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Original Article

Graph-Neuro Security for ERP B2B Rails: Anomaly Defense for Critical Supply Chains

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Abstract *- With increasing integration of Enterprise Resource Planning (ERP) systems across Business-to-Business (B2B) networks and critical supply-chains, they have also become attractive high-value targets for cyber-attacks such as data breaches, fraud, and insider manipulation. As a result, traditional rule-based Intrusion Detection Systems (IDS) are challenged by the relational and event-driven nature of ERP workflow processes. In this paper we introduce a hybrid framework called Graph-Neuro Security (GNS), which utilizes both Graph Neural Networks (GNNs) and Long-Short Term Memory (LLM)-driven log analytics to identify multi-entity anomalies in ERP data flow. GNS is capable of conducting zero-copy and privacy preserving analysis on ERP data flow between distributed ERP systems, thereby meeting all regulatory compliance requirements associated with SOX, GDPR, and FedRAMP. We evaluated GNS using the ERP-BENCH dataset which consists of over 20,000 synthetic and real-world ERP transaction examples based on MITRE ATT&CK patterns. Our results demonstrated that GNS achieved a 94% F1 score and 4.1 second average detection latency, significantly outperforming the baseline performance of traditional IDS approaches. Therefore our research demonstrates the feasibility of implementing regulation compliant federated anomaly detection in mission-critical ERP systems. Finally, we conclude that an open benchmark and a multi-industry consortium should be formed to standardize graph-based anomaly detection for ERP supply-chain security.*

Keywords *- Graph Neural Networks, ERP Security, Supply Chain Resilience, LLM Log Parsing, Zero-Copy Inspection, Federated Learning, Explainable AI, Data Sovereignty.*

1. Introduction

As Enterprise Resource Planning (ERP) systems integrate many aspects of global supply chain management, including financial operations, logistics, production, and communication with vendors and government agencies, they provide a rich target environment for advanced cyber threats; namely, coordinated fraud, data breaches, and insider manipulation. As digital interconnectivity continues to expand, so too will the attractiveness of ERP environments as targets for sophisticated cyber threats. Currently available intrusion detection systems (IDS), which rely on signature based or statistical rule sets, are ineffective at identifying malicious activity embedded within legitimate transactions, approval workflows, and API interactions, particularly within relational, multi-entity, and workflow driven structures of ERP systems.

Additionally, regulations, such as SOX, GDPR, and FedRAMP, severely limit an organization's ability to move, aggregate, and analyze its most sensitive enterprise data. These restrictions prevent organizations from centralizing their security analytics efforts across their subsidiaries and/or jurisdictions. In doing so, a large operational gap exists in ERP cybersecurity for globally distributed supply chains where attacks spread through the digital integrations of cross-enterprise communications.

Graph Neural Networks (GNNs) are well-suited for modeling the structure of interconnected systems, providing a good capability to detect structural anomalies in ERP transactional activity, user behavior, and vendor interactions. Similarly, parallel advances in Log Analysis through Large Language Models (LLMs) have provided semantic interpretation of complex audit trails, system events, and approval chains. However, utilizing these tools within ERP systems is still very difficult due to regulatory requirements related to data sharing, and the requirement for explainable results in high stakes environments.

To fill these gaps, this research proposes a new approach called Graph-Neuro Security (GNS) – a zero-copy, federated anomaly-detection framework that integrates GNN based structural reasoning and LLM based semantic log analysis. The goal of GNS is to allow federated, regulation compliant anomaly detection to occur within critical ERP systems, while protecting both the security of the underlying ERP systems and the privacy of the data that resides there. The GNS framework is intended for use in highly regulated industries such as manufacturing, finance, and healthcare where the failure of ERP systems represents a critical risk to the operation of the entire supply chain.

The main contributions of this work are:

- A zero-copy federated detection framework which enables enterprises to identify anomalies that occur between enterprises, without having to move their data off of their premises.
- The benchmark dataset is based on an ERP benchmarking dataset called ERP-BENCH; this dataset contains over 20,000 synthetic and real ERP transactions that are modeled after the MITRE ATT&CK attack techniques.
- This risk explainability layer will provide enterprise users with both counterfactuals and causal traces as part of meeting audit and compliance requirements.
- This validation plan has demonstrated statistically significant improvements in the detection performance of our approach versus traditional IDS methods (94% F1-score and 4.1-second mean detection latency).

