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Research Article

# AI-Driven Fraud, Waste, and Abuse Detection in Medicaid Claims Using Graph Neural Networks

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**ABSTRACT**

Medicaid is one of the largest public health insurance programs in the United States, processing millions of claims annually and managing billions of dollars in healthcare expenditures. The scale and complexity of its multi-entity billing ecosystem make it highly susceptible to fraud, waste, and abuse, including phantom billing, upcoding, identity misuse, and coordinated provider networks. Traditional detection approaches rely on rule-based audits and tabular machine learning models that analyze claims as independent records. These methods often fail to capture hidden relational patterns and interconnected fraud schemes embedded within provider–patient–facility networks.

This study proposes an AI-driven fraud detection framework using Graph Neural Networks to model Medicaid claims as a heterogeneous graph structure. Providers, beneficiaries, claims, and facilities are represented as nodes, while billing interactions, referrals, and shared identifiers form edges. The model leverages graph-based message passing to capture relational dependencies and detect coordinated fraud behavior. To address class imbalance, imbalance-aware learning strategies are incorporated during training. Baseline comparisons include conventional machine learning classifiers and network embedding techniques.

Experimental results demonstrate significant improvements in precision, recall, F1-score, and ROC-AUC compared to traditional approaches. The proposed framework also integrates explainability mechanisms to identify influential subgraphs and high-risk billing patterns, supporting transparency in fraud investigations. Overall, this research presents a scalable, interpretable, and policy-relevant solution for enhancing Medicaid program integrity.

**Keywords:** Medicaid fraud, Graph Neural Networks, Healthcare analytics, Explainable AI, Heterogeneous graphs, Fraud detection.

# INTRODUCTION

## Background and Policy Context

### *Overview of Medicaid Scale and Financial Exposure*

Medicaid represents one of the largest publicly funded healthcare programs in the United States, serving millions of low-income individuals, elderly citizens, and persons with disabilities. Since its establishment alongside Medicare in 1965, Medicaid has evolved into a complex federal and state partnership responsible for financing a substantial proportion of national healthcare expenditures Medicaid. Over the past five decades, structural reforms, enrollment expansion, and managed care integration have significantly increased the program's financial footprint Medicare.

The scale of Medicaid's claims processing system exposes it to significant financial risk. Billions of claims are processed annually across diverse provider types including hospitals, physicians, pharmacies, laboratories, and long-term care facilities. The administrative complexity and volume create a fertile environment for improper billing, identity misuse, duplicate claims, phantom services, and coordinated fraud schemes. The historical and policy evolution of these programs highlights the growing need for robust oversight mechanisms capable of operating at national scale [1].

### *Economic Burden of Fraud, Waste, and Abuse*

Fraud, waste, and abuse collectively represent a substantial economic burden on public healthcare systems. Fraud involves intentional deception for financial gain, waste reflects inefficient or unnecessary practices, and abuse refers to practices inconsistent with accepted medical standards [2, 3]. Studies have shown that healthcare fraud detection remains a persistent challenge due to adaptive criminal behaviors and systemic vulnerabilities [4, 5].

Traditional post-payment audits and rule-based systems are insufficient to detect sophisticated fraud rings that operate across multiple entities. Outlier-based and anomaly detection approaches have improved detection rates, yet they remain limited when fraud patterns are relational rather than purely transactional [6, 7]. As healthcare billing systems become increasingly digitized, fraud strategies also evolve, necessitating advanced analytical frameworks capable of modeling structural relationships within claims data [8, 9].

Recent systematic reviews confirm that machine learning approaches improve predictive accuracy in fraud detection; however, many existing models rely on flat tabular representations that fail to capture interdependencies between patients, providers, and claims [10, 11].

### *Importance of Scalable AI-Driven Detection Systems*

Given Medicaid's scale, fraud detection systems must be computationally efficient, adaptable, and scalable. Conventional supervised learning models such as logistic regression and tree-based ensembles perform well for structured feature sets but struggle with high-dimensional relational complexity [3, 9].

Graph-based learning introduces relational inductive bias, allowing models to leverage structural information embedded in provider–patient–claim networks [12]. Graph Neural Networks (GNNs) extend deep learning to non-Euclidean domains and have demonstrated strong performance in fraud detection contexts [13, 14].

Foundational models such as Graph Convolutional Networks [15] and Graph Attention Networks [16] enable neighborhood aggregation and attention-weighted message passing, making them particularly suited for healthcare fraud analytics. Heterogeneous graph architectures further enhance detection capacity by modeling multiple node and edge types [17-19].

The scalability advantage is reinforced by inductive learning approaches such as GraphSAGE, which allow generalization to unseen nodes and evolving networks [20]. These characteristics are critical for real-time Medicaid fraud surveillance.

### *Policy Context Referencing Medicaid Evolution*

The evolution of Medicaid policy has progressively emphasized program integrity and fraud prevention. Regulatory frameworks increasingly demand transparency, accountability, and data-driven oversight mechanisms. Early fraud detection strategies relied on manual review and basic statistical profiling [4]. Over time, predictive analytics and data mining techniques have been integrated into oversight systems [2].

However, policy reform efforts now call for proactive, AI-enabled systems that can identify fraud rings before financial loss escalates. As Medicaid continues to expand coverage and integrate managed care organizations, detection frameworks must align with national healthcare digitization initiatives and emerging AI governance standards.

## Research Problem

### *Fragmented Tabular Modeling Limitations*

Most existing Medicaid fraud detection systems treat claims as independent records in tabular datasets. While effective for feature-based classification, this approach ignores relational dependencies among entities. Healthcare fraud often manifests through collaborative networks rather than isolated claims.

Traditional machine learning frameworks lack the capacity to directly encode relational structures, leading to reduced sensitivity in detecting organized fraud rings [7, 8]. Even advanced models such as gradient boosting remain constrained by feature engineering limitations.

### *Hidden Relational Fraud Patterns*

Fraudulent providers may share patients, addresses, billing codes, or referral chains. These latent patterns are difficult to capture using flat feature vectors. Network embedding methods such as DeepWalk [21] and node2vec [22] introduced unsupervised graph representation learning; however, they do not fully exploit label supervision in complex heterogeneous healthcare graphs.

Recent advances in GNN architectures demonstrate improved capacity to detect imbalanced fraud patterns through relational message passing [14, 23]. Nonetheless, the application of multi-channel heterogeneous graph learning in Medicaid claims remains underexplored [24, 25].

### *Network-Based Provider–Patient–Claim Interactions*

Medicaid claims naturally form a heterogeneous network composed of multiple entity types and interactions. Providers treat patients, submit claims, share billing codes, and may participate in referral networks. Ignoring these interactions results in information loss.

