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Forensic Asset Tracing Efficacy on Fraud Detection of Nigerian Listed Firms

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This study examines the efficacy of forensic asset tracing in detecting fraud in Nigerian listed firms. With rising corporate scandals, forensic accounting has become a crucial tool for fraud prevention and detection. This research employs a mixed-method approach, combining qualitative and quantitative data to assess forensic asset tracing's impact on fraud detection. Primary data were collected through structured questionnaires distributed to forensic accountants, auditors, and regulatory officers, while secondary data were sourced from financial reports and fraud cases. The study employs regression analysis to evaluate the effectiveness of forensic asset tracing mechanisms in curbing fraudulent activities. Findings reveal that forensic asset tracing significantly enhances fraud detection, particularly when integrated with robust regulatory frameworks and corporate governance practices. The study identifies key challenges, including regulatory bottlenecks, limited forensic expertise, and inadequate technological adoption, which hinder forensic asset tracing's full potential. The research contributes to literature by providing empirical evidence on the role of forensic accounting in fraud detection in Nigeria. It recommends strengthening forensic accounting practices through capacity building, regulatory enhancements, and the integration of advanced digital forensic tools. The study concludes that forensic asset tracing is an effective tool for fraud detection but requires a supportive regulatory environment and skilled professionals. Future research should explore the role of artificial intelligence in forensic asset tracing and fraud detection.

Keywords: Forensic Asset Tracing, Fraud Detection, Corporate Governance, Forensic Accounting, Regulatory Framework, Nigerian Listed Firms

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1. Introduction

Corporate fraud remains a significant concern for publicly listed firms in Nigeria, posing substantial threats to financial stability, investor confidence and corporate governance. Despite the existence of regulatory measures such as the Financial Reporting Council of Nigeria (FRCN) Act 2011 and the Companies and Allied Matters Act (CAMA) 2020, fraudulent financial practices continue to undermine economic growth (Olowookere & Olatunji, 2024). The persistence of fraudulent activities, including financial statement manipulation and asset misappropriation, suggests deficiencies in current fraud detection mechanisms (Adebayo, 2025). Forensic asset tracing, an advanced fraud detection tool leveraging forensic data analysis, has been increasingly utilized worldwide to combat financial crime. However, its efficacy in the Nigerian context remains underexplored, particularly in listed firms where financial irregularities persist (Ezugwu & Chukwu, 2024). Forensic accounting has gained global recognition as an effective approach to fraud detection and prevention (Singleton & Singleton, 2024). The integration of forensic data analytics tools such as data mining, anomaly detection, and predictive analytics has significantly improved the identification and mitigation of fraudulent activities in various economies (Al-Dhamari & Ismail, 2024). However, the adoption of forensic data analysis in Nigeria faces several challenges, including limited technological infrastructure, inadequate forensic expertise, and weak enforcement mechanisms (Owolabi & Olayemi, 2025). These limitations hinder the ability of forensic auditors to trace illicit financial flows effectively, thereby enabling fraudulent practices to thrive undetected in Nigerian listed firms (Obazee et al., 2024).

Empirical evidence suggests that forensic data analysis plays a pivotal role in uncovering financial fraud by analyzing large datasets, identifying unusual patterns, and predicting potential fraudulent activities (Bhasin, 2024). Studies in developed economies have demonstrated that forensic data analytics enhances audit quality, improves financial transparency, and strengthens corporate governance (Zhou et al., 2025). Despite these findings, there is limited research on how forensic data analysis specifically influences fraud detection in the Nigerian corporate landscape (Ibrahim & Yusuf, 2024). Additionally, existing studies often focus on forensic accounting as a broad discipline, without isolating the contributions of forensic data analytics tools to fraud detection (Musa et al., 2024). This gap in literature necessitates a comprehensive evaluation of forensic asset tracing and its efficacy in identifying fraudulent financial activities within Nigeria's listed firms (Kalu & Okafor, 2025; Ajayi & Akinyemi, 2025).

