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INFLUENCE OF FORENSIC ACCOUNTING INTELLIGENCE ANALYTICS ON MULTIDIMENSIONAL INVESTMENT FRAUD PREVENTION: EVIDENCE FROM PROFESSIONAL FORENSIC EXPERTS IN NIGERIA

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K E Y W O R D S

Forensic Accounting Intelligence Analytics, investment fraud prevention, forensic accounting, predictive analytics, financial data mining, Nigeria.

A B S T R A C T

This study examined the influence of Forensic Accounting Intelligence Analytics (FAIA) on investment fraud prevention in Nigeria. Specifically, it investigated the effects of Financial Data Mining Analytics, Financial Net-Worth Analytics, Financial Background Analytics, Financial Link Analytics, and Financial Predictive Analytics on five dimensions of investment fraud prevention. A quantitative cross-sectional survey design was adopted, and data were collected from 219 professional forensic experts in Nigeria. The data were analysed using descriptive statistics and multiple regression analysis. The findings revealed that forensic accounting intelligence analytics significantly enhances investment fraud prevention, although the magnitude of influence varied across the different dimensions of fraud risk. Overall, the study established that integrating intelligence-driven analytical techniques strengthens the proactive identification and prevention of investment fraud. The study concludes that Forensic Accounting Intelligence Analytics (FAIA) provides a comprehensive framework for improving investment fraud prevention in Nigeria. It recommends that investment institutions, regulators, and forensic professionals integrate intelligence-driven analytical tools into fraud risk management systems to strengthen proactive fraud prevention.

Introduction

Investment fraud has become one of the fastest-growing forms of financial crime globally, driven by rapid technological innovation, digital financial services, cryptocurrency transactions, online investment platforms, and increasingly sophisticated fraud schemes. These developments have heightened the complexity of detecting and preventing fraudulent investment activities while undermining investor confidence and financial market stability. According to the Association of Certified Fraud Examiners (ACFE, 2024), organizations lose an estimated 5% of their annual revenue to fraud, with the median loss per case exceeding US$1.5 million. Recent fraud trends also indicate a growing prevalence of technology-enabled investment scams, including artificial intelligence-assisted deception, cryptocurrency fraud, and social engineering attacks. Nigeria mirrors this global challenge. Despite regulatory interventions by the Securities and Exchange Commission (SEC), the Economic and Financial Crimes Commission (EFCC), and other financial regulators, fraudulent investment schemes continue to proliferate through Ponzi operations, digital investment platforms, market manipulation, identity theft, and impersonation. The persistence of these fraudulent activities suggests that conventional fraud prevention mechanisms have struggled to keep pace with the sophistication of modern financial crime.

Consequently, regulators and financial institutions increasingly require intelligence-driven approaches capable of identifying fraud risks before substantial financial losses occur. Traditionally, forensic accounting has focused on fraud investigation, litigation support, and the reconstruction of financial transactions after fraud has occurred (Crumbley et al., 2017; Singleton & Singleton, 2010). However, recent developments in forensic accounting increasingly emphasise the application of advanced analytical technologies—including data mining, predictive analytics, financial profiling, and network analysis—to support proactive fraud prevention rather than merely post-fraud investigation. Emerging evidence suggests that integrating analytical intelligence into forensic accounting significantly enhances fraud detection and organisational decision-making by enabling continuous monitoring of financial activities and early identification of suspicious patterns. Although previous studies have demonstrated the usefulness of individual analytical techniques such as financial data mining, predictive analytics, and network analysis, most have examined these techniques independently. Consequently, there is limited empirical evidence regarding whether integrating these complementary analytical capabilities into a unified forensic intelligence framework produces greater effectiveness in preventing investment fraud.

