Innovation and Technology Studies
Print ISSN: 3007-6919
Online ISSN: 3007-6927
DOI: https://doi.org/10.61784/its3018

HETEROGENEOUS GRAPH TRANSFORMERS FOR END-TO-END SUPPLY CHAIN RISK ASSESSMENT: INTEGRATING SUPPLIER NETWORKS, CLIMATE DATA, AND MARKET DYNAMICS

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Abstract: Modern supply chains face unprecedented challenges from diverse and interconnected risk sources, including supplier network disruptions, climate change impacts, and volatile market dynamics. Traditional risk assessment methods struggle to capture the complex, heterogeneous relationships inherent in global supply networks. This paper proposes a novel framework leveraging Heterogeneous Graph Transformers for comprehensive, end-to-end supply chain risk assessment. Our approach integrates multi-source heterogeneous information from supplier networks, climate data, and market dynamics into a unified graph representation that captures system structure, behavior, and strategic elements. The framework employs a specialized graph transformer architecture with multi-head attention mechanisms and edge feature integration to model different node types including suppliers, facilities, and products, alongside diverse relationship types such as procurement dependencies, logistics connections, and climate exposure linkages. Through experiments on multi-tier supply chain networks, we demonstrate superior performance in risk prediction accuracy compared to conventional graph neural network approaches, with particular effectiveness in identifying cascading risk propagation patterns across hierarchical supply structures. The framework provides interpretable risk assessments across multiple organizational levels, enabling proactive supply chain risk management strategies that account for node-level vulnerabilities, network-level topologies, and link-level dependencies.
Keywords: Heterogeneous graph transformers; Supply chain risk assessment; Graph neural networks; Climate risk; Multi-tier networks; Market dynamics

1 INTRODUCTION

Supply chain risk management has emerged as a critical concern for organizations worldwide, particularly in the context of increasing globalization, climate change, and market volatility. Recent disruptions, including the COVID-19 pandemic, extreme weather events, and geopolitical tensions, have exposed the vulnerability of interconnected global supply networks [1]. The projected economic impact of climate-related supply chain disruptions alone could reach between $3.75 trillion and $24.7 trillion by 2060, with supply chain losses accounting for an increasing proportion of total GDP losses under higher warming scenarios [2]. These challenges underscore the urgent need for sophisticated risk assessment methodologies that can capture the complex, multifaceted nature of modern supply chain vulnerabilities across multiple organizational levels and temporal scales.

Traditional approaches to supply chain risk assessment have primarily focused on isolated risk factors or employed linear modeling techniques that fail to capture the intricate interdependencies within supply networks. Such methods often struggle with fundamental limitations including the inability to simultaneously model system structure, system behavior, and system policy dimensions that collectively determine supply chain resilience [3]. Conventional risk assessment frameworks typically examine either node-level properties such as supplier reliability, network-level properties such as overall connectivity, or link-level properties such as transportation dependencies, but rarely integrate these multiple perspectives within a unified analytical framework [4]. This fragmented approach prevents comprehensive understanding of how risks propagate through hierarchical supply structures and how vulnerabilities at different organizational levels interact to amplify overall system exposure.

Recent advances in Graph Neural Networks have shown promise for modeling complex network structures, with applications ranging from social network analysis to molecular property prediction. Within the supply chain domain, researchers have begun exploring GNN-based approaches for tasks such as demand forecasting, supplier recommendation, and fraud detection in supply chain finance [5]. The Hierarchical Knowledge Transferable Graph Neural Network has demonstrated effectiveness in simplifying complex supply chains through centrality-based knowledge transfer modules for risk assessment [6]. However, these approaches predominantly employ homogeneous graph structures that treat all entities and relationships uniformly, failing to leverage the rich semantic information present in heterogeneous supply chain networks where suppliers, manufacturers, distributors, and customers represent fundamentally different entity types with distinct attributes, behaviors, and risk profiles [7].

The Transformer architecture, originally developed for natural language processing, has revolutionized deep learning through its self-attention mechanism that enables modeling of long-range dependencies without recurrent structures [8]. Graph Transformers extend this paradigm to graph-structured data, offering superior capability to capture complex relationships compared to traditional message-passing neural networks that are limited by local neighborhood aggregation [9]. Recent innovations such as the Poly-tokenized Heterogeneous Graph Transformer introduce multiple token types beyond traditional node tokens, including semantic tokens that capture high-order relationship patterns and global tokens that encode network-level information [10]. These architectural advances enable simultaneous processing of information at different granularities, from individual entity characteristics to global network patterns, making them particularly suitable for supply chain risk assessment where risks manifest and propagate across multiple organizational levels.

