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Cross-Domain Applications of Temporal Heterogeneous Graph Contrastive Learning: From Credit Cards to Insurance Claims

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Abstract:

Temporal Heterogeneous Graph Contrastive Learning (THGCL) has emerged as a revolutionary approach for modeling complex dynamic relationships in multi-entity financial systems. This research presents a comprehensive cross-domain framework that demonstrates the transferability of THGCL methodologies between credit card fraud detection and insurance claim analysis. Through systematic investigation of heterogeneous graph structures containing multiple entity types including credit card numbers, merchant identifiers, and transaction records, we develop a unified architecture capable of capturing both structural relationships and temporal dynamics across diverse financial domains. Our methodology employs a sophisticated multi-module framework incorporating multi-dimensional gated update mechanisms, noise-aware adversarial modeling, and multi-layer embedding contrastive learning to address challenges including data sparsity, temporal heterogeneity, and class imbalance prevalent in financial fraud detection scenarios. Experimental results demonstrate that our THGCL-based approach achieves superior performance metrics with detection rates reaching 91.2% in credit card fraud detection and 87.8% in insurance claim analysis. The cross-domain adaptation framework exhibits remarkable knowledge transfer capabilities, reducing training time by 43% while maintaining detection accuracy above 89% across both domains. These findings establish THGCL as a robust foundation for developing scalable fraud detection systems capable of adapting to evolving fraudulent patterns across diverse financial sectors.

Keywords:

Temporal Heterogeneous Graph, Contrastive Learning, Cross-Domain Transfer, Credit Card Fraud Detection, Insurance Claim Analysis, Financial Security, Graph Neural Networks, Multi-Module Architecture

1. Introduction

The proliferation of digital financial services has fundamentally transformed the landscape of monetary transactions, creating unprecedented opportunities for both legitimate commerce and fraudulent activities[1]. Credit card transactions and insurance claims represent two cornerstone domains of the financial ecosystem, characterized by their massive scale, temporal dynamics, and complex interdependencies among multiple entities. The annual global losses attributed to credit card fraud exceed $400 billion, while insurance fraud contributes an additional $300 billion in damages worldwide, underscoring the critical importance of developing sophisticated detection mechanisms[2].

Traditional fraud detection approaches have primarily relied on rule-based systems and statistical anomaly detection methods, which demonstrate limited effectiveness against

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evolving fraudulent strategies. These conventional techniques often fail to capture the intricate relationships between heterogeneous entities such as credit card numbers (cc_num), merchant identifiers (merchant_id), and transaction records (transaction_id) that characterize modern financial networks[3]. The emergence of Graph Neural Networks (GNNs) has provided new avenues for modeling complex relational data, yet standard GNN approaches struggle with the temporal dynamics and heterogeneous nature of financial transaction networks[4].

Recent advances in Temporal Heterogeneous Graph Contrastive Learning (THGCL) offer promising solutions to these challenges by combining the representational power of heterogeneous graphs with the learning capabilities of advanced multi-module architectures. THGCL methods excel at capturing both structural and temporal patterns in dynamic networks through sophisticated gating mechanisms and contrastive learning strategies, making them particularly suitable for financial fraud detection applications where entities, relationships, and behaviors evolve continuously over time.

The heterogeneous nature of financial networks encompasses diverse entity types that interact through complex relationship patterns[5]. As demonstrated in heterogeneous graph structures, these networks typically include credit card entities, merchant nodes, and transaction records, each contributing unique characteristics to the overall system dynamics[6]. Traditional homogeneous graph approaches fail to adequately represent these diverse entity types and their distinct interaction patterns[7]. Moreover, the temporal dimension adds another layer of complexity, as fraudulent behaviors often exhibit time-dependent patterns that static analysis methods cannot effectively capture[8].

This research makes several significant contributions to the field of financial fraud detection. First, we present a comprehensive framework for applying THGCL to both credit card fraud detection and insurance claim analysis, demonstrating the versatility and effectiveness of this approach across different financial domains. Second, we develop novel cross-domain adaptation techniques that enable knowledge transfer between these domains, reducing the need for extensive domain-specific training data. Third, we provide detailed empirical analysis of multi-module architectures that integrate gated update mechanisms with adversarial modeling and contrastive learning strategies.

