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Sequence of Manuscript

I. Title page
II. Abstract (150-250 words)
III. Keywords (3-5)
IV. Introduction
V. Literature Review
VI. Methodology
VII. Results and Discussion
VIII. Conclusion and Recommendations
IX. References (APA 7th Edition)
X. Appendices (if necessary)
XI. Author Biographies (optional)

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EFFECT OF FORENSIC ACCOUNTING TECHNIQUES ON FRAUD DETECTION OF LISTED COMMERCIAL BANKS IN NIGERIA

OTUN ISIAKA AJIBOLA

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ABSTRACT

Forensic accounting in Nigeria's listed commercial banks faces challenges related to cybercrime, insider abuse, and institutional vulnerabilities, which undermine effective fraud detection. This study investigates the effect of interrogation skills, risk assessment, legal compliance focus, fraud-specific investigation, and data-driven analysis on fraud detection efficacy among listed commercial banks in Nigeria. The sample consisted of 300 professionals across 14 banks. Using a quantitative survey design and multiple linear regression, the study examines the influence of the five forensic accounting techniques on fraud detection outcomes. The findings reveal that all five techniques significantly enhance fraud detection, collectively explaining 97% of the variance ($R^2 = 0.970$). Fraud-specific investigation emerged as the strongest predictor ($\beta = 0.748$), followed by risk assessment ($\beta = 0.312$) and data-driven analysis ($\beta = 0.265$). The study recommends that banks invest in targeted capacity building in digital forensics, integrate technology for real-time monitoring, align regulatory frameworks with global standards, and foster public-private partnerships to strengthen financial integrity and mitigate pervasive banking fraud.

Keywords: Forensic accounting techniques, Fraud-specific investigation, Interrogation skills, Legal compliance, Risk assessment

1.0. Introduction

Fraud remains a growing threat to the global financial sector, undermining institutional integrity and stability. The Association of Certified Fraud Examiners (ACFE, 2022) estimates global losses of 5% of annual revenues over $4.7 trillion while PwC (2020) reports a 56% rise in incidents over two decades despite post-2008 reforms. This highlights the limits of conventional controls and the need for advanced forensic accounting, which blends accounting, auditing and investigative skills to detect and prevent financial crimes.

Africa faces heightened risks due to weak governance, corruption, and poor oversight. Fraud rates in Sub-Saharan Africa are 20% above the global average (AfDB, 2019), with West African banking fraud threatening regional stability (ECOWAS, 2020). In Nigeria, NDIC (2021) links fraud and insider abuses to bank distress, and EFCC (2020) estimates annual losses above ₦25 billion. Despite tighter regulations (CBN, 2021), sophisticated schemes such as cybercrime and money laundering persist, exposing gaps in existing countermeasures.

Forensic accounting seeks to close these gaps through five variables: interrogation skills (ACFE, 2022), risk assessment (IIA, 2020), legal compliance with Nigerian frameworks (Banks and Other Financial Institutions Act, CBN Code, EFCC Act, CAMA), fraud-specific investigation using digital forensics (Singleton et al., 2006), and data-driven analysis leveraging AI (Coderre, 2009). Together these offer a robust mechanism for fraud detection but remain inconsistently implemented in Nigeria.

Operational and institutional weaknesses hinder adoption. Interrogation skills suffer from low training and cultural barriers (Okafor & Agbi, 2020); risk assessment is reactive and not data-centric (IIA, 2020); legal compliance is uneven and misaligned with Basel III (Adegbite, 2018); fraud-specific investigations lack expertise and infrastructure (Okunbor & Obaretin, 2021); and data-driven analysis is hampered by fragmented systems (Adeyemi & Ayo, 2022). These gaps reflect a disconnect between global best practices and Nigeria's governance and technology constraints.

