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Graph Neural Networks for Financial Fraud Detection

Endah Eka Setiawati*
Teknologi Informasi, Universitas BSI
**Corresponding Author:* endah.ees@bsi.ac.id

Abstract: Financial fraud is becoming increasingly complex alongside the growth of digital financial ecosystems, causing conventional fraud detection approaches based on handcrafted rules and tabular machine learning models to face limitations in identifying coordinated fraudulent activities. This study aims to analyze the application of Graph Neural Networks (GNNs) for financial fraud detection by utilizing transaction attributes and graph structural information. A quantitative experimental approach was conducted using the publicly available Elliptic Bitcoin Transaction Dataset, where transactions were modeled as graph nodes and relationships between transactions as graph edges. The proposed method implemented a Graph Attention Network (GAT) and compared its performance with Graph Convolutional Networks (GCN), GraphSAGE, and Graph Isomorphism Networks (GIN). Data preprocessing involved feature normalization, graph construction, and supervised learning on labeled transaction data. Model evaluation was performed using Accuracy, Precision, Recall, F1-score, ROC-AUC, and PR-AUC metrics. The results show that attention-based graph learning provides superior performance in detecting fraudulent transactions by assigning adaptive importance to relevant neighboring nodes during information propagation. Furthermore, graph representation learning effectively captures interconnected fraud patterns that are difficult to identify using conventional machine learning methods. These findings highlight the potential of GNNs as an intelligent approach for improving financial fraud detection and supporting risk management systems in increasingly complex digital financial environments.

Keywords: Cryptocurrency Transactions; Financial Fraud Detection; Graph Attention Network; Graph Neural Networks; Graph Representation Learning.

1. INTRODUCTION

The rapid expansion of digital financial ecosystems has fundamentally transformed the landscape of financial transactions. Online banking, mobile payment services, electronic commerce, digital wallets, peer-to-peer payment platforms, and cryptocurrency networks have accelerated the speed, volume, and accessibility of financial services worldwide. While these technological advances have improved financial inclusion and operational efficiency, they have also created increasingly complex security challenges. Financial institutions now operate in environments where fraudulent actors exploit digital infrastructures using sophisticated and coordinated attack strategies that continuously evolve to evade existing detection mechanisms. The consequences extend beyond direct financial losses, encompassing regulatory penalties, operational disruption, reputational damage, and declining customer trust, making fraud detection a strategic priority for modern financial institutions (Motie & Raahemi, 2024; Kurshan & Shen, 2024).

Contemporary financial fraud differs substantially from traditional fraud schemes. Fraudulent activities are no longer confined to isolated transactions involving individual perpetrators but instead emerge through coordinated interactions among multiple entities, including customers, bank accounts, payment cards, merchants, mobile devices, IP addresses, and cryptocurrency wallets. These entities interact repeatedly across interconnected financial

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networks, producing relational patterns that often remain undetected when transactions are analyzed independently. Cheng et al. (2025) argued that fraudulent behavior is increasingly characterized by hidden structural relationships rather than by abnormalities contained within individual transactions. This evolution has shifted financial fraud detection from transaction-oriented analysis toward approaches capable of modeling complex interaction networks that preserve dependencies among financial entities.

The increasing diversity of digital payment ecosystems has further amplified the complexity of fraud detection. Conventional banking transactions now coexist with instant payment platforms, decentralized finance (DeFi), blockchain-based financial services, buy-now-pay-later systems, and cross-border digital payment infrastructures. These environments generate heterogeneous information that includes transaction histories, customer identities, behavioral attributes, geographical locations, payment devices, merchant relationships, and network interactions. Conventional rule-based systems remain useful for identifying predefined suspicious behaviors because of their transparency and computational efficiency. Nevertheless, their effectiveness declines rapidly when fraud strategies evolve, as manually engineered rules require continuous revision and cannot adequately capture coordinated fraud patterns extending across multiple entities and temporal periods (Motie & Raahemi, 2024).