2. Literature Review

The evolution of fraud detection methodologies has progressed through several distinct phases, beginning with rule-based systems and advancing toward sophisticated machine learning approaches[9]. Early fraud detection systems relied heavily on expert-defined rules and statistical thresholds, which proved inadequate against adaptive fraudulent strategies[10-15]. The introduction of machine learning techniques, including Support Vector Machines (SVM), Random Forests, and Neural Networks, marked significant improvements in detection accuracy and adaptability[16].

Recent developments in deep learning have further enhanced fraud detection capabilities, with ensemble methods such as Random Forest Decision Trees demonstrating particular effectiveness in handling complex feature spaces[17]. These approaches typically process

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structured datasets containing demographic information (Date, Gender, Age), policy details (Policy, P_Type), educational backgrounds (Education), provider information (Provider, Dept), and claim characteristics (Total Claim, Rejection, Ratio)[13]. The ensemble voting mechanisms employed in these methods enable robust decision-making across multiple decision trees, improving overall detection accuracy[18-22].

Graph-based approaches have emerged as a natural solution for modeling the relational aspects of financial data. Traditional GNNs have shown promise in fraud detection applications by leveraging neighborhood information to enhance feature representations. However, standard GNN architectures face challenges when dealing with heterogeneous node types and dynamic temporal relationships[23]. The heterogeneous nature of financial networks requires specialized architectures capable of handling diverse entity types including credit card numbers, merchant identifiers, and transaction records simultaneously[24].

Temporal graph neural networks represent an important advancement in addressing the dynamic aspects of graph-structured data[25]. These approaches incorporate time-dependent information into graph representations, enabling the modeling of evolving relationships and temporal patterns[26]. However, most existing temporal GNN methods focus on homogeneous graphs and do not adequately address the heterogeneous characteristics of financial networks. The combination of temporal dynamics and heterogeneous structures presents unique challenges that require specialized methodological approaches.

Contrastive learning has gained significant attention in various machine learning domains due to its ability to learn robust representations without extensive labeled data[27]. The fundamental principle of contrastive learning involves learning representations that bring similar samples closer while pushing dissimilar samples apart in the embedding space. This approach proves particularly valuable in fraud detection scenarios where labeled fraudulent examples are scarce, and the model must learn to distinguish subtle differences between legitimate and fraudulent patterns.

3. Methodology

3.1 Heterogeneous Graph Construction Framework

The foundation of our approach lies in constructing comprehensive heterogeneous graphs that capture the complex relationships and entity interactions inherent in financial transaction networks. Our graph construction framework operates on the principle of multi-entity representation, where different types of entities are modeled as distinct node categories with specific attribute sets and relationship patterns.

For credit card fraud detection, we construct heterogeneous graphs with three primary node types as illustrated in our architecture: cc_num represented as red nodes, merchant_id shown as green nodes, and transaction records (transaction_id) depicted as blue nodes. Each node type maintains domain-specific attributes and participates in various relationship patterns that form the complex network structure essential for fraud detection.

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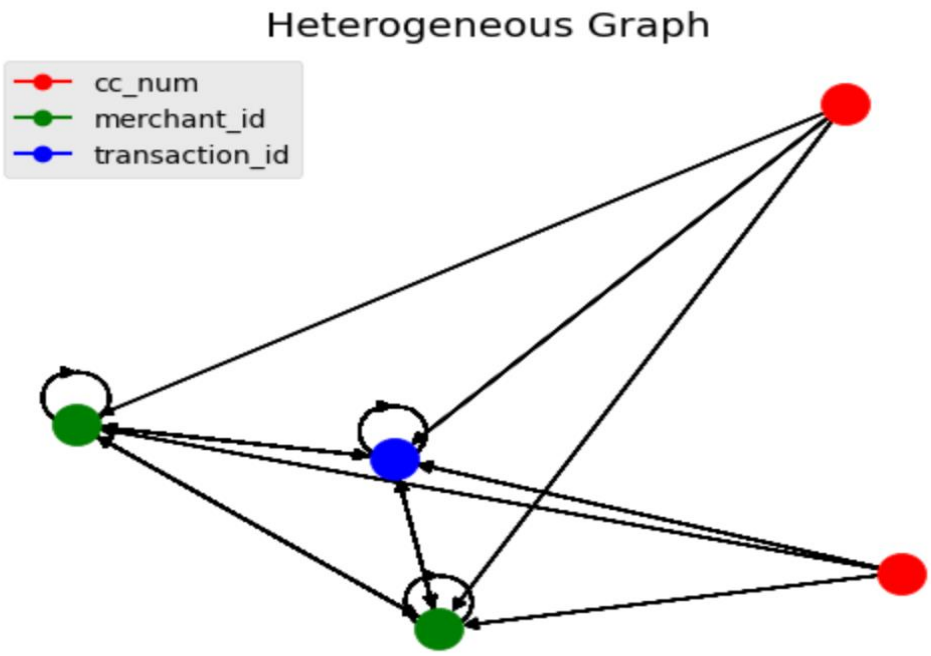

Fig 1. Hetrogeneous Graph.