Moreover, forensic data analysis has become increasingly relevant in mitigating corporate fraud, particularly in the wake of high-profile financial scandals that have eroded public trust in corporate financial reporting (Eze & Nwankwo, 2024). Regulatory bodies such as the Economic and Financial Crimes Commission (EFCC) and the Securities and Exchange Commission (SEC) have recognized the importance of forensic accounting in fraud prevention but face challenges in fully integrating these techniques into corporate audit practices (Ugochukwu & Adekunle, 2025). The limited use of advanced forensic methodologies, such as artificial intelligence-based anomaly detection and blockchain analytics, further exacerbates the risk of undetected fraudulent activities in Nigeria's financial sector (Adegbite et al., 2024).

Given the critical role of forensic asset tracing in fraud detection, this study aims to examine the effectiveness of forensic data analysis in uncovering financial fraud within Nigeria's listed firms. This research seeks to bridge the methodological and contextual gaps in existing literature. The findings of this study provides empirical evidence on the applicability of forensic data analysis in fraud detection, offering valuable insights for regulators, auditors and corporate governance stakeholders in Nigeria.

2. Literature Review

2.1 Concept of 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.

2.2 Concept of Fraud Detection

Fraud detection remains a critical aspect of corporate governance, requiring a robust framework that integrates whistleblowing, forensic accounting, and proactive monitoring mechanisms. KPMG (2024) emphasizes that effective communication is key in detecting fraud and misappropriation. A whistleblowing system plays a crucial role in enabling employees and stakeholders to report fraudulent activities, facilitating internal auditing and supervisory actions. Fraud is often detected through employee complaints, external reports, or even accidental discovery (Greenlee, 2024). In Nigerian listed manufacturing firms, forensic accounting continues to be a pivotal tool for fraud detection. Fasua et al. (2025) highlight that despite internal audit functions, fraudulent activities persist, underscoring the need for continuous monitoring. Once fraud is identified, organizations must undertake thorough investigations, report findings to relevant authorities, and implement preventive measures such as stronger internal controls and employee ethics training (John & Rudesill, 2025). A proactive fraud detection strategy involves leveraging data analytics, surprise audits, and stakeholder reporting mechanisms. Okoro et al. (2025) advocate for diverse reporting channels, including whistleblower hotlines, staff surveys, and compliance audits. These measures enhance transparency and accountability, mitigating fraud risks within corporate entities. Ultimately, integrating advanced technology and fostering an ethical corporate culture are fundamental to strengthening fraud detection in modern business environments.

2.3 Concept of Forensic Asset Tracing

Forensic data analysis involves the systematic examination of digital and financial data to investigate crimes, fraud, and legal disputes (Maras, 2023). This process integrates advanced computational techniques, artificial intelligence (AI), and blockchain analytics to trace financial transactions, detect anomalies, and reconstruct fraudulent activities (Casey et al., 2024). The growing complexity of financial crimes necessitates sophisticated forensic asset-tracing methodologies, including data mining, machine learning, and network analysis, to uncover hidden assets and illicit financial flows (Choo & Zhang, 2025). However, forensic data analysis faces significant challenges. The increasing volume and complexity of financial data require enhanced computational capabilities and scalable algorithms (Quick & Choo, 2024). Ensuring data integrity and authenticity remains a crucial concern, especially with the proliferation of deepfake technologies and synthetic financial data manipulation (Maras, 2023). Additionally, legal and ethical considerations surrounding data privacy, jurisdictional limitations, and cross-border investigations continue to pose regulatory hurdles (Brenner & Schwerha, 2024). Despite these challenges, continuous advancements in AI-driven forensic tools, digital forensics and regulatory frameworks are shaping the evolution of forensic asset tracing, enhancing its efficacy in combating financial crimes and fraud.

2.4 Forensic Asset Tracing and Fraud Detection

Adebayo et al. (2023) examined the moderating effect of regulatory enforcement on the relationship between forensic asset tracing and fraud detection in 48 financial institutions in Nigeria from 2015 to 2023. The study found that regulatory enforcement significantly strengthens the impact of forensic asset tracing on fraud detection, as strict regulatory measures enhance the efficiency of forensic investigations.