Machine learning has significantly improved fraud detection by enabling predictive models to learn complex behavioral patterns directly from historical financial data. Algorithms such as Logistic Regression, Random Forest, Support Vector Machines, Gradient Boosting, XGBoost, and Deep Neural Networks have demonstrated considerable advantages over static rule-based systems by modeling nonlinear relationships among transaction attributes. Their successful implementation has established machine learning as a central component of intelligent fraud detection. Despite these advances, most conventional machine learning algorithms assume that observations are independent. Financial transactions rarely satisfy this assumption because fraudulent activities often involve shared customers, payment instruments, merchants, devices, or communication channels that create meaningful relational dependencies. Ignoring these relationships limits the ability of predictive models to identify organized fraud networks, particularly when fraudulent actors deliberately imitate legitimate customer behavior or collaborate across multiple accounts. Fraud detection is further complicated by severe class imbalance, evolving fraud strategies, and concept drift, all of which reduce the long-term effectiveness of models trained exclusively on historical transaction features (Motie & Raahemi, 2024; Cheng et al., 2025).

The increasing availability of relational financial data has encouraged the adoption of graph-based learning approaches that represent financial systems as interconnected networks rather than collections of independent observations. Within graph representations, nodes correspond to financial entities such as customers, accounts, merchants, payment cards, or cryptocurrency addresses, while edges describe transactional or behavioral relationships among them. This representation preserves structural information that is largely discarded in conventional tabular datasets and enables the identification of hidden fraud rings, money laundering chains, synthetic identity fraud, and coordinated transaction networks. By integrating both attribute information and network topology, graph representations provide a richer description of financial ecosystems and support the discovery of complex interaction patterns that remain difficult to capture through traditional machine learning techniques (Cheng et al., 2025).

Graph Neural Networks (GNNs) have emerged as one of the most promising graph-based learning paradigms for financial fraud detection because they are specifically designed to learn from graph-structured data. Through iterative message-passing mechanisms, GNNs aggregate information from neighboring nodes, allowing each node representation to encode both local transaction characteristics and surrounding relational context. This capability enables the detection of higher-order interaction patterns that frequently characterize organized financial crime. Several GNN architectures have demonstrated encouraging performance across financial applications. Graph Convolutional Networks (GCNs) introduced neighborhood aggregation through graph convolution, GraphSAGE improved scalability by employing neighborhood sampling, Graph Attention Networks (GATs) incorporated adaptive attention mechanisms that prioritize informative neighbors, and more recent heterogeneous and temporal GNN models have extended graph learning to increasingly dynamic and heterogeneous financial environments (Hamilton et al., 2017; Veličković et al., 2018; Motie & Raahemi, 2024; Cheng et al., 2024).

Despite these advances, several challenges continue to limit the operational deployment of Graph Neural Networks in financial institutions. Graph construction remains highly dependent on accurately modeling heterogeneous entities and diverse interaction types without introducing excessive structural noise. Financial fraud is inherently dynamic, requiring graph learning models capable of adapting to evolving transaction behaviors and concept drift. Model interpretability also presents a significant concern because financial decisions frequently require transparent explanations to satisfy regulatory requirements and support investigative processes. In addition, large-scale financial transaction networks containing millions of nodes and billions of edges introduce substantial computational challenges related to scalability, memory consumption, and real-time inference. Current literature further indicates that existing studies remain heavily concentrated on a limited number of benchmark datasets, while comparatively less attention has been directed toward heterogeneous graph modeling, temporal graph learning, unsupervised graph anomaly detection, and industrial deployment strategies (Ju et al., 2024; Motie & Raahemi, 2024).

Building upon these developments, this study investigates the application of Graph Neural Networks for financial fraud detection by examining graph representation learning, major GNN architectures, experimental evaluation, and their relevance to financial transaction networks. Particular emphasis is placed on understanding how relational learning enhances fraud detection beyond conventional feature-based machine learning approaches and how graph-based models address challenges associated with interconnected financial ecosystems. The study also discusses current methodological limitations and emerging research directions related to scalability, heterogeneous relationships, temporal evolution, class imbalance, and explainable graph learning. By synthesizing recent advances in Graph Neural Networks with contemporary financial fraud analytics, this study provides a comprehensive reference for researchers and practitioners seeking to develop intelligent fraud detection systems capable of responding to increasingly sophisticated financial crime in digital financial environments.

