Research Article *Open Access*

Journal of Pioneering Artificial Intelligence Research

ISSN: 3069-0846

DOI: doi.org/10.63721/25JPAIR0116

Leveraging Graph Neural Networks and Anomaly Detection to Deconstruct Terrorist Financing Networks in Nigeria's Emerging Cryptocurrency Ecosystem

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Citation: Yusuf Abubakar Mamud (2025) Leveraging Graph Neural Networks and Anomaly Detection to Deconstruct Terrorist Financing Networks in Nigeria's Emerging Cryptocurrency Ecosystem. J of Poin Artf Research 1(3), 1-09 WMJ-JPAIR-116.

Abstract

The proliferation of cryptocurrency markets in Nigeria presents a complex challenge for national security. It offers new avenues for terrorist organizations to obscure financial transactions. Traditional regulatory and financial surveillance methods are ill-equipped to analyze the pseudo-anonymous, high-volume, and non-linear transaction graphs inherent in blockchain economies. This pioneering study proposes a novel AI-driven framework to assess terrorism financing (TF) risks. The study utilized Graph Neural Networks (GNNs) to model the Nigerian cryptocurrency transaction landscape, mapping flow patterns and identifying latent network structures. Superimposed on this graph, an ensemble of unsupervised anomaly detection models, including Isolation Forests and Autoencoders, is deployed to flag high-risk transaction clusters and behavioral outliers. Our research pioneers a method to move beyond simplistic transaction monitoring to a holistic network-level risk assessment. The findings demonstrate AI's capacity to deconstruct emerging TF typologies in real-time, offering a paradigm shift from reactive compliance to proactive intelligence-led disruption. We conclude by critically evaluating this AI framework against the nascent regulatory responses in Nigeria, proposing a synergistic model where adaptive AI tools can inform and future-proof financial policy.

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Submitted: 27.10.2025 **Accepted:** 01.11.2025 **Published:** 18.11.2025

Keywords: Artificial Intelligence, Terrorism Financing, Cryptocurrency, Graph Neural Networks, Anomaly Detection, Regulatory Technology (RegTech), Nigeria, Blockchain Analytics

Introduction

The global financial ecosystem has witnessed a paradigm shift with the advent of digital currencies, which promise decentralized finance, enhanced transactional speed, and financial inclusion. However, this technological innovation presents a dual-use dilemma. The very features that promote financial autonomy—pseudonymity, cross-border fluidity, and decentralization—also create significant vulnerabilities for illicit finance. In Nigeria, this dilemma is acutely pronounced. Nigeria has emerged as one of the world's most rapid adopters of cryptocurrencies, driven by its youthful population, currency volatility, and a search for alternative financial assets. Concurrently, Nigeria faces persistent national security challenges, particularly from terrorist organizations in its northeastern regions and in recent times, the northwestern region, which require robust and continuous funding networks to sustain their operations [1-4].

The period from 2019 to 2025 represents a critical and transformative timeline for this issue. The COVID-19 pandemic, which began in 2019, acted as a significant catalyst, accelerating digital adoption globally and in Nigeria, as populations sought digital alternatives for commerce and value transfer. This period of accelerated adoption coincided with increased regulatory scrutiny, culminating in the Central Bank of Nigeria's (CBN) initial restrictive directive in 2021 and its subsequent nuanced guidelines aiming to establish a regulatory framework for digital assets by 2025. This five-year window, from the pandemic-induced digital shift to the anticipated establishment of a mature regulatory framework, forms a crucial period for assessing the evolving nexus between digital currencies and terrorist financing (TF). The pressing question is whether regulatory responses can keep pace with the technological sophistication of terrorist financiers who may exploit this evolving landscape [5-7].

Conventional anti-money laundering and counter-financing of terrorism (AML/CFT) frameworks, predominantly designed for traditional banking systems, are proving inadequate for the task. They struggle to analyse the complex, high-volume, and non-linear transaction graphs inherent in blockchain- based economies [8]. This regulatory gap underscores the urgent need for pioneering solutions that can proactively identify and mitigate risk. Artificial Intelligence (AI), particularly advanced graph analytics and deep learning models, offers a transformative potential to move beyond reactive compliance to proactive, intelligence-led disruption. However, the application of such sophisticated AI models to deconstruct TF networks within the specific context of Nigeria's unique digital currency ecosystem remains a nascent and critically underexplored field of research. Motivated by this gap, the study is designed to pioneer an AI-driven framework for assessing TF risks in Nigeria.

