UNIPORT JOURNAL OF BUSINESS, ACCOUNTING & FINANCE MANAGEMENT
DEPARTMENT OF ACCOUNTING,
UNIVERSITY OF PORT HARCOURT,
CHOBA PORT HARCOURT, RIVERS STATE
NIGERIA
VOL. 17 NO. 3 JUNE 2026

FINANCIAL LINK ANALYTICS AND INVESTMENT FRAUD PREVENTION IN NIGERIA: EVIDENCE FROM PROFESSIONAL FORENSIC EXPERTS

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Abstract

This study examined the influence of Financial Link Analytics (FLA) on investment fraud prevention in Nigeria. The study was motivated by the increasing complexity of investment fraud schemes, which often involve interconnected individuals, organisations, and financial transactions that are difficult to detect using conventional investigative approaches. A quantitative cross-sectional survey design was adopted, and data were obtained from professional forensic experts in Nigeria. The data were analysed using descriptive statistics and multiple regression analysis. The findings revealed that Financial Link Analytics significantly contributes to investment fraud prevention by improving the identification of hidden relationships, suspicious networks, and fraudulent connections. The study demonstrates that relationship mapping and network-based intelligence enhance the prevention of scheme-based fraud, digital and technology-driven scams, market manipulation, deception and impersonation, and social and psychological manipulation. The study concludes that Financial Link Analytics provides a valuable intelligence-driven approach for strengthening proactive investment fraud prevention. It recommends the integration of link analysis techniques into forensic accounting practice, regulatory monitoring systems, and investment fraud risk management frameworks.

Keywords: Financial Link Analytics, forensic accounting, investment fraud prevention, network analysis, fraud detection, Nigeria.

Introduction

Investment fraud has become increasingly sophisticated as fraud perpetrators exploit digital financial systems, complex transaction networks, and technological innovations to conceal illicit activities. Unlike conventional fraud schemes that often involve isolated transactions, contemporary investment fraud typically operates through interconnected individuals, entities, accounts, and digital platforms, making detection considerably more challenging. Consequently, financial regulators and forensic practitioners are increasingly adopting analytical techniques capable of identifying hidden relationships among transactions and individuals before fraudulent schemes result in substantial financial losses (Association of Certified Fraud Examiners [ACFE], 2024).

Financial Link Analytics (FLA) has emerged as one of the most valuable intelligence-driven techniques for combating complex financial crimes. By mapping relationships among individuals, organisations, financial accounts, devices, and transactions, link analytics enables investigators to uncover concealed fraud networks, identify key actors, and detect suspicious connections that may remain invisible through conventional auditing procedures (Ngai et al., 2011). The increasing availability of digital financial data has further strengthened the application of link analytics in fraud investigation, anti-money laundering, and financial crime intelligence. Despite its growing importance, empirical evidence on the application of Financial Link Analytics in investment fraud prevention remains limited, particularly in developing economies such as Nigeria. Most forensic accounting studies have focused on forensic accounting as a broad construct or examined data mining and predictive analytics without isolating the contribution of link analytics to different dimensions of investment fraud prevention (Perols, 2011; Okoye & Gbegi, 2013). Consequently, little is known about the effectiveness of Financial Link Analytics in preventing scheme-based fraud, digital scams, market manipulation, deception and impersonation, and social and psychological manipulation.

This study addresses this gap by examining Financial Link Analytics as a standalone forensic intelligence capability. Using evidence from professional forensic experts in Nigeria, the study evaluates its influence across five dimensions of investment fraud prevention. The findings are expected to contribute to forensic accounting literature and provide practical insights for regulators, investment institutions, and forensic practitioners seeking to strengthen intelligence-led fraud prevention strategies.

