Application of Artificial Intelligence in Forensic Accounting for Fraud Detection: Evidence from the Nigerian Financial Sector

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Abstract

Financial fraud remains a persistent threat to the integrity of Nigeria's financial sector, and conventional audit and forensic methods that depend on sampling and manual reconciliation struggle to cope with the volume and speed of modern transactions. Artificial Intelligence (AI) offers a means of closing this gap, yet empirical evidence on its application in forensic accounting for fraud detection in developing economies such as Nigeria is scarce. This study therefore examines the application of AI in forensic accounting for fraud detection in Nigeria's financial sector. Adopting a descriptive survey and explanatory design, 215 structured questionnaires were administered to professionals selected through multi-stage sampling from 13 deposit money banks and 7 fintech companies in Nigeria, of which 200 were retrieved and usable. Data were analysed using hierarchical moderated regression. Findings reveal that AI capability ($\beta = .317$, $t = 6.245$, $p < .001$) and forensic accounting techniques ($\beta = .351$, $t = 6.966$, $p < .001$) each exert a positive and significant direct effect on fraud detection efficiency, alongside IT infrastructure and staff expertise ($\beta = .261$, $t = 5.119$, $p < .001$) and the regulatory environment ($\beta = .228$, $t = 4.473$, $p < .001$), with the overall model explaining 57.5% of the variance in detection outcomes ($R^2 = .575$). However, the interaction terms were not significant for AI × forensic technique ($\beta = .036$, $p = .486$), AI × IT infrastructure and staff expertise ($\beta = -.054$, $p = .284$) or AI × regulatory environment ($\beta = .009$, $p = .864$), indicating additive rather than synergistic effects. The study recommends continued investment in both AI systems and core forensic skills, alongside intentional workflow integration.

Keywords: Artificial Intelligence, Forensic Accounting, Fraud Detection, Financial Sector, Nigeria

Introduction

The financial industry globally has progressed from manual record-keeping and occasional audit checks to digitally enabled operations, which has broadened the financial transaction landscape, accelerated its pace, and introduced new avenues for financial fraud (Alaka et al., 2025; Zakaria et al., 2025). Conventional accounting and audit processes, which are based on retrospective sampling and rule-based checks, have failed to keep up with fraud schemes that now unfold in real time, thereby placing forensic accounting at the heart of

the efforts to safeguard financial integrity (Otun & Mlanga, 2025; Rozali & Mwakapemba, 2025).

Despite the efforts of the Central Bank of Nigeria (CBN), the Nigeria Deposit Insurance Corporation (NDIC) and the Nigeria Inter-Bank Settlement System (NIBSS) to curb financial fraud, it continues to be a problem in Nigeria (CBN, 2024; Economic and Financial Crimes Commission [EFCC], 2024; NDIC, 2024; NIBSS, 2024). Several studies have attributed insider abuse, cyber-enabled theft and financial statement manipulation to weak internal controls and the slow uptake of technology in banks, insurance companies and the fast-growing fintech sub-sector (Garba, 2024; Maidarasu et al., 2025; Otun & Mlanga, 2025).

In Nigeria, forensic accounting practice has gone beyond litigation support and expert testimony to become a common practice in banks and other regulated institutions for the purpose of establishing facts admissible in a court of law (Okonta & Nnamdi, 2025; Otun & Mlanga, 2025). However, the tools at the disposal of forensic accountants have traditionally relied on sampling, manual reconciliation and interviews, which are slow relative to the volume and velocity of present-day financial data. AI, through machine learning, data analytics and natural language processing (NLP), has been introduced to fill this void (Ikilidih et al., 2026; Ikumapayi & Ayankoya, 2025).

In a study of 186 accounting professionals drawn from banks, insurance companies and fintech firms in Nigeria, Adeyemi and Ojogbede (2026) discovered that the use of AI-enabled accounting information systems significantly enhanced the effectiveness of fraud detection and auditing. Similar results have been reported in international studies. For instance, Meneses Cerón et al. (2026), after reviewing 76 studies published in Scopus, found that machine learning and NLP were consistently superior to rule-based approaches in detecting fraudulent patterns, provided that data quality and forensic interpretation ability were present.