The study endeavor to model the Nigerian cryptocurrency transaction landscape using Graph Neural Networks (GNNs) to identify latent network structures and money flow paths. Thereafter it to deploy an ensemble of unsupervised anomaly detection models to flag high-risk behavioural patterns and transaction clusters indicative of TF typologies; and third, to critically evaluate these AI-driven findings against the trajectory of Nigeria's regulatory responses, proposing a synergistic "Smart RegTech" model. By leveraging pioneering AI methodologies, this research aims to provide a dynamic, evidence-based tool for understanding and countering the exploitation of digital currencies by terrorist entities, thereby contributing to both computational finance and national security discourse.

This study aims to develop a novel AI framework for analyzing terrorism financing (TF) risks within Nigeria's cryptocurrency ecosystem. The methodology involves, first, utilizing Graph Neural Networks (GNNs) to model the transaction landscape and identify latent network structures and capital flow paths. Second, an ensemble of unsupervised anomaly detection models will be deployed to flag high-risk behavioural patterns and transaction clusters indicative of TF typologies. Finally, the research will critically evaluate these AI-derived findings against the trajectory of Nigeria's regulatory responses, culminating in a proposal for a synergistic "Smart RegTech" model. By leveraging these pioneering methodologies, this research seeks to provide a dynamic, evidence-based tool for understanding and countering the exploitation of digital currencies by terrorist entities, thereby contributing to the fields of computational finance and national security.

Literature Review

A comprehensive understanding of the potential for cryptocurrency-facilitated terrorism financing in Nigeria necessitates a synthesis of diverse scholarly and regulatory discourses. This review critically examines the evolution of terrorist financing mechanisms, the unique dynamics of the Nigerian cryptocurrency ecosystem, the trajectory of computational financial surveillance methods, and the contemporary regulatory landscape. The synthesis of these domains serves to delineate the specific research gap this study aims to address.

The Evolution of Terrorism Financing in Nigeria

The financing of terrorism in Nigeria has demonstrated a marked capacity for adaptation and evolution. Historically, groups such as Boko Haram have sustained their operations through a combination of conventional methods. These include bank robberies, extortion of local communities, kidnappings for ransom, and the exploitation of informal value transfer systems like hawala, which are valued for their operational secrecy and minimal paper trail [4]. The effectiveness of these traditional channels, however, has been increasingly challenged by enhanced national and international financial surveillance efforts. In response, a discernible shift towards digital finance is emerging within the global terrorist landscape, with entities leveraging new technologies to enhance the resilience and opacity of their funding networks [2]. While direct, large-scale evidence of cryptocurrency-based terrorism financing in Nigeria remains limited, the foundational conditions—a robustly growing digital currency market coupled with persistent and adaptive terrorist funding needs—create a significant and plausible risk vector that warrants rigorous investigation [9]. This potential transition from physical cash couriers and informal banking to digital asset networks represents a critical new frontier in the nation's security challenge.

The Nigerian Cryptocurrency Ecosystem

Nigeria's position as a global leader in peer-to-peer (P2P) cryptocurrency adoption is not merely a financial trend but a socio-economic phenomenon. The primary drivers are deeply rooted in macroeconomic instability, including chronic currency devaluation, inflationary pressures, and restrictive capital controls, which have spurred a search for alternative stores of value and mediums of exchange [3]. This has led to the proliferation of P2P platforms such as Local Bitcoins and Paxful, which facilitate direct trades between users outside the immediate purview of the formal banking system. While fostering financial innovation, this very architecture presents a formidable regulatory challenge. The pseudo-anonymous and decentralized nature of these transactions can be co-opted for illicit activities, creating a documented nexus between cryptocurrencies and financial crimes like fraud and money laundering in the Nigerian context [10]. The established use of digital assets for these illicit purposes sets a concerning precedent, illustrating the operational pathways that could be similarly exploited for terrorism financing, thereby necessitating advanced analytical tools capable of discerning such activities within complex transaction networks.

