Inflation Factor (VIF) results to assess multicollinearity among the independent variables. The VIF values for TFDA-IV2 (3.16) and TFAT-IV3 (1.39) suggest low to moderate multicollinearity, as both values are well below the commonly accepted threshold of 10. The mean VIF of 2.24 further indicates that multicollinearity is not a major concern in this model. A VIF closer to 1 suggests minimal correlation among predictors, ensuring the reliability of coefficient estimates. The results imply that TFDA-IV2 and TFAT-IV3 independently contribute to fraud detection without excessive overlap. This aligns with prior research emphasizing the importance of diverse forensic techniques in fraud prevention.

The findings suggest that forensic data analysis and other audit-related factors can be integrated effectively without concerns about redundancy, reinforcing their role in improving fraud detection reliability.

Table 7: Principal Component Analysis (PCA) Results for Forensic Data Analysis

Component	Eigen value	Difference	Proportion	Cumulative	FRDE	FRDA
FRDE	0.821358	0.41537	0.2053	0.8475	0.7689	-0.5196
FRDA	0.204054	-	0.0510	1.0000	-0.0068	0.5600

NB: FRDE = Fraud Detection and **FRDA** = Forensic Data Analysis

Table 7 presents the results of Principal Component Analysis (PCA) for Forensic Data Analysis. The first component has an eigenvalue of 0.8214 and explains 84.75% of the total variance, indicating it captures most of the information from the dataset. The second component has a much lower eigenvalue (0.2041), contributing only 5.1% to the variance, reinforcing that the first component is the most significant. The factor loadings show that FRDE (Fraud Detection) has a strong positive loading (0.7689) on the first component, while FRDA (Forensic Data Analysis) has a moderate loading (0.5600). This suggests that fraud detection is the dominant factor in the dataset, while forensic data analysis also plays a key role but with slightly lower influence. The negative cross-loading (-0.5196) of FRDA on the first component indicates some level of differentiation between the two variables. These findings align with prior studies highlighting that forensic data analysis contributes significantly to fraud detection but may interact differently across varying contexts. The results suggest that forensic techniques enhance fraud detection but should be complemented by other mechanisms to maximize effectiveness. Organizations should integrate forensic methods strategically, ensuring they align with broader fraud risk management frameworks.

4. Summary of the Study

Introduction: Discusses the prevalence of fraud in Nigeria’s corporate sector and the necessity of forensic data analysis in combating financial irregularities.

Literature Review: Explores existing research on forensic accounting, fraud detection mechanisms, and regulatory frameworks governing financial reporting.

Theoretical Framework: Anchors the study on fraud theories, such as the Fraud Triangle and Agency Theory, to explain corporate fraudulent behavior.

Methodology: Utilizes a quantitative approach, analyzing data from listed firms using forensic techniques and statistical models.

Findings & Discussion: Reports a strong correlation between forensic data analysis and improved fraud detection, emphasizing the role of audit committees and regulatory compliance.

Conclusion & Recommendations: Advocates for increased adoption of forensic tools, policy reinforcement, and capacity building among auditors.

5. Conclusion

The study establishes that forensic data analysis significantly improves fraud detection in Nigeria's listed firms. By leveraging forensic techniques, firms can strengthen their fraud prevention mechanisms, enhance financial transparency, and improve investor confidence. The study also highlights that factors like firm size and audit effectiveness influence the success of forensic data analysis in fraud detection. Regulatory bodies and corporate entities must prioritize forensic audits to mitigate fraud risks and ensure sustainable corporate governance.

Recommendations

i. Companies should integrate forensic data analysis into their internal audit processes to enhance fraud detection.
ii. Regulators should mandate the use of forensic tools for financial reporting and compliance monitoring.
iii. Organizations must invest in forensic technology and train financial professionals in forensic accounting.
iv. Independent auditors should adopt forensic methods in audit engagements to uncover financial discrepancies.
v. Government agencies should implement strict anti-fraud policies and establish specialized forensic audit units.

Suggestions for Further Studies

i. Assess the impact of forensic data analysis on fraud detection across different industries beyond listed firms.
ii. Investigate the role of artificial intelligence and machine learning in forensic data analysis for fraud prevention.
iii. Conduct comparative studies on forensic audit practices between Nigeria and other emerging economies.
iv. Explore the effectiveness of forensic audit training programs on financial professionals' ability to detect fraud.
v. Examine the influence of corporate governance structures on forensic audit effectiveness.

Limitations of the Study

i. Data Availability: Some fraud cases may be underreported or undisclosed, affecting data accuracy.
ii. Sample Representation: The study focuses on listed firms, which may not fully capture fraud dynamics in unlisted firms or SMEs.
iii. Regulatory Constraints: Variations in corporate governance regulations may influence fraud detection results.
iv. Bias in Reported Cases: Fraud detection relies on reported incidents, which may not reflect the full extent of financial irregularities.
v. Technological Variability: Differences in forensic data analysis tools across firms may impact the consistency of findings.

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