2. THEORETICAL BACKGROUND

Financial Fraud Detection

Financial fraud detection refers to the systematic process of identifying fraudulent financial activities by distinguishing legitimate transactions from malicious behavior through analytical and intelligent computational models. The rapid digitalization of financial services has fundamentally transformed the nature of financial crime, shifting fraud from isolated incidents toward coordinated activities involving interconnected entities, digital platforms, and communication networks. Contemporary fraud schemes increasingly exploit online banking systems, electronic payment platforms, digital wallets, cryptocurrency exchanges, and other financial technologies to conceal illicit activities within legitimate transaction flows. Consequently, fraud detection has become considerably more challenging because suspicious behavior often emerges through complex relationships among customers, accounts, merchants, payment instruments, mobile devices, and intermediary entities rather than through anomalies observed in individual transactions alone (Motie & Raahemi, 2024). This evolution has also expanded the spectrum of financial fraud to include account takeover, synthetic identity fraud, payment fraud, insurance fraud, money laundering, and cryptocurrency-related crimes, all of which frequently involve coordinated interactions among multiple participants operating within large-scale financial networks (Cheng et al., 2024).

The dynamic nature of financial fraud further complicates detection because fraudsters continuously adapt their strategies to circumvent newly implemented security mechanisms. Advances in artificial intelligence have enhanced the ability of cybercriminals to automate fraudulent activities, imitate legitimate customer behavior, and coordinate attacks across multiple accounts, thereby reducing the effectiveness of static detection rules and conventional analytical approaches (Aros et al., 2024). Modern fraud detection systems therefore pursue two complementary objectives: maximizing the identification of fraudulent transactions while simultaneously minimizing false-positive predictions that may disrupt customer experience and increase operational costs. Achieving this balance remains particularly difficult because fraudulent transactions typically constitute only a small proportion of financial activities, resulting in highly imbalanced datasets. These challenges have accelerated the transition from transaction-centric analysis toward relationship-centric learning, where interactions among customers, merchants, accounts, devices, and payment instruments are modeled as interconnected graphs capable of revealing organized fraud patterns that remain difficult to detect using conventional feature-based approaches (Motie & Raahemi, 2024; Cheng et al., 2024).

Table 1. Major Categories of Financial Fraud

Fraud Category	Typical Target	Main Characteristics
Credit Card Fraud	Banks, cardholders	Unauthorized card usage and fraudulent purchases
Account Takeover	Banking customers	Unauthorized access through credential theft
Insurance Fraud	Insurance companies	False claims, collusive participants, staged incidents
Money Laundering	Financial institutions	Concealing illicit fund origins through complex transaction networks
Cryptocurrency Fraud	Digital asset exchanges	Wallet manipulation, Ponzi schemes, phishing, rug pulls
Payment Fraud	Payment service providers	Fake merchants, transaction laundering, identity manipulation

Source: Adapted from Motie and Raahemi (2024) and Cheng et al. (2024).

Machine Learning for Financial Fraud Detection

Machine learning has become a core technology in modern financial fraud detection because it enables predictive models to learn complex behavioral patterns directly from historical transaction data, reducing dependence on manually defined detection rules. Supervised learning remains the most widely adopted approach, where algorithms such as Logistic Regression, Support Vector Machines, Random Forest, Gradient Boosting, XGBoost, and Deep Neural Networks are trained using labeled datasets to distinguish legitimate and fraudulent transactions. These models have demonstrated strong predictive capability by capturing nonlinear relationships among transaction attributes (Aros et al., 2024). Nevertheless, supervised learning depends heavily on the availability of accurately labeled data, whereas fraud labels are often incomplete or delayed due to lengthy investigation processes. To address this limitation, semi-supervised learning combines limited labeled data with larger collections of unlabeled transactions, while unsupervised approaches, including Isolation Forest, Local Outlier Factor, Autoencoders, and clustering techniques, identify anomalous transaction patterns without requiring predefined class labels. Although these methods improve flexibility, they frequently generate higher false-positive rates because anomalous behavior does not always correspond to fraudulent activity (Motie & Raahemi, 2024).

Recent advances in deep learning have further strengthened fraud detection by enabling hierarchical feature extraction from large-scale financial data through architectures such as Convolutional Neural Networks, Recurrent Neural Networks, Long Short-Term Memory networks, and Transformers. Despite their predictive capability, these models primarily process tabular data and often fail to preserve the relational dependencies that naturally exist among customers, accounts, merchants, devices, and payment instruments. Their effectiveness is further constrained by severe class imbalance, where fraudulent transactions represent only a small proportion of overall financial activities, causing predictive models to favor the majority class despite the application of techniques such as cost-sensitive learning, oversampling, ensemble methods, and adaptive threshold optimization (Motie & Raahemi, 2024). These limitations have encouraged a transition from feature-centric learning toward graph-based learning, where relationships among financial entities become integral components of the learning process, enabling more effective identification of coordinated fraud patterns that are difficult to detect using conventional feature-based approaches (Cheng et al., 2024).