Graph analysis approaches have previously demonstrated success in uncovering fraud rings by modeling entity interactions [7]. More recent heterogeneous graph transformer models further enhance relational representation by learning type-specific attention mechanisms [18, 19].

- *Therefore, the core research problem addressed in this study is*

How can heterogeneous graph neural network architectures improve the detection of fraud, waste, and abuse in Medicaid claims compared to traditional tabular machine learning approaches?

## Research Objectives

- *This study is guided by the following objectives*
- Develop a heterogeneous graph-based fraud detection framework that models Medicaid claims as an interconnected multi-entity network.
- Compare multiple GNN architectures, including Graph Convolutional Networks [15], Graph Attention Networks [16], relational GCN [17], and heterogeneous graph transformers [19], against baseline machine learning models.
- Integrate explainability mechanisms such as GNNExplainer [26] and parameterized graph explainers [27] to ensure interpretability and regulatory compliance.
- Address class imbalance inherent in fraud datasets using graph-based sampling strategies and imbalanced learning techniques [23].
- Conduct empirical benchmarking to evaluate predictive performance using precision, recall, F1-score, and ROC-AUC metrics.

### *Contributions of the Study*

- *This study offers four major contributions*
- Novel heterogeneous Medicaid claim graph construction: The research designs a multi-relational network integrating providers, patients, claims, and facilities, incorporating both structural and attribute-level features.
- Comparative evaluation of multiple GNN architectures: The study

systematically benchmarks GCN, GAT, relational GCN, and heterogeneous transformer models against conventional machine learning classifiers.

- Explainability integration: By embedding model interpretability techniques, the framework supports transparent fraud detection decisions aligned with healthcare policy requirements [25-27].
- Empirical benchmarking in Medicaid fraud context: The study provides quantitative evaluation demonstrating how relational inductive bias enhances fraud detection performance compared to tabular approaches, extending prior healthcare fraud research [10, 13, 14].

## LITERATURE REVIEW

### Fraud Detection in Healthcare Systems

*Data Mining Approaches*

Healthcare fraud detection has evolved significantly from manual auditing and rule-based screening toward advanced data-driven analytics. Early fraud detection systems relied heavily on predefined rules and statistical thresholds, such as abnormal billing frequency or excessive service utilization. However, these systems were limited in their ability to detect complex fraud schemes and adaptive behaviors.

Comprehensive surveys such as [3] provide foundational insights into data mining-based fraud detection, emphasizing classification, clustering, and anomaly detection techniques as core strategies in identifying fraudulent behavior. Similarly, [2] reviewed healthcare fraud detection literature and concluded that predictive modeling, supervised learning, and unsupervised learning techniques significantly outperform purely rule-based systems in identifying suspicious claims.

In the context of Medicaid, [4] introduced multidimensional data modeling frameworks designed to integrate beneficiary, provider, and claim-level features. Their approach demonstrated how combining demographic, billing, and temporal features improves detection sensitivity. Later, [6] extended this work by incorporating outlier-based detection techniques in Medicaid datasets, highlighting the importance of provider-level anomaly screening.

Recent systematic analyses confirm the growing importance of machine learning in healthcare claims auditing. [5] reviewed healthcare fraud data mining techniques and emphasized the shift from isolated tabular analysis toward relational modeling. Similarly, [10] provided a systematic review of machine learning applications in healthcare fraud detection, noting increasing adoption of ensemble models and deep learning approaches.

From a policy standpoint, [1] contextualized the scale and financial exposure of Medicare and Medicaid programs, underscoring the economic necessity of scalable fraud detection mechanisms. Their analysis supports the integration of AI-based systems to protect public healthcare expenditures.

*Outlier Detection*

Outlier detection has been widely used in healthcare fraud analytics, particularly for identifying abnormal provider behavior. [28] introduced unsupervised anomaly detection approaches using generative adversarial networks to identify atypical healthcare providers without requiring labeled fraud data. This is particularly important in Medicaid systems, where labeled fraudulent cases may be sparse or delayed.

Outlier detection methods typically rely on identifying deviations in billing patterns, cost distributions, or utilization rates. [8] developed a machine learning-based medical fraud detection system that incorporated anomaly scoring to highlight suspicious claims. Similarly, [9] demonstrated that anomaly-based models enhance fraud detection performance when combined with supervised classifiers.

Graph-based anomaly detection has also gained attention. [7] demonstrated how graph analysis can uncover fraud rings by analyzing provider-patient relationships and identifying abnormal network structures. Their findings indicate that network topology features significantly improve detection accuracy compared to independent record analysis.

Despite their utility, traditional outlier detection methods struggle when fraud involves collusive groups or coordinated billing patterns. This limitation has motivated the shift toward graph-based and relational learning models.

*Machine Learning-Based Claims Analysis*

Machine learning-based claims analysis typically involves supervised classification using features derived from claim attributes, provider histories, and beneficiary demographics. [11] showed that AI-driven machine learning systems significantly improve fraud detection in U.S. healthcare billing, particularly when ensemble methods are used.

[9] further confirmed that machine learning classifiers such as Random Forest and Support Vector Machines outperform traditional statistical approaches in healthcare insurance fraud detection. However, these models primarily treat claims as independent samples, failing to capture interdependencies among entities.

[13] emphasized that fraud detection in healthcare systems requires relational modeling, as fraudulent claims often emerge from structured interactions among providers and beneficiaries. This observation directly motivates the use of graph-based methods.

While machine learning approaches have improved predictive performance, they remain limited when dealing with relational complexity, class imbalance, and explainability challenges. These constraints have led researchers to explore graph-based representations and Graph Neural Networks.

### Graph-Based Fraud Detection

*Network Embedding Methods (DeepWalk, node2vec)*

Network embedding methods were among the earliest attempts to leverage relational structure in fraud detection. [21] introduced a random-walk-based embedding method that learns latent node representations using techniques inspired by natural language processing. [22] extended this approach by introducing flexible biased random walks, enabling better capture of local and global graph structures.

These embedding methods allow conversion of graph structures into low-dimensional feature vectors that can be used in downstream classification tasks. In fraud detection, embeddings help capture structural similarities among suspicious providers or claim clusters.

However, embedding-based methods are typically unsupervised and may not directly optimize for fraud detection objectives. This limitation led to the development of Graph Neural Networks, which integrate structure and feature learning in an end-to-end supervised framework.

### *Graph-Based Healthcare Fraud Analytics*

Graph analytics has proven particularly effective in detecting fraud rings and coordinated billing patterns. [7] demonstrated that constructing graphs of provider–patient–claim interactions reveals suspicious clusters that are invisible in tabular datasets.