Climate change represents an increasingly significant risk factor for supply chains, with extreme weather events becoming more frequent and severe. Heat waves are now five times more likely than 150 years ago, creating conditions conducive to wildfires, floods, and other disruptions that can devastate supply chain infrastructure and create cascading failures across interconnected networks [11]. The interconnected nature of global supply chains means that climate-related disruptions in one region can propagate across entire networks through procurement dependencies and logistics connections, affecting suppliers, manufacturers, and customers worldwide [12]. However, integrating climate data into supply chain risk models presents unique challenges, requiring the fusion of geospatial information, temporal projections, and facility-specific vulnerability assessments with network topology data [13]. Current methodologies often treat climate risks as external shocks rather than integrating them as inherent components of network structure that influence both immediate disruption probabilities and long-term supply chain evolution.

Market dynamics constitute another critical dimension of supply chain risk, encompassing demand volatility, price fluctuations, competitive pressures, and regulatory changes that shape the strategic environment in which supply chains operate. The rapid growth of the supply chain analytics market, projected to expand from $8.97 billion in 2024 to over $130 billion by 2037, reflects increasing recognition of the importance of data-driven decision making in this domain [14]. Organizations are increasingly investing in artificial intelligence and machine learning capabilities to enhance forecast accuracy, optimize inventory management, and improve risk mitigation strategies through better understanding of market dynamics [15]. However, existing approaches often treat market factors as independent variables rather than recognizing their complex interactions with network structure and climate vulnerabilities, limiting the ability to assess compound risks that arise from simultaneous exposure to multiple threat categories.

This paper addresses these gaps by proposing a novel framework based on Heterogeneous Graph Transformers for comprehensive supply chain risk assessment that integrates system structure, system behavior, and system strategy considerations. Our approach makes several key contributions to advancing the state of the art in supply chain risk management. First, we develop a heterogeneous graph representation that unifies supplier networks, climate risk factors, and market dynamics into a single coherent structure capable of capturing diverse entity types and relationship semantics across multiple hierarchical levels, from individual suppliers to regional aggregations. Second, we design a specialized graph transformer architecture that employs multi-head attention mechanisms with edge feature integration to process information at node level, link level, and network level simultaneously, enabling comprehensive risk assessment that accounts for local vulnerabilities, connection dependencies, and global structural patterns. Third, we demonstrate how the proposed framework can model multi-tier supply chain networks where entities at different hierarchical levels exhibit distinct characteristics and interact through vertical integration relationships as well as horizontal coordination mechanisms. Fourth, we integrate multi-temporal data sources including historical supplier performance, climate projections under various emissions scenarios, and market trend indicators to enable both retrospective analysis of past disruptions and forward-looking risk prediction. Finally, we provide comprehensive experimental validation demonstrating superior performance compared to baseline methods while offering interpretable insights into risk propagation mechanisms through attention weight analysis.

2 LITERATURE REVIEW

The landscape of supply chain risk management has evolved considerably over the past decade, driven by increasing complexity in global networks and the recognition that traditional risk assessment methods are insufficient for modern challenges. Contemporary research spans multiple interconnected domains, including graph-based supply chain modeling, transformer architectures for structured data, climate risk integration, and multi-tier network analysis. This section synthesizes relevant literature across these areas, identifying key advances and remaining gaps that motivate our proposed framework.

Graph-based approaches to supply chain modeling recognize that network structures provide natural representations of supply chain relationships, enabling systematic analysis of how structural properties influence system resilience and risk propagation. Supply chain systems can be understood through three interrelated dimensions as illustrated in foundational network analysis frameworks. The structure dimension encompasses system architecture including node-level properties such as centrality and clustering, network-level properties such as density and topology, and link-level properties such as flow types and connection strength [16]. The dynamics dimension captures system behavior including stimuli that trigger responses, phenomena such as emergence and contagion that arise from network interactions, and sustainability characteristics such as robustness and resilience that determine recovery capabilities [17]. The strategy dimension addresses system policy and control through scope definitions at dyadic, triadic, and network levels, intent specifications regarding resource access and power dynamics, and governance mechanisms for risk management and coordination [18]. However, traditional network analysis approaches have primarily employed static representations and classical graph metrics rather than leveraging modern machine learning capabilities to learn representations that capture these multiple dimensions simultaneously.