Despite this, the utility of AI in forensic accounting practice remains a topic of debate. Its use in forensic auditing practice in Nigeria has been reported to be low (Ikilidih et al., 2026), and research on AI and forensic accounting in Africa is minimal compared with the vulnerability of the region to fraud (Meneses Cerón et al., 2026). Empirical evidence on the role of AI in forensic accounting for fraud detection in Nigeria's financial sector is therefore scarce. This study addresses this gap by examining the use of AI in forensic accounting for fraud detection in Nigeria's financial sector.

Literature Review and Hypothesis Development

Artificial Intelligence and Fraud Detection

Artificial Intelligence refers to computer systems that can learn, reason, identify patterns and make decisions with very little human intervention. In forensic accounting, it is largely manifested through machine learning, data analytics and automated detection systems that continuously analyse data in search of irregularities (Ikumapayi & Ayankoya, 2025; Meneses Cerón et al., 2026). Unlike rule-based systems, which only flag transactions once they reach a certain threshold, AI-based systems continuously learn and adapt to new fraud patterns, enabling forensic accountants to spot hidden patterns that a manual sample may overlook (Alaka et al., 2025).

Adeyemi and Ojogbede (2026) surveyed 186 accounting professionals in Nigerian banks, insurance companies and fintech firms and found that accounting information systems (AIS) using AI tools substantially increased the effectiveness of fraud detection, and that NLP further strengthened this relationship. The study by Mamidu et al. (2026) with 120 forensic accountants in Nigeria also confirmed a strong positive relationship between the use of AI and the effectiveness of fraud detection, which the authors interpreted within Fraud Triangle Theory and Agency Theory. In a comprehensive analysis of 261 publications indexed in Scopus, Zakaria et al. (2025) uncovered a significant increase in scholarly interest in the role of AI in forensic accounting since 2017, coinciding with the growing acceptance across jurisdictions of the value of AI to detection efficiency. The efficiency of AI-based fraud detection is likely to increase as AI becomes a more integral part of forensic accounting work. For this reason, we hypothesised that:

Ho1: AI tools have no significant effect on fraud detection efficiency in the Nigerian financial sector.

Forensic Accounting Techniques and Fraud Detection

Regardless of the technology at one's disposal to assist in the detection of fraud, forensic accounting tools such as interrogation, risk assessment, fraud-specific investigation and continuous auditing are still key elements in fraud detection (Otun & Mlanga, 2025; Rozali & Mwakapemba, 2025). Otun and Mlanga (2025) surveyed 300 professionals in 14 listed commercial banks in Nigeria and found that five forensic accounting techniques jointly predicted fraud detection outcomes, explaining 97% of the variance, with fraud-specific investigation emerging as the strongest predictor, followed by risk assessment and data-driven analysis.

Garba (2024), in a study of deposit money banks in Benue State, established that the use of forensic accountants significantly increased the chances of detecting fraud, whereas the use of litigation support had no significant effect, indicating that investigative and analytical techniques are more important than the litigation support function. The results indicated that the effectiveness of an institution's forensic accounting techniques is closely related to the extent of fraud detection. We therefore hypothesised that:

Ho2: There is no significant relationship between forensic accounting techniques and fraud detection in the Nigerian financial sector.

Integration of Artificial Intelligence and Forensic Accounting Techniques

While AI can play a strong role in its own right in fraud detection, the synergy of AI and forensic accounting methods is anticipated to deliver greater value than either could achieve on its own, since AI is expected to extend the reach and speed of investigation while forensic accounting analysis provides the context needed to interpret AI-generated signals properly (Dhillon, 2025; Meneses Cerón et al., 2026). Through a documentary approach, Okonta and Nnamdi (2025) discovered that AI-powered forensic techniques, when implemented effectively into the current forensic investigation process, could improve fraud prevention by providing continuous monitoring and proactive anomaly detection.

A similar conclusion was reached by Maidarasu et al. (2025), who found that the best results in detecting fraud occurred when sufficient regulatory frameworks were in place and there was a high level of technological adoption, and by Hernandez Aros et al. (2024), who found that machine learning models yielded good precision in detecting credit card fraud, the most widely modelled application. We therefore hypothesised that:

Ho3: The integration of AI and forensic accounting techniques has no significant effect on fraud detection efficiency in the Nigerian financial sector.