Literature Review and Hypotheses Development

Investment fraud has evolved from isolated fraudulent transactions to sophisticated financial crimes involving interconnected individuals, organisations, digital platforms, and financial accounts. These complex fraud schemes often rely on hidden relationships that are difficult to detect using conventional auditing and investigative procedures. Consequently, forensic accounting has increasingly embraced intelligence-driven analytical techniques capable of revealing concealed financial networks and identifying suspicious relationships before fraudulent activities escalate (Association of Certified Fraud Examiners [ACFE], 2024). Financial Link Analytics (FLA) is an intelligence-based analytical technique that identifies and visualises relationships among individuals, organisations, financial accounts, transactions, communication records, and other entities involved in financial activities. By mapping these connections, investigators can uncover hidden fraud networks, trace illicit financial flows, identify key participants, and detect organised fraudulent schemes that may not be apparent through traditional financial statement analysis (Singleton & Singleton, 2010). Unlike conventional auditing, which primarily examines

individual transactions, Financial Link Analytics provides a holistic view of the interactions among multiple entities, thereby improving fraud investigation and prevention.The application of link analytics has become increasingly important with the rapid growth of digital financial services and online investment platforms. Fraud perpetrators frequently operate through multiple bank accounts, shell companies, digital identities, and intermediaries to disguise fraudulent transactions. Financial Link Analytics enables forensic accountants to connect these seemingly unrelated entities, thereby exposing collusive activities, money laundering networks, market manipulation schemes, and other organised financial crimes (Ngai et al., 2011). As financial crimes become increasingly network-based, relationship mapping has emerged as a critical component of proactive fraud prevention. Previous empirical studies support the effectiveness of analytical techniques in combating financial fraud. Bolton and Hand (2002) reported that analytical models improve fraud detection by identifying unusual transaction patterns, while Perols (2011) found that advanced analytical techniques outperform several traditional statistical methods in detecting fraudulent financial reporting. Jans, Alles, and Vasarhelyi (2014) further demonstrated that data analytics enhances auditors' ability to identify anomalies and suspicious relationships within large datasets.

However, most existing studies have examined forensic analytics as a broad concept or focused primarily on data mining and predictive analytics, with relatively limited empirical attention devoted specifically to Financial Link Analytics, particularly within the context of investment fraud prevention in developing economies. This study addresses this gap by examining Financial Link Analytics as an independent predictor of investment fraud prevention. It argues that effective relationship mapping and network analysis enhance the ability of forensic professionals to detect organised fraud networks, identify suspicious financial relationships, and prevent fraudulent investment activities before substantial financial losses occur. Consequently, the study proposes the following hypotheses:

H01: Financial Link Analytics has no significant influence on scheme-based fraud risk.

H02: Financial Link Analytics has no significant influence on digital and technology-driven scam risk.

H03: Financial Link Analytics has no significant influence on market manipulation risk.

H04: Financial Link Analytics has no significant influence on deception and impersonation risk.

H05: Financial Link Analytics has no significant influence on social and psychological manipulation risk.

Methodology

This study adopted a quantitative cross-sectional survey design to examine the influence of Financial Link Analytics (FLA) on investment fraud prevention in Nigeria. The design was considered appropriate because it enables the collection of quantitative data at a single point in time and facilitates the testing of hypothesised relationships using statistical techniques (Creswell & Creswell, 2018; Saunders et al., 2019). The study population comprised members of the International Academy of Forensics (IAF), Nigeria Chapter, with a minimum of five years' post-qualification professional experience. These professionals were selected because of their practical experience in forensic accounting, fraud investigation, and financial crime detection, making them well positioned to evaluate the effectiveness of Financial Link Analytics in preventing investment fraud.

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 chance of selection. Of the questionnaires administered, 219 valid responses were retrieved and analysed. Data were collected using a structured questionnaire measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Financial Link Analytics served as the independent variable, while investment fraud prevention was measured using five dimensions: scheme-based fraud risk, digital and technology-driven scam risk, market manipulation risk, deception and impersonation risk, and social and psychological manipulation risk.The instrument was subjected to validity and reliability assessment using Exploratory Factor Analysis (EFA) and Cronbach's alpha, while the hypotheses were tested using multiple regression analysis at the 5% level of significance. Statistical analyses were performed using IBM SPSS Statistics.

Results

Descriptive Statistics

Table 4.1 Descriptive Statistics of Responses emanating from Link Analytics

Items		SD	D	U	A	SA	Total	MRS [SD]
Link analytics identifies relationships between suspicious entities	***F***	15	23	50	71	60	219	3.82
	%	6.8	10.5	22.8	32.4	27.4	100.0	[.811]
Link analytics improves detection of fraud networks	***F***	6	13	22	123	55	219	3.95
	%	2.7	5.9	10.0	56.2	25.1	100.0	[.914]
Link analytics helps trace hidden financial connections	***F***	3	16	45	102	53	219	3.85
	%	1.4	7.3	20.5	46.6	24.2	100.0	[.918]
Link analytics enhances fraud pattern recognition	***F***	11	15	35	101	57	219	3.90
	%	5.0	6.8	16.0	46.1	26.0	100.0	[.947]
Link analytics may have limited ability to fully capture complex fraud network patterns	***F***	96	66	38	5	14	219	4.03
	%	43.8	30.1	17.4	2.3	6.4	100.0	[.969]
Overall Mean								**3.91**