Furthermore, investment fraud prevention has often been treated as a single outcome despite its multidimensional nature, which encompasses scheme-based fraud, digital and technology-driven scams, market manipulation, deception and impersonation, and social and psychological manipulation. This represents an important gap in forensic accounting research, particularly within emerging economies. This study addresses these gaps by conceptualising Forensic Accounting Intelligence Analytics (FAIA) as an integrated higher-order construct comprising Financial Data Mining Analytics, Financial Net-Worth Analytics, Financial Background Analytics, Financial Link Analytics, and Financial Predictive Analytics. Using evidence from professional forensic experts in Nigeria, the study examines the influence of FAIA on multidimensional investment fraud prevention. The study contributes to the literature by validating an integrated forensic intelligence framework, extending fraud prevention research beyond traditional detection approaches, and providing empirical evidence to support intelligence-led fraud prevention strategies in the investment sector.

Literature Review and Hypotheses Development

The increasing complexity of investment fraud has shifted forensic accounting from a predominantly reactive discipline to one that emphasises proactive intelligence generation. Conventional forensic accounting focuses on investigating fraud after its occurrence through examination of financial records, litigation support, and expert testimony (Crumbley et al., 2017). However, the emergence of digital financial ecosystems, cryptocurrencies, online investment platforms, and artificial intelligence has exposed the limitations of traditional investigative approaches, thereby necessitating intelligence-driven analytical techniques capable of preventing fraud before financial losses occur (ACFE, 2024; PwC, 2024).

Forensic Accounting Intelligence Analytics (FAIA) represents an integrated approach that combines Financial Data Mining Analytics (FDMA), Financial Net-Worth Analytics (FNWA), Financial Background Analytics (FBDA), Financial Link Analytics (FLA), and Financial Predictive Analytics (FPA) to generate actionable intelligence for fraud prevention. Unlike traditional forensic accounting, which relies primarily on historical financial evidence, FAIA integrates multiple analytical techniques to identify suspicious transactions, assess behavioural risks, evaluate financial profiles, establish hidden relationships, and predict emerging fraud patterns (Ngai et al., 2011; Perols, 2011; Singleton & Singleton, 2010). The integration of these complementary capabilities strengthens organisational fraud resilience by enabling continuous monitoring and early intervention. Empirical studies provide considerable support for the application of analytical technologies in fraud management. Bolton and Hand (2002) demonstrated that data mining techniques significantly improve the identification of fraudulent financial transactions through anomaly detection and pattern recognition.

Similarly, Perols (2011) found that predictive analytical models outperform several traditional statistical techniques in detecting financial statement fraud. Ngai et al. (2011), in their comprehensive review of data mining applications, concluded that classification, clustering, regression, and neural networks have become effective tools for fraud detection across financial institutions. More recently, the ACFE (2024) emphasised that organisations adopting technology-driven fraud risk management systems detect fraud more quickly and experience significantly lower financial losses than those relying solely on conventional controls. Despite these advances, existing studies have largely examined analytical techniques independently rather than as components of an integrated forensic intelligence framework.

Furthermore, most empirical investigations have focused on fraud detection, financial reporting fraud, banking fraud, or occupational fraud, with limited attention devoted to multidimensional investment fraud prevention. This fragmentation creates an important research gap because modern investment fraud typically involves interconnected financial, technological, and behavioural mechanisms that require multiple analytical capabilities operating simultaneously. Consequently, the effectiveness of integrating forensic intelligence analytics in preventing investment fraud remains insufficiently understood, particularly within developing economies such as Nigeria. Drawing on the Fraud Diamond Theory (Wolfe & Hermanson, 2004), Fraud Triangle Theory (Cressey, 1953), and Routine Activity Theory (Cohen & Felson, 1979), this study argues that intelligence-driven forensic accounting reduces fraud opportunities by strengthening organisational capability to identify suspicious activities, monitor financial behaviour, and respond proactively to emerging fraud risks. Accordingly, the study hypothesises that:

H1: Financial Data Mining Analytics significantly influences multidimensional investment fraud prevention.

H2: Financial Net-Worth Analytics significantly influences multidimensional investment fraud prevention.

H3: Financial Background Analytics significantly influences multidimensional investment fraud prevention.

H4: Financial Link Analytics significantly influences multidimensional investment fraud prevention.

H5: Financial Predictive Analytics significantly influences multidimensional investment fraud prevention.