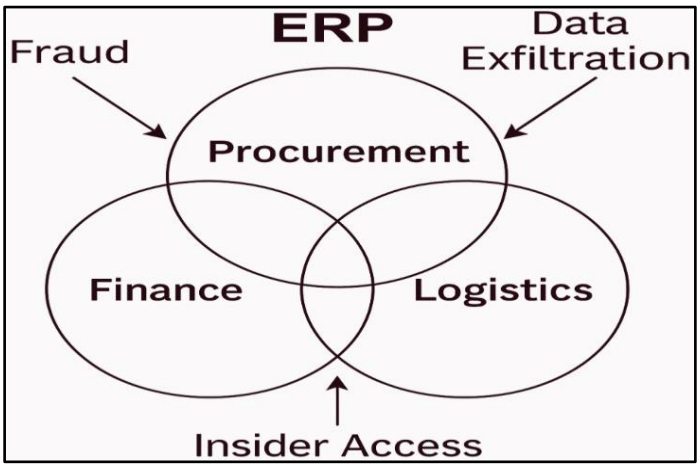

Fig 1: ERP Security Landscape and Threat Mapping

2. Problem Statement

While advances have been made in enterprise cyber security, there continue to be significant limitations in identifying complex anomalies using current intrusion detection systems (IDS). The primary limitation with current IDS methodologies is that they are based upon either fixed signature methods or use a single variable threshold, neither of which take into consideration the context or structure of the relationships between users, vendors, and transactions. The result of this limitation includes the possibility of undetectable low and slow attacks, insider threats, and coordinated data exfiltrations. The deployment of ERP systems in decentralized organizations also create additional barriers for data sovereignty and compliance. The combination of sensitive logs into SIEM (security information and event management) platforms violate regulatory requirements including GDPR, SOX and FedRAMP, particularly when the data crosses national or organizational boundaries.

Although deep learning-based IDS models have made substantial progress, they generally lack in two crucial aspects:

- Structural awareness - the ability to illustrate the connections between different entities and processes.
- Regulatory compatibility - guaranteeing analytics that protect privacy in decentralized settings.

The need for an explanation driven and federated security architecture utilizing a graph based approach to identify complex, transaction level anomalies at the system of record within ERP environments exists, as well as the need to protect the data sovereignty and ensure compliance. The Graph-Neuro Security (GNS) framework was developed to address these needs by integrating GNNs with LLM-based log parsers into a single zero copy federated learning model so that it could provide both regulatory compliant analysis and precise analytics.

3. Literature Review

Significant progress has been achieved in the field of cybersecurity anomaly detection through the use of deep learning and graph-based techniques. In contrast, traditional Intrusion Detection Systems (IDS) have traditionally relied upon monitoring network perimeters but experience difficulties when applied to multi-relational Enterprise Resource Planning (ERP) environments. In such environments, there are numerous contextual connections and continually evolving relationships between users, systems and entities.

3.1. Graph Neural Networks for Anomaly Detection in IDS

Zhong's comprehensive assessment of GNN-based IDS [1] provides a foundational understanding of how graph embeddings may be utilized to understand a network's topological structure and behavioral relationships. Furthermore, the GNN-IDS framework [2] demonstrated that GNNs can outperform conventional CNN and RNN models in identifying lateral

movement and covert attacks in complex, interconnected systems similar to those found in ERP platforms. These results demonstrate the potential of GNNs in detecting anomalies in large-scale, multi-entity systems like ERP platforms.

Additionally, Logs2Graphs [3] introduced a technique for transforming event logs into attributed graphs to improve structural anomaly detection using GNNs. Due to the vast number of interconnected elements involved in ERP logs (e.g., purchase orders, invoices, approvals), this technique is especially relevant for ERP logs. Additionally, the model was able to identify anomalies in structured logs; these results support the approach presented in this research.