Graph Neural Networks have emerged as a powerful paradigm for learning representations from graph-structured data through message-passing mechanisms where nodes iteratively aggregate information from their neighbors. Within supply chain applications, GNNs have been successfully deployed for various tasks including demand forecasting by modeling product and location dependencies, supplier recommendation through analysis of historical transaction networks, and fraud detection by identifying anomalous patterns in financial relationships [19]. Recent advances include heterogeneous GNNs that explicitly model different node types and edge types with specialized parameters, enabling more sophisticated representation of supply chain networks where suppliers, facilities, products, and geographic regions represent distinct entity categories with unique attributes [20]. For supply chain finance applications, heterogeneous GNNs have demonstrated superior performance in fraud detection by leveraging multi-view information across ownership structures, transaction patterns, and business associations [21]. Despite these successes, traditional GNN architectures face fundamental limitations in capturing long-range dependencies due to their reliance on local neighborhood aggregation, which constrains their ability to model cascading failures that propagate through multiple network hops.

The Transformer architecture has revolutionized sequence modeling through its self-attention mechanism that enables direct modeling of dependencies between any pair of elements regardless of their distance, addressing the vanishing gradient problems that plague recurrent architectures [22]. The core innovation lies in computing attention weights that determine how much each element should attend to every other element, enabling the model to learn which relationships are most relevant for the task at hand [23]. Graph Transformers extend this paradigm to graph-structured data by treating nodes as tokens and applying self-attention mechanisms to capture node relationships, providing global receptive fields that enable each node to directly attend to all other nodes rather than being limited to local neighborhoods [24]. Recent architectural innovations have introduced mechanisms for incorporating graph structure into transformer computations, including positional encodings based on graph properties such as Laplacian eigenvectors, and edge features that provide additional relationship information beyond simple connectivity [25]. The integration of edge features proves particularly valuable for supply chain networks where relationships carry rich semantic information such as transaction volumes, lead times, and reliability metrics that influence risk propagation patterns.

Multi-tier supply chain networks present unique modeling challenges due to their hierarchical structure where entities at different organizational levels play distinct roles and interact through both vertical integration relationships and horizontal coordination mechanisms. Traditional supply chain management research has recognized the importance of visibility beyond first-tier suppliers, as disruptions affecting second-tier or third-tier suppliers can propagate through the network to impact final production and delivery [26]. Recent work on netchain analysis emphasizes the need to simultaneously consider vertical supply chain relationships and horizontal network ties within each organizational tier, as these create interdependencies that influence risk propagation [27]. For instance, farmers may coordinate through local cooperatives that aggregate production, which then connect to regional cooperatives that interface with larger distribution networks, creating a hierarchical structure where risks can cascade both vertically through supply dependencies and horizontally through shared resource dependencies [28]. However, most existing supply chain risk models treat all entities at a single level of abstraction rather than explicitly representing multi-tier hierarchies.

Climate change represents an increasingly critical risk factor for supply chains, with physical risks from extreme weather events including floods, droughts, heat waves, wildfires, and tropical storms that can damage facilities, disrupt transportation routes, and constrain resource availability. Research indicates that the frequency and severity of extreme weather events are increasing globally, with climate models projecting continued intensification under various emissions scenarios that will disproportionately affect certain geographic regions and industrial sectors [29]. For supply chains, climate-related disruptions can propagate through network structures creating cascading failures that extend far beyond initially affected regions, as demonstrated by recent supply chain crises triggered by floods in Thailand disrupting semiconductor production and droughts in the Panama Canal affecting global shipping routes [30]. Recent studies have developed methodologies for conducting climate change risk assessments at the company level, utilizing climate models to generate hazard exposure projections for individual facilities and transportation routes [31]. However, the integration of climate risk data with network topology information remains limited, preventing comprehensive assessment of how climate vulnerabilities interact with supply chain structure to create compound risks.