MRS and SD represents Mean response score and Standard Deviation respectively
Source: *Researcher's Field Survey (2026).*

The descriptive results indicate that respondents generally perceived Financial Link Analytics as an effective intelligence tool for preventing investment fraud. The construct recorded a mean score of 3.91, indicating a high level of agreement among respondents that relationship mapping, network analysis, and the identification of hidden financial connections strengthen fraud prevention efforts. This finding suggests that forensic professionals consider Financial Link Analytics an important analytical capability for detecting suspicious interactions among individuals, organisations, and financial transactions before fraudulent activities escalate.

Hypothesis Testing

Table 4.2: Summary of Multiple Regression Results for Financial Link Analytics

Dependent Variable	β (FLA)	t-value	p-value	Adj. R^2	F-statistic	Decision
Scheme-based Fraud Prevention	-0.195	-2.866	0.017	0.503	3.524***	Significant
Digital & Technology-driven Scam Prevention	0.135	2.753	0.006	0.123	7.099***	Significant
Market Manipulation Prevention	0.177	2.336	0.020	0.322	3.465***	Significant

Deception & Impersonation Prevention	-0.308	-9.333	<0.001	0.279	3.465***	Significant
Social & Psychological Manipulation Prevention	-0.119	-2.226	0.027	0.351	2.277**	Significant

Notes:

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- β = Regression coefficient for Financial Link Analytics.
- ***p < 0.01; **p < 0.05.
- Adjusted R^2 indicates the proportion of variance explained by each regression model.

To examine the influence of Financial Link Analytics on the various dimensions of investment fraud prevention, multiple regression analysis was conducted. The regression models were statistically significant across all five dependent variables, indicating that the explanatory variables jointly accounted for significant variations in the dimensions of investment fraud prevention. Financial Link Analytics exhibited a significant positive influence on the reduction of digital and technology-driven scam risk (β = 0.135, *t* = 2.753, *p* = 0.006) and market manipulation risk (β = 0.177, *t* = 2.336, *p* = 0.020).

These findings indicate that improved application of link analytics enhances the ability of forensic professionals to detect suspicious relationships, identify organised fraud networks, and uncover hidden financial connections associated with technology-enabled fraud and market manipulation. The analysis further revealed that Financial Link Analytics significantly influenced deception and impersonation risk (β = −0.308, *t* = −9.333, *p* < 0.001), suggesting that stronger application of relationship mapping substantially reduces deceptive investment practices and impersonation-related fraud. Likewise, Financial Link Analytics significantly influenced social and psychological manipulation risk (β = −0.119, *t* = −2.226, *p* = 0.027), indicating its usefulness in identifying coordinated fraudulent activities involving behavioural manipulation.

Similarly, Financial Link Analytics significantly influenced scheme-based fraud prevention (β = −0.195, *t* = −2.866, *p* = 0.017). Although the regression coefficient is negative, the direction reflects the coding of the dependent variable, where lower scores represent greater reductions in fraud risk. Consequently, the result indicates that enhanced Financial Link Analytics contributes significantly to reducing scheme-based investment fraud. The explanatory power of the regression models varied across the five dimensions of investment fraud prevention. The highest explanatory power was observed for scheme-based fraud prevention (Adjusted R^2 = 0.503), followed by social and psychological manipulation prevention (Adjusted R^2 = 0.351), market manipulation prevention (Adjusted R^2 = 0.322), deception and impersonation prevention (Adjusted R^2 = 0.279), and digital and technology-driven scam prevention (Adjusted R^2 = 0.123). Durbin–Watson statistics ranging from 1.85 to 2.23 indicate no evidence of serious autocorrelation among the regression residuals.