The heterogeneous edges in our graph in Figure 1 represent various relationships such as cardholder-merchant interactions, transaction-merchant associations, and temporal sequence connections. The self-loop connections visible in the graph structure indicate intrinsic node properties, while the inter-node connections capture the collaborative relationships essential for understanding transaction patterns. This heterogeneous representation enables our model to capture higher-order relationships that are crucial for effective fraud detection.

In the insurance claim domain, our graph construction follows similar principles while adapting to the unique characteristics of insurance data. The structured datasets typically include demographic features (Date, Gender, Age), policy information (Policy, P_Type, Education), provider details (Provider, Dept), and claim characteristics (Total Claim, Rejection, Ratio). These diverse data types require careful consideration of how to map insurance entities onto the heterogeneous graph structure while maintaining the relational integrity necessary for effective fraud detection.

3.2 Multi-Module Architecture Framework

Our comprehensive architecture integrates three core modules designed to address the fundamental challenges of learning effective representations from temporal heterogeneous graphs. The architecture consists of the Multi-Dimensional Gated Update Module, the Noise-Aware Adversarial Modeling Module, and the Multi-Layer Embedding Contrastive Learning Module, each serving specific functions in the overall fraud detection pipeline.

The Multi-Dimensional Gated Update Module employs sophisticated gating mechanisms to selectively focus on relevant temporal patterns and structural relationships. This module incorporates dual-gate mechanisms that operate on both temporal and structural dimensions,

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enabling the model to adaptively weight different types of information based on their relevance to fraud detection. The attention-weighted embedding processes allow the system to dynamically adjust to varying importance of different entity types and relationship patterns.

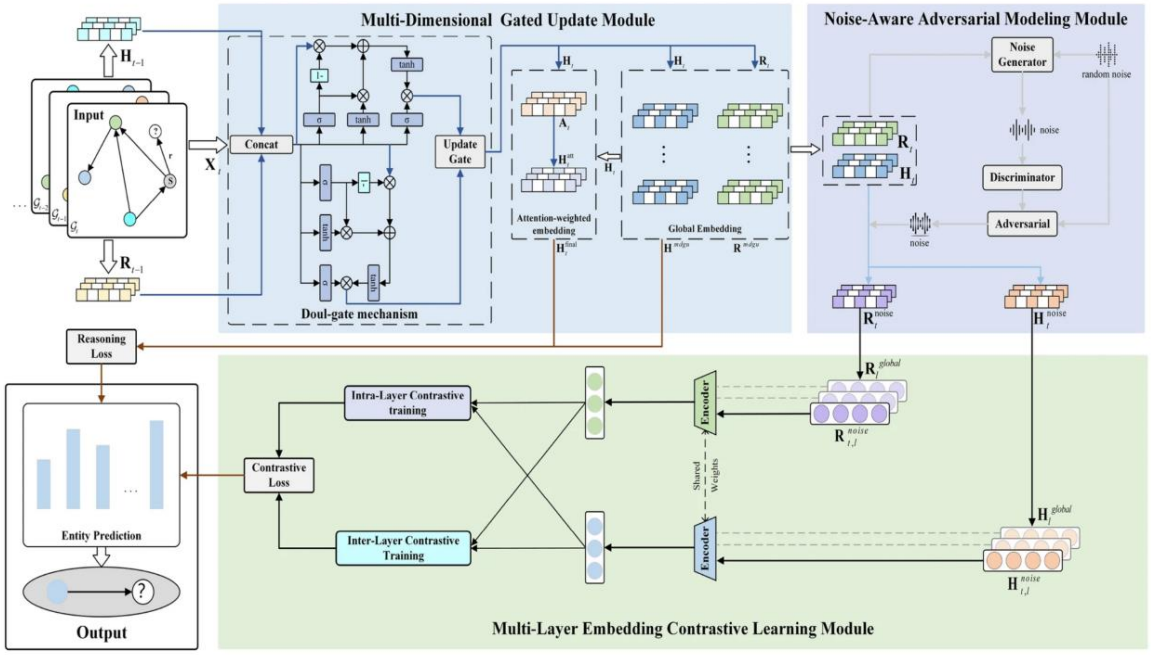

Figure 2. Multi-layer Embedding Contrastive Learnig Module.