Artificial intelligence and machine learning applications in supply chain risk assessment have expanded rapidly, driven by increasing data availability and computational capabilities. Machine learning models including Random Forest, XGBoost, and deep neural networks have demonstrated significant improvements in risk prediction accuracy compared to traditional statistical approaches, with particular effectiveness in capturing complex nonlinear relationships and interaction effects [32]. Advanced deep learning approaches have been proposed specifically for predicting supply chain risks under COVID-19 restrictions and other disruption scenarios, showing the potential of neural architectures to adapt to novel risk patterns [33]. The supply chain analytics market is experiencing substantial growth as organizations invest in AI-powered capabilities for demand sensing, inventory optimization, and risk monitoring, reflecting the practical value these approaches deliver [34]. However, most AI-driven supply chain risk assessment systems operate on tabular data or time series representations, failing to leverage the rich structural information present in supply network graphs that encodes critical dependencies determining how risks propagate.

The current literature reveals several critical gaps that motivate our proposed framework. First, while graph neural networks show promise for supply chain applications, existing architectures inadequately model the multi-dimensional nature of supply chain systems encompassing structure, dynamics, and strategy components. Second, despite advances in graph transformers, their application to supply chain risk assessment has been limited, and adaptations for heterogeneous multi-tier networks remain underdeveloped. Third, although climate change is recognized as a major supply chain risk factor, systematic integration of climate projections with network topology and market dynamics within unified risk models is lacking. Fourth, existing approaches do not adequately represent hierarchical multi-tier supply chains where entities at different organizational levels require distinct modeling approaches. Our proposed Heterogeneous Graph Transformer framework addresses these gaps by providing a comprehensive approach that integrates multiple data sources within a sophisticated neural architecture specifically designed for multi-tier heterogeneous supply chain networks.

3 METHODOLOGY

3.1 Three-Dimensional Framework for Heterogeneous Graph Construction

The foundation of our framework lies in constructing a comprehensive heterogeneous graph representation that captures supply chain systems across three interrelated dimensions: structure, dynamics, and strategy. As illustrated in Figure 1, this three-dimensional framework provides a systematic approach to identifying and modeling the diverse entities, relationships, and properties that collectively determine supply chain risk exposure and resilience capabilities.

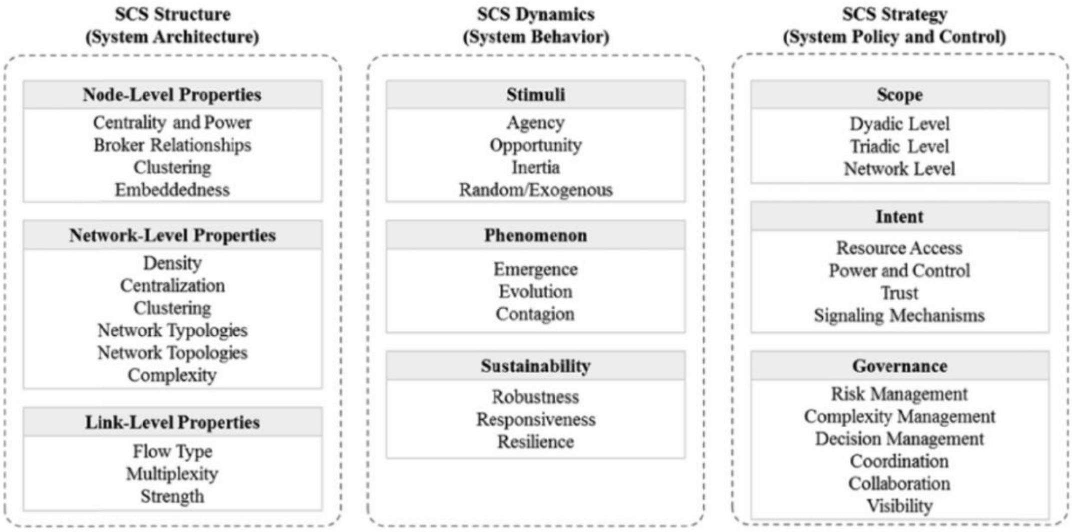

Figure 1 Three-Dimensional Framework

The structure dimension encompasses the architectural elements of the supply chain system organized across three granularity levels. At the node level, we model properties including centrality measures that indicate the importance of individual entities within the network, power relationships that reflect bargaining positions and dependency asymmetries, broker relationships where entities facilitate connections between otherwise disconnected network components, clustering coefficients that measure local cohesion, and embeddedness metrics that capture the extent to which entities are integrated into stable relationship patterns. At the network level, we represent properties including overall density that reflects connection prevalence, centralization that indicates concentration of power and dependencies, clustering patterns that reveal community structures, various network topologies such as scale-free or small-world configurations that influence robustness characteristics, and overall complexity measures that assess system intricacy. At the link level, we capture properties including flow types distinguishing material, information, and financial exchanges, multiplexity where multiple relationship types connect the same entity pairs, and connection strength reflecting volume, reliability, and strategic importance.