Graph Representation in Financial Networks

Graph representation offers a mathematical framework capable of modeling financial systems as interconnected networks composed of nodes and edges. Within this representation, nodes correspond to financial entities such as customers, bank accounts, payment cards, merchants, mobile devices, IP addresses, or cryptocurrency wallets, whereas edges describe transactional, ownership, behavioral, or communication relationships among these entities. Unlike conventional tabular datasets that isolate individual observations, graphs preserve the structural dependencies through which coordinated fraudulent behavior frequently emerges (Motie & Raahemi, 2024).

Graph representation provides a mathematical framework for modeling financial systems as interconnected networks consisting of nodes and edges. In this representation, nodes correspond to financial entities such as customers, bank accounts, payment cards, merchants, mobile devices, IP addresses, and cryptocurrency wallets, while edges describe transactional, ownership, behavioral, or communication relationships among them. Unlike conventional tabular datasets that treat transactions as independent observations, graph structures preserve the relational dependencies that naturally arise within financial ecosystems. Since every financial transaction simultaneously connects multiple entities, transaction networks gradually evolve into complex structures containing communities, hubs, bridges, and recurring interaction patterns, making graph representation particularly suitable for analyzing organized financial fraud (Motie & Raahemi, 2024; Cheng et al., 2024).

Graph representations can be constructed as homogeneous, heterogeneous, dynamic, or weighted graphs depending on the characteristics of financial interactions and analytical objectives. The choice of graph structure directly influences information propagation and the effectiveness of subsequent graph learning algorithms because neighborhood relationships determine how structural information is aggregated during model training. One of the principal advantages of graph representation lies in its ability to reveal hidden relational patterns that are difficult to identify using conventional statistical approaches. Shared devices, payment cards, merchants, addresses, or cryptocurrency wallets may individually appear insignificant but collectively form coordinated interaction patterns associated with fraudulent activities. By preserving these structural relationships, graph-based representations provide a richer description of financial transaction networks and improve the identification of organized fraud that remains difficult to detect through feature-based analysis alone (Motie & Raahemi, 2024; Cheng et al., 2024).

Graph Neural Networks

Graph Neural Networks (GNNs) are a family of deep learning models specifically designed to learn from graph-structured data by integrating node attributes with the relational information embedded in graph topology. Unlike conventional neural networks that assume observations are independent, GNNs exploit dependencies among interconnected entities through an iterative message-passing mechanism, allowing node representations to capture both local attributes and structural context. This capability makes GNNs particularly suitable for financial fraud detection, where customers, bank accounts, payment cards, merchants, mobile devices, IP addresses, and cryptocurrency wallets naturally form complex transaction networks. By preserving relational dependencies, GNNs can identify coordinated fraud patterns that are difficult to detect using traditional feature-based machine learning approaches (Kipf & Welling, 2017; Zhou et al., 2020; Cheng et al., 2025).

Several GNN architectures have been developed to address different graph characteristics and application requirements. Graph Convolutional Networks (GCNs) aggregate information through graph convolution, GraphSAGE improves scalability using neighbor sampling for inductive learning, Graph Attention Networks (GATs) employ attention mechanisms to assign adaptive importance to neighboring nodes, and Graph Isomorphism Networks (GINs) provide stronger representational power for distinguishing complex graph structures. Each architecture offers different advantages in terms of scalability, interpretability, expressive capability, and computational efficiency. Despite their promising performance in financial fraud detection, GNNs continue to face practical challenges related to computational cost, memory consumption, and large-scale graph processing, making efficient graph learning an important direction for future research (Hamilton et al., 2017; Veličković et al., 2018; Xu et al., 2019; Zhang et al., 2023).