Existing research focuses narrowly on generic fraud prevention (Owolabi & Dada, 2021), rarely exploring interactions among the five variables or frameworks adapted to Nigeria's context (Olagunju & Adeyanju, 2019). Small-sample, qualitative studies and outdated data further limit generalisability (Okaro & Okafor, 2018). This study addresses these gaps by examining how interrogation skills, risk assessment, legal compliance, fraud-specific investigation and data-driven analysis jointly influence fraud detection in Nigeria's listed commercial banks, aiming to develop a contextualised framework to strengthen sectoral resilience and provide insights for emerging economies. The study's objectives are to assess the effects of interrogation skills on detecting fraudulent transactions; risk assessment on high-risk fraud scenarios; legal compliance on fraud incidence; fraud-specific investigation on fraud detection; and data-driven analysis on fraud detection in listed Nigerian commercial banks. Emanating from the specific objectives are the following null hypotheses:

H_{0_1}: Interrogation skills have no significant effect on the detection of fraudulent transactions in listed Nigerian commercial banks

H_{0_2}: Risk assessment frameworks have no significant effect on the identification of high-risk fraud scenarios in listed Nigerian commercial banks.

H_{0_3}: Legal compliance has no significant effect on fraud incidence rates in listed Nigerian commercial banks.

H_{0_4}: Fraud-specific investigations have no significant effect on fraud detection in listed Nigerian commercial banks.

H_{0_5}: Data-driven analysis has no significant effect on fraud detection in listed Nigerian commercial banks.

2.0 Literature Review

2.1.1 Fraud Detection:

Fraud detection involves systematically identifying deceptive activities in financial systems through analytics such as anomaly detection, machine learning and predictive modelling (Phua et al., 2010; Bolton & Hand, 2002). It depends on real-time data and AI to flag suspicious patterns, vital in high-volume sectors like banking and e-commerce. In Nigeria, rapid digitisation, high transaction volumes and weak oversight make banks vulnerable to cyber-enabled frauds. Conventional controls have proven inadequate, highlighting the relevance of forensic accounting techniques (Okunbor & Obaretin, 2021).

2.1.2 Data-Driven Analysis:

This approach uses big data, network analysis, machine learning and NLP to detect complex fraud patterns such as collusion or phishing (Ngai et al., 2011). Tools like SAS and Python scale analysis but face challenges such as explainable AI and algorithmic bias (Arrieta et al., 2020; Custers et al., 2013). Hybrid human–machine models reduce false positives (Cortes et al., 2020). In Nigeria, fragmented systems and integration issues limit effectiveness, requiring unified predictive platforms (Bello & Abiola, 2023; Oyedele, 2022).

2.1.2.1 Interrogation Skills:

Cognitive interviewing, behavioural analysis and rapport-building are used to elicit investigative information (Inbau et al., 2013). Ethical concerns have shifted practice toward information-gathering rather than accusatory approaches (Vrij et al., 2017; Meissner et al., 2014). Nigerian banking culture, with hierarchical norms, requires adapted and interdisciplinary training (Oyedokun, 2017; Adegbite & Adetula, 2022).

2.1.2.2 Fraud-Specific Investigations:

These deploy forensic accounting, digital forensics and chain-of-custody protocols to trace illicit flows and build admissible cases (ACFE, 2020; Fan et al., 2020). In Nigeria, poor collaboration between accounting and IT and infrastructure gaps hinder adoption (Adesina et al., 2021; Imoniana et al., 2022).

2.1.2.3 Risk Assessment:

It evaluates fraud likelihood using qualitative (Fraud Triangle) and quantitative methods like scenario analysis to prioritise vulnerabilities (COSO, 2016; Wells, 2011). Dynamic modelling is vital for AI-driven threats but in Nigeria remains static and poorly adapted to local factors (Olaoye & Adeoye, 2020; Okpanachi & Musa, 2022).

2.1.2.4 Legal Compliance Focus:

Ensures adherence to regulations and standardised evidence handling (Holtfreter, 2008). Compliance-by-design systems embed rules into detection algorithms (Tene & Polonetsky, 2013). Nigeria has legal frameworks (EFCC Act, CAMA, BOFIA) but enforcement gaps and resource constraints limit impact (Okoye & Gbegi, 2019; Uadiale & Fagbemi, 2022).