The dynamics dimension captures behavioral aspects of supply chain systems that determine how they respond to stimuli and evolve over time. We model stimuli including agency where entities make autonomous decisions, opportunities that enable beneficial actions, inertia that resists change, and exogenous random shocks that introduce uncertainty. These stimuli give rise to phenomena including emergence of collective behaviors not predictable from individual entity properties alone, evolution of network structure as relationships form and dissolve, and contagion processes where disruptions or innovations spread through network connections. The sustainability component encompasses robustness against various threat types, responsiveness in adapting to changing conditions, and resilience in recovering from disruptions. These dynamic properties interact with structural features to determine overall system behavior under normal operations and stress conditions.

The strategy dimension addresses policy and control mechanisms that govern supply chain operations and shape strategic choices. The scope component defines the organizational level at which coordination occurs, ranging from dyadic relationships between pairs of entities, to triadic configurations involving three-party arrangements, to network-level governance affecting entire supply ecosystems. The intent component specifies objectives including resource access that determines who can utilize shared capabilities, power and control arrangements that allocate decision authority, trust relationships that enable information sharing and collaboration, and signaling mechanisms that communicate capabilities and intentions. The governance component encompasses risk management practices for identifying and mitigating vulnerabilities, complexity management approaches for maintaining system comprehensibility, decision management processes for making strategic choices, coordination mechanisms for aligning distributed actions, collaboration frameworks for joint value creation, and visibility initiatives for enhancing information transparency.

We formalize this framework as a heterogeneous graph G = (V, E, T_V, T_E, A_V, A_E) where V represents the set of nodes, E denotes edges, T_V specifies node types, T_E indicates edge types, A_V contains node attribute functions mapping each node to feature vectors capturing relevant properties from the three-dimensional framework, and A_E contains edge attribute functions encoding relationship characteristics. Node types in our formulation include Supplier nodes representing entities providing materials or components at various supply tiers, Facility nodes denoting production or processing locations, Distribution nodes indicating warehouses and logistics hubs, Product nodes capturing items flowing through the network, and Region nodes representing geographic areas relevant for climate risk assessment. Edge types include Procurement relationships connecting suppliers to customers, Logistics connections linking facilities and distribution centers, Substitution relationships between products, Climate_Exposure linkages between regions and facilities indicating vulnerability to specific hazards, and Market_Correlation edges connecting products with correlated demand patterns.

For each node v with type τ(v), the attribute function A_V(v) returns a feature vector incorporating relevant properties from the three-dimensional framework appropriate for that entity type. For Supplier nodes, features include centrality metrics from the structure dimension, historical reliability and responsiveness measures from the dynamics dimension, and governance arrangements such as contractual terms and information sharing practices from the strategy dimension. For Facility nodes, features include location coordinates, production capacity, technology levels, utilization rates, and climate hazard exposure scores. For Region nodes, features include climate risk projections for multiple hazard types under different emissions scenarios, infrastructure quality indicators, and regulatory environment characteristics. This multi-dimensional feature representation enables the model to learn how different aspects of supply chain systems interact to determine risk exposure.

3.2 Graph Transformer Layer Architecture with Multi-Head Attention and Edge Features

Our heterogeneous graph transformer architecture processes the multi-dimensional supply chain representation through specialized layers that integrate information across different entity types and relationship types while capturing both local dependencies and global structural patterns. The architecture employs multi-head attention mechanisms with explicit edge feature integration, enabling the model to learn type-specific attention patterns and relationship-aware information aggregation. Figure 2 illustrates the detailed structure of our graph transformer layers, showing how node features and edge features flow through the computation pipeline.