Moderating Role of Staff Expertise, IT Infrastructure and Regulatory Environment on the Relationship between AI and Fraud Detection Efficiency

Staff skills, IT infrastructure and a conducive regulatory framework are essential for the successful application of AI in forensic accounting, as these determine whether the insight gained from AI can be translated into action (Rozali & Mwakapemba, 2025). Although incorporating AI into forensic auditing is technically feasible, Ikilidih et al. (2026) observed that forensic auditors in Enugu State made little use of the technology, which they attributed to poor technological readiness rather than to the AI technology itself.

The same trend was observed globally by Rozali and Mwakapemba (2025), who reported that infrastructural gaps, lack of resources and regulatory uncertainty are major challenges in the adoption of AI in developing economies as compared with developed economies, while Alaka et al. (2025) cited algorithmic bias, data privacy concerns and a lack of AI professionals who can interpret AI-generated results as persistent challenges

even within global financial institutions. Institutions with more expert staff, stronger infrastructure and clearer regulatory requirements are thus likely to gain more from AI in terms of fraud detection. We therefore hypothesised that:

Ho4: Staff expertise, IT infrastructure, and regulatory environment do not significantly moderate the relationship between AI and fraud detection in the Nigerian financial sector.

Figure 1 presents the conceptual model that guides the study. Artificial Intelligence (AI) and Forensic Accounting Techniques (FAT) are the independent variables, and Fraud Detection Efficiency (FDE) is the dependent variable (Ho1 and Ho2). The integration of AI and FAT is captured by their interaction term (Ho3), while IT Infrastructure and Staff Expertise (ITI) and the Regulatory Environment (REN) are the moderating variables that condition the relationship between AI and FDE (Ho4).

Figure 1: Conceptual Model of the Study

Source: Authors' conceptualisation, 2026.

Methodology

The study adopted a descriptive survey research design with an explanatory approach. The population of the study comprises all licensed financial services institutions in Nigeria, namely deposit money banks and fintech companies. The target respondents are employees of these institutions in the departments most directly involved in fraud detection, namely information technology, internal audit, risk management, compliance, forensic investigation and operations, because of their knowledge of fraud detection systems.

A multi-stage sampling technique was adopted. In the first stage, the institutions were stratified into deposit money banks and fintech companies, to ensure representation across contexts in which AI adoption may vary. In the second stage, all 13 listed deposit money banks were selected, while the twelve (12) major fintech companies operating in Nigeria's financial technology formed the fintech frame, out of which seven (7) were purposively selected as the sample for this study. In all, 20 institutions were used (13 deposit money banks and 7 fintech companies). In the third stage, purposive sampling was used to select, within each institution, respondents who are directly involved in or knowledgeable about AI-related fraud detection. To allow for copies that might not be returned or might be unusable, 215 copies of the questionnaire were distributed across the 20 institutions, and 200 copies were retrieved and usable, which formed the sample analysed.

The selected respondents were asked to provide the needed information through a structured questionnaire developed around a five-point Likert scale. Face and content validity were confirmed through expert evaluation, a Cronbach's alpha coefficient of 0.85 was obtained in the pilot test, and SPSS was used to analyse the data.

Measurement of Variables

The variables of the study and the proxies used to measure each of them are summarised in the table below.

Variable

Proxy / Measurement

Artificial Intelligence

Machine learning capability, data analytics, automated detection systems

Forensic Accounting Techniques

Investigation technique, digital forensics, continuous auditing

Fraud Detection Efficiency

Detection speed, detection accuracy, fraud prevention capability

IT Infrastructure and Staff Expertise

Network capability, digital infrastructure, staff competence

Regulatory Environment

Compliance requirement, legal framework, regulatory support

Consistent with the hierarchical moderated regression reported in Section 4.4, the functional relationship is expressed as:

FDE = f(AI, FAT, ITI, REN, AI×FAT, AI×ITI, AI×REN)

Step 1 (direct effects):

FDE = $\beta 0 + \beta 1AI + \beta 2FAT + \beta 3ITI + \beta 4REN + \mu$

Step 2 (full model, adding mean-centred interaction terms):

FDE = $\beta 0 + \beta 1AI + \beta 2FAT + \beta 3ITI + \beta 4REN + \beta 5(AI \times FAT) + \beta 6(AI \times ITI) + \beta 7(AI \times REN) + \mu$

Where:

FDE = Fraud Detection Efficiency

AI = Artificial Intelligence (composite of machine learning capability, data analytics and automated detection systems)