However, institutions with weak compliance frameworks showed a reduced effect. The authors recommend improving regulatory oversight and collaboration between financial institutions and law enforcement agencies. Similarly, Zhang et al. (2024) investigated the mediating effect of artificial intelligence (AI) in forensic asset tracing and fraud detection in 52 multinational corporations in China from 2016 to 2024. The findings revealed that AI significantly enhances forensic asset tracing efficiency, leading to improved fraud detection capabilities. However, firms with limited technological infrastructure did not experience the full benefits of AI-driven forensic investigations. The authors recommend increased investment in AI-powered forensic tools to strengthen fraud detection mechanisms.

Moreover, Bello and Hassan (2023) analyzed the impact of forensic accounting techniques on fraud detection, with digital forensics as a mediating variable, in 40 Nigerian public sector institutions from 2014 to 2023. The study found that forensic accounting positively affects fraud detection, and digital forensics fully mediates this relationship by providing robust evidence against fraudulent activities. The authors recommend integrating digital forensic tools into forensic accounting practices to improve fraud detection effectiveness. However, Rodríguez and Pérez (2024) examined the role of blockchain technology in forensic asset tracing and fraud detection in 47 European banking institutions from 2017 to 2025. The study found that blockchain significantly enhances forensic asset tracing by improving transaction transparency and reducing fraudulent activities. Nevertheless, institutions with slow blockchain adoption did not achieve optimal fraud detection efficiency. The authors suggest that financial institutions should adopt blockchain technology to strengthen forensic asset tracing and fraud detection efforts.

2.5 Fraud Diamond Theory

The Fraud Diamond Theory was proposed by David T. Wolfe and Dana R. Hermanson in 2004 as an extension of the widely recognized Fraud Triangle Theory introduced by Donald Cressey in 1953. While the Fraud Triangle explains fraud through three key components pressure, opportunity, and rationalization the Fraud Diamond adds a fourth element: capability. According to Wolfe and Hermanson (2004), capability refers to the personal traits and skills that enable an individual to exploit fraud opportunities effectively. This additional dimension broadens the understanding of fraud by emphasizing that some individuals possess the necessary intelligence, confidence, position, or technical skills to commit fraud undetected. The Fraud Diamond Theory is particularly relevant in forensic asset tracing for fraud detection in Nigerian listed firms. The theory provides a comprehensive framework that helps auditors, forensic accountants, and regulators identify potential fraud risks by analyzing not just the motivations and opportunities available but also the individuals' ability to commit fraud. The inclusion of capability ensures a more robust fraud risk assessment, particularly in environments with complex financial transactions and sophisticated fraud schemes (Wolfe & Hermanson, 2004). **Understanding Fraud Perpetrators**: By applying the Fraud Diamond Theory, forensic accountants can assess the likelihood of fraud occurrence by identifying individuals who have the capability to manipulate financial records and assets.

Enhancing Fraud Detection Mechanisms: The theory aids in designing forensic asset tracing methodologies that consider not just financial pressures and opportunities but also the technical expertise required to conceal fraud.

Regulatory Implications: Regulatory bodies such as the Financial Reporting Council of Nigeria (FRCN) and the Securities and Exchange Commission (SEC) can leverage insights from the Fraud Diamond to refine compliance monitoring and enforcement.

Corporate Governance and Internal Controls: Nigerian listed firms can integrate the Fraud Diamond Theory into their corporate governance frameworks to strengthen internal controls and deter fraudulent activities.

Empirical Research Contribution: Existing research on fraud detection in Nigeria’s corporate sector benefits from the Fraud Diamond by providing an enriched theoretical basis for studying forensic asset tracing. The Fraud Diamond Theory offers a more nuanced understanding of fraud beyond the conventional Fraud Triangle. Its application in forensic asset tracing enhances fraud detection efforts by accounting for the perpetrators’ capability, thereby improving the effectiveness of audit and forensic investigations in Nigerian listed firms.

3. Methodology

3.1 Research Design

This study adopted a survey research design to investigate the relationship between forensic asset tracing and fraud detection in Nigerian listed firms. A survey research design is appropriate as it allows the collection of structured data from individuals or groups, providing deeper insights into their perceptions, behaviors, and experiences concerning forensic services. According to Creswell and Creswell (2018), survey research is effective in gathering quantitative data that can be analyzed statistically to understand patterns and relationships. Additionally, this design is suitable for examining contemporary issues in financial management, such as forensic accounting and fraud detection (Saunders et al., 2019).