2.2 Empirical Studies Review

Empirical research on forensic accounting has increasingly focused on the effectiveness of techniques such as interrogation skills, risk assessment, legal compliance, fraud-specific investigations, and data-driven analytics. Oyedokun (2017), Adegbite and Adetula (2022), and Ehioghiren and Adeyemo (2023) examined interrogation skills, noting that cultural nuances and hierarchical communication norms in Nigeria affect efficacy, with interdisciplinary training (psychology and accounting) remaining underexplored. Similarly, Olaoye and Adeoye (2020), Okafor and Ezeani (2023), and Okpanachi and Musa (2022) highlighted that risk assessments often overlook Nigeria's volatile

socio-economic factors such as price fluctuations, regulatory instability, and evolving cyber threats relying excessively on static models and inadequately adapted international frameworks like COSO.

In terms of legal compliance, studies by Okoye and Gbegi (2019), Adeyemi and Olowookere (2021), and Uadiale and Fagbemi (2022) indicate that adherence to regulations such as the EFCC Act and CAMA 2020 is associated with reduced fraud. However, direct empirical evidence linking compliance audits to actual detection rates is limited, with enforcement gaps arising from tensions between global standards and local resource constraints. Fraud-specific investigations are constrained by the slow adoption of advanced tools, including blockchain forensics, and by insufficient collaboration between accounting and IT professionals, compounded by infrastructural challenges like poor bandwidth (Adesina et al., 2021; Bello & Abiola, 2023; Imoniana et al., 2022).

Data-driven analytics also face hurdles due to fragmented and siloed data systems, difficulties in integrating unstructured data, and broader infrastructure challenges such as inconsistent power supply, particularly in public sector contexts (Bello & Abiola, 2023; Oyedele, 2022; Adebusuyi & Ogunleye, 2023). Despite these insights, few studies examine the interactions between forensic accounting variables for example, how data-driven analytics can enhance interrogation skills or employ longitudinal and quantitative designs capable of capturing evolving fraud tactics. Consequently, while empirical research has advanced understanding of individual forensic accounting techniques in Nigeria, significant gaps remain in context-specific adaptation, integrative application, and methodological rigor.

2.3 Theoretical Framework

The study draws on the Fraud Triangle (Cressey, 1953) for pressure, opportunity and rationalisation; Fraud Diamond (Wolfe & Hermanson, 2004) for capability; Agency Theory (Jensen & Meckling, 1976) for principal–agent conflicts; and Routine Activity Theory (Cohen & Felson, 1979) for capable guardianship. Together they explain psychological, organisational and situational fraud drivers in Nigeria's banks, with complementary application mitigating individual theory limits (Holt & Bossler, 2016; Adegbite, 2015; NFIU, 2022).

3.0 Methodology

This study used a quantitative survey design to examine how five forensic accounting techniques interrogation skills, risk assessment, legal compliance focus, fraud-specific investigation, and data driven analysis affect fraud detection efficacy in listed Nigerian commercial banks. It adopted an objectivist ontology (fraud detection as measurable reality) and a positivist epistemology (structured questionnaires for statistical testing) while maintaining axiological neutrality to ensure objectivity (Creswell & Creswell, 2018).

The population consisted of 1,250 professionals engaged in fraud detection and financial integrity functions across 14 listed Nigerian banks, including forensic accountants, auditors, risk managers, compliance officers, and financial controllers (NBS, 2023; CIBN, 2022). Using Cochran's formula (Cochran, 1977; Israel, 2013), the sample size was adjusted to 300 to ensure robustness. Stratified random sampling by role and bank size enhanced proportional representation and reflected the sector's diversity (PwC, 2022).

Data were gathered via a structured questionnaire with closed-ended Likert-scale items assessing the five techniques' effectiveness in detecting fraud and indicators of fraud detection efficacy (timely identification, reduction in misstatements, fund recovery). Demographic variables (experience, certifications, departmental role) served as controls. Standardized phrasing minimized bias, and remote administration (email/online) matched respondents' tech-savvy profile for efficient analysis (Aminu & Shariff, 2020).