FAT = Forensic Accounting Techniques

ITI = IT Infrastructure and Staff Expertise

REN = Regulatory Environment

AI×FAT = Interaction term between AI and FAT, testing the integration effect specified in H03

AI×ITI, AI×REN = Interaction terms between AI and the moderating variables, testing the moderation effect specified in H04

$\beta 0$ = Constant

$\beta 1$ - $\beta 7$ = Regression coefficients

μ = Error term

Theoretical Framework

Technology Acceptance Model (TAM)

The Technology Acceptance Model was propounded by Davis (1989) to explain why individuals adopt new technologies. According to the model, two constructs, perceived usefulness and perceived ease of use, influence technology acceptance and represent the functional and attitudinal foundation for technology

adoption or rejection. Perceived usefulness is the degree to which an individual believes a technology will enhance his or her job performance, while perceived ease of use is the degree to which the technology is perceived as easy to use (Davis, 1989).

AI is more likely to be used in forensic accounting in financial institutions where employees and management perceive that the technology can enhance the accuracy of fraud detection and curtail financial losses (Ikilidih et al., 2026). TAM is therefore pertinent because it helps explain why, despite the availability of AI tools, their adoption in forensic accounting practice in Nigeria has not been uniform, as the studies reviewed above point to the perception and readiness of organisations, rather than the AI tool itself, as the underlying factor. The implication for this study is that the effect of AI capability on fraud detection efficiency (H01) is expected to depend on how useful and usable the technology is perceived to be, which is why IT infrastructure, staff expertise and the regulatory environment are examined as moderating conditions (H04).

Fraud Diamond Theory

A fourth element, capability, was added to the fraud triangle by Wolfe and Hermanson (2004), who stated that, in addition to the other three elements, the offender must possess the skill and position necessary to perpetrate and cover up the fraud. It is believed that AI will reduce the capability of skilled offenders to go undetected within a certain range, while increasing the capability of the forensic accountant to detect hidden wrongdoing (Adeyemi & Ojogbede, 2026). This theory extends the fraud triangle by focusing on the skill dimension of fraud, the area where AI is likely to have the most direct impact on forensic accounting practice. The implication for this study is that AI tools and forensic accounting techniques are expected to strengthen the detection capability of institutions, narrowing the room within which skilled offenders can operate undetected (H01 to H03).

Fraud Triangle Theory

This theory is built around the premise that fraud is the product of three elements: pressure, opportunity and rationalisation (Cressey, 1953). Pressure is a financial or personal reason to defraud, opportunity is the presence of weak internal controls, and rationalisation is the justification that an individual gives for the fraudulent act. AI is applicable to this theory mainly through the opportunity element, as automated monitoring is continuous and reduces the window available to exploit weak controls without being detected (Mamidu et al., 2026). The implication for this study is that stronger AI capability and forensic accounting techniques should raise the likelihood of detection and thereby reduce the perceived opportunity to commit fraud in financial institutions (H01 to H03).

The study uses the Technology Acceptance Model and the Fraud Triangle Theory as its foundation, as they directly speak to the adoption of AI in organisations and the mechanism by which fraud opportunity is expected to be reduced; the Fraud Diamond Theory is complementary in that it explains the capability dimension that AI is expected to influence. Together, these theories provide a framework for examining the relationship between AI, forensic accounting techniques, and fraud detection within Nigeria's financial sector.

Findings and Discussions

Response Rate and Respondent Profile

Table 4.1 presents the administration and retrieval of the questionnaire. A total of 215 copies of the structured questionnaire were administered to staff of the Information Technology, Internal Audit, Risk Management, Compliance, Forensic Investigation and Operations departments across the 13 deposit money banks and 7 fintech companies selected for the study, following the multi-stage sampling procedure described in the methodology. Of these, 200 copies were retrieved and found usable, representing a response rate of 93.0%,

while 15 copies (7.0%) were not retrieved or were discarded. The 200 usable copies form the sample analysed in the sections that follow. This high retrieval rate reflects the purposive, direct-administration approach adopted for the survey and supports the reliability of the analysis that follows.

Table 4.1: Questionnaire Administration

S/N

Questionnaire Status

Frequency

Percentage (%)

1

Retrieved and usable

200

93.0

2

Not retrieved / discarded

15

7.0

Total

215

100.0

Source: Field Survey, 2026.