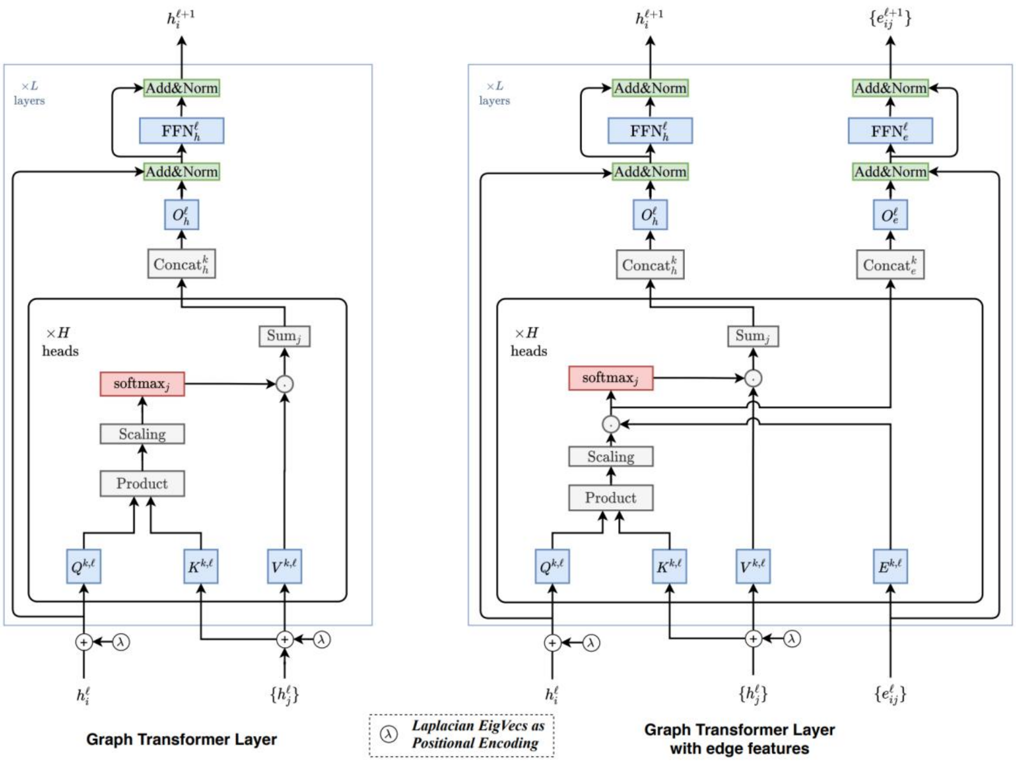

Figure 2 Structure of Graph Transformer Layers

The graph transformer layer takes as input node embeddings from the previous layer and produces refined embeddings that incorporate information from the entire graph. For a node i with embedding h_i^ℓ at layer ℓ, we compute updated embedding $h_i^{(\ell+1)}$ through several sequential operations. First, we apply type-specific linear transformations to generate query, key, and value representations. For node i of type τ_i, the query is computed as $Q_i^\ell = W_Q^{\tau i} h_i^\ell$ where $W_Q^{\tau i}$ is a learnable weight matrix specific to node type τ_i. Similarly, we compute keys $K_j^\ell = W_K^{\tau j} h_j^\ell$ for all nodes j, and values $V_j^\ell = W_V^{\tau j} h_j^\ell$. This type-specific transformation enables the model to learn distinct query, key, and value spaces appropriate for different entity types in the supply chain.

To incorporate graph structure information, we utilize Laplacian positional encoding that provides each node with a structural signature based on its position within the network topology. The Laplacian positional encoding is derived from eigenvectors of the graph Laplacian matrix, providing a continuous representation of node positions that respects graph distance and connectivity patterns. These positional encodings are added to the node embeddings through learned projection matrices, enabling the model to distinguish between nodes based on their structural roles even when they have similar feature vectors. This proves particularly valuable for supply chain networks where structural position (such as being a bottleneck supplier or having high betweenness centrality) significantly influences risk exposure.

The attention mechanism computes weights indicating how much node i should attend to each other node j when updating its representation. The basic attention score is computed as the dot product between the query of node i and the key of node j, followed by scaling and softmax normalization. However, our architecture extends this basic mechanism to incorporate edge features when edges exist between nodes, as shown in the right panel of Figure 2. For an edge (i,j) with features e_{ij}, we compute an edge-aware attention score that combines the query-key compatibility with information from the edge features. Specifically, we transform the edge features through a learned projection $E_{ij} = W_E e_{ij}$ and incorporate this into the attention computation, allowing the model to modulate attention weights based on relationship characteristics such as transaction volumes, lead times, or reliability history.