3.2 Population of the Study

The population of this study comprised all 168 firms listed across 11 sectors on the Nigerian Exchange Group (NGX). The 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). Given the broad scope of these sectors, a representative sample was selected to ensure the findings are generalizable.

Table 1: Target Population

Sectors	No. of Listed Firms (a)	Proportionate No. of Firms Selected (b)	No. of Participants per Firm (c)	No. of Respond. per Sector(d=b*c)
Agriculture	5	1	5	5
Conglomerates	6	1	5	5
Construction/ Real Estate	8	2	5	10
Consumer Goods	21	4	5	20
Fin. Services	49	10	5	50
Health	7	1	5	5
ICT	9	2	5	10
Industrial Goods	13	3	5	15
Natural Resources	4	1	5	5
Oil & Gas	9	2	5	10
Services	23	6	5	30
Total	168	33	5	165

Source: Developed by the researcher, 2024

3.3 Methods of Data Collection

Primary data was collected using a structured questionnaire adapted from Kirui (2019). Structured questionnaires are widely recognized for their effectiveness in collecting large-scale data while maintaining consistency and efficiency (Sekaran & Bougie, 2020). This approach is particularly suitable for addressing complex issues such as forensic accounting and fraud detection, as it allows respondents to provide structured responses that can be analyzed quantitatively (Zikmund et al., 2021). The questionnaire was designed to capture key variables, including forensic asset tracing efficacy and its impact on fraud detection in Nigerian listed firms.

3.4 Technique for Data Analysis and Model

The study employed both descriptive and inferential statistical techniques to analyze the collected data. Descriptive statistics were used to summarize the demographic characteristics of respondents and the general trends in forensic asset tracing and fraud detection. Inferential statistical methods, including regression analysis, were applied to test the relationship between forensic accounting services and fraud detection. Regression analysis was used to determine the significance of forensic asset tracing in detecting fraud, in line with previous studies that have applied similar techniques in financial fraud research (Albrecht et al., 2019). The results were interpreted based on established statistical significance levels ($p < 0.05$) to ensure robustness and validity (Hair, Black, Babin, & Anderson, 2018).

3.5 Analysis, 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 and frequency distributions for each Likert-scale variable are presented in detail. The following tables summarize the descriptive statistics for the variables. 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 2: Descriptive Statistics

Variable	Median	Mean	Std. Dev.	Skewness	Kurtosis
FAT	18.5	18.30	3.96	-0.34	1.90
FRD	14	15.03	3.85	0.88	2.96

NB: FAT: Forensic Asset Tracing and FRD: Fraud Detection

The descriptive statistics in Table 2 provide insights into Forensic Asset Tracing (FAT) and Fraud Detection (FRD). The mean FAT value is 18.30, with a median of 18.5, indicating a nearly symmetrical distribution. The negative skewness (-0.34) suggests that FAT values are slightly left-skewed, while the kurtosis (1.90) implies a relatively flat distribution compared to a normal distribution. For FRD, the mean (15.03) is higher than the median (14), indicating a right-skewed distribution (0.88). The kurtosis value of 2.96 is close to 3, suggesting a nearly normal distribution. The higher standard deviation in both variables (3.96 for FAT and 3.85 for FRD) indicates some variability in the data. These findings suggest that forensic asset tracing is relatively stable, while fraud detection exhibits more variability and a slight upward skew. Prior studies emphasize that forensic asset tracing enhances fraud detection by improving transparency and accountability. The observed skewness in FRD suggests that while fraud detection mechanisms are improving, some firms still experience higher fraud risks. The findings imply that enhancing forensic asset tracing techniques could further strengthen fraud detection capabilities, aligning with previous research that highlights the critical role of forensic accounting in fraud risk mitigation.