Table 4.2 summarises the profile of the 200 respondents by institution type, gender, age, years of working experience, educational qualification and department. Staff of deposit money banks formed the larger share of the sample (65.0%), consistent with their weight among the sampled institutions (13 of the 20), while male respondents (54.5%) slightly outnumbered female respondents (45.5%). Most respondents (62.0%) fell within the 25-44 age bracket, and a substantial majority (65.0%) had five or more years of working experience, indicating a sample well positioned by tenure to assess institutional fraud detection practice. Educational qualification was similarly skewed toward advanced training, with 79.5% of respondents holding a first degree or higher, and respondents were fairly evenly spread across the information technology, internal audit, risk management and compliance departments (20.0% each), with forensic investigation (12.5%) and operations (7.5%) making up the remainder, all of which are directly engaged in fraud detection activity.

Table 4.2: Respondent Profile (N = 200)

Items

Classification

Frequency

Percentage (%)

Institution Type

Deposit Money Bank

130

65.0

Fintech Company

70

35.0

Gender

Male

109

54.5

Female

91

45.5

Age

Below 25 years

17

8.5

25 - 34

72

36.0

35 - 44

52

26.0

45 - 54

49

24.5

55 years and above

10

5.0

Years of Experience

Less than 5 years

70

35.0

5 - 10 years

66

33.0

11 - 15 years

44

22.0

Above 15 years

20

10.0

Educational Qualification

HND

16

8.0

B.Sc.

82

41.0

Master's Degree

66

33.0

Professional Qualification

25

12.5

Ph.D

11

5.5

Department

Information Technology

40

20.0

Internal Audit

40

20.0

Risk Management

40

20.0

Compliance

40

20.0

Forensic Investigation

25

12.5

Operations

15

7.5

Source: Field Survey, 2026.

Reliability of Research Instrument

Table 4.3 presents the reliability statistics of the research instrument. Internal consistency was re-assessed on the full sample using Cronbach's alpha, with a minimum acceptable threshold of 0.70 (Hair et al., 2019). All five constructs exceeded this threshold, ranging from .853 to .878, and the overall 25-item instrument returned a coefficient of .908, closely corroborating the 0.85 pilot-test coefficient reported in the methodology and confirming that the instrument was reliable for the purpose of this study.

Table 4.3: Reliability Statistics

Construct	No. of Items	Cronbach's Alpha	Remark
Artificial Intelligence (AI)	5	.853	Reliable
Forensic Accounting Techniques (FAT)	5	.870	Reliable
Fraud Detection Efficiency (FDE)	5	.877	Reliable
IT Infrastructure & Staff Expertise (ITI)	5	.858	Reliable
Regulatory Environment (REN)	5	.878	Reliable
Overall Instrument	25		

.908

Reliable

Source: Field Survey, 2026.

Descriptive Analysis of Study Variables

Table 4.4 presents the descriptive statistics for the twenty-five questionnaire items, all measured on a five-point Likert scale. The item means cluster above the scale midpoint, ranging from 3.33 ("Existing regulations support the use of AI in forensic accounting") to 3.62 ("My institution has adequate IT infrastructure to support AI in forensic accounting"). At the construct level (Table 4.4b), IT Infrastructure and Staff Expertise recorded the highest composite mean (3.53), while Fraud Detection Efficiency recorded the lowest composite mean (3.39). This pattern indicates a broadly positive, above-midpoint perception across all five constructs, with respondents rating institutional IT infrastructure and staff expertise marginally ahead of the other dimensions and fraud detection efficiency itself trailing slightly behind the enabling constructs, consistent with the view that detection outcomes lag the inputs that drive them.

Table 4.4: Descriptive Statistics of Study Constructs (N = 200)

No.

Item

Mean

Std. Dev.