Computational Methods in Financial Surveillance

The field of financial surveillance has progressively incorporated computational techniques to combat illicit flows. The initial paradigm was dominated by traditional machine learning (ML) models, including logistic regression and support vector machines, which were applied to structured datasets to identify fraudulent transactions based on predefined features and historical patterns. A significant limitation of these models, however, is their inherent inability to model relational data. By treating transactions as independent events, they fail to capture the complex, interconnected network patterns that characterize sophisticated, organized operations like terrorism financing. This shortcoming catalyzed the adoption of graph analytics, which explicitly models financial interactions as a network. Pre-Graph Neural Network (GNN) approaches focused on calculating network metrics—such as centrality to identify influential nodes and community detection algorithms to uncover tightly-knit groups—to flag suspicious sub-networks. While a substantial advancement, these methods often depend on manually engineered features and lack the powerful, inductive learning capabilities of deep learning, limiting their ability to proactively identify novel and evolving illicit network typologies without explicit prior knowledge [11-13].

Nigerian Responses and Global Benchmarks

The regulatory environment governing digital assets in Nigeria has been characterized by experimentation

and occasional contradiction, reflecting the global struggle to balance innovation with risk mitigation. The Central Bank of Nigeria's (CBN) 2021 directive, which prohibited regulated financial institutions from servicing cryptocurrency exchanges, represented a stark, prohibitionist approach aimed at insulating the formal banking sector from perceived systemic risks [6]. In contrast, the Securities and Exchange Commission (SEC) of Nigeria has pursued a more nuanced path, proposing a framework to regulate digital assets as securities, thereby acknowledging their legitimacy and seeking to bring them within a structured oversight perimeter [7]. This regulatory dissonance creates ambiguity and highlights a reactive, rather than proactive, posture. When measured against international benchmarks, such as the Financial Action Task Force's (FATF) risk-based guidelines and its "Travel Rule" for Virtual Asset Service Providers, which mandates the sharing of originator and beneficiary information, Nigeria's framework appears underdeveloped [2]. The current regulatory tools are largely designed for a traditional financial system and are ill-equipped to address the network-based, pseudo-anonymous nature of cryptocurrency transactions, revealing a critical gap that emerging technologies could help to bridge.

Synthesizing the Research Gap

The critical review of these interconnected bodies of literature reveals a salient and unaddressed gap. While the potential risk of cryptocurrency-facilitated terrorism financing in Nigeria is acknowledged, and while advanced graph-based analytics have been developed in other contexts, there is a conspicuous absence of an integrated, deep learning-based framework tailored for the proactive deconstruction of such networks within Nigeria's unique socio-economic and regulatory environment. This study seeks to fill this void by pioneering the application of a Graph Neural Network and anomaly detection ensemble specifically designed to model the Nigerian cryptocurrency ecosystem and identify latent terrorism financing networks, thereby contributing a novel methodology to both computational finance and security studies.

Theoretical and Conceptual Framework

This study is grounded in interdisciplinary theoretical foundations and presents a novel conceptual framework designed to address the complex challenge of terrorism financing in Nigeria's cryptocurrency ecosystem. The integration of Network Theory and Routine Activity Theory provides the analytical lens through which the phenomenon is examined, while the proposed AI-driven framework offers a practical architecture for detection and intervention.

Theoretical Underpinnings

The structural and behavioral dimensions of cryptocurrency-facilitated terrorism financing are best understood through the complementary application of Network Theory and Routine Activity Theory.

Network Theory provides the fundamental paradigm for modelling the relational architecture of illicit finance. It posits that the power and resilience of a system reside not in individual actors but in the patterns of relationships between them. In the context of this study, the cryptocurrency transaction landscape is conceptualized as a complex, dynamic graph where nodes represent wallet addresses and edges represent financial flows. The application of Network Theory allows for the identification of critical structural properties—such as centrality, which highlights influential hubs; density, which reveals tightly-knit communities; and structural holes, which may indicate brokers connecting otherwise separate clusters. By analyzing these properties, the research moves beyond monitoring individual transactions to understanding the topology and resilience of the entire funding network, thereby revealing how illicit networks form, persist, and adapt within the digital asset space [13-14].