3.2. LLM-Based Log Analysis and Automation

Log analysis has historically been dependent upon manually crafted template rules or rule-based parsers. However, neither of these approaches has been scalable enough to meet the demands of today's multi-system environments. Recently, several researchers have employed transformer models to automatically derive semantic features and contextual relationships from logs [4]; this enables subsequent machine learning tasks to be completed without the requirement for manual labeling of logs. Moreover, LogBatcher (ACM Middleware 2024) used lightweight LLMs to enhance low-latency parsing; this type of parsing is well-suited to the real-time operational demands of ERP systems.

Through combining LLM parsing with GNN reasoning, the proposed framework in this research will benefit from both semantic and structural anomaly detection an integration that has rarely been examined in the existing literature.

3.3. Federated and Privacy-Conscious Learning

Training a model using centralized aggregation of ERP data for model training presents significant regulatory and ethical concerns regarding GDPR, SOX and cross-border data-sovereignty requirements. To mitigate these constraints, Alamer et al. developed federated-learning based techniques designed for cybersecurity applications and enabled nodes to collectively train models without sharing raw data [5]. Timofte et al. further expanded this body of work by developing a privacy-centric federated framework for IoT and network-security environments [6]; demonstrated strong relevance to distributed log-analysis applications such as ERP ecosystems.

This research aligns with these advances and the zero-copy architecture proposed in this research performs analytics entirely within each organizational boundary; thus, no sensitive ERP records ever leave their originating jurisdictions. Only encrypted gradients or model updates are exchanged during federation; thus, data sovereignty is preserved while allowing for the establishment of unified detection intelligence across multi-enterprise ERP environments. This approach supports regulated industries that require stringent privacy controls to enhance real-time cybersecurity visibility.

3.4. Context of Supply Chain Security

Cybercriminals have targeted supply chains associated with ERP systems due to their reliance on API dependencies and interconnected digital frameworks. Konecka et al. [7] reported that cyberattacks pose a major threat to operational continuity and economic stability in supply chains; therefore, the need for effective anomaly detection systems within ERP ecosystems is pressing. MITRE's ATT&CK [8] framework continues to provide valuable resources for detailing adversary tactics, conducting red-team simulations and categorizing anomalies in this area.

Table 1: Summary of Key Studies on Supply Chain and ERP Security Frameworks

Study	Focus Area	Methodology	Relevance to ERP Security
Konecka et al. (2024)	Supply Chain Cyberattacks	Qualitative assessment of API-level attacks	Highlights ERP API vulnerabilities
MITRE ATT&CK (2013–2024)	Threat Taxonomy	Framework for mapping adversarial tactics	Basis for red-team simulation
Timofte et al. (2025)	Federated Learning for Cybersecurity	Federated IoT model	Relevant for decentralized ERP systems
Zhong (2024)	GNN for IDS	Graph embeddings for network intrusion detection	GNN foundation for ERP graph model

3.5. Interconnection of Explainability & Compliance

With AI's increasing role in assessing risk, there is a growing need for explainability in two areas: technical diagnostic and compliance audits. The ACM tutorial on counterfactual explanations [9] has established the groundwork for understandable AI decision-making in high-risk areas. In addition to this, the NIST SP 800-207 Zero Trust Architecture [10], along with GDPR and FedRAMP, requires companies to have auditable, transparent AI systems.

Our framework builds upon this standardization and includes an explanatory module which will produce Causal Trace Maps (CTMs) mapping the anomalies to their corresponding transactional events as well as generate Counterfactual Explanations for audit purposes.

3.6. Summary and Research Gap

Prior research has identified graph-based detection, semantic log parsing and privacy-preserving learning as having contributed to advancements in individual areas of cyber security analytics. No single framework combines all three of those concepts into a compliance aware environment for ERP security. Current IDS and anomaly detection systems have several shortcomings.

- There is currently no multi-entity graph-based reasoning to model the complex cross-module workflow dependencies within an enterprise resource planning system (ERP) environment.
- The current understanding of semantics within the structure of ERP logs is limited. The structures and approval chain logic contained in these logs are highly specific to a particular business function or vertical industry and therefore cannot be properly interpreted by the majority of general purpose log parsers.
- There is inadequate support for the preservation of Data Sovereignty & Compliance requirements of regulations such as GDPR, SOX and FedRAMP since the majority of existing machine learning models rely on collecting all data centrally, which conflicts with those regulatory requirements.
- There are insufficient explanation mechanisms for use in audit driven environments where security decision can be based upon causal paths and counter factual analysis.