1

AI systems detect suspicious financial transactions quickly

3.39

1.16

2

Machine learning improves the accuracy of fraud detection

3.48

1.13

3

Data analytics helps identify unusual transaction patterns

3.42

1.12

4

Automated detection systems reduce false fraud alerts

3.46

1.07

5

AI reduces the time needed to investigate suspected fraud

3.50

1.09

6

Forensic accounting techniques improve the identification of financial irregularities

3.47

1.08

7

Digital forensic tools enhance fraud investigation

3.42

1.10

8

Continuous auditing strengthens fraud detection

3.51

1.13

9

Forensic accountants apply investigative skills effectively in fraud cases

3.45

1.12

10

Forensic accounting techniques support the tracing of concealed assets

3.54

1.07

11

Fraudulent transactions are detected promptly

3.40

1.21

12

Fraud detection accuracy has improved

3.46

1.15

13

Financial losses resulting from fraud have reduced

3.34

1.17

14

Fraud prevention has strengthened within my institution

3.35

1.14

15

Fraud cases are resolved more efficiently than before

3.41

1.14

16

My institution has adequate IT infrastructure to support AI in forensic accounting

3.62

1.15

17

Staff have the technical skill needed to operate AI-based fraud detection tools

3.54

1.06

18

Employees receive adequate training on forensic accounting technology

3.56

1.15

19

Existing systems integrate well with AI-driven fraud detection tools

3.52

1.11

20

My institution invests in upgrading digital infrastructure for fraud detection

3.44

1.06

21

Existing regulations support the use of AI in forensic accounting

3.33

1.17

22

Regulatory guidelines provide clear direction on AI adoption in fraud detection

3.46

1.16

23

Compliance requirements strengthen fraud detection practice

3.37

1.20

24

Regulators provide adequate guidance on emerging fraud detection technologies

3.48

1.18

25

The legal framework supports the use of AI evidence in fraud investigations

3.40

1.16

Source: Field Survey, 2026.

Table 4.4b: Composite Construct Means (N = 200)

Construct

Mean

Std. Dev.

Artificial Intelligence (AI)

3.45

.88

Forensic Accounting Techniques (FAT)

3.48

.89

Fraud Detection Efficiency (FDE)

3.39

.95

IT Infrastructure and Staff Expertise (ITI)

3.53

.88

Regulatory Environment (REN)

3.41

.96

Source: Field Survey, 2026.

Regression Analysis and Test of Hypotheses

Tables 4.5 to 4.7 present the results of the two-step hierarchical multiple regression used to test the study's hypotheses. Item scores were summed into composite construct scores for AI, FAT, FDE, ITI and REN before the models were estimated. Step 1 entered the direct effects of AI, FAT, ITI and REN on FDE, reproducing the base model $FDE = \beta0 + \beta1AI + \beta2FAT + \beta3ITI + \beta4REN + \mu$ and directly addressing H01 and H02. Step 2 added three mean-centred interaction terms, namely AI × FAT (testing the integration effect specified in H03), AI × ITI and AI × REN (testing the moderation effect specified in H04), to form the full model $FDE = \beta0 + \beta1AI + \beta2FAT + \beta3ITI + \beta4REN + \beta5(AI \times FAT) + \beta6(AI \times ITI) + \beta7(AI \times REN) + \mu$. Variance Inflation Factors for the four direct predictors ranged from 1.11 to 1.16, well below the threshold of 10, confirming that multicollinearity did not distort the estimates.

Step 1: Direct Effects of AI, FAT, ITI and REN (Test of H01 and H02)

Table 4.5: Regression Model Summary

Model

R

R Square

Adjusted R Square

Std. Error

R^2 Change

F Change

df1

df2

Sig. F Change

1 (Direct effects)

.756

.572

.563

3.1437

.572

65.202

4

195

.000

2 (+ Interaction terms)

.759

.575

.560

3.1562

.003

.486

3

192

.692

Source: Field Survey, 2026.

As shown in Table 4.5, Step 1 returned an R Square of .572, indicating that AI, FAT, ITI and REN jointly explain 57.2% of the variance in fraud detection efficiency (Adjusted R Square = .563), and the model was statistically significant, $F(4, 195) = 65.202$, $p < .001$. Step 2 raised R Square only marginally to .575, an increment of .003 that was not statistically significant, F change $(3, 192) = .486$, $p = .692$. The negligible and non-significant gain from adding the interaction terms indicates that AI, forensic accounting technique, IT infrastructure and the regulatory environment contribute to fraud detection efficiency largely as independent, additive factors rather than through reinforcing or moderating interactions.

Table 4.6: ANOVA (Full Model)

Model

Sum of Squares

df

Mean Square

F

Sig.

Regression

2592.101

7

370.300

37.172

.000[b]

Residual

1912.654

192

9.962

Total

4504.755

199

Source: Field Survey, 2026. Dependent Variable: FDE.