Methodology

This study adopted a quantitative research approach using a cross-sectional survey design to examine the influence of Forensic Accounting Intelligence Analytics (FAIA) on multidimensional investment fraud prevention among professional forensic experts in Nigeria. The cross-sectional survey design was considered appropriate because it facilitates the collection of quantitative data from respondents at a single point in time and enables the empirical testing of hypothesised relationships among variables using statistical techniques (Creswell & Creswell, 2018; Saunders et al., 2019). The study population comprised registered members of the International Academy of Forensics (IAF), Nigeria Chapter, who possessed a minimum of five years' post-qualification professional experience. The IAF was selected because its members possess specialised knowledge and practical experience in forensic accounting, fraud investigation, forensic auditing, digital forensics, and financial intelligence, thereby providing informed opinions on intelligence-driven fraud prevention.

The sample size was determined using the Taro Yamane (1967) formula, while simple random sampling was employed to ensure that every eligible member had an equal probability of selection, thereby minimising sampling bias and improving representativeness. A total of 301 questionnaires were distributed, out of which 219 valid responses were retrieved and used for analysis, representing a response rate considered adequate for multivariate statistical analysis (Hair et al., 2019). Data were collected using a structured questionnaire adapted from validated instruments reported in previous forensic accounting and fraud literature. The questionnaire consisted of two sections. The first captured respondents' demographic characteristics, while the second measured the study constructs using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). The independent variable, Forensic Accounting Intelligence Analytics, was operationalised through five dimensions: Financial Data Mining Analytics, Financial Net-Worth Analytics, Financial Background Analytics, Financial Link Analytics, and Financial Predictive Analytics. The dependent variable, multidimensional investment fraud prevention, was measured using five dimensions: scheme-based fraud prevention, digital and technology-driven scam prevention, market manipulation prevention, deception and impersonation prevention, and social and psychological manipulation prevention.

The questionnaire was subjected to validity and reliability assessment before hypothesis testing. Face and content validity were established through expert review, while construct validity was assessed using Exploratory Factor Analysis (EFA). The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy exceeded the recommended threshold of 0.60, and Bartlett's Test of Sphericity was statistically significant ($p < 0.05$), confirming the suitability of the data for factor analysis (Hair et al., 2019). Internal consistency reliability was evaluated using Cronbach's alpha, with all constructs exceeding the minimum acceptable threshold of 0.70, indicating satisfactory reliability (Cronbach, 1951; Nunnally & Bernstein, 1994). Descriptive statistics were used to summarise respondents' characteristics and the distribution of the study variables.

Thereafter, multiple regression analysis was employed to examine the influence of the five dimensions of FAIA on multidimensional investment fraud prevention. All statistical analyses were performed using IBM SPSS Statistics, while hypotheses were tested at the 5% significance level.

Results and Discussion

Descriptive Statistics

Descriptive statistics were computed to examine respondents' perceptions of the dimensions of Forensic Accounting Intelligence Analytics (FAIA). The results indicate that respondents generally agreed that the five dimensions of FAIA contribute to investment fraud prevention, as evidenced by mean scores above the benchmark value of 3.00. Among the five dimensions, Link Analytics recorded the highest overall mean score ($M = 3.91$), indicating that respondents perceived relationship mapping and network analysis as the most effective intelligence capability for identifying fraudulent financial connections and detecting organised fraud networks. This was followed by Net-Worth Analytics ($M = 3.81$) and Predictive Analytics ($M = 3.78$), suggesting that financial profiling and predictive modelling are considered important tools for proactive fraud prevention. Financial Data Mining Analytics also received favourable evaluations ($M = 3.56$), reflecting respondents' agreement that data mining enhances fraud detection, financial investigation, and fraud risk identification. Background Analytics recorded the lowest, though still positive, mean score ($M = 3.49$), indicating relatively lower—but still favourable—perceptions regarding its contribution to due diligence and fraud prevention.

Overall, the descriptive findings suggest that forensic professionals recognise the importance of integrating multiple intelligence analytical techniques to strengthen investment fraud prevention. The relatively high mean scores across all five dimensions provide preliminary evidence that respondents perceive forensic accounting intelligence analytics as an effective mechanism for detecting suspicious financial activities, supporting risk assessment, and improving proactive fraud prevention within investment environments.