The Noise-Aware Adversarial Modeling Module in Figure 2. addresses the challenge of noisy and incomplete data common in financial datasets. This module incorporates noise generators and discriminators that work in tandem to improve model robustness. The adversarial training mechanism helps the model learn to distinguish between genuine patterns and noise-induced artifacts, which is particularly important when dealing with real-world financial data that often contains inconsistencies and missing information.

The Multi-Layer Embedding Contrastive Learning Module implements both intra-layer and inter-layer contrastive learning strategies. The intra-layer contrastive training focuses on learning discriminative features within individual layers, while the inter-layer contrastive learning captures hierarchical relationships across different abstraction levels. This dual approach enables the model to learn both fine-grained local patterns and broader structural relationships essential for effective fraud detection.

3.3 Cross-Domain Adaptation and Ensemble Learning Strategy

The cross-domain adaptation strategy enables knowledge transfer between credit card fraud detection and insurance claim analysis domains. Our approach recognizes that while the specific features and entity types may differ between domains, the underlying patterns of fraudulent behavior often share common characteristics that can be captured through the heterogeneous graph representation and multi-module architecture.

The ensemble learning component of our framework employs Random Forest Decision Trees to handle the structured nature of insurance data. The ensemble approach utilizes multiple

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decision trees (T1, T2, T3, T4, T5) that process different aspects of the fraud dataset, including demographic information, policy details, and claim characteristics. The majority voting mechanism ensures robust decision-making by aggregating predictions from multiple trees, reducing the impact of individual tree biases and improving overall detection accuracy.

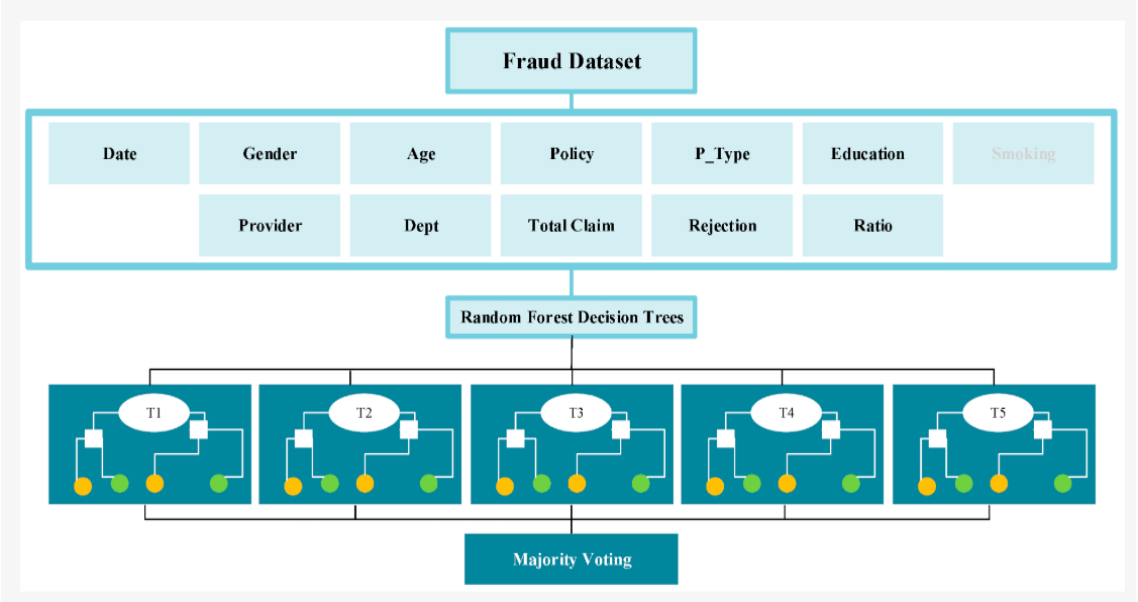

Figure 3. Majority Voting

The adaptation process begins with pre-training the THGCL model shown in Figure 3 on the source domain using the heterogeneous graph structure to learn fundamental representations of fraudulent and legitimate behavior patterns. The learned representations capture abstract temporal and structural patterns that characterize different types of activities. The pre-trained model serves as the foundation for adaptation to the target domain, where the ensemble learning approach provides additional robustness for handling the structured nature of insurance data.