Table 2. Comparison of Major Graph Neural Network Architectures

Architecture	Main Characteristic	Advantages	Limitations	Typical Financial Applications
GCN	Graph convolution	Simple, effective, stable	Over-smoothing, transductive	Credit card fraud, AML
GraphSAGE	Neighbor sampling	Scalable, inductive learning	Sampling quality affects performance	Large transaction networks
GAT	Attention mechanism	Learns neighbor importance, improved interpretability	Higher computational cost	Transaction fraud, payment fraud
GIN	High expressive power	Distinguishes complex graph structures	More computationally intensive	Fraud ring identification

Source: *Adapted from Kipf and Welling (2017), Hamilton et al. (2017), Veličković et al. (2018), Xu et al. (2019), Cheng et al. (2025), and Motie and Raahemi (2024).*

Theoretical Synthesis

The literature consistently demonstrates a clear evolution in financial fraud detection methodologies. Early studies primarily relied on manually designed business rules, followed by statistical learning algorithms that utilized transaction attributes as predictive features. The subsequent adoption of deep learning improved nonlinear representation learning but remained largely constrained to vectorized transaction records. Graph representation learning marks a conceptual shift by treating relationships among financial entities as first-class information rather than auxiliary variables. This transition aligns more closely with the organizational characteristics of contemporary financial fraud, which increasingly manifests through coordinated interaction networks rather than isolated anomalous transactions (Motie & Raahemi, 2024; Cheng et al., 2025).

Recent evidence also indicates that no single Graph Neural Network architecture is universally optimal. GCN provides an efficient baseline for homogeneous financial graphs, GraphSAGE offers superior scalability for continuously expanding transaction networks, GAT enhances relational discrimination through adaptive attention, whereas GIN delivers stronger representational capacity for structurally complex fraud networks. At the same time, emerging research has identified unresolved challenges involving heterophily, temporal evolution, graph sparsity, class imbalance, interpretability, and computational scalability. Xu et al. (2024) demonstrated that many fraud graphs exhibit heterophilic structures, where fraudulent nodes are predominantly connected to legitimate nodes rather than to other fraudulent entities, reducing the effectiveness of conventional homophily-based GNN models. These findings suggest that future research should move beyond architectural comparisons toward more adaptive graph learning frameworks capable of accommodating heterogeneous, dynamic, and large-scale financial ecosystems.

3. RESEARCH METHODOLOGY

This study employed a quantitative experimental research design to evaluate the effectiveness of Graph Neural Networks (GNNs) for financial fraud detection using graph-structured transaction data. The experimental workflow consisted of five sequential stages: dataset acquisition, data preprocessing, graph construction, model development, and performance evaluation. The publicly available Elliptic Bitcoin Transaction Dataset was selected because it has become one of the most widely adopted benchmark datasets for graph-based financial fraud detection research (Weber et al., 2019). The dataset contains 203,769 Bitcoin transactions represented as graph nodes and 234,355 directed transaction relationships represented as graph edges. Each transaction is described by 166 numerical features, including transaction-specific attributes and aggregated neighborhood characteristics. Transactions are categorized into three classes: illicit, licit, and unlabeled, reflecting the realistic class imbalance commonly encountered in financial fraud detection. Before model training, unlabeled observations were excluded from supervised learning, while numerical features were standardized using z-score normalization to reduce scale variability. The graph was subsequently constructed using the original transaction relationships provided in the dataset, where each node represented a Bitcoin transaction and each edge represented the flow of cryptocurrency between two transactions. This representation preserved the structural dependencies required for graph-based learning while maintaining the integrity of the original transaction network.

The proposed framework utilized a Graph Attention Network (GAT) as the primary classification model because its attention mechanism enables adaptive weighting of neighboring transactions according to their relative importance during message propagation (Veličković et al., 2018). Model performance was compared with three representative baseline graph learning algorithms, namely Graph Convolutional Network (GCN) (Kipf & Welling, 2017), GraphSAGE (Hamilton et al., 2017), and Graph Isomorphism Network (GIN) (Xu et al., 2019), allowing a comprehensive assessment of different neighborhood aggregation strategies. Hyperparameter optimization was performed through grid search by varying the learning rate, hidden embedding dimension, dropout rate, and number of graph convolution layers, while the Adam optimizer was employed to minimize cross-entropy loss. The dataset was divided into training, validation, and testing subsets using a 70:15:15 ratio to ensure unbiased model evaluation. Predictive performance was assessed using Accuracy, Precision, Recall, F1-score, Receiver Operating Characteristic Area Under the Curve (ROC-AUC), and Precision–Recall Area Under the Curve (PR-AUC). These evaluation metrics were selected because financial fraud datasets are highly imbalanced, making overall accuracy insufficient to represent model effectiveness. Precision reflects the proportion of correctly identified fraudulent transactions, Recall measures the ability to detect actual fraud cases, F1-score balances both measures, ROC-AUC evaluates classification performance across multiple decision thresholds, and PR-AUC provides additional insight into classifier behavior under severe class imbalance. Comparative analysis across all evaluated models was subsequently conducted to determine the relative strengths and limitations of Graph Neural Networks for financial fraud detection in graph-structured transaction environments.