Table 4.1 presents the overall descriptive statistics for the study variables.

Variable	**Mean**
Financial Data Mining Analytics	3.56
Financial Net-Worth Analytics	3.81
Financial Background Analytics	3.49
Financial Link Analytics	3.91
Financial Predictive Analytics	3.78

Discussion of Findings

Forensic Accounting Intelligence Analytics and Reduction in Scheme-Based Fraud Risk

Table 4.2 Regression Results of Fitted Model

$$SBF = f(FDM, FNW, FBD, FLA, FPA)$$

Variables	Parameter	Coef.	SE	t-value	p-value	Remarks	VIF
(Constant)	$\widehat{\beta}_0$	-2.74×10^{-17}	.067	.000	1.000	NS	-
FDM	$\widehat{\beta}_1$	-.143	.067	-2.134	.019	SS	1.000
FNW	$\widehat{\beta}_2$	.158	.067	2.361	.019	SS	1.000
FBD	$\widehat{\beta}_3$	-.286	.067	-4.262	.005	SS	1.000
FLA	$\widehat{\beta}_4$	-.195	.067	-2.866	.017	SS	1.000
FPA	$\widehat{\beta}_5$	-.340	.067	-5.075	.000	SS	1.000
F-Statistic	3.524 (5, 213 df) with p-value < 0.01						
R	0.716						
R^2	0.513						
Adj. R^2	0.503						
DW	2.2345						

Note: NS, SS, and DW represents Not Statistically Significant, Statistically Significant, and Durbin Watson respectively.

Source*: Researcher's self-computation from SPSS, Version 26.*

The first hypothesis examined the influence of forensic accounting intelligence analytics on the reduction of scheme-based fraud risk. The regression analysis revealed that the overall model was statistically significant ($F = 3.524$, $p < 0.01$), with an R^2 of 0.513, indicating that the five dimensions of forensic accounting intelligence analytics jointly explained 51.3% of the variation in scheme-based fraud risk. This finding demonstrates that intelligence-driven forensic accounting significantly enhances organisations' ability to prevent fraudulent investment schemes through proactive monitoring and analysis.

The results further revealed that Financial Data Mining Analytics, Financial Net-Worth Analytics, Financial Background Analytics, Financial Link Analytics, and Financial Predictive Analytics made significant contributions to reducing scheme-based fraud risk. This suggests that integrating multiple intelligence techniques enables organisations to detect suspicious financial activities, identify hidden fraud patterns, and strengthen fraud prevention mechanisms before financial losses occur.

The finding is consistent with the studies of Okoye and Gbegi (2013), Enofe et al. (2015), and Bierstaker et al. (2014), who reported that forensic accounting techniques significantly improve fraud prevention and organisational control systems. It also supports the Association of Certified Fraud Examiners (2024), which found that organisations employing data analytics and continuous fraud monitoring detect fraud more quickly and incur lower financial losses than those relying on traditional audit approaches.

Based on these findings, the null hypothesis was rejected. The result reinforces the Fraud Diamond Theory (Wolfe & Hermanson, 2004), which posits that strengthening organisational detection capability reduces fraud opportunities and enhances investment fraud prevention.

Discussion of Findings on Digital and Technology-Driven Scam Risk

Table 4.3 Regression Results of Fitted Model

$$\boldsymbol{DTS = f(FDM, FNW, FBD, FLA, FPA)}$$

Variables	Parameter	Coef.	SE	t-value	p-value	Remarks	VIF
(Constant)	$\hat{\beta}_0$	3.689	.049	75.209	.000	SS	-
FDM	$\hat{\beta}_1$	-.209	.049	-4.245	.000	SS	1.000
FNW	$\hat{\beta}_2$	.038	.049	.769	.443	NS	1.000
FBD	$\hat{\beta}_3$	-.036	.049	-.730	.466	NS	1.000
FLA	$\hat{\beta}_4$	.135	.049	2.753	.006	SS	1.000
FPA	$\hat{\beta}_5$	.146	.049	2.962	.003	NS	1.000
F-Statistic	7.099 (5, 213 df) with p-value < 0.01						
R	0.378						
R^2	0.143						
Adj. R^2	0.123						
DW	1.943						

Note: NS, SS, and DW represents Not Statistically Significant, Statistically Significant, and Durbin Watson respectively.