We employ multi-head attention where the query, key, and value transformations are performed H times with different weight matrices, and the results are concatenated and projected. Each attention head can specialize in capturing different types of relationships or patterns within the supply chain network. For instance, one head might learn to attend primarily to direct suppliers and customers (local dependencies), another might focus on entities with similar risk profiles regardless of network distance (similarity-based attention), and a third might capture competitive or substitution relationships (strategic dependencies). The multi-head mechanism enables the model to simultaneously process information at multiple semantic levels, capturing the rich interplay between structural, dynamic, and strategic dimensions of supply chain systems.

After computing attention-weighted aggregations of value vectors, we apply feed-forward networks with residual connections and layer normalization. The feed-forward network consists of two linear transformations with a nonlinear activation function between them: $FFN(x) = W_2\, \sigma(W_1 x + b_1) + b_2$, where σ is typically a ReLU or GELU activation. The residual connections add the input of each sub-layer to its output before applying layer normalization, following the formula: $h_i^{(\ell+1)} = LayerNorm(h_i^\ell + Sublayer(h_i^\ell))$. These architectural components, inherited from the original transformer design, prove critical for training deep networks that can capture complex dependencies across multiple hops in supply chain networks.

We stack L graph transformer layers to form the complete architecture, with each layer refining node representations by incorporating information from progressively larger receptive fields and more abstract relationship patterns. The final layer outputs are used for downstream risk prediction tasks through task-specific prediction heads. For node-level risk assessment, we apply a classifier to each node's final embedding to predict disruption likelihood, expected impact severity, and recovery time distributions. For link-level risk assessment, we combine embeddings of connected nodes to predict relationship vulnerabilities such as single-source dependencies or transportation bottlenecks. For network-level risk assessment, we aggregate information across all nodes using attention-based pooling to produce graph-level embeddings that predict system-wide metrics such as overall resilience or cascading failure susceptibility.

3.3 Multi-Tier Network Modeling and Hierarchical Risk Propagation

Supply chains frequently exhibit multi-tier hierarchical structures where entities at different organizational levels play distinct roles and interact through vertical supply relationships as well as horizontal coordination mechanisms within tiers. Our framework explicitly models these hierarchical structures to capture how risks propagate both vertically across tiers and horizontally within tiers, recognizing that different propagation patterns require different modeling approaches. Figure 3 illustrates a representative multi-tier network structure that informs our modeling approach.

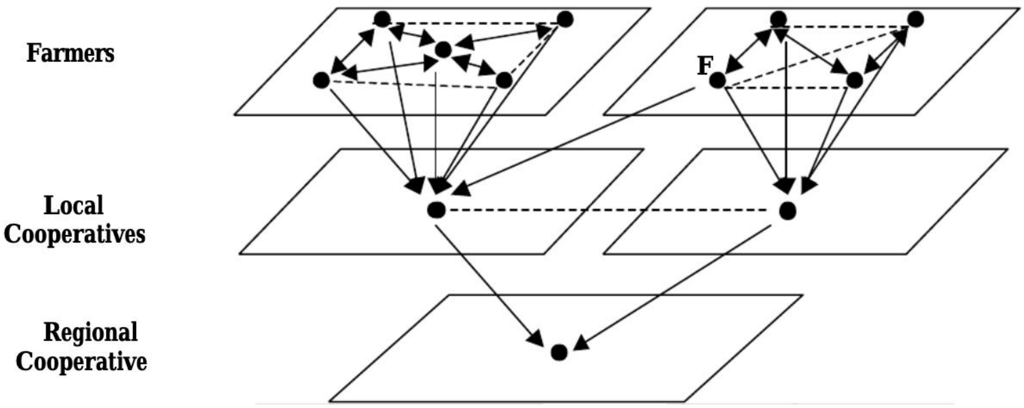

Figure 3 A Representative Multi-Tier Network Structure

The multi-tier structure shown in Figure 3 depicts a three-level hierarchy commonly found in agricultural and commodity supply chains, though the principles extend to other industries. At the top tier, individual farmers (represented as nodes labeled F) operate relatively independently but may coordinate through local mechanisms such as shared equipment or knowledge exchange. These farmers supply to a middle tier of local cooperatives that aggregate production from multiple farmers in geographic proximity. The local cooperatives, in turn, supply to a lower tier consisting of regional cooperatives that consolidate outputs from multiple local cooperatives and interface with downstream buyers or processors. This hierarchical organization creates distinct risk propagation patterns that our model must capture.