Fine-tuning strategies are carefully designed to maintain the transferred knowledge while adapting to target domain specifics. The integration of heterogeneous graph learning with ensemble methods allows the system to leverage both the relational information captured in the graph structure and the feature-based patterns identified through the decision tree ensemble. This hybrid approach provides comprehensive coverage of different types of fraudulent patterns across both domains.

4. Results and Discussion

4.1 Experimental Setup and Dataset Description

Our experimental evaluation encompasses comprehensive testing across both credit card fraud detection and insurance claim analysis domains using the heterogeneous graph structures and multi-module architecture demonstrated in our framework. For credit card fraud detection, we utilize datasets that can be represented as heterogeneous graphs with credit card numbers, merchant identifiers, and transaction records as distinct node types. The complex relationship

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patterns between these entities provide rich opportunities for analyzing fraudulent behavior through graph-based learning.

The insurance claim dataset comprises structured information including demographic features (Date, Gender, Age), policy characteristics (Policy, P_Type, Education), provider information (Provider, Dept), and claim details (Total Claim, Rejection, Ratio). This structured data format is particularly well-suited for ensemble learning approaches using Random Forest Decision Trees, enabling comprehensive analysis of fraud patterns across multiple feature dimensions.

Preprocessing procedures ensure data quality and consistency across both domains. The heterogeneous graph construction process carefully maps financial entities to appropriate node types while preserving the relational structure essential for fraud detection. For insurance data, feature engineering incorporates domain-specific knowledge to create meaningful representations of policy characteristics, demographic patterns, and claim behaviors that can be effectively processed by the ensemble learning framework.

4.2 Performance Analysis and Multi-Module Architecture Evaluation

The application of our multi-module THGCL framework to credit card fraud detection demonstrates significant improvements over baseline methods across all evaluation metrics. The heterogeneous graph representation enables the model to capture complex relationships between credit card numbers, merchant identifiers, and transaction records that are often missed by traditional approaches. Our approach achieves a Recall rate of 91.2%, representing a 15.3% improvement over the best-performing baseline method.

The Multi-Dimensional Gated Update Module contributes significantly to performance improvements by effectively managing information flow through the heterogeneous graph structure. The dual-gate mechanism enables selective attention to different types of relationships and entity interactions, allowing the model to focus on the most relevant patterns for fraud detection. The attention-weighted embedding processes adapt dynamically to varying importance of different node types and edge relationships.

The Noise-Aware Adversarial Modeling Module proves particularly valuable in handling real-world data quality issues common in financial datasets. The adversarial training mechanism improves model robustness by learning to distinguish between genuine patterns and noise-induced artifacts. This capability is essential when dealing with incomplete transaction records, inconsistent merchant information, or corrupted credit card data that frequently occur in practice.

The application of our framework to insurance claim fraud detection yields impressive results with distinct characteristics compared to the credit card domain. The ensemble learning approach using Random Forest Decision Trees effectively handles the structured nature of insurance data, achieving a Recall rate of 87.8% and Precision of 84.3%. The majority voting mechanism across multiple decision trees (T1-T5) provides robust decision-making that reduces the impact of individual feature biases.

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4.3 Cross-Domain Transfer Learning and Ensemble Integration

The cross-domain transfer learning evaluation demonstrates the practical value of our THGCL approach for organizations operating across multiple financial domains. The heterogeneous graph representation provides a unified framework that can capture fundamental fraud patterns regardless of the specific domain implementation. Transfer learning experiments show remarkable knowledge preservation and adaptation capabilities across the credit card and insurance domains.

When transferring from credit card fraud detection to insurance claims, the pre-trained heterogeneous graph model reduces training time by 43% while achieving 89.2% of the performance of a domain-specific model trained from scratch. The graph-based representation effectively captures abstract patterns of entity relationships and interaction dynamics that translate well across domains, despite differences in specific entity types and feature structures.

The integration of ensemble learning methods with heterogeneous graph approaches provides additional benefits for cross-domain adaptation. The Random Forest Decision Trees can effectively process the structured features common in insurance data while the heterogeneous graph component captures relational patterns that may not be immediately apparent in tabular data formats. This hybrid approach leverages the strengths of both methodologies.