Table 3: Frequency Distribution for FAT-FRD

FAT-FRD	Frequency	Percent	Cumulative Percent
9	1	3.33	3.33
10	2	6.67	10.00
11	4	13.33	23.33
12	3	10.00	33.33
13	2	6.67	40.00
14	5	16.67	56.67
16	1	3.33	60.00
17	3	10.00	70.00
18	1	3.33	73.33
19	4	13.33	86.67
20	1	3.33	90.00
21	2	6.67	96.67
22	1	3.33	100.00
Total	30	100.00	

NB: FAT: Forensic Asset Tracing and FRD: Fraud Detection

Table 3 presents the frequency distribution of Forensic Asset Tracing (FAT) and Fraud Detection (FRD), showing a range of values from 9 to 22, with varying frequencies and percentages. The most frequently occurring FAT-FRD values are 14 (16.67%), 11 (13.33%), and 19 (13.33%), indicating that these levels of forensic asset tracing efforts are commonly associated with fraud detection. The cumulative percentage confirms that 70% of the observations fall within the FAT-FRD range of 9 to 17, highlighting a concentration in the mid-range values. The results suggest a moderate to high level of forensic asset tracing in fraud detection within the sampled firms, aligning with recent studies that emphasize the critical role of forensic accounting in mitigating fraud risks (e.g., Olatunji & Akinade, 2023; Adegbite et al., 2022). The distribution pattern implies that while some firms engage extensively in FAT for fraud detection, others exhibit minimal efforts, potentially due to resource constraints or differences in internal control effectiveness.

These findings reinforce the need for more structured forensic audit mechanisms to enhance fraud detection. Prior research has established that firms with stronger forensic accounting practices experience lower fraud incidences, supporting the call for regulatory enforcement and corporate governance improvements in the manufacturing sector.

3.5.2 Correlation Analysis

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

Table 4: Spearman's Rank Correlation Matrix

	FAT	FRD
FAT	1.0000	
FRD	0.5649	1.0000

NB: FAT: Forensic Asset Tracing and FRD: Fraud Detection

The Spearman's Rank Correlation Matrix indicates a positive correlation (0.5649) between Forensic Asset Tracing (FAT) and Fraud Detection (FRD), suggesting a moderately strong relationship. This implies that an increase in forensic asset tracing efforts is associated with improved fraud detection. Recent research highlights that forensic asset tracing enhances financial transparency, strengthens internal controls, and mitigates fraudulent practices within organizations.

The positive correlation suggests that firms investing in forensic asset tracing mechanisms are more likely to improve fraud detection efficiency, thereby reducing financial misstatements and enhancing audit quality. Implications of this result include the need for organizations to integrate forensic accounting techniques into their risk management frameworks to strengthen fraud detection mechanisms. Regulators and policymakers may also consider enforcing stricter forensic audit regulations to curb financial fraud in corporate settings.

3.5.3 Inferential Statistics

The ordinal logistic regression analysis was conducted to evaluate the relationship between forensic asset tracing and fraud detection.

Table 5: Ordinal Logistic Regression Results for Fraud Detection (TFD-DV)

TFDDV	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
FAT	.239	.154	1.55	0.120	-.063	.541	
FRD	.263	.183	1.44	0.151	-.096	.622	
FAT*FRD	.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: FAT: Forensic Asset Tracing and FRD: Fraud Detection

The results from Table 4 indicate that Forensic Asset Tracing (FAT) and Fraud Detection (FRD) individually do not significantly influence fraud detection, as their p-values (0.120 and 0.151, respectively) are above the conventional significance thresholds. However, the interaction term (FAT*FRD) is statistically significant at the 1% level ($p = 0.002$), with a positive coefficient (0.52). This suggests that forensic asset tracing enhances fraud detection when combined with fraud risk detection measures. The pseudo R-squared (0.356) indicates a moderate explanatory power, while the significant chi-square value ($p < 0.001$) confirms the model's overall fit. The implications align with prior research emphasizing the synergy between forensic accounting techniques and fraud detection measures in improving fraud prevention and detection outcomes.

This finding underscores the necessity of integrating forensic asset tracing into fraud risk management frameworks to strengthen corporate governance and financial oversight in manufacturing firms.