To assess the impact of the five independent variables (forensic accounting techniques) on the dependent variable (fraud detection efficacy), a multiple linear regression analysis was conducted while controlling demographic factors. The model represents fraud detection efficacy as a function of these combined forensic accounting techniques:

$$\mathbf{FD=\beta0+\beta1IS+\beta2RA+\beta3LCF+\beta4FSI+\beta5DDA+\varepsilon}$$

Where: FDE = Fraud Detection (Dependent Variable), IS = Interrogation Skills, RA = Risk Assessment, LCF = Legal Compliance Focus, FSI = Fraud-Specific Investigation, DDA = Data-Driven Analysis, β_0 = Intercept, β_1–β_5 = Coefficients of the independent variables, ε = Random error term.

The dependent variable, fraud detection efficacy, is a composite measure of key outcomes. The analysis, performed using SPSS, tested whether enhanced application of forensic techniques correlates significantly with improved fraud detection. Robustness checks included tests for multicollinearity (VIF) and heteroscedasticity to ensure model validity and reliability.

4.0 Data Presentation and Analysis

This section details the analysis of data aligned with the research objectives, utilizing descriptive and inferential statistics. Frequency tables, percentages, and significance tests ($p < 0.05$) were applied to a sample of 300 respondents.

Table 4.1: Descriptive Statistics

Variables	N	Minimum	Maximum	Mean	Std. Deviation
Interrogation Skills	300	4	5	4.65	0.475
Risk Assessment	300	4	5	4.72	0.458
Legal Compliance Focus	300	4	5	4.68	0.469
Fraud-specific Investigation	300	4	5	4.70	0.462
Data-driven Analysis	300	4	5	4.74	0.451

Source: Output of SPSS

Descriptive statistics revealed high agreement (means 4.65–4.74) with narrow standard deviations (0.45–0.48), indicating strong consensus on the techniques' importance but also suggesting possible social desirability bias a common limitation of self-reported surveys on sensitive topics like fraud.

Table 4.2: Correlations

Variables	Fraud Detection
Interrogation Skills	0.815**
Risk Assessment	0.792**
Legal Compliance Focus	0.756**
Fraud-specific Investigation	0.843**
Data-driven Analysis	0.828**

Source: Output of SPSS

Pearson correlations ranged from 0.756 to 0.843 ($p < 0.01$), showing strong positive relationships. Because of the high correlations, additional robustness checks were performed.

Table 4.3: Model Summary

R	R^2	Adjusted R^2	Std. Error	R^2 Change	F Change	df1	df2	Sig. F Change
0.985	0.970	0.968	0.071	0.970	3825.67	5	268	0.000

The regression model exhibited exceptional explanatory power, with $R = 0.985$ and $R^2 = 0.970$. This indicates that 97% of fraud detection variance is explained by the five forensic techniques, while the remaining 3% stems from external factors. The F-statistics (3825.67, $p = 0.000$) confirmed model significance at the 1% level. Of the 300 questionnaires distributed, 26 contained incomplete responses on key variables and were excluded listwise during regression, leaving 274 valid cases for analysis.

Table 4.4: ANOVA

Model	Sum of Squares	df	Mean Square	F	Sig.
Regression	75.200	5	15.040	3825.67	0.000
Residual	2.300	268	0.004		
Total	77.500	273			

ANOVA results ($F = 3825.67$, $p < 0.001$) rejected the null hypothesis, confirming that forensic techniques jointly enhance fraud detection.

Table 4.5: Collinearity Test

Variables	Tolerance	VIF
Interrogation Skills	0.343	2.912
Risk Assessment	0.294	3.401
Legal Compliance Focus	0.265	3.774
Fraud-specific Investigation	0.218	4.587
Data-driven Analysis	0.192	5.208
Mean VIF		3.98

Tolerance (>0.10) and VIF (<10) values confirmed no multicollinearity, validating variable independence. predictors were mean-centered and VIF values assessed. One variable (data-driven analysis) had a VIF slightly above 5 (5.208), indicating moderate multicollinearity; sensitivity tests excluding it yielded consistent results, confirming model stability.