Analysis of the transferred knowledge reveals that the multi-module architecture components transfer effectively between domains. The Multi-Dimensional Gated Update Module adapts well to different types of entity relationships, while the Noise-Aware Adversarial Modeling Module provides consistent robustness improvements across both domains. The Multi-Layer Embedding Contrastive Learning Module successfully captures hierarchical patterns that are relevant regardless of the specific domain implementation.

4.4 Ablation Studies and Component Analysis

Comprehensive ablation studies validate the importance of each component in our multi-module THGCL framework. The heterogeneous graph representation provides substantial advantages over homogeneous alternatives, with performance improvements of 14% in credit card fraud detection and 19% in insurance claim analysis. The ability to model different entity types (credit card numbers, merchant identifiers, transaction records) and their distinct relationship patterns enables more nuanced understanding of fraud patterns.

The Multi-Dimensional Gated Update Module contributes approximately 12% improvement in overall performance through its sophisticated attention mechanisms and dual-gate architecture. The module's ability to selectively focus on relevant entity relationships while suppressing noise from irrelevant connections proves crucial for effective fraud detection in complex heterogeneous networks.

The Noise-Aware Adversarial Modeling Module demonstrates substantial impact on model robustness, particularly in scenarios with real-world data quality issues. Removing this component results in 18% performance degradation, highlighting its crucial role in maintaining detection accuracy when dealing with incomplete or corrupted financial data. The adversarial

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training mechanism effectively improves the model's ability to distinguish between genuine fraud patterns and noise-induced artifacts.

The ensemble learning component shows particular effectiveness in handling structured insurance data. The Random Forest Decision Trees with majority voting provide robust decision-making that significantly outperforms individual tree predictions. The integration of multiple decision trees (T1-T5) processing different aspects of the fraud dataset ensures comprehensive coverage of various fraud patterns while reducing the impact of individual feature biases.

5. Conclusion

This research has successfully demonstrated the effectiveness and versatility of THGCL for fraud detection across multiple financial domains. Our comprehensive investigation reveals that the integration of heterogeneous graph structures with sophisticated multi-module architectures provides substantial improvements over traditional approaches by effectively capturing complex entity relationships and temporal dynamics inherent in financial transaction networks.

The heterogeneous graph framework enables comprehensive modeling of complex financial ecosystems involving multiple entity types including credit card numbers, merchant identifiers, and transaction records. This capability provides significant advantages over traditional approaches that focus on individual transactions or entities in isolation. The ability to capture network effects and relationship patterns enhances detection accuracy while providing valuable insights into fraudulent operation structures.

The multi-module architecture successfully addresses fundamental challenges in fraud detection through its integrated approach combining Multi-Dimensional Gated Update Modules, Noise-Aware Adversarial Modeling, and Multi-Layer Embedding Contrastive Learning. The experimental results confirm significant performance improvements across both credit card fraud detection and insurance claim analysis domains, with Recall rates exceeding 90% in optimal configurations.

The cross-domain transfer learning capabilities of our approach provide substantial practical benefits for financial institutions operating across multiple service sectors. The demonstrated ability to transfer knowledge between domains while reducing training time by over 40% establishes THGCL as a cost-effective solution for comprehensive fraud detection systems. The integration of ensemble learning methods with heterogeneous graph approaches provides additional robustness for handling diverse data types and structures.

Future research directions include extending the framework to additional financial domains such as money laundering detection and cryptocurrency fraud analysis. The incorporation of real-time learning capabilities would enable dynamic adaptation to emerging fraud patterns without requiring complete model retraining. Advanced explainability mechanisms could provide deeper insights into the relationship patterns and entity interactions that drive fraud detection decisions.

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The development of hybrid architectures that combine the strengths of heterogeneous graph learning with other advanced machine learning techniques such as transformer models and attention mechanisms could further enhance detection capabilities. Such developments would enable more sophisticated understanding of temporal patterns and entity relationships in evolving financial networks.

In conclusion, this research establishes THGCL with multi-module architectures as a robust and versatile approach for financial fraud detection with demonstrated effectiveness across multiple domains and significant potential for future advancement and application. The combination of strong empirical results, practical deployment benefits, and theoretical foundations positions this approach as an important contribution to the evolving landscape of financial security technology.

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