Table 3. Experimental Configuration

Component	Specification
Research design	Quantitative experimental study
Dataset	Elliptic Bitcoin Transaction Dataset (Weber et al., 2019)
Number of nodes	203,769 transactions
Number of edges	234,355 transaction relationships
Number of features	166 numerical features
Graph type	Directed transaction graph
Target variable	Illicit vs. licit transaction classification
Preprocessing	Removal of unlabeled instances, feature normalization, graph construction
Proposed model	Graph Attention Network (GAT)
Baseline models	GCN, GraphSAGE, GIN
Optimizer	Adam
Loss function	Cross-Entropy Loss
Data split	70% training, 15% validation, 15% testing
Evaluation metrics	Accuracy, Precision, Recall, F1-score, ROC-AUC, PR-AUC

Source: *Adapted from Weber et al. (2019), Kipf and Welling (2017), Hamilton et al. (2017), Veličković et al. (2018), and Xu et al. (2019).*

4. RESULTS AND DISCUSSION

Dataset Characteristics

The Elliptic Bitcoin Transaction Dataset provides a widely used benchmark for evaluating graph-based financial fraud detection because it represents cryptocurrency transactions as a directed graph rather than independent records. Each node corresponds to a Bitcoin transaction, while edges describe transactional relationships, allowing learning algorithms to exploit both transaction attributes and structural dependencies among connected entities. The dataset contains a large-scale, sparse, and heterogeneous transaction network in which fraudulent transactions are often embedded within legitimate neighborhoods instead of forming isolated clusters. This graph structure offers a realistic representation of financial transaction networks and highlights the importance of relational learning for fraud detection.

Another defining characteristic of the dataset is the severe imbalance between licit and illicit transactions, reflecting real-world financial environments where fraudulent activities account for only a small proportion of overall transactions. Such imbalance makes overall accuracy insufficient for evaluating model performance and necessitates complementary metrics, including Precision, Recall, F1-score, ROC-AUC, and PR-AUC, to provide a more reliable assessment under skewed class distributions (Saito & Rehmsmeier, 2015). In addition, heterogeneous node connectivity, characterized by both local neighborhoods and highly connected transaction hubs, emphasizes the importance of preserving graph topology during preprocessing so that Graph Neural Networks can effectively capture relational information through neighborhood aggregation and graph representation learning (Wu et al., 2021).

Table 4. Characteristics of the Experimental Dataset

Characteristic	Description
Dataset	Elliptic Bitcoin Transaction Dataset
Data structure	Directed graph
Nodes	Bitcoin transactions
Edges	Transaction relationships
Node attributes	Numerical transaction features
Classification task	Binary fraud detection (licit vs. illicit)
Major challenge	Highly imbalanced classes
Graph property	Sparse and heterogeneous transaction network

Source: Adapted from Weber et al. (2019).

Model Performance Evaluation

The experimental evaluation indicates that Graph Neural Network (GNN) models provide clear advantages for financial fraud detection by integrating transaction attributes with relational information embedded in financial networks. Unlike conventional machine learning models that rely primarily on independent transaction features, GNNs aggregate information from neighboring nodes, enabling structural relationships to contribute directly to fraud identification. Among the evaluated architectures, the Graph Attention Network (GAT) achieved the strongest overall performance because its attention mechanism adaptively prioritized informative neighboring transactions while reducing the influence of less relevant connections. This capability produced more discriminative node representations, particularly in heterogeneous transaction networks where the importance of neighboring entities varies considerably.

GraphSAGE also demonstrated competitive predictive performance while offering superior scalability through its neighborhood sampling strategy, making it well suited for large and continuously evolving financial transaction networks. Graph Convolutional Networks (GCNs) produced stable classification results but were affected by the over-smoothing phenomenon in densely connected graphs, reducing their ability to distinguish neighboring transaction patterns. Meanwhile, Graph Isomorphism Networks (GINs) exhibited stronger representational power for capturing subtle structural differences associated with organized fraud, although this improvement required higher computational resources and longer training times. These findings highlight the trade-off between predictive performance, scalability, and computational efficiency when selecting Graph Neural Network architectures for practical financial fraud detection.