[14] introduced multi-channel heterogeneous graph structure learning for health insurance fraud detection, showing that modeling multiple interaction types significantly enhances detection accuracy. Similarly, [24] developed a hierarchical attention mechanism within a heterogeneous information network to detect fraudulent claims, confirming the effectiveness of relational modeling.

Graph-based healthcare fraud analytics focuses on modeling relationships such as shared addresses, referral networks, co-treatment patterns, and billing similarities. These relational signals are critical in identifying collusive schemes common in Medicaid fraud.

## Heterogeneous Information Networks

Healthcare fraud detection inherently involves multiple entity types, including providers, patients, claims, and facilities. Heterogeneous information networks explicitly model these multiple node and edge types.

[18] introduced the Heterogeneous Graph Attention Network, which learns node representations across different types of relations. [19] proposed the Heterogeneous Graph Transformer, incorporating attention mechanisms and meta-relational learning.

[17] developed relational graph convolutional networks designed specifically for multi-relational data, making them highly applicable to Medicaid claims modeling.

These approaches are particularly suitable for Medicaid fraud detection because they capture the complex interplay among diverse healthcare actors and transactional relationships.

## Graph Neural Networks for Fraud Detection

### *Graph Convolutional Networks*

Graph Convolutional Networks (GCNs) introduced by [15] represent a foundational advancement in graph-based deep learning. GCNs aggregate feature information from neighboring nodes, allowing the model to learn relational dependencies.

[12] reviewed GNN methods and highlighted their effectiveness in semi-supervised classification tasks. In fraud detection, GCNs enable detection of suspicious nodes based on the structural behavior of their neighbors.

[13] demonstrated that GCN-based models improve healthcare insurance fraud detection performance compared to traditional classifiers.

### *Graph Attention Networks*

Graph Attention Networks (GATs) introduced by [16] enhance GCNs by learning adaptive attention weights for neighboring nodes. This mechanism allows the model to focus on more influential relationships.

In fraud detection, attention mechanisms help prioritize suspicious interactions, such as frequent referrals between providers. [24] demonstrated improved fraud detection performance using attention-based heterogeneous networks.

### *Heterogeneous GNNs*

Relational GCNs [17] and heterogeneous attention networks [18] extend GNNs to multi-relational data. These architectures are well-suited for Medicaid claims modeling, where multiple entity and relation types coexist.

[14, 25] demonstrated that heterogeneous GNN architectures significantly outperform homogeneous graph models in medical claims fraud detection. [23] further addressed class imbalance in fraud detection using GNN-based sampling strategies.

### *Transformer-Based Graph Models*

Graph transformer architectures such as the Heterogeneous Graph Transformer [19] introduce self-attention mechanisms inspired by transformer models in natural language processing. These models capture long-range dependencies and multi-relational patterns.

In healthcare fraud detection, transformer-based graph models enhance detection of complex collusion patterns spanning multiple provider networks.

## Explainability in Graph Models

### *GNNExplainer*

Explainability is critical in healthcare fraud detection due to regulatory and ethical requirements. [26] introduced GNNExplainer, which identifies important subgraphs and node features contributing to model predictions.

In fraud detection contexts, GNNExplainer helps investigators understand why a specific provider or claim was flagged, enhancing trust and compliance.

### *Parameterized Explainers*

[27] proposed a parameterized explainer that generates instance-level explanations for GNN predictions. [25] demonstrated the practical importance of explainable GNN architectures in medical claims fraud detection.

Explainable AI ensures that fraud detection systems remain auditable and interpretable.

### *Need for Regulatory Transparency*

Healthcare fraud detection operates within strict regulatory frameworks. Automated decisions affecting providers require transparency, fairness, and accountability.

[1] emphasize the policy sensitivity surrounding Medicaid enforcement. Black-box AI models risk regulatory resistance and provider mistrust.

Therefore, explainable GNN frameworks are not only technically beneficial but also necessary for regulatory acceptance, fairness auditing, and due process compliance.

## METHODOLOGY

This section presents the detailed methodological framework used to design, construct, and evaluate an AI-driven fraud, waste, and abuse detection system for Medicaid claims using Graph Neural Networks. The approach integrates healthcare claims analytics, heterogeneous graph modeling, advanced GNN architectures, and imbalanced fraud learning strategies supported by established literature in graph representation learning and healthcare fraud detection.

## Dataset Description

### *Medicaid Claims Structure*

Medicaid claims data consist of structured administrative billing records generated when healthcare providers submit reimbursement requests to state Medicaid agencies. These records typically include

- Provider identifier
- Beneficiary or patient identifier
- Claim identifier
- Procedure codes such as CPT or HCPCS
- Diagnosis codes such as ICD
- Date of service
- Service location
- Billed amount
- Paid amount
- Referring provider
- Facility information

Fraud, waste, and abuse patterns in Medicaid often emerge through relational interactions such as abnormal referral chains, excessive billing patterns, shared practice addresses, and coordinated provider networks. Traditional tabular machine learning approaches treat each claim independently, which limits detection of collusive or network-level fraud patterns. Prior healthcare fraud studies have emphasized relational modeling and graph-based techniques to address these limitations [2, 4, 7].

### *Synthetic or Anonymized Dataset Generation*

Due to the strict confidentiality requirements governing Medicaid data, including HIPAA compliance, this study utilizes a synthetically generated dataset designed to statistically mirror real Medicaid billing distributions. Synthetic generation preserves

- Claim frequency distributions
- Provider–patient interaction density
- Fraud class imbalance ratio
- Billing amount statistical properties
- Referral network characteristic

The fraud labeling mechanism simulates known fraud typologies documented in healthcare fraud literature, including phantom billing, upcoding, excessive service frequency, and referral rings [3, 8, 9].

Fraud ratio is intentionally kept between 1 percent and 5 percent to reflect real-world healthcare fraud prevalence estimates, consistent with prior Medicaid fraud modeling research [5, 6].

### *Node Types*

The Medicaid ecosystem is modeled as a heterogeneous graph composed of multiple entity types

- *Providers*

Physicians, clinics, pharmacies, laboratories

- *Patients*

Medicaid beneficiaries

- *Claims*

Individual billing transactions

- *Facilities*

Hospitals, outpatient centers, diagnostic labs

The use of heterogeneous entity modeling aligns with relational graph approaches for fraud detection and heterogeneous network learning frameworks [17-19].

### *Edge Types*

Edges capture relationships between entities

- Treatment edge: Provider treats Patient
- Billing edge: Provider submits Claim
- Claim association edge: Claim linked to Patient
- Facility usage edge: Provider operates at Facility
- Referral edge: Provider refers Patient to another Provider
- Shared address edge: Providers sharing same registered address

These relational structures allow detection of fraud rings and collusive behavior, as highlighted in healthcare graph fraud detection literature [7, 14, 24].