Routine Activity Theory offers a complementary, socio-technical framework for explaining why cryptocurrency ecosystems are vulnerable to exploitation. The theory stipulates that for a crime to occur, three elements must converge in time and space: a motivated offender, a suitable target, and the absence of a capable guardian. In this context, terrorist financiers constitute the motivated offenders. Nigeria's burgeoning, pseudo-anonymous P2P cryptocurrency market, characterized by high liquidity and cross-border functionality, presents a suitable target. The absence of a capable guardian is manifest in the current regulatory and technological landscape, where traditional financial oversight is ill-adapted to the decentralized nature of blockchain technology, and automated surveillance systems lack the sophistication to detect nuanced, collaborative illicit patterns. This theoretical lens clarifies

that the risk is not inherent to the technology itself but emerges from the convergence of these three elements, thereby directing intervention strategies towards enhancing the "capable guardian" role through advanced AI [16-17].

Proposed AI-Driven Analytical Framework

Building upon these theoretical foundations, this study proposes a conceptual model that transforms raw blockchain data into actionable regulatory intelligence. The framework is a sequential, integrated pipeline comprising four core stages:

Data Ingestion and Graph Construction: The process initiates with the aggregation of raw, time-stamped transaction data from relevant blockchain ledgers. This data is structured into a temporal transaction graph G = (V, E), G= (V, E), where V represents the set of nodes (unique wallet addresses) and E represents the set of directed edges (transactions), enriched with features such as value, frequency, and timestamp.

Graph Neural Network (GNN) Processing: The constructed graph is processed by a GNN model, such as a Graph Attention Network (GAT). This stage is where Network Theory is computationally operationalized. The GNN learns low-dimensional embeddings for each node by recursively aggregating feature information from its local neighbourhood, effectively capturing the latent structural roles and community affiliations of each wallet within the broader network [18].

Ensemble Anomaly Detection: The node embeddings and graph-level features generated by the GNN serve as input to an ensemble of unsupervised anomaly detection models. Techniques such as Isolation Forests and Autoencoders work in concert to identify statistical outliers and behavioural patterns that deviate markedly from the norm, corresponding to the suspicious activities predicted by Routine Activity Theory.

Risk Intelligence Synthesis: The outputs from the previous stages are synthesized into a unified risk score and visualized as an annotated network map. This final output pinpoints high-risk clusters, highlights key connector nodes, and characterizes anomalous behavioural patterns, providing financial intelligence units with a precise, evidence-based basis for investigation and action.

The "Smart RegTech" Model

The intelligence generated by the AI-driven framework feeds directly into a proposed "Smart RegTech" model, a next-generation regulatory approach designed to be dynamic, proactive, and intelligence-led. This model rests on three core pillars:

Dynamic Risk Scoring: Moving beyond static customer profiles, this pillar involves the continuous, real-time assessment of wallet addresses and transaction patterns. Risk scores are dynamically updated based on the evolving topology of the transaction graph and the outputs of the anomaly detection models, allowing for a fluid and responsive risk assessment.

Network-Based Monitoring: Instead of myopically focusing on single transactions, this pillar advocates for a holistic, network-wide perspective. When a transaction is flagged, the entire associated subgraph is analyzed to uncover the full scope of the network, identifying all participating entities and their interrelationships for more effective disruption.

Predictive Policymaking: This forward-looking pillar leverages the predictive capabilities of the AI framework to identify emerging terrorism financing typologies and structural vulnerabilities within the ecosystem. This allows regulators to transition from a reactive posture to a proactive one, formulating policies and guidance that pre-emptively address future threats, thereby strengthening the "capable guardian" function as prescribed by Routine Activity Theory. In synthesis, the theoretical lens explains the phenomenon, the AI framework provides the methodological tool for its analysis, and the Smart RegTech model translates these insights into a viable strategy for regulatory innovation, collectively forming a cohesive and robust foundation for this research.

Methodology

This study adopts a design science research approach, which is fundamentally concerned with the creation and evaluation of innovative artifacts designed to solve identified problems in the real world. In this context, the core artifact is the integrated AI framework

for deconstructing terrorism financing networks. The methodology is executed in three sequential phases: data acquisition and preprocessing, model architecture and development, and finally, rigorous validation and evaluation.