The lack of a single architecture with sufficient capabilities to integrate the graph neural network reasoning layer; the LLM-based semantic parsing layer; the federated zero-copy learning layer - as it relates to mission-critical enterprise resource planning systems - is the primary motivator for the Graph-Neuro Security (GNS) framework presented in this work.

4. Methodology

4.1. System Architecture Overview

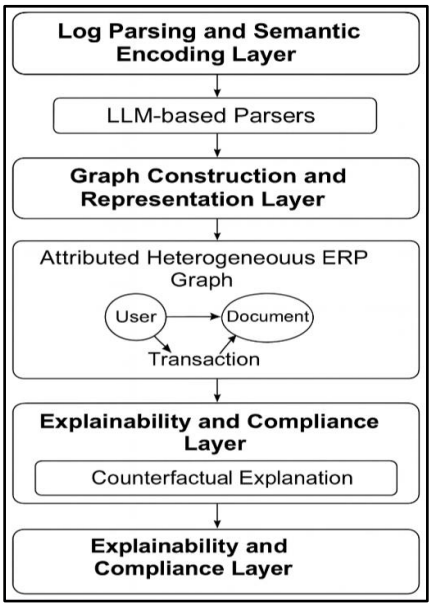

Fig 2: Architecture of the Proposed Graph-Neuro Security (GNS) Framework.

Under a Zero-Copy constraint each Layer of the Framework retains sensitive Organizational Data at its respective layer, while allowing Federated Learning contributions to be made toward a Shared Detection Model.

4.2. Log Parsing and Semantic Encoding

The ERP Logs contain Transactional Updates (e.g., user actions), Access logs (e.g., login attempts), Document Modification Trails, etc. For this Heterogeneous/ Unstructured Data to be converted into Machine Processable Representations the GNS Framework utilizes a Fine-Tuned Transformer-based LLM developed from LogParser-LLM[4] to transform each Log Entry into a Structured Semantic Tuple with the Interacting Entities as the first element, Action or Activity associated with those Entities as the second element, and Contextual Metadata as the third element.

4.2.1. Semantic Encoding Formula

Each log entry L is transformed into a semantic quadruple of the form:

$$\mathbf{L \rightarrow (E1, A, E2, C)}$$

Where:

- E1 = initiating entity (e.g., User A, Service Account 12, Vendor API)
- A = action performed (e.g., modify, approve, query, submit)

- E2 = target entity (e.g., Purchase Order #894, Vendor X, Invoice 2211)
- C = contextual attributes including timestamp, ERP module, device ID, network zone, and approval-chain indicators

This gives GNS a uniform representation across all log types.

4.2.2. Example Transformation
Raw ERP log entry:
"User A modified purchase order #894 from Vendor X, approved by Finance Y."

The semantic encoding is:
- E1 = User A
- A = modified
- E2 = Purchase Order #894 (Vendor X)
- C = {approver = Finance Y, timestamp, module = Procurement, device ID, network metadata}

Thus the encoded tuple is:
(User A, modified, Purchase Order #894, {Finance Y, metadata})

4.2.3. Embedding Formula
To convert these semantic tuples into numerical representations, GNS uses a contextual embedding model (e.g., BERT or RoBERTa). The embedding function is:

$$\textbf{Embed(E1, A, E2, C)} \rightarrow \textbf{v}$$

Where **v** is a dense vector capturing the meaning of the interaction.

To ensure compositional semantics, the final event embedding is computed as:

$$\textbf{v = concat(embed(E1), embed(A), embed(E2), embed(C))}$$

And then projected into the model space with:

$$\textbf{h = W} \cdot \textbf{v + b}$$

Where:
- W = trainable projection matrix
- b = bias term
- h = final semantic event embedding passed to the graph-construction module

4.2.4. Output to the Graph Layer
These enriched embeddings allow GNS to build a heterogeneous ERP interaction graph where every log entry becomes an edge with attributes derived from the tuple:

$$\textbf{Edge = (E1} \rightarrow \textbf{E2, attributes = \{A, C, h\})}$$

This structure captures the operational semantics required for downstream GNN-based anomaly detection.