Table 4.6 shows that the ANOVA result for the full model, $F(7, 192) = 37.172$, $p < .001$, confirms that the full regression model, including the interaction terms, remains highly significant overall, driven principally by the strength of the four direct effects rather than by the interaction terms themselves.

Table 4.7: Regression Coefficients (Full Model)

Variable

B

Std. Error

Beta

t

Sig.

Decision

(Constant)

-4.181

1.356

-3.083

.002

AI

.341

.055

.317

6.245

.000

Reject H01

FAT

.373

.054

.351

6.966

.000

Reject H02

ITI

.280

.055

.261

5.119

.000

Significant predictor

REN

.226

.051

.228

4.473

.000

Significant predictor

AI × FAT (Interaction)

.008

.012

.036

.699

.486

Fail to reject H03

AI × ITI

-.014

.013

-.054

-1.075

.284

Fail to reject H04

AI × REN

.002

.011

.009

.171

.864

Fail to reject H04

Source: Field Survey, 2026. Dependent Variable: FDE.

Table 4.7 presents the coefficients of the full model, on which the decision on each hypothesis is based. Each hypothesis is decided from the t-statistic and significance value (p) of its own focal coefficient at the 5% level, and not from the overall model F-statistic. The standardised beta (β) is used to compare the relative strength of the predictors, because it expresses each effect in standard deviation units and is therefore comparable across variables regardless of their measurement scale, whereas the unstandardised coefficient (B) depends on the units of each composite score and cannot be compared directly (Hair et al., 2019). Accordingly, the statements on the relative strength of the predictors in the sections that follow (for example, which predictor is the strongest) rest on β, while B and its standard error (SE) are reported to show the size and precision of each estimate.

Hypothesis Testing

Ho1: AI tools have no significant effect on fraud detection efficiency in the Nigerian financial sector. This hypothesis is rejected (B = .341, SE = .055, β = .317, t = 6.245, $p < .001$); AI capability is the second-strongest predictor in the model, consistent with Adeyemi and Ojogbede (2026) and Mamidu et al. (2026) on the predictive strength of AI-enabled accounting information systems.

Ho2: There is no significant relationship between forensic accounting techniques and fraud detection in the Nigerian financial sector. This hypothesis is rejected (B = .373, SE = .054, β = .351, t = 6.966, $p < .001$), as forensic accounting techniques emerged as the strongest predictor in the model, consistent with Otun and Mlanga (2025) and Garba (2024), who found that investigative and analytical techniques are the most important determinants of fraud detection outcomes.

Ho3: The integration of AI and forensic accounting techniques has no significant effect on fraud detection efficiency in the Nigerian financial sector. This hypothesis is not rejected (B = .008, SE = .012, β = .036, t = .699, p = .486). While AI and forensic accounting technique each contribute significantly to fraud detection, the statistical interaction between them is not significant, indicating that they do not synergise with each other, contrary to the expectation of Meneses Cerón et al. (2026) and Okonta and Nnamdi (2025) that the two reinforce each other's value. This suggests that, at the current state of adoption, they operate side by side as independent, additive contributors rather than as integrated ones.

Ho4: Staff expertise, IT infrastructure, and regulatory environment do not significantly moderate the relationship between AI and fraud detection in the Nigerian financial sector. This hypothesis is not rejected, as neither the AI × ITI interaction (B = -.014, SE = .013, β = -.054, t = -1.075, p = .284) nor the AI × REN interaction (B = .002, SE = .011, β = .009, t = .171, p = .864) was statistically significant. IT infrastructure and staff expertise (B = .280, SE = .055, β = .261, t = 5.119, $p < .001$) and the regulatory environment (B = .226, SE = .051, β = .228, t = 4.473, $p < .001$) are still important direct determinants of fraud detection efficiency, but the data do not support the specific claim that they amplify or diminish the effect of AI itself. This is consistent with Ikilidih et al. (2026) and Rozali and Mwakapemba (2025), who suggest that technological readiness is an enabling condition for the use of AI rather than a multiplier of its impact.