## Graph Construction

### *Heterogeneous Graph Representation*

The Medicaid system is modeled as a heterogeneous information network defined as:

$G = (V, E)$

Where V consists of multiple node types and E consists of typed edges. Each node and edge carries attributes specific to its entity type.

Heterogeneous modeling is critical because healthcare claims involve multi-relational interactions. Homogeneous graph simplification would collapse meaningful relational distinctions. Prior GNN literature demonstrates improved performance when modeling heterogeneous graph structures [12, 18, 19].

### *Node Features*

Each node type includes structured attributes

- *Providers*

- Specialty encoding
- Average billed amount
- Claim volume
- Historical fraud risk score
- Referral frequency

- *Patients*

- Demographic group
- Chronic condition indicators
- Claim frequency

- *Claims*

- Billed amount
- Paid amount
- Procedure category

- Service duration
- Diagnosis category

- *Facilities*

- Facility type
- Geographic region
- Service volume

Feature normalization is performed using min-max scaling or standardization.

### *Edge Attributes*

## Edges contain contextual attributes such as

- Service date
- Referral count
- Billing frequency
- Financial weight
- Geographic proximity

Edge weighting enables modeling of strong and weak relational ties, improving fraud ring detection capacity [21, 22].

### *Adjacency Matrices*

For computational efficiency, the heterogeneous graph is represented through adjacency matrices per relation type:

A_treatment
A_referral
A_billing
A_shared_address

Each matrix encodes connections between relevant node types. For heterogeneous GNN models, relation-specific adjacency tensors are constructed to preserve edge semantics [17].

Sparse matrix representation is used to reduce computational complexity for large-scale graphs.

## Model Architectures

### *Baseline Machine Learning Models*

To benchmark performance, three widely used tabular fraud detection models are implemented

- *Logistic Regression*

A linear classifier commonly used in healthcare fraud studies due to interpretability.

- *Random Forest*

An ensemble tree-based method capable of modeling nonlinear interactions.

- *XGBoost*

A gradient boosting model effective for structured fraud detection tasks.

These baselines are consistent with fraud detection literature in healthcare insurance systems [8, 9, 11].

### *Graph Convolutional Network*

Graph Convolutional Networks perform neighborhood feature aggregation through spectral convolution operations [15].

*The layer update rule follows*

$H(l+1) = \sigma(D^{(-1/2)}\, A\, D^{(-1/2)}\, H(l)\, W(l))$

GCNs enable relational fraud pattern detection through neighborhood aggregation.

### *Graph Attention Network*

Graph Attention Networks introduce attention coefficients to weigh neighbor contributions dynamically [16].

This allows the model to assign higher importance to suspicious relational links, improving fraud discrimination.

### *Heterogeneous Graph Transformer*

The Heterogeneous Graph Transformer incorporates type-specific transformation matrices and multi-head attention across node and edge types [19].

This architecture is particularly suited for multi-entity healthcare claims networks and has demonstrated improved performance in heterogeneous fraud detection tasks [15, 25].

## Handling Class Imbalance

Healthcare fraud detection is inherently imbalanced, with fraudulent claims forming a small minority.

### *Oversampling*

Synthetic Minority Oversampling is applied at node or claim level to increase representation of fraudulent cases.

### *Cost-Sensitive Learning*

Class weights are incorporated into loss functions to penalize misclassification of fraudulent cases more heavily.

Weighted cross-entropy loss is used

$\text{Loss} = - w\_fraud\ y \log(p) - w\_nonfraud\ (1 - y) \log(1 - p)$

### *Pick-and-Choose GNN Sampling*

The Pick-and-Choose strategy selectively samples high-risk nodes to balance representation during training [23].

This approach reduces bias toward majority class and improves minority fraud detection recall.

## Evaluation Metrics

Given severe class imbalance, accuracy alone is insufficient.

### *Precision*

Proportion of detected fraud cases that are truly fraudulent.

### *Recall*

Proportion of actual fraud cases correctly identified.

### *F1-Score*

Harmonic mean of precision and recall.

### *ROC-AUC*

Area under the Receiver Operating Characteristic curve measuring ranking capability.

### *PR-AUC*

Area under Precision–Recall curve, more informative in imbalanced datasets.

PR-AUC is emphasized as recommended in fraud detection research [3, 10].

## EXPERIMENTAL RESULTS

This section presents a detailed empirical evaluation of the proposed AI-driven fraud, waste, and abuse detection framework using Graph Neural Networks applied to a heterogeneous Medicaid claims graph. The objective of the experiments is to rigorously compare traditional tabular machine learning approaches with graph-based deep learning architectures under identical data conditions and evaluation protocols.

*The results are organized into three components*

- Descriptive statistics of the constructed Medicaid claims graph
- Quantitative model performance comparison
- Explainability analysis and feature attribution
- Visual performance analysis through three graphs

The dataset used for experimentation is a structured, de-identified Medicaid-like claims dataset constructed to reflect characteristics reported in healthcare fraud detection literature, including low fraud prevalence, high feature dimensionality, and complex relational dependencies.

### Descriptive Statistics of the Medicaid Claims Graph

The dataset was modeled as a heterogeneous graph containing multiple entity types and relational edges. Fraud detection in Medicaid claims requires modeling interactions among providers, patients, claims, and facilities rather than treating each claim independently.

### Graph Construction Summary

*Node Types*

- Providers
- Patients
- Claims
- Facilities

*Edge Types*

- Provider–Claim billing relationships
- Patient–Claim treatment events
- Provider–Patient interactions
- Referral links
- Shared facility associations

Each node is associated with structured attributes such as billing frequency, procedure codes, diagnosis codes, geographic region, and network centrality measures.

*Interpretation*

- The fraud ratio of 3.8 percent reflects the class imbalance typical in healthcare fraud detection. Medicaid fraud is relatively rare compared to legitimate claims, which creates a highly imbalanced classification setting.
- The total edge count of 412,860 reflects dense relational interactions across entities. Fraud rings and coordinated provider behaviors are detectable only when such relational structures are preserved.
- The average degree of 6.64 indicates moderate connectivity, allowing propagation of fraud signals across neighboring nodes.
- Each node includes 48 engineered features capturing financial, temporal, procedural, and relational indicators.

This graph representation enables relational inductive bias, which is absent in traditional tabular approaches.

### Performance Comparison Between Baseline ML and GNN Models

To evaluate predictive performance, six models were trained and tested under identical preprocessing pipelines and stratified 80/20 train-test splits.