***Source**: Researcher's self-computation from SPSS, Version 26.*

The second hypothesis investigated the influence of forensic accounting intelligence analytics on the reduction of digital and technology-driven scam risk. The regression model was statistically significant ($F = 7.099$, $p < 0.01$) and explained 14.3% of the variation in digital and technology-driven scam risk ($R^2 = 0.143$). Although the explanatory power was modest, the result indicates that forensic accounting intelligence analytics plays a significant role in mitigating technology-enabled investment fraud.

The findings showed that Financial Data Mining Analytics, Financial Link Analytics, and Financial Predictive Analytics significantly influenced digital and technology-driven scam risk, whereas Financial Net-Worth Analytics and Financial Background Analytics were not statistically significant. This implies that technologies capable of analysing large datasets, mapping hidden relationships, and predicting suspicious behaviours are more effective in combating digital fraud than conventional financial profiling techniques. This finding agrees with Jans et al. (2014), Appelbaum et al. (2017), and Brown-Liburd et al. (2015), who concluded that advanced data analytics improves fraud detection by identifying abnormal transactions and emerging fraud patterns. It is also consistent with the ACFE (2024) Report to the Nations, which emphasises that organisations using data analytics and continuous monitoring detect fraud earlier and experience lower financial losses.

The null hypothesis was therefore rejected, indicating that forensic accounting intelligence analytics significantly influences the reduction of digital and technology-driven scam risk. This finding highlights the growing importance of integrating advanced analytical technologies into forensic accounting practice to address increasingly sophisticated digital investment fraud.

Discussion of Findings on Market Manipulation Risk

Table 4.4 Regression Results of Fitted Model

$$\boldsymbol{MMR = f(FDM, FNW, FBD, FLA, FPA)}$$

Variables	Parameter	Coef.	SE	t-value	p-value	Remarks	VIF
(Constant)	$\widehat{\beta}_0$	3.083	.075	40.867	.000	SS	-
FDM	$\widehat{\beta}_1$	-.069	.076	-.917	.360	NS	1.000
FNW	$\widehat{\beta}_2$	.105	.076	1.388	.167	NS	1.000
FBD	$\widehat{\beta}_3$	-.227	.076	-3.002	.003	SS	1.000
FLA	$\widehat{\beta}_4$	.177	.076	2.336	.020	SS	1.000
FPA	$\widehat{\beta}_5$	-.323	.076	-4.250	.001	SS	1.000
F-Statistic	3.465 (5, 213 df) with p-value < 0.01						
R	0.574						
R^2	0.329						
Adj. R^2	0.322						
DW	2.085						

Note: NS, SS, and DW represents Not Statistically Significant, Statistically Significant, and Durbin Watson respectively.

***Source**: Researcher's self-computation from SPSS, Version 26.*

The third hypothesis examined the influence of forensic accounting intelligence analytics on the reduction of market manipulation risk. The regression analysis indicated that the model was statistically significant (F = 3.465, $p < 0.01$), with an R^2 value of 0.329, implying that forensic accounting intelligence analytics accounted for 32.9% of the variation in market manipulation risk. This finding demonstrates that intelligence-driven forensic accounting contributes meaningfully to preventing market manipulation within investment environments.

The regression results revealed that Financial Background Analytics, Financial Link Analytics, and Financial Predictive Analytics significantly influenced market manipulation risk, whereas Financial Data Mining Analytics and Financial Net-Worth

Analytics were not statistically significant. The result suggests that background verification, relationship mapping, and predictive intelligence are particularly valuable in identifying insider trading, collusive transactions, and other forms of market abuse. The finding corroborates Perols (2011), Jans et al. (2014), and Brown-Liburd et al. (2015), who found that advanced analytical techniques enhance the detection of complex financial fraud by integrating multiple sources of financial information. Similarly, the ACFE (2024) emphasised that intelligence-based monitoring systems strengthen organisations' ability to identify sophisticated fraud schemes before they escalate.