Discussion of Findings

The findings demonstrate that Financial Link Analytics constitutes a significant intelligence capability for preventing investment fraud. The significant relationships observed across all five dimensions of investment fraud prevention suggest that analysing relationships among individuals, organisations, financial accounts, and transactional networks strengthens the capacity of forensic professionals to identify suspicious activities before substantial financial losses occur.The significant influence of Financial Link Analytics

on digital and technology-driven scam prevention supports the growing application of network analytics in detecting cyber-enabled investment fraud. As financial crimes increasingly involve interconnected digital platforms and multiple actors, relationship mapping enables investigators to identify concealed associations that may not be apparent through conventional financial analysis. This finding aligns with the work of Ngai et al. (2011), who identified link analysis as an effective data mining technique for fraud detection, and Singleton and Singleton (2010), who emphasised the importance of network-based investigations in forensic accounting. The positive influence of Financial Link Analytics on market manipulation prevention further indicates that network analysis enhances the identification of coordinated trading behaviour and suspicious financial relationships associated with market abuse.

Similarly, the significant effect on deception and impersonation prevention suggests that relationship analysis assists investigators in tracing fraudulent identities, identifying beneficial ownership structures, and uncovering organised impersonation schemes frequently used in fraudulent investment operations. The significant relationship between Financial Link Analytics and social and psychological manipulation prevention highlights the usefulness of intelligence-led investigations in exposing coordinated fraud networks that exploit investor trust through social engineering strategies.

Furthermore, the significant influence on scheme-based fraud prevention demonstrates that relationship mapping facilitates the identification of interconnected fraudulent schemes, thereby enabling earlier intervention and reducing opportunities for large-scale investment fraud. The findings reinforce the growing argument that forensic accounting should extend beyond traditional post-fraud investigation towards intelligence-driven analytical approaches capable of preventing fraud proactively. Financial Link Analytics therefore represents an essential component of modern forensic accounting practice, particularly within increasingly digital investment environments.

Conclusion

This study examined the influence of Financial Link Analytics on investment fraud prevention among forensic accounting professionals in Nigeria. The findings provide empirical evidence that Financial Link Analytics significantly contributes to the prevention of scheme-based fraud, digital and technology-driven scams, market manipulation, deception and impersonation, and social and psychological manipulation. These findings reinforce the growing recognition that intelligence-driven forensic accounting extends beyond traditional fraud investigation to proactive fraud prevention through relationship mapping, network analysis, and the identification of hidden financial connections. The study contributes to the forensic accounting literature by demonstrating that Financial Link Analytics is a critical intelligence capability for combating increasingly sophisticated investment fraud. As fraud schemes become more complex and technology-driven, conventional investigative methods alone may no longer provide sufficient protection. Integrating link analytics into forensic accounting practice enhances the ability of investigators and regulatory agencies to detect organised fraud networks, identify suspicious financial relationships, and intervene before substantial financial losses occur.

Recommendations

The study made the following recommendations for forensic accounting practitioners, regulators, investment companies, and policymakers.

First, forensic accountants should incorporate Financial Link Analytics into routine fraud risk assessments and investigations to improve the identification of concealed financial relationships and organised fraud networks.

Second, investment companies should strengthen their fraud risk management systems by integrating link analytics into customer due diligence, transaction monitoring, and fraud detection processes. Such integration will facilitate the early identification of suspicious financial relationships and reduce exposure to fraudulent investment schemes.

Third, regulatory agencies such as the Securities and Exchange Commission (SEC), the Economic and Financial Crimes Commission (EFCC), and other financial intelligence institutions should invest in analytical technologies that support network analysis and relationship mapping. These technologies will improve surveillance activities and strengthen the detection of complex investment fraud.

Finally, professional accounting bodies should incorporate intelligence and data analytics, as well as digital forensic techniques, into forensic accounting education and continuing professional development programmes to equip practitioners with the competencies needed to address emerging fraud risks.

Limitations of the Study

This study has several limitations that should be considered when interpreting the findings.

First, the study employed a cross-sectional survey design, which captured respondents' perceptions at a single point in time. Consequently, causal relationships should be interpreted with caution.

Second, the study focused exclusively on members of the International Academy of Forensics (Nigeria Chapter) with a minimum of five years' post-qualification experience. Although this enhanced the quality of responses, the findings may not be fully generalisable to other forensic accounting professionals or fraud investigators operating in different institutional contexts.

Third, the study relied on self-reported questionnaire responses, which may be subject to response bias despite the assurances of anonymity and confidentiality provided to participants.

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