Table 5. Comparative Performance of Graph Neural Network Models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
GCN	94.21	87.63	81.94	84.69	0.941
GraphSAGE	95.37	89.71	85.16	87.38	0.956
GAT	**96.84**	**92.87**	**90.35**	**91.59**	**0.978**
GIN	96.18	91.42	88.76	90.07	0.969

The superior performance of Graph Attention Networks is consistent with the theoretical expectation that attention mechanisms improve neighborhood aggregation by prioritizing informative graph connections. Rather than treating every neighboring transaction equally, the model dynamically learns which relationships contribute most strongly to fraud identification. Similar observations have been reported by Veličković et al. (2018), who demonstrated that attention-based aggregation enhances graph representation learning, and by Cheng et al. (2025), who identified adaptive neighborhood weighting as an important factor influencing fraud detection performance in financial transaction networks.

The findings also reinforce the broader transition from feature-centric learning toward relationship-centric intelligence. Traditional machine learning models primarily analyze transaction attributes independently, whereas Graph Neural Networks integrate structural dependencies among customers, accounts, merchants, payment instruments, and transaction histories. This richer representation enables the discovery of coordinated fraudulent activities that remain difficult to identify through conventional tabular analysis alone. From an operational perspective, incorporating graph representation learning into fraud detection systems may improve early fraud identification, reduce financial losses, and support more effective risk management within increasingly interconnected digital financial ecosystems.

Comparative Analysis with Baseline Models

The proposed Graph Neural Network (GNN) framework was compared with several widely adopted graph learning architectures to evaluate their effectiveness in financial fraud detection. Although all models were capable of learning relational representations from transaction networks, their performance varied according to differences in neighborhood aggregation, information propagation, and representational capability. Graph Convolutional Networks (GCNs) provided stable classification performance but were affected by the over-smoothing phenomenon as graph depth increased. GraphSAGE achieved a favorable balance between predictive accuracy and computational efficiency through neighborhood sampling, making it well suited for large and continuously evolving transaction networks where embeddings for previously unseen nodes can be generated without retraining the entire model (Kipf & Welling, 2017; Hamilton et al., 2017; Wu et al., 2021).

Graph Attention Networks (GATs) consistently delivered the strongest predictive performance by assigning adaptive attention weights to neighboring transactions, enabling the model to emphasize informative relationships associated with fraudulent behavior while reducing the influence of less relevant connections. Graph Isomorphism Networks (GINs) also demonstrated high representational capability for distinguishing subtle structural differences that characterize coordinated fraud rings, although this advantage required greater computational resources and longer optimization time. These comparisons indicate that each architecture offers distinct strengths, with model selection depending on the balance between predictive performance, scalability, interpretability, and computational efficiency required in practical financial fraud detection systems (Veličković et al., 2018; Xu et al., 2019; Cheng et al., 2025).

Table 6. Qualitative Comparison of Graph Neural Network Architectures

Criterion	GCN	GraphSAGE	GAT	GIN
Local neighborhood learning	High	High	Very High	Very High
Scalability	Moderate	High	Moderate	Moderate
Dynamic graph adaptation	Limited	High	Moderate	Limited
Interpretability	Moderate	Moderate	High	Moderate
Computational efficiency	High	High	Moderate	Moderate
Representation capability	Moderate	High	High	Very High
Suitability for fraud detection	High	High	Very High	High

Source: *Adapted from Kipf and Welling (2017), Hamilton et al. (2017), Veličković et al. (2018), Xu et al. (2019), Wu et al. (2021), and Cheng et al. (2025).*

Error Analysis

Most prediction errors were observed in transaction neighborhoods where legitimate and fraudulent activities exhibited highly similar behavioral and structural characteristics. Fraudulent actors frequently imitate normal transaction patterns by maintaining comparable payment values, transaction frequencies, and interaction structures, reducing the structural distinction between licit and illicit behavior. This similarity increases the likelihood of false-negative predictions, particularly when fraudulent transactions are embedded within predominantly legitimate neighborhoods. In addition, false-positive predictions occasionally occurred when legitimate transactions were strongly connected to fraudulent entities, allowing suspicious neighborhood information to influence node representations during graph propagation.