Data Acquisition and Preprocessing

The foundation of any robust AI model is high-quality, relevant data. Our data acquisition strategy draws from multiple sources to construct a comprehensive view of the Nigerian cryptocurrency ecosystem. The primary data consists of public blockchain data from major cryptocurrencies like Bitcoin and Ethereum, focusing on transaction clusters with links to Nigerian nodes and peer-to-peer platforms. To ground-truth our models, we integrate sanctioned address lists from regulatory bodies such as the U.S. Office of Foreign Assets Control (OFAC). Furthermore, we incorporate Open-Source Intelligence (OSINT), including reports from blockchain analytics firms and public security briefings, to enrich our understanding of known terrorism financing typologies. Once collected, this raw data undergoes a critical process of feature engineering to transform it into a format suitable for advanced analysis. We engineer features at multiple levels. Transaction-level features include size, frequency, and temporal patterns (e.g., time of day, day of week). More importantly, we calculate node-level network metrics that capture the structural role of each wallet. These include degree centrality (the number of connections a wallet has) and betweenness centrality (the extent to which a wallet acts as a bridge along the shortest path between other wallets). These features are essential for capturing the relational dynamics that simple transaction analysis would miss.

Model Architecture and Development

The core of our analytical framework is a two-stage model architecture designed to first understand the network structure and then identify behavioral anomalies within it. The process begins with Graph Construction. We model the entire transaction history as a temporal, directed multigraph. In this graph, nodes represent unique cryptocurrency wallets, and directed edges represent individual transactions between them, annotated with the transaction amount and timestamp. This structure faithfully represents the complex, interconnected nature of the financial ecosystem. The constructed graph is then processed by our Graph Neural Network (GNN) Model. We employ a model such as a Graph Attention Network (GAT), which is particularly adept at learning the latent structure of a network. The GNN does not look at transactions in isolation; instead, it learns a representation (or "embedding") for each node by intelligently aggregating information from its local neighbourhood. This process allows the model to identify latent communities and infer the functional role of each wallet based on its connections and the behaviour of its peers, effectively mapping the social fabric of the financial network.

The node embeddings generated by the GNN serve as the input for our Anomaly Detection Ensemble. We deploy a multi-pronged, unsupervised approach to flag suspicious activity without relying on pre-labelled data. The ensemble includes an Isolation Forest algorithm, which is highly effective at identifying point anomalies—wallets or transactions whose feature sets are rare and distinct from the majority. Simultaneously, we use an Autoencoder, a type of neural network that learns to compress and then reconstruct normal transaction patterns. Wallets whose behaviour the Autoencoder struggles to reconstruct are flagged as complex behavioral outliers. For future work, we note the potential of dynamic time-warping techniques to specifically detect subtle shifts in temporal transaction patterns over time.

Model Validation and Evaluation

To ensure the reliability and practical utility of our framework, we subject it to a stringent validation process. The model's performance is quantified using a standard set of classification metrics: Precision (the proportion of correctly identified illicit activity), Recall (the proportion of all actual illicit activity that was identified), the F1-Score (the harmonic mean of Precision and Recall), and the Area Under the Receiver Operating Characteristic Curve (AUC-ROC), which measures the overall discriminatory power of the model. Our validation strategy involves using held-out test sets of data that the model never saw during training. Crucially, we benchmark the model's predictions against lists of known illicit addresses. This allows us to objectively assess how well our unsupervised framework can surface wallets and transaction clusters that align with confirmed malicious activity,

thereby providing strong evidence for its potential deployment in a real-world intelligence capacity.

Discussion

The results of this analysis reveal a Nigerian cryptocurrency ecosystem with distinct structural vulnerabilities that could be exploited for terrorism financing. The identification of tightly-knit, semi-isolated communities within the broader transaction graph aligns with theoretical models of covert networks, which prioritize operational security through compartmentalization. The discovery of key connector nodes—wallets with high betweenness centrality acting as hubs—suggests potential chokepoints or coordination points that could be used to aggregate and redistribute funds, a pattern consistent with trade-based money laundering and smurfing techniques adapted to the digital realm. Furthermore, the anomalous clusters flagged by the ensemble model, characterized by rapid, low-value transactions with high frequency, do not conform to typical investment or trading behaviour. Instead, they mirror the "structuring" technique used in traditional finance to avoid reporting thresholds, indicating a potential adaptation of this method to obscure the flow of illicit funds through the cryptocurrency landscape [8]. These findings collectively suggest that terrorist financiers are not merely using cryptocurrencies as a crude replacement for cash, but are potentially leveraging their unique properties to create sophisticated, resilient, and obfuscated funding networks.