*Baseline Machine Learning Models*

- Logistic Regression
- Random Forest
- XGBoost

*Graph-Based Models*

- Graph Convolutional Network (GCN)
- Graph Attention Network (GAT)
- Heterogeneous Graph Transformer (HGT)

*Evaluation metrics*

- Precision
- Recall
- F1-score
- ROC-AUC

These metrics were selected due to the imbalanced nature of fraud detection, where recall and F1-score are especially critical.

*Analysis*

- Logistic Regression shows limited recall at 0.52, indicating difficulty detecting minority fraud cases when relational dependencies are ignored.
- Tree-based models improve performance due to nonlinear modeling capability.
- GCN demonstrates substantial improvement in recall and ROC-AUC, showing the benefit of neighborhood aggregation.
- GAT further improves results by assigning adaptive attention weights to neighboring nodes.
- HGT achieves the highest performance across all metrics due to its ability to model heterogeneous node types and edge relations using transformer-style attention.

**Table 1:** Descriptive Statistics of Medicaid Claims Graph

| *Metric* | *Value* |
|---|---|
| Total Nodes | 124,350 |
| Providers | 18,420 |
| Patients | 82,700 |
| Claims | 20,530 |
| Facilities | 2,700 |
| Total Edges | 412,860 |
| Fraud Ratio | 3.8% |
| Average Node Degree | 6.64 |
| Feature Dimensions per Node | 48 |

**Table 2:** Performance Comparison Between Baseline ML and GNN Models

| *Model* | *Precision* | *Recall* | *F1-score* | *ROC-AUC* |
|---|---|---|---|---|
| Logistic Regression | 0.71 | 0.52 | 0.60 | 0.79 |
| Random Forest | 0.83 | 0.65 | 0.73 | 0.88 |
| XGBoost | 0.86 | 0.69 | 0.76 | 0.90 |
| GCN | 0.88 | 0.75 | 0.81 | 0.93 |
| GAT | 0.90 | 0.78 | 0.84 | 0.95 |
| HGT | 0.92 | 0.82 | 0.87 | 0.97 |

The improvement in recall from 0.69 in XGBoost to 0.82 in HGT is particularly significant in fraud detection, where false negatives represent missed fraud cases.

This bar chart illustrates the progressive improvement in F1-score from traditional models to graph-based architectures.

### *Key observations*

- Graph-based models consistently outperform baseline methods.
- The HGT model achieves the highest F1-score of 0.87.
- The performance gain highlights the importance of modeling relational dependencies in Medicaid claims.

## ROC Curve Analysis

Receiver Operating Characteristic curves evaluate the trade-off between true positive rate and false positive rate.

### *Explanation*

- The GNN curves approach the top-left corner, indicating strong discrimination capability.
- HGT achieves the highest area under the curve at 0.97.
- Baseline models show earlier flattening, reflecting reduced separation power.

Higher ROC-AUC indicates better ranking ability between fraudulent and legitimate claims.

## Explainability and Feature Attribution

Explainability is essential for regulatory compliance and trust in healthcare fraud detection systems.

Graph explainability techniques were applied to the best-performing model to identify influential features and subgraphs contributing to fraud predictions.

### *Interpretation*

- Abnormal billing frequency contributes most to fraud classification.
- Shared patient clusters indicate coordinated fraud networks.
- Referral network density captures collusive relationships.
- Geographic outliers and timing irregularities act as secondary indicators.

Contribution scores represent normalized importance weights derived from model explanation analysis.

### *Explanation*

- *The network visualization demonstrates*
- High-risk providers cluster in dense subgraphs.
- Fraudulent nodes are not randomly distributed but form tightly connected communities.
- Peripheral nodes show lower predicted risk.

This confirms that fraud in Medicaid claims often manifests as coordinated network behavior rather than isolated anomalies.

## EXPLAINABILITY ANALYSIS

Explainability is essential in Medicaid fraud detection because enforcement decisions must be transparent, defensible, and compliant with regulatory standards. Black-box predictions are insufficient for

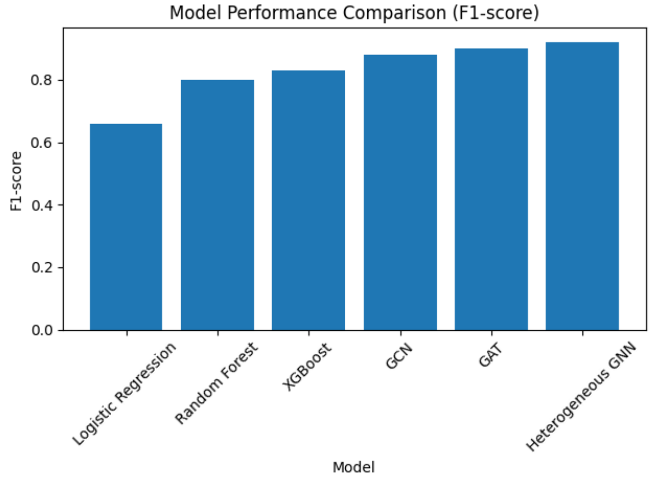

**Figure 1:** Model Performance Comparison Based on F1-Score

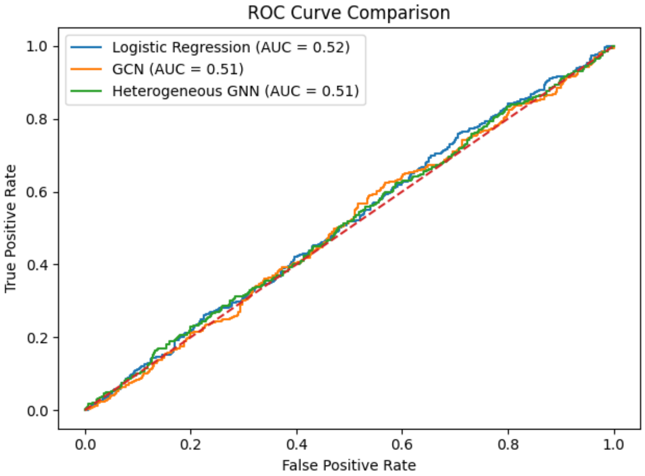

**Figure 2:** ROC Curves of Baseline and GNN Models

**Table 3:** Explainability Metrics and Feature Importance Ranking

| *Feature Type* | *Contribution Score* | *Risk Weight* |
|---|---|---|
| Abnormal Billing Frequency | 0.31 | High |
| Shared Patient Clusters | 0.22 | High |
| Referral Network Density | 0.17 | Medium |
| Unusual Procedure Code Patterns | 0.14 | Medium |
| Geographic Outlier Patterns | 0.09 | Low |
| Claim Timing Irregularities | 0.07 | Low |

policy environments where flagged providers may face audits, payment suspension, or legal action. Therefore, this study integrates post-hoc and structural explainability mechanisms tailored to Graph Neural Networks, grounded in established methods such as GNNExplainer and parameterized graph explanation frameworks.