Discussion of Findings

The results show that both AI capability and forensic accounting techniques are statistically significant and unique predictors of fraud detection efficiency in the Nigerian financial sector, with forensic accounting techniques (β = .351, t = 6.966, $p < .001$) marginally outperforming AI capability (β = .317, t = 6.245, $p < .001$). It is instructive that, although scholarly interest in AI-powered detection tools has increased (Alaka et al., 2025; Zakaria et al., 2025), the human-centred discipline of forensic investigation and continuous auditing appears to be at least as important to detection results. This is consistent with Otun and Mlanga (2025), who found that five forensic accounting techniques jointly explained 97% of the variance in fraud detection outcomes in Nigerian listed commercial banks.

The lack of a significant AI × FAT interaction is a subtle but important finding. It does not imply a lack of usefulness of the combination of AI and forensic technique, as both are strong and independently significant predictors, but rather that, at current levels of institutional adoption, the two are independent, additive inputs. This aligns with the findings of Ikilidih et al. (2026) that the use of AI in forensic auditing practice is still low compared with the availability of AI tools, meaning that forensic accountants and AI systems are likely not to be fully integrated. Viewed through the Technology Acceptance Model, this points to a perception gap, a workflow integration gap, or both, rather than a technical gap in either capability.

Additionally, IT infrastructure and staff expertise (β = .261, t = 5.119, $p < .001$) and the regulatory environment (β = .228, t = 4.473, $p < .001$) also proved to be direct contributors to fraud detection efficiency, supporting Rozali and Mwakapemba's (2025) assertion that infrastructural adequacy and regulatory clarity are not peripheral issues but foundational ones. Neither construct, however, significantly moderated the AI-fraud

detection relationship specifically, indicating that the marginal impact of AI does not rely on the level of infrastructural adequacy or regulatory clarity of the institution in which it is embedded (Alaka et al., 2025). This suggests that AI reduces the opportunity aspect of fraud in a relatively consistent manner across institutions with varying levels of infrastructural and regulatory maturity, whereas the capability aspect of Fraud Diamond Theory is better understood as a direct, additive impact of forensic technique and infrastructure rather than as an amplification of AI's impact.

Conclusion and Recommendations

Conclusion

The aim of this study was to examine the use of Artificial Intelligence in forensic accounting for fraud detection in the financial sector of Nigeria. Data were collected from 200 professionals drawn through multi-stage sampling from 13 deposit money banks and 7 fintech companies. The results indicate that AI capability and forensic accounting techniques have a positive and significant direct effect on fraud detection efficiency, in addition to IT infrastructure and staff expertise and the regulatory environment, and the overall model accounts for 57.5% of the variance in fraud detection outcomes. The interaction tests, however, did not confirm the expectation that AI and forensic techniques reinforce each other, or that infrastructure, staff expertise or regulation moderate the effect of AI. AI, forensic accounting techniques, IT infrastructure and staff expertise, and the regulatory environment therefore contribute to fraud detection efficiency as independent, additive factors rather than as synergistic ones at the current stage of adoption. This introduces a crucial caveat to the positive outlook on the synergy of AI and forensic judgement, as highlighted in some of the literature examined (Meneses Cerón et al., 2026; Okonta & Nnamdi, 2025): while both approaches individually enhance detection results, their combined effect has not yet been statistically realised in the Nigerian financial sector under study.

Recommendations

Based on these findings, the following four recommendations are made, each corresponding to one of the four hypotheses tested:

- Financial institutions should continue to invest in AI-based detection systems, since AI capability has a positive and significant effect on fraud detection efficiency (H01).
- Financial institutions should strengthen core forensic accounting techniques, namely investigative skill, digital forensics and continuous auditing, since these emerged as the strongest predictor of fraud detection efficiency, and AI should complement these techniques rather than replace them (H02).
- Given that the AI × forensic technique interaction was not statistically significant, simply having both does not result in synergy. Institutions should therefore integrate their workflows intentionally, for example by sending AI-identified anomalies straight to the formal forensic investigation process, and should review the relationship between AI and forensic technique periodically, as synergy may be realised when the use of AI becomes more mature and forensic accountants become more skilled in interpreting AI signals (H03).
- Although this study does not establish that IT infrastructure, staff expertise or the regulatory environment enhance the marginal impact of AI on detection efficiency, each of them has a significant direct effect on detection efficiency. Institutions should therefore continue to invest in IT infrastructure and staff technical training, and the Nigeria Deposit Insurance Corporation, the Central Bank of Nigeria and other regulators should continue and broaden their guidance on the adoption of AI in forensic accounting (H04).

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