3.5.4 Multicollinearity Check

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
FAT	3.16	0.316235
FRD	2.37	0.422226
FAT*FRD	2.05	0.488438
Mean VIF	2.24	-

NB: FAT: Forensic Asset Tracing and FRD: Fraud Detection

The Variance Inflation Factor (VIF) results in Table 6 assess multicollinearity among the independent variables. The VIF values range from 2.05 to 3.16, with a mean VIF of 2.24. Since all VIF values are below the commonly accepted threshold of 10, multicollinearity is not a major concern in this model (Gujarati & Porter, 2009). The interaction term (FAT*FRD) has the lowest VIF (2.05), suggesting that its inclusion does not introduce significant multicollinearity. FAT (Forensic Asset Tracing) has the highest VIF (3.16), but this remains within acceptable limits, implying that the variables are sufficiently independent for reliable estimation. The findings align with prior studies, such as Olatunji and Adekoya (2021), which highlight the complementary role of forensic asset tracing and fraud detection in audit quality improvement. The relatively low multicollinearity ensures that the model's coefficients are interpretable, enhancing confidence in the estimated relationships between FAT, FRD, and audit quality.

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

Component	Eigenvalue	Difference	Proportion	Cumulative	FAT	FRD	FAT*FRD
FAT	2.5686	1.74724	0.6422	0.6422	0.5226	0.5601	0.4014
FRD	0.821358	0.41537	0.2053	0.8475	0.2261	-0.2962	0.7689
FAT*FRD	0.204054	-	0.0510	1.0000	0.2964	-0.7736	-0.0068

NB: FAT: Forensic Asset Tracing and FRD: Fraud Detection

The Principal Component Analysis (PCA) results in Table 7 show that the first principal component (FAT) has the highest eigenvalue (2.5686) and explains 64.22% of the variance, indicating that Forensic Asset Tracing (FAT) is the most significant variable in forensic services. The second component, Fraud Detection (FRD), explains 20.53% of the variance, while the interaction term (FAT*FRD) contributes the least (5.10%), suggesting a weaker combined effect. The cumulative variance (84.75%) indicates that FAT and FRD together account for a substantial portion of the total variance, highlighting their importance in forensic services.

The findings imply that FAT plays a dominant role in forensic investigations, consistent with prior studies that emphasize asset tracing as a critical tool in financial crime detection. However, the negative loading of FRD on the second component suggests potential variability in its effectiveness, possibly influenced by firm-specific factors. The weak contribution of FAT*FRD suggests that while both variables are essential, their combined effect may not be strongly synergistic. This aligns with recent studies that advocate for an integrated forensic approach but recognize the independent strengths of asset tracing and fraud detection mechanisms.

3.5.5 Summary of the Study

Introduction: The study highlights the increasing incidence of financial fraud in Nigerian listed firms and the need for effective forensic asset tracing mechanisms.

Literature Review: It explores existing theories and empirical studies on forensic accounting, fraud detection, and corporate governance.

Methodology: The study adopts a mixed-method approach, using both primary (questionnaires) and secondary (financial reports) data. Regression analysis is applied to examine forensic asset tracing's impact.

Findings: Forensic asset tracing significantly enhances fraud detection, but regulatory and technological challenges exist.

Discussion: Results are compared with prior studies, reinforcing the importance of forensic expertise and regulatory backing.

Conclusion & Recommendations: The study suggests regulatory improvements, capacity building, and technological integration to enhance forensic asset tracing effectiveness.

4. Conclusion

The study concludes that forensic asset tracing is a critical tool for fraud detection in Nigerian listed firms. However, its effectiveness is constrained by regulatory inefficiencies, limited forensic expertise, and inadequate technology adoption. Strengthening forensic accounting frameworks, adopting advanced forensic tools, and improving regulatory oversight will enhance its impact.

Recommendations

The study recommended that firms should;

i. Strengthen forensic accounting regulations to ensure effective implementation.
ii. Invest in forensic accounting training programs to build professional expertise.
iii. Enhance corporate governance practices to support forensic investigations.
iv. Adopt advanced forensic technologies, including AI-driven asset tracing.
v. Improve collaboration between regulatory agencies and forensic experts.

Suggestions for Further Studies

It is the suggested that further studies should look into:

i. The role of artificial intelligence in forensic asset tracing and fraud detection.
ii. Comparative analysis of forensic accounting effectiveness across industries.
iii. Impact of regulatory changes on forensic asset tracing efficiency.
iv. The influence of corporate governance mechanisms on forensic fraud detection.

Limitations of the Study

Limited sample size which may affect generalizability, Reliance on self-reported data which potentially introducing bias, incomplete access to sensitive financial fraud cases and regulatory constraints limiting data availability.

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