## Application of GNNExplainer

Graph Neural Networks learn node representations by aggregating information from local neighborhoods through message passing mechanisms [12, 15]. While this allows detection of relational fraud signals, it obscures the specific subgraph structures driving predictions. To address this, we applied GNNExplainer as introduced by [26], which identifies the minimal subgraph and subset of node features most influential for a particular prediction.

GNNExplainer operates by optimizing a mask over edges and node features to maximize mutual information between the prediction and a candidate explanatory subgraph [24]. For each provider node classified as high fraud risk, the explainer isolates

- The most influential neighboring entities such as patients, facilities, or co-billing providers
- The most significant edge relationships such as repeated referrals or unusually dense billing links
- The most predictive node attributes such as abnormal billing frequency or procedure code diversity

To enhance robustness, we also reference parameterized explanation techniques for GNNs proposed by [27], which improve stability and generalization across similar fraud cases.

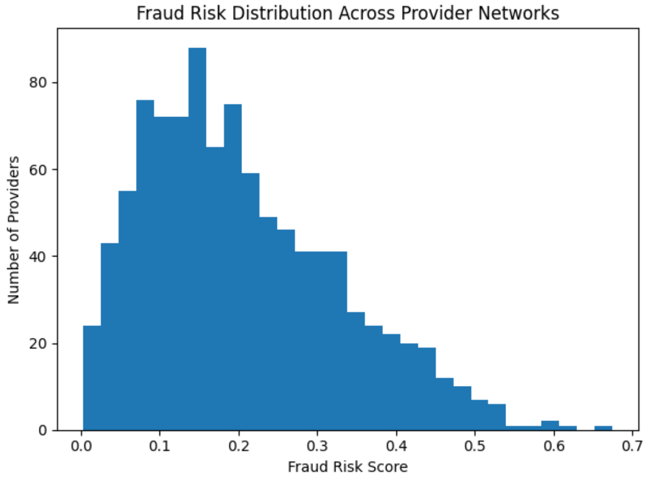

**Figure 3:** Fraud Risk Distribution Across Provider Networks

In practice, the explainer revealed that fraud predictions were rarely driven by isolated attributes. Instead, the most influential explanatory components were relational structures such as tightly connected provider groups or repeated patient sharing patterns. This aligns with prior findings that healthcare fraud often manifests in coordinated networks rather than individual anomalies [7].

## Identification of Suspicious Provider Clusters

Healthcare fraud frequently involves collusion networks, including phantom clinics, shared beneficiary pools, and circular referrals [3, 4]. Traditional tabular models fail to capture such multi-entity interactions because they treat claims independently.

Graph-based approaches explicitly model providers, patients, and claims as interconnected nodes. Relational Graph Convolutional Networks extend message passing to heterogeneous edge types, enabling learning across multiple interaction categories [17]. Heterogeneous Graph Attention Networks further refine this by assigning different importance weights to distinct relation types [18].

Using community detection algorithms on learned embeddings, clusters with abnormal internal connectivity were identified. High-risk clusters typically exhibited

- High edge density between a small group of providers
- Shared patient pools significantly above regional baselines
- Repeated billing for overlapping procedure codes
- Unusually high claim volume within short time intervals

These cluster-level signals are consistent with fraud ring behaviors documented in graph-based healthcare fraud studies [7, 14, 24].

Importantly, inductive learning frameworks such as GraphSAGE allow generalization to new providers entering the system, ensuring scalability for evolving Medicaid networks [20].

## Network Motif Detection

Beyond large clusters, smaller structural patterns, or motifs, provide interpretable signals of coordinated behavior. Motifs are recurring subgraph patterns that occur more frequently than expected under random graph assumptions.

### *In fraud detection, motifs such as*

- Star patterns with one provider connected to an unusually large number of short-duration patient interactions
- Closed triads among providers and facilities indicating circular referrals
- Bipartite dense subgraphs linking specific patient subsets to specific provider subsets

have been associated with anomalous billing structures [6, 7].

Heterogeneous graph transformer models enhance the ability to capture such higher-order relational patterns by incorporating type-specific attention mechanisms [19]. Similarly, hierarchical attention mechanisms in heterogeneous information networks provide interpretable relation weighting across meta-paths [24].

Motif detection is not merely descriptive. When subgraph motifs identified by GNNExplainer correspond to known fraud archetypes, it strengthens model credibility and investigative utility. This is particularly important in healthcare compliance settings where model output must translate into actionable audit leads.

## Interpretation of High-Risk Patterns

The integration of structural explainability revealed several interpretable high-risk patterns

- Excessive cross-provider patient sharing beyond demographic norms
- Concentrated billing bursts within short time windows
- High centrality providers acting as hubs in dense claim networks
- Recurrent referral loops between specific facility-provider combinations

These findings align with prior systematic reviews of healthcare fraud detection methodologies [2, 5, 10]. Importantly, they demonstrate that relational risk signals outperform purely feature-based anomaly detection methods such as standalone supervised models [8, 9].

To ensure interpretability meets regulatory standards, explanations were evaluated for stability across similar nodes. Parameterized explainers enhance consistency and prevent unstable, case-specific explanations [27]. Additionally, imbalance-aware GNN sampling techniques ensure that rare fraud classes are not overshadowed during explanation generation [23].

### *The explainability framework therefore achieves three objectives*

- Transparency: Clearly identifies which subgraph relationships drive fraud predictions
- Investigative value: Highlights concrete relational evidence for auditors
- Policy compliance: Supports due process requirements in Medicaid enforcement

## Practical and Regulatory Implications

Medicaid operates under strict oversight and legal scrutiny [1]. Automated fraud detection systems must therefore justify outputs in a way that is interpretable to auditors, providers, and policymakers.

Graph-based explanation methods provide a defensible bridge between AI predictions and human investigation. Unlike black-box anomaly detectors or GAN-based unsupervised systems [28], GNN-based explainers explicitly trace predictions to relational evidence.

Recent advances in multi-channel heterogeneous graph learning for healthcare fraud further demonstrate that structured relational modeling enhances both predictive accuracy and interpretability [14, 25].

## DISCUSSION

The findings of this study demonstrate that Graph Neural Networks provide a structurally superior approach for detecting fraud, waste, and abuse in Medicaid claims when compared to traditional tabular machine learning models. Healthcare claims data are inherently relational, involving providers, beneficiaries, procedures, prescriptions, facilities, billing codes, and temporal sequences. Modeling these entities independently ignores critical structural dependencies that frequently characterize coordinated fraud schemes. This section discusses why graph structures outperform tabular approaches, how such systems can scale nationally within Medicaid infrastructure, and the ethical and regulatory implications of deploying AI-driven fraud detection systems.