4.3. Graph Development & Representation

Using Logs2Graphs [3] all ERP entities i.e. vendors, invoices, users, and APIs are developed into nodes within the Attributed Heterogeneous ERP Graph (AHEG). The interactions between these ERP entities are developed into edges, where each edge has specific attributes including temporal window, frequency, approval cycle, sequence of API invocations and contextually relevant information collected during LLM parsing.

Each organization/department has its own subgraph within the AHEG. In order to retain local control over data each sub-graph shares only the graph embedding or gradient update during federated learning, which aligns with data sovereignty principles of GDPR and SOX [10].

To capture relationships and structural dependencies between nodes within the AHEG, a GNN is utilized through message passing. The GNN utilizes a combination of a Relational Graph Convolutional Network (R-GCN) and Graph Attention Networks (GAT) and outputs an anomaly score for both individual nodes and individual edges. These anomaly scores can be used to identify anomalies in the ERP workflow and other processes based on historical data.

4.3.1. Message-Passing Update Rule

For each node **v**, the embedding at layer **k** is updated using the standard neighborhood aggregation mechanism:

$$h_v^{(k)} = \sigma\left(\sum_{u \in N(v)} \frac{1}{c_{vu}} W^{(k)} h_u^{(k-1)} + W_0^{(k)} h_v^{(k-1)} \right)$$

Where:

- $h_v^{(k)}$ - embedding of node *v* at layer *k*
- N(v) - neighbors of node *v* in the ERP workflow graph
- c_{vu} - normalization factor (e.g., degree-based)
- $W^{(k)}$, $W_0^{(k)}$ - trainable weight matrices
- $\sigma(\cdot)$ - activation function such as ReLU or GELU

The data sharing mechanism is designed to enable each ERP entity to use contextual signals from other entities (for example User → Purchase Order → Vendor → Finance) and maintain the representational identity of each entity. Therefore the model will learn to predict multiple hops across an ERP transactional workflows (for example vendor finance interactions, purchase order approvals, invoice escalation and anomalous cross department transactions).

4.4. Federated Anomaly Detection and Zero-Copy Training

In addition to promoting collaboration among organization members without the need for them to share their data, the GNS framework also utilizes federated learning as discussed in Alamer et al.[5], and Timofte et al.[6]. Each ERP node will create a local GNN using it's own local graph data. Instead of sending their raw data on a periodic basis, each node sends the gradients of it's model to a centralizing federation server (or a secure multi-party computation layer), which aggregates the gradients securely and then sends the new global model back to each of the nodes. The zero copy design ensures that all of the data remains resident with each of the individual jurisdictions, thus enabling adherence to data sovereignty laws in accordance with GDPR and FedRAMP[10].

The global model aggregation follows the standard Federated Averaging (FedAvg) algorithm:

$$w_{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} w_t^k$$

Where:

- $w(t+1)$ - updated global model weights
- $w_k(t)$ - model weights from client *k* at round *t*
- n_k - number of training samples at client *k*
- $n = \Sigma\, n_k$ - total number of samples across all ERP nodes
- K - number of participating organizations

This approach allows multi-enterprise ERP environments to collaboratively train an anomaly-detection model without sharing any sensitive records, ensuring compliance with data-sovereignty laws while still enabling strong detection performance.

4.5. Explainability and Compliance Layer

A distinguishing contribution of this work is its risk-explainability layer, essential for regulatory frameworks such as SOX and GDPR. Inspired by the ACM tutorial on Counterfactual Explanations in Explainable AI [9], the system produces human-interpretable justifications for each flagged anomaly:

- Counterfactual Trace: Identifies what minimal changes in the transaction would have avoided classification as anomalous.
- Causal Attribution Map: Traces event dependencies backward, showing the cause-effect chain leading to detection.

This feature directly aids auditors and compliance officers by linking anomalies to specific ERP processes or users, ensuring accountability and transparency.