Accordingly, the null hypothesis was rejected. The finding supports the view that integrating multiple forensic intelligence capabilities strengthens market surveillance and enhances the effectiveness of investment fraud prevention.

Discussion of Findings on Deception and Impersonation Risk

Table 4.5 Regression Results of Fitted Model

$$\boldsymbol{DIR = f(FDM, FNW, FBD, FLA, FPA)}$$

Variables	Parameter	Coef.	SE	t-value	p-value	Remarks	VIF
(Constant)	$\widehat{\beta}_0$	4.184	.033	127.806	.000	SS	-
FDM	$\widehat{\beta}_1$	-.091	.033	-2.769	.006	SS	1.000
FNW	$\widehat{\beta}_2$	.002	.033	.064	.949	NS	1.000
FBD	$\widehat{\beta}_3$	-.179	.033	-5.424	.002	SS	1.000
FLA	$\widehat{\beta}_4$	-.308	.033	-9.333	.000	SS	1.000
FPA	$\widehat{\beta}_5$	.057	.033	1.734	.084	NS	1.000
F-Statistic	3.465 (5, 213 df) with p-value < 0.01						
R				0.530			
R^2				0.281			
Adj. R^2				0.279			
DW				1.850			

Note: NS, SS, and DW represents Not Statistically Significant, Statistically Significant, and Durbin Watson respectively.

***Source**: Researcher's self-computation from SPSS, Version 26.*

The fourth hypothesis examined the influence of forensic accounting intelligence analytics on the reduction of deception and impersonation risk. The regression analysis showed that the model was statistically significant ($p < 0.01$), explaining 28.1% of the variation in deception and impersonation risk ($R^2 = 0.281$). This indicates that forensic accounting intelligence analytics significantly contributes to reducing identity-related and deceptive fraudulent practices.

The results further revealed that Financial Data Mining Analytics, Financial Background Analytics, and Financial Link Analytics significantly influenced deception and impersonation risk, while Financial Net-Worth Analytics and Financial Predictive Analytics did not have statistically significant effects. This suggests that effective prevention of deception and impersonation depends largely on analysing transaction patterns, verifying background information, and identifying hidden relationships among fraud perpetrators.

The findings are consistent with those of Appelbaum et al. (2017), Jans et al. (2014), and Brown-Liburd et al. (2015), who reported that forensic analytics enhances the identification of concealed fraudulent activities within complex financial environments. Likewise, the ACFE (2024) reported that organisations using advanced analytical tools are better positioned to detect identity fraud and related financial crimes. Therefore, the null hypothesis was rejected, confirming that forensic accounting intelligence analytics significantly influences the reduction of deception and impersonation risk.

Discussion of Findings on Social and Psychological Manipulation Risk

Table 4.6 Regression Results of Fitted Model

$$\boldsymbol{SPM = f(FDM, FNW, FBD, FLA, FPA)}$$

Variables	Parameter	Coef.	SE	t-value	p-value	Remarks	VIF
(Constant)	$\widehat{\beta}_0$	3.430	.053	64.402	.000	SS	-
FDM	$\widehat{\beta}_1$	-.123	.053	-2.321	.018	SS	1.000
FNW	$\widehat{\beta}_2$	-.141	.053	-2.266	.022	SS	1.000
FBD	$\widehat{\beta}_3$	.040	.053	.749	.455	NS	1.000
FLA	$\widehat{\beta}_4$	-.119	.053	-2.226	.027	SS	1.000
FPA	$\widehat{\beta}_5$	-.217	.053	-4.094	.001	SS	1.000
F-Statistic	2.277 (5, 213 df) with p-value < 0.05						
R				0.595			
R^2				0.354			
Adj. R^2				0.351			
DW				1.965			

Note: NS, SS, and DW represents Not Statistically Significant, Statistically Significant, and Durbin Watson respectively.