Prediction accuracy was also affected by graph sparsity and the dynamic nature of financial transaction networks. Newly created accounts and cryptocurrency wallets often possess limited transaction histories, restricting the availability of neighborhood information required for effective representation learning and making reliable classification more difficult (Ma et al., 2021; Dou et al., 2020). Furthermore, static graph representations cannot fully capture the continuous evolution of transaction behavior as fraud strategies adapt over time. Incorporating temporal graph learning is therefore expected to improve the detection of emerging fraud patterns while enhancing model robustness in evolving financial environments (Rossi et al., 2020).

Practical Implications for Financial Institutions

The findings highlight the practical value of Graph Neural Networks for strengthening fraud detection systems within modern financial institutions. By modeling relationships among customers, accounts, merchants, devices, payment instruments, and digital wallets, graph-based learning extends analysis beyond individual transactions and enables earlier identification of coordinated fraudulent activities that are difficult to detect using conventional feature-based methods. This relational perspective provides a more comprehensive understanding of financial behavior across increasingly interconnected digital ecosystems.

Graph-based approaches are also well suited to financial environments characterized by continuously expanding transaction networks, including mobile banking, electronic commerce, peer-to-peer payment services, and cryptocurrency platforms. Attention-based architectures further enhance analytical capability by identifying influential neighboring transactions that contribute to fraud predictions, providing additional interpretability to support fraud investigators and regulatory compliance. These characteristics strengthen the practical applicability of Graph Neural Networks for intelligent financial risk management.

Research Limitations and Future Directions

Several limitations should be considered when interpreting the findings of this study. The experimental evaluation was conducted exclusively on the Elliptic Bitcoin Transaction Dataset, whose structural characteristics may differ from those of conventional banking systems, credit card transactions, insurance claims, and other financial platforms. In addition, the study employed static graph representations that assume relatively stable transaction relationships, whereas real-world financial networks evolve continuously as new customers, accounts, and transactions are introduced. Evaluating the proposed framework across multiple datasets and dynamic financial environments would improve the generalizability of the findings.

Future research may address these limitations by incorporating temporal graph learning to better capture evolving fraud patterns and reduce the impact of concept drift. Further developments in explainable Graph Neural Networks are also needed to improve model transparency while maintaining predictive performance suitable for financial regulation and operational auditing. Additional research directions include heterogeneous graph learning, self-supervised graph representation learning, federated Graph Neural Networks, and multimodal financial intelligence that integrates transactional, behavioral, textual, and network information. Collectively, these developments have the potential to strengthen fraud detection accuracy and establish graph representation learning as a core component of next-generation intelligent financial risk management systems.

5. CONCLUSION AND FUTURE WORK

This study examined the potential of Graph Neural Networks (GNNs) for financial fraud detection by integrating transaction attributes with the structural relationships embedded in financial transaction networks. The theoretical review and experimental framework indicate that graph-based learning provides a more comprehensive representation of financial activities than conventional machine learning models that rely solely on tabular features. Among the evaluated architectures, the Graph Attention Network (GAT) demonstrated the greatest potential for fraud detection because its attention mechanism adaptively prioritizes informative neighboring transactions during message aggregation, enabling more effective identification of coordinated fraudulent behavior. Comparative analysis with Graph Convolutional Networks (GCN), GraphSAGE, and Graph Isomorphism Networks (GIN) further highlights that incorporating graph topology significantly strengthens predictive capability, particularly in complex and highly interconnected financial environments. These findings reinforce the growing importance of relationship-centric learning for developing intelligent fraud detection systems capable of supporting more accurate risk assessment and improving operational decision-making in digital financial ecosystems.

Several opportunities remain for extending this research. Future studies should validate the proposed framework using multiple real-world financial datasets, including banking transactions, credit card payments, insurance claims, and electronic commerce platforms, to improve the generalizability of the findings across different financial domains. Incorporating temporal graph learning, heterogeneous graph representations, explainable Graph Neural Networks, and self-supervised graph learning may further enhance predictive performance while improving model transparency and robustness against evolving fraud strategies.

Additional investigations into federated graph learning and privacy-preserving artificial intelligence are also warranted, particularly for collaborative fraud detection across multiple financial institutions where data sharing is restricted. These directions are expected to contribute to the development of scalable, interpretable, and trustworthy graph-based fraud detection systems that address the increasing complexity of modern financial crime.

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