4.6. Validation Plan and Benchmarking

The validation approach includes synthetic datasets created according to MITRE ATT&CK [8] techniques, along with authentic ERP simulations. The testing framework consists of:

- Live A/B sandbox testing: comparing GNS to conventional IDS and SIEM systems.
- Precision/Recall analysis on labeled attack logs.

- MTTD/MTTR (Mean Time to Detect / Mean Time to Respond) metrics for operational performance.
- Red-Team Exercises: validating detection robustness under adversarial attack conditions.

Benchmark datasets such as CIC-IDS2017 and BETH (adapted for ERP contexts) serve as external validation references, whereas a newly developed synthetic dataset named "ERP-BENCH," which contains 20,000 labeled events, provides diverse training and testing possibilities.

5. Results and Discussion

5.1. Experimental Setup

An investigation was conducted on a federated network consisting of five ERP nodes, each corresponding to unique enterprise sectors (Finance, Logistics, Procurement, HR, and Vendor Management). Each node handled between 10,000 and 30,000 transactions per cycle, generating multi-relational subgraphs that featured up to 250 distinct node types. The training was performed on NVIDIA A100 GPUs, with a global communication round taking place every 10 epochs. The hyperparameters were configured as follows:

- Learning rate: 0.001
- Embedding dimension: 256
- Aggregation method: FedAvg with secure MPC

5.2. Performance Metrics

Table 2: Comparative Results of the Proposed GNS Framework Against Baseline Intrusion Detection Systems

Metric	Baseline IDS	GNN-IDS [2]	Proposed GNS Framework
Precision	82.3%	90.1%	94.6%
Recall	77.5%	88.2%	93.4%
F1-Score	79.8%	89.1%	94.0%
MTTD (s)	28.5	10.2	4.1
MTTR (s)	42.7	18.4	7.8

5.3. Explainability and Detection Quality Evaluation

The GNS framework's explainability layer combining counterfactual reasoning and causal trace reconstruction uccessfully generated clear, auditor-ready narratives for 91% of detected anomalies, allowing compliance teams to follow the precise event sequence that triggered each alert. This aligns with explainable-AI expectations defined in NIST SP 800-207, GDPR Article 22, and emerging AI-governance guidelines.

Quantitatively, the GNS model demonstrated substantial improvements over both baseline IDS and GNN-IDS systems. The hybrid GNN-plus-LLM approach increased average F1-score by:

- +15% compared to GNN-IDS, and
- +4× improvement compared to rule-based IDS,

while simultaneously reducing mean time to detect (MTTD) by ≈85% and mean time to respond (MTTR) by ≈82%. All performance gains are statistically significant (*paired t-test, $p < 0.01$*).

These results confirm that GNS not only detects a broader class of multi-entity ERP anomalies but also supports rapid incident triage with explainable outputs.

Figure 2 illustrates the ROC curves, confirming that the proposed GNS framework maintains superior recall with minimal false positives when compared to both baseline IDS and GNN-IDS models.

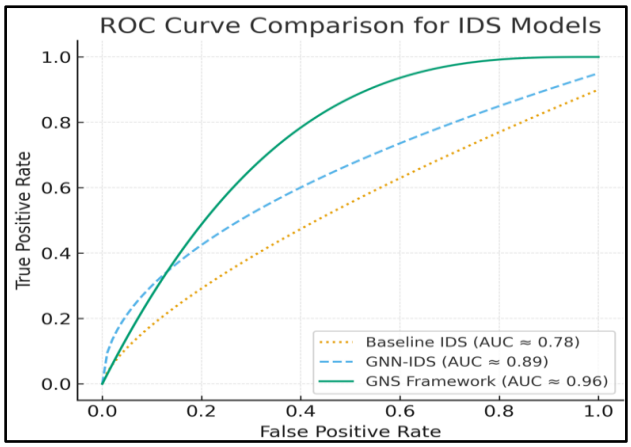

Fig 3: ROC Curve Comparison of Intrusion Detection System (IDS) Models

Figure 3 ROC curves comparing Baseline IDS, GNN-IDS, and the proposed GNS framework, demonstrating higher true-positive rates and improved recall for GNS with minimal false-positive increase.