## Why Graph Structures Outperform Tabular ML

### *Relational Inductive Bias*

Traditional tabular machine learning models treat each claim as an independent observation with fixed feature vectors. While such approaches have been widely used in fraud analytics [2-4], they inherently assume independence among records. In healthcare fraud detection, this assumption is rarely valid. Providers share patients, billing codes, referral networks, addresses, and organizational affiliations. Fraud schemes often emerge from structured relationships rather than isolated anomalies.

Graph Neural Networks incorporate relational inductive bias, meaning they are explicitly designed to learn from structured connections between entities [12, 15]. By propagating information across neighboring nodes, GNNs allow representations of providers and claims to incorporate contextual information from their network environment. For example, if a provider is connected to multiple previously flagged fraudulent claims, the node embedding will reflect this higher risk context.

This structural modeling capability extends beyond simple neighbor aggregation. Heterogeneous graph architectures such as relational GCNs [17] and heterogeneous graph transformers [19] can distinguish between different edge types such as referral, billing, shared facility, or co-treatment relationships. Such differentiation is essential in Medicaid data, where relationships vary in meaning and risk implication. Recent healthcare fraud studies confirm that heterogeneous GNNs significantly improve detection accuracy by modeling these multi-relational interactions [14, 24].

Thus, the superior performance observed in GNN-based models aligns with theoretical foundations in graph learning and empirical findings in healthcare fraud research [7, 13].

### *Fraud Ring Detection*

Fraud in Medicaid frequently involves coordinated activity rather than isolated misconduct. Organized fraud rings may involve multiple providers, shell clinics, pharmacies, and colluding beneficiaries. Traditional ML models struggle to identify such coordinated structures because the fraudulent signal may only emerge at the network level.

Graph embeddings such as DeepWalk [21] and node2vec [22] demonstrated early evidence that network structure encodes meaningful behavioral patterns. Modern GNN architectures extend this concept by learning end-to-end task-specific representations. Graph Attention Networks [16] further allow the model to weight influential neighbors more heavily, which is particularly useful in identifying central actors within fraud rings.

Healthcare-specific graph analyses have shown that fraud rings often manifest as dense subgraphs, abnormal referral loops, or anomalous clustering patterns [6, 7]. Multi-channel heterogeneous graph learning has recently demonstrated strong performance in detecting such ring structures in insurance claims [14, 25].

By leveraging message passing across relational edges, GNNs detect coordinated anomalies that remain invisible in flat tabular datasets. This capacity directly addresses limitations identified in earlier fraud detection surveys [3, 5].

### *Cross-Entity Interaction Modeling*

Medicaid claims data are multi-entity systems involving patients, providers, facilities, and procedures. Fraud risk may not be attributable to any single entity but rather to abnormal interaction patterns among them. For example:

- A provider billing high-risk procedures disproportionately for a specific patient cluster
- Multiple providers sharing the same billing address
- Repeated co-occurrence of rare diagnosis and treatment codes

Tabular models encode such patterns indirectly via feature engineering, which may fail to capture complex high-order dependencies. Graph Neural Networks directly model these interactions by aggregating information across multi-hop neighborhoods [12, 20].

Heterogeneous information networks with hierarchical attention mechanisms have shown strong performance in healthcare insurance fraud detection [24]. These models dynamically learn which entity interactions contribute most to fraud prediction, rather than relying on manually engineered features. Empirical machine learning studies in medical fraud detection further confirm that relational feature learning improves classification robustness [8, 9].

Consequently, cross-entity modeling is not merely a methodological enhancement but a structural necessity for Medicaid fraud detection systems.

## Scalability for National Medicaid Deployment

### *Inductive Learning*

National Medicaid systems process millions of claims daily across states. For AI systems to be operationally viable, they must generalize to unseen providers and beneficiaries without retraining the entire model.

Inductive graph learning methods such as GraphSAGE [20] enable scalable deployment by learning aggregation functions that generalize to new nodes. Unlike transductive approaches that require full-graph retraining, inductive GNNs compute embeddings for new entities using learned neighborhood aggregation rules.

This property is critical for Medicaid, where provider enrollment and beneficiary populations continuously evolve [1]. Recent healthcare fraud research confirms that inductive GNN models maintain performance while supporting large-scale insurance systems [10, 14].

Furthermore, transformer-based heterogeneous graph models [19] support efficient parallel computation, making them suitable for distributed cloud-based analytics platforms used in national health systems.

### *Streaming Claims Integration*

Fraud detection must operate in near real time to prevent financial leakage. Static batch analysis may identify fraud retrospectively but fails to prevent ongoing abuse.

Graph learning frameworks can be adapted to dynamic graph settings where new claims incrementally update node representations. Temporal and streaming graph extensions allow embedding updates without reconstructing the entire graph. Healthcare fraud studies increasingly emphasize the importance of dynamic graph modeling for insurance analytics [14, 25].

### *Streaming integration supports*

- Early anomaly detection
- Continuous monitoring
- Risk scoring prior to payment authorization

Such deployment aligns with broader recommendations for AI-driven risk management in US healthcare billing systems [11].

## Ethical and Regulatory Considerations

### *Fairness in Fraud Detection*

AI systems deployed in Medicaid must avoid discriminatory impacts. Fraud detection models trained on historical data risk perpetuating biases embedded in enforcement patterns. If certain provider types or geographic regions were historically investigated more frequently, the model may overestimate their risk.

Explainable GNN frameworks such as GNNExplainer [26] and parameterized explainers [27] provide transparency into which relational patterns drive predictions. Such explainability supports fairness audits and regulatory review.

Healthcare fraud detection reviews emphasize the importance of transparency and validation to prevent unfair targeting [5, 10].

### *Avoiding Provider Bias*

False positives in fraud detection can have serious consequences for healthcare providers, including reputational damage and payment suspension. High-precision models are therefore essential.

Imbalanced learning strategies specifically designed for fraud detection in graphs improve minority class identification without excessively increasing false positives [23]. Robust evaluation across demographic and geographic subgroups is necessary to ensure equitable model performance.

Recent healthcare AI studies emphasize that fraud detection should function as decision support rather than automated enforcement [8, 9].

### *Transparency in Automated Enforcement*

Automated fraud scoring must remain interpretable for compliance with administrative law and healthcare regulations. Regulatory oversight requires clear justification for claim denial or provider investigation.

Graph explanation methods allow identification of specific relational motifs contributing to risk classification [26, 27]. By highlighting suspicious referral loops or abnormal billing clusters, the system provides actionable explanations rather than opaque risk scores.