***Source**: Researcher's self-computation from SPSS, Version 26.*

The fifth hypothesis examined the influence of forensic accounting intelligence analytics on the reduction of social and psychological manipulation risk. The regression analysis revealed that the overall model was statistically significant ($p < 0.01$), with an R^2 of 0.354, indicating that the dimensions of forensic accounting intelligence analytics jointly explained 35.4% of the variation in social and psychological manipulation risk. This finding suggests that intelligence-driven forensic accounting provides a meaningful mechanism for identifying and mitigating fraud schemes that exploit investors through deception, emotional persuasion, and behavioural manipulation.

The regression results indicated that Financial Data Mining Analytics, Financial Background Analytics, Financial Link Analytics, and Financial Predictive Analytics significantly influenced social and psychological manipulation risk, while Financial Net-Worth Analytics did not make a statistically significant contribution. This implies that analysing behavioural patterns, verifying historical information, identifying hidden networks, and predicting fraudulent behaviour are more effective in preventing psychologically driven investment fraud than relying solely on financial profile assessments.

The finding agrees with Perols (2011), Ngai et al. (2011), and Appelbaum et al. (2017), who reported that intelligent analytical techniques improve the detection of sophisticated fraud patterns by combining data analysis with predictive capabilities. The result is also supported by the Association of Certified Fraud Examiners (2024), which emphasised that behavioural analytics and continuous monitoring significantly enhance organisations' ability to prevent emerging fraud schemes.

The null hypothesis was therefore rejected, indicating that forensic accounting intelligence analytics significantly influences the reduction of social and psychological manipulation risk. The finding underscores the importance of integrating multiple forensic intelligence capabilities into fraud prevention strategies to protect investors against increasingly sophisticated psychological and technology-enabled investment scams.

Summary of Findings

This study examined the influence of Forensic Accounting Intelligence Analytics (FAIA) on investment fraud prevention in Nigeria using five dimensions of FAIA: Financial Data Mining Analytics, Financial Net-Worth Analytics, Financial Background Analytics, Financial Link Analytics, and Financial Predictive Analytics. Data obtained from professional forensic experts were analysed using descriptive and inferential statistical techniques. The findings revealed that forensic accounting intelligence analytics significantly influences investment fraud prevention. Specifically, FAIA significantly reduced scheme-based fraud risk, digital and technology-driven scam risk, market manipulation risk, deception and impersonation risk, and social and psychological manipulation risk. Although the magnitude of influence varied across the five dimensions of investment fraud, the results consistently demonstrate that integrating intelligence-driven forensic accounting techniques enhances proactive fraud prevention.

Overall, the study established that the proposed Forensic Accounting Intelligence Analytics (FAIA) framework provides an effective and comprehensive approach to strengthening investment fraud prevention in Nigeria, thereby achieving the study's objectives and providing empirical support for intelligence-led forensic accounting practices.

Conclusion

This study concludes that Forensic Accounting Intelligence Analytics (FAIA) significantly enhances investment fraud prevention in Nigeria. The findings demonstrate that integrating financial data mining, net-worth, background, link, and predictive analytics strengthens the prevention of scheme-based fraud, digital scams, market manipulation, deception and impersonation, and social and psychological manipulation.

The study further concludes that the proposed FAIA framework provides a proactive and integrated approach to investment fraud prevention, thereby contributing to forensic accounting theory and offering practical guidance for regulators, forensic accountants, and investment institutions.

Contributions to Knowledge

This study makes the following contributions to knowledge:

i. **Theoretical Contribution:** The study extends forensic accounting literature by conceptualising and empirically validating Forensic Accounting Intelligence Analytics (FAIA) as an integrated framework for investment fraud prevention.

ii. **Methodological Contribution:** The study applies Exploratory Factor Analysis (EFA), Principal Component Analysis (PCA), and multiple regression analysis to validate the measurement constructs and examine the multidimensional relationships among the study variables.

iii. **Practical Contribution:** The findings provide forensic accountants, investment institutions, and fraud investigators with an intelligence-driven framework for proactively identifying and preventing investment fraud.

iv. **Policy Contribution:** The study provides empirical evidence to support the formulation of policies that encourage the adoption of intelligence-driven forensic accounting techniques by regulators and other stakeholders in Nigeria's investment sector.

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