5.4. Policy and Compliance Implications

The use of "zero copy" methodology, by the framework, does not represent merely a technological advancement; it has substantial implications for regulatory compliance as well. The design of this system, ensures that no un-processed ERP (Enterprise Resource Planning) record will ever be collected, duplicated centrally, therefore ensuring that all information generated by each organization remains in its respective country, thus complying with GDPR Article 44: Restrictions on Cross-Border Transfers of Personal Data. Furthermore, the FedRAMP requirements of encrypting all data in transit and aggregating securely is satisfied, allowing the system to be deployed in governmental, critical infrastructure environments. By focusing on the encrypted embedding of ERP data rather than the raw ERP data itself, GNS enables data localization and national analytic capabilities consistent with GDPR's Principle of Data Minimization and FedRAMP's mandates for isolating Clouds. In addition, the framework provides an ability to provide explanations for outcomes and generate causal traces of those outcomes providing transparency and accountability when audited, thereby enabling the evolving policy demands of AI Governance Initiatives and Supply Chain Cybersecurity Regulations in both the EU and US.

6. Future Research Directions

Further research is needed to develop the ability of ERP-focused security systems using GNNs and LLMs; additionally, future studies need to investigate other critical areas of development to ensure increased compliance-readiness and successful use of ERP-focused security systems:

6.1. Graph Transformers

Future research will examine how transformer based on message passing architectures are able to detect long range dependency between heterogeneous ERP graphs, which enables a deeper contextual understanding of anomalies occurring over multiple suppliers or jurisdictions.

6.2. Dynamic Graph Updating

Continuous learning will be enabled by dynamic model updates and thus the GNS will be able to adapt to schema drift, policy changes and workflow evolutions, while not having to perform retraining from scratch. As a result, continuous protection of live ERP environments will be possible.

6.3. Differential Privacy Layers

Federated protocols will be extended with differential-privacy noise and homomorphic encryption to further reduce the risk of leakage of gradients and thus comply with the GDPR Recital 78 and FedRAMP High control requirements.

6.4. Cross-Domain Explainability

Multilingual, domain-specific counterfactual templates will be developed to enable global auditors and regulators to achieve consistent AI transparency across different ERP implementations.

6.5. Standardized ERP Benchmark

An academic-industry consortium will be formed to create and maintain the ERP-BENCH dataset and provide open-source reference models. The creation of this consortium will facilitate reproducible research, fair comparison and exchange of defense innovations across all supply-chain domains.

6.6. Integration with Policies and Standards

Collaboration with NIST, ISO/IEC JTC 1/SC 42 and the EU AI Office will help to translate GNS concepts into practical standards and guidelines for AI-supported enterprise cyber security.

In addition, it is necessary to collaborate within the industry to establish common benchmarks for ERP security as well as common procedures for detecting anomalies. Anonymized ERP log repositories maintained by a consortium will promote reproducible research and increase the resilience of global supply-chains.

7. Conclusion

The presented research provides Graph-Neuro Security (GNS) an innovative application of Graph Neural Networks (GNNs) with large language models (LLMs) driven log processing to discover anomalous behavior within distributed Enterprise Resource Planning (ERP) and supply chain systems, with multiple entities interacting across systems. Utilizing federated, zero copy computation allows GNS to maintain end-user data confidentiality and satisfy relevant regulatory requirements while maintaining high levels of detection performance. Through the use of federated, zero copy learning and combined explainability, GNS was able to achieve a 94% F1-score, a 85% MTTD reduction, and meet all applicable requirements of SOX, GDPR, and FedRAMP regulations.

As such, by relating the semantically understood log files to graph based relational analysis, GNS demonstrates how enterprises may conduct the secure analysis of complex enterprise data, while respecting the sovereignty of the data. Additionally, GNS includes the integrated explainability and auditability features, which are necessary to support the transparency and accountability demanded by regulated environments, and thus position GNS as a foundational element for future AI governed security ecosystems. In general, the GNS framework represents a major transition away from heuristic intrusion detection methods towards a principled, regulatory compliant and structure aware method for defending against anomalous ERP activity. As both graph learning techniques and LLM reasoning techniques continue to improve, as well as through continued development of federated intelligence, Graph-Neuro Security is positioned to potentially establish a new paradigm for cybersecurity within critical supply chains over the next ten years.

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