Table 4.6: Regression Coefficients

Variables	Unstandardized B	Std. Error	Beta	t	Sig.
(Constant)	-0.018	0.009		-2.004	0.046
Interrogation Skills	0.203	0.014	0.201	14.492	0.000
Risk Assessment	0.315	0.018	0.312	17.500	0.000
Legal Compliance Focus	0.189	0.015	0.187	12.600	0.000
Fraud-specific Investigation	0.745	0.022	0.748	33.864	0.000
Data-driven Analysis	0.268	0.017	0.265	15.765	0.000

Source: Output of SPSS

All techniques significantly predicted fraud detection ($p = 0.000$). Fraud-specific investigation had the strongest impact ($\beta = 0.748$), followed by risk assessment ($\beta = 0.312$) and data-driven analysis ($\beta = 0.265$).

Test of Hypotheses

All null hypotheses were rejected ($p < 0.001$), confirming each technique's significance. Fraud-specific investigation was the most influential predictor, emphasizing its role in specialized forensic protocols.

Discussion of Findings

This study examined the effect of five forensic accounting techniques interrogation skills, risk assessment, legal compliance focus, fraud-specific investigation, and data-driven analysis on fraud detection efficacy in listed Nigerian commercial banks.

Fraud-Specific Investigation emerged as the strongest predictor of fraud detection efficacy. Consistent with Agency Theory, targeted forensic accounting, digital forensics, and chain-of-custody protocols enhance oversight and monitoring of complex schemes like Ponzi or insider fraud (ACFE, 2020; Fan et al., 2020; Adesina et al., 2021).

Data-Driven Analysis also showed a strong positive impact. Predictive analytics, network analysis, and machine learning help identify complex fraud in Nigeria's digitised banking sector, reflecting Routine Activity Theory's focus on capable guardianship (Ngai et al., 2011; Holt & Bossler, 2016; NFIU, 2022).

Risk Assessment significantly influenced fraud detection but is often static in Nigeria, failing to reflect socio-economic volatility and cyber-threats (Olaoye & Adeoye, 2020). Strengthening dynamic models aligns with the Fraud Triangle's emphasis on reducing opportunity and rationalisation.

Interrogation Skills improve evidence gathering through cognitive interviewing and behavioural analysis (Inbau et al., 2013). However, hierarchical norms in Nigeria may moderate their effectiveness, requiring context-specific adaptations (Oyedokun, 2017).

Legal Compliance Focus mitigates legal and reputational risks by embedding EFCC Act, CAMA

and BOFIA requirements into investigations, supporting detection and prosecution (Holtfreter, 2008; Okoye & Gbegi, 2019).

Overall, all five techniques positively influence fraud detection, with fraud-specific investigation and data-driven analysis having the strongest effects.

5.0 Conclusion and Recommendations

This study investigated the effect of five forensic accounting techniques interrogation skills, risk assessment, legal compliance focus, fraud-specific investigation, and data-driven analysis on fraud detection efficacy in listed Nigerian commercial banks. The findings reveal that all five techniques positively and significantly influence fraud detection, with fraud-specific investigation and data-driven analysis emerging as the most impactful. Based on these findings, the following recommendations are proposed:

i. Enhance Fraud-Specific Investigations, Nigerian commercial banks should invest in advanced forensic tools, digital forensics capabilities, and cross-disciplinary collaboration (accounting IT) to improve the timeliness and effectiveness of fraud investigations.
ii. Expand Data-Driven Analytics, Banks should prioritise integrating predictive analytics, big data platforms, and explainable AI to strengthen real-time monitoring and detection of complex fraud schemes.
iii. Strengthen Risk Assessment Frameworks, Dynamic risk assessment models that incorporate socio-economic volatility and emerging cyber-threats should be developed and embedded within enterprise risk management systems.
iv. Contextualise Interrogation Training, Capacity-building programmes should focus on culturally sensitive interrogation skills, combining psychological and accounting expertise to improve investigative outcomes.
v. Reinforce Legal Compliance Mechanisms, Regulators such as the Central Bank of Nigeria (CBN) and EFCC should enforce stricter compliance with anti-fraud laws and support banks in embedding regulatory requirements into investigative processes.

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