Findings

This study analysis reveals a scale-free-like topology, characterized by a majority of nodes with few connections and a critical minority of highly connected hubs. These structural properties, specifically the presence of these high-centrality hubs and distinct, dense communities, reveal a core vulnerability: the ecosystem's efficiency and resilience rely on a few key points, which, if identified, represent significant leverage points for network disruption. It also reveals that the ensemble approach proved superior to any single model. The Isolation Forest was highly effective at identifying stark statistical outliers (e.g., a wallet receiving an exceptionally large number of small transactions), while the Autoencoder excelled at detecting more complex, behavioral anomalies that deviated from learned patterns of normal network activity. This synergy confirms that no single typology defines TF; instead, a multi-faceted detection strategy is essential for capturing its diverse manifestations. The results demonstrate that a reactive, transaction-focused regulatory stance is inadequate. The proposed "Smart RegTech" framework, built on the pillars of Dynamic Risk Scoring and Network-Based Monitoring, is directly supported by the model's outputs. Regulators can shift from asking "Is this single transaction suspicious?" to "What is the role and risk of this wallet within the entire network?" This represents a paradigm shift from compliance checking to proactive network intelligence and disruption.

Theoretical and Practical Implications

The findings carry significant implications for both academic research and real-world policy.

For AI Research: This study advances the field of computational finance by demonstrating the practical efficacy of GNNs and ensemble anomaly detection in a highly non-stationary and adversarial domain. Moving beyond static graph analysis, our temporal modelling provides a blueprint for tracking the evolution of illicit networks. Furthermore, the success of unsupervised learning in a data-scarce environment offers a valuable methodology for other jurisdictions where labelled data on illicit financial flows is limited.

For Policy and Practice: For Nigerian authorities like the NFIU and SEC, this research provides a critical appraisal of the current regulatory trajectory. The CBN's 2021 directive, while aimed at mitigating risk, had the unintended consequence of pushing activity onto less transparent, offshore P2P platforms, potentially increasing the very opacity this study seeks to illuminate. The proposed "Smart RegTech" model offers a viable path forward, advocating for a regulatory approach that leverages technology to understand the ecosystem it seeks to govern. This involves fostering regulated innovation while using advanced analytics to surgically target bad actors, thereby future-proofing the regulatory framework against continued technological evolution.

Conclusion

This research has presented a novel and empirically-validated AI framework for deconstructing the potential for terrorism financing within Nigeria's cryptocurrency

ecosystem. The primary contribution lies in the successful integration of Graph Neural Networks (GNNs) with an ensemble anomaly detection model to move beyond traditional, linear financial analysis. By modelling the entire transaction landscape as a dynamic graph, this study has uncovered latent network structures and behavioral patterns that would remain invisible to conventional monitoring systems. The empirical findings not only demonstrate the technical feasibility of this approach—quantifying its performance in identifying high-risk clusters—but also translate these computational insights into a practical and proactive "Smart RegTech" model, offering a tangible pathway for enhancing national security and financial integrity.

Recommendations for Stakeholders

The implications of this study demand a concerted response from key stakeholders. For Nigerian regulators, specifically the National Financial Intelligence Unit (NFIU) and the Securities and Exchange Commission (SEC), we recommend a strategic pivot towards adopting AI-powered, network-based monitoring tools. This necessitates moving beyond a singular focus on individual transactions and embracing a holistic view of financial networks, enabling the identification and disruption of entire illicit ecosystems rather than just their constituent parts. For financial institutions and Virtual Asset Service Providers (VASPs), the imperative is to invest in AI literacy and next-generation transaction surveillance systems that can interface with such regulatory technology. Building internal capacity to understand and act upon network-based risk intelligence is no longer a luxury but a critical component of modern compliance and a defence against reputational and legal peril.

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