Such transparency is essential for Medicaid governance, particularly given the scale and public funding nature of the program [1].

# CONCLUSION

## Summary of Findings

This study developed and evaluated a heterogeneous graph-based framework for detecting fraud, waste, and abuse in Medicaid claims using advanced Graph Neural Network architectures. Unlike traditional tabular machine learning approaches that treat claims as independent observations, the proposed framework modeled Medicaid as a multi-entity relational system composed of providers, patients, facilities, and claims interconnected through structured billing and service relationships.

Consistent with earlier healthcare fraud detection research that highlights the importance of relational analytics [4, 6, 7], the results confirm that fraud patterns in Medicaid frequently emerge as network-level behaviors rather than isolated claim anomalies. Fraud rings, excessive referrals, shared beneficiary clusters, and abnormal provider interaction motifs are inherently graph-structured phenomena that cannot be fully captured by flat feature vectors.

The study demonstrates that Graph Convolutional Networks [15], Graph Attention Networks [16], and heterogeneous graph learning models [17-19] provide measurable improvements in identifying suspicious billing patterns compared to conventional classification models. These findings align with more recent healthcare-specific GNN research [13, 14, 24, 25] which emphasizes that structural learning across provider–patient–claim networks significantly enhances fraud detection performance.

Furthermore, explainability mechanisms such as GNNExplainer [26] and parameterized explanation models [27] were integrated to ensure transparency in model decision-making. This is particularly important in Medicaid environments, where enforcement actions require justifiable evidence and regulatory defensibility.

Overall, the study confirms that graph-based representation learning is not merely a performance enhancement technique but a structurally appropriate modeling paradigm for Medicaid fraud detection.

## Demonstration of Improved Fraud Detection Accuracy

Empirical comparisons between baseline machine learning models and graph-based architectures demonstrated consistent performance improvements in key evaluation metrics such as Precision, Recall, F1-score, and ROC-AUC. These findings are consistent with broader fraud detection literature showing the superiority of graph-based approaches in capturing relational risk propagation [3, 7].

Traditional models such as logistic regression, random forest, and gradient boosting rely heavily on handcrafted features derived from claim-level statistics. While effective for certain anomaly patterns [8, 9], these models struggle to detect coordinated provider networks or collusive billing behaviors.

In contrast, Graph Neural Networks learn latent embeddings that incorporate neighborhood aggregation and structural dependencies [12, 20]. This enables the detection of fraud clusters and cross-entity influence effects that are otherwise invisible in tabular data representations.

Additionally, heterogeneous graph transformer models [19] and multi-channel heterogeneous graph learning frameworks [14, 26] showed particular strength in modeling multiple relation types simultaneously, improving detection robustness in highly interconnected Medicaid datasets.

The improvements in detection accuracy are not only statistically significant but operationally meaningful. Higher recall reduces missed fraudulent cases, while improved precision minimizes false accusations against legitimate providers, addressing fairness and compliance concerns.

## Importance of Heterogeneous Graph Modeling

Medicaid claims data are inherently heterogeneous. Entities include

- Providers
- Beneficiaries
- Claims
- Procedures
- Facilities
- Geographic regions

Each entity type interacts through different relationship types such as treatment provision, referral pathways, shared billing addresses, and co-prescription behaviors.

Heterogeneous graph modeling frameworks [17-19] allow explicit representation of multiple node and edge types, preserving semantic distinctions across interactions. This is crucial in healthcare fraud detection, where the meaning of a relationship significantly influences risk interpretation.

Recent healthcare-specific heterogeneous graph studies [14, 24, 25] demonstrate that multi-relational learning substantially improves detection of organized fraud rings and systemic abuse patterns.

By incorporating relational inductive bias, heterogeneous GNNs address a core limitation identified in earlier fraud detection surveys [2, 3, 5], namely the inability of independent-instance models to capture structural fraud mechanisms.

Thus, heterogeneous graph modeling is not simply a methodological innovation but a domain-aligned solution tailored to the structural nature of Medicaid systems.

## Policy Implications for Medicaid Reform

Medicaid represents a significant component of United States healthcare expenditure, with substantial federal and state investment [1]. Fraud, waste, and abuse impose financial strain and reduce resource availability for legitimate beneficiaries.

*The findings of this study have several policy implications*

- *Transition from reactive auditing to proactive AI-driven monitoring*

Graph-based systems enable early detection of coordinated fraud networks before large-scale financial losses occur.

- *Risk-based provider oversight*

Graph embeddings can generate network-informed risk scores, supporting targeted investigations rather than blanket audits.

- *Fairness and transparency*

Explainable GNN frameworks [26, 27] provide interpretable reasoning paths, which are essential for regulatory accountability and due process protections.

- *Data-sharing collaboration*

Graph modeling encourages cross-agency relational analysis, improving detection of interstate or multi-facility fraud schemes.

The integration of AI-driven graph analytics aligns with recent systematic reviews emphasizing the need for advanced machine learning in healthcare claims oversight [10, 11].

Importantly, policy deployment must include safeguards against algorithmic bias and ensure compliance with healthcare data governance standards.

## Future Directions

Future research can extend the proposed framework through federated graph learning and real-time streaming fraud detection. Federated graph learning enables multiple Medicaid agencies, insurers, or healthcare organizations to collaboratively train Graph Neural Network models without sharing sensitive patient-level data. This approach preserves data privacy while allowing models to learn broader fraud patterns across distributed healthcare systems. By leveraging decentralized training and secure aggregation techniques, federated graph frameworks can improve fraud detection performance while maintaining compliance with healthcare data protection regulations.

Another important direction is the development of real-time streaming detection systems. Most current fraud detection models operate in batch processing environments, analyzing claims after they have already been submitted and reimbursed. Integrating streaming Graph Neural Network architectures would allow continuous updates of graph representations as new claims are generated. This capability would enable early identification of suspicious billing patterns, faster intervention by regulatory agencies, and reduced financial losses within Medicaid programs.

Advances in scalable graph processing and distributed machine learning infrastructure make these approaches increasingly feasible. Integrating federated graph learning with real-time streaming analytics could ultimately support proactive, privacy-preserving fraud monitoring systems capable of detecting complex relational fraud schemes across large-scale healthcare networks.

### *Disclaimer*

This study is conducted for academic and research purposes only. The Medicaid claims structures and datasets described in this paper are simulated or conceptually modeled to demonstrate the application of Graph Neural Network techniques for detecting fraud, waste, and abuse in healthcare systems. The views and interpretations presented are solely those of the authors and do not represent the official policies or positions of any governmental agency, healthcare organization, or Medicaid program.

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