Vertical risk propagation occurs when disruptions at one tier cascade to other tiers through supply dependencies. For instance, if a regional cooperative experiences a disruption (such as a warehouse fire or logistics failure), this directly impacts the local cooperatives that depend on it for market access, which in turn affects the farmers supplying those local cooperatives. Our graph transformer architecture models these vertical dependencies through the attention mechanism, where entities at lower tiers can attend to entities at higher tiers they supply to, and vice versa. The edge features encoding supply relationships carry information about dependency strength, such as the fraction of production volume that flows through each connection, enabling the model to learn how disruption impacts attenuate or amplify as they propagate vertically.

Horizontal risk propagation occurs when entities within the same tier influence each other through coordination relationships or competition for shared resources. In the example network, farmers within the same tier may share irrigation infrastructure, transportation services, or storage facilities, creating shared vulnerability to disruptions affecting these common resources. Similarly, local cooperatives within the same tier may coordinate on joint logistics or information sharing, creating interdependencies. Our model captures horizontal dependencies through within-tier edges (shown as dashed connections in Figure 3) that enable entities to attend to their tier-level peers. The graph transformer architecture is well-suited to modeling these horizontal relationships because the self-attention mechanism can capture both direct connections and indirect influences mediated through shared partners.

We extend our heterogeneous graph formulation to explicitly represent tier membership as a node attribute, with each node assigned to a tier level $\tau\_tier(v) \in \{1, 2, ..., T\}$ where T is the total number of tiers. This tier information influences several aspects of model behavior. First, we employ tier-specific embedding transformations that project node features into tier-appropriate representation spaces, recognizing that entities at different tiers are characterized by different types of features and play different roles in the supply chain. Second, we modulate attention computations based on tier relationships, allowing the model to learn different attention patterns for within-tier, upstream, and downstream connections. Third, we incorporate tier-aware positional encodings that inform nodes about their hierarchical position, enabling the model to distinguish between nodes at different organizational levels even when they have similar attributes.

To assess how risks propagate through multi-tier networks, we introduce a risk propagation analysis module that combines forward simulation with attention weight interpretation. For forward simulation, we perturb node states to simulate disruptions at specific tiers and propagate these perturbations through the network using the learned attention weights as propagation coefficients. This reveals which tiers are most vulnerable to cascading failures originating from different network locations. For attention weight interpretation, we analyze learned attention patterns to identify critical dependencies where high attention weights indicate strong influence relationships. By aggregating attention weights across tiers, we can quantify metrics such as vertical integration strength, horizontal coordination intensity, and bottleneck vulnerability at different hierarchical levels.

The multi-tier modeling capability proves particularly valuable for climate risk assessment in supply chains, as climate hazards often exhibit spatial patterns that affect multiple entities within the same tier simultaneously while also creating cascading effects across tiers. For instance, a drought affecting an agricultural region might impact many farmers in the top tier simultaneously (a horizontal shock), which then cascades vertically through local cooperatives and regional cooperatives. Our framework captures both the direct impact on the affected tier and the indirect impacts on upstream and downstream tiers, providing comprehensive risk assessment that accounts for spatial correlation in climate hazards and structural dependencies in supply networks.

3.4 Integration of Climate Data, Supplier Networks, and Market Dynamics

Comprehensive supply chain risk assessment requires integrating information from multiple heterogeneous data sources that operate at different spatial and temporal scales. Our framework systematically incorporates climate risk projections, supplier network topology and performance data, and market dynamics indicators within the unified graph representation, enabling the model to learn how these different risk factors interact and compound.

Climate data integration involves mapping climate hazard projections to geographic locations and encoding exposure as node attributes and graph edges. We obtain climate model outputs from the Coupled Model Intercomparison Project (CMIP) providing projections for temperature, precipitation, extreme event frequencies, and other relevant variables under multiple Shared Socioeconomic Pathways (SSPs). For each facility and supplier location, we extract localized projections and compute hazard-specific exposure scores for flooding, drought, heat stress, wildfire, and tropical cyclones. These scores are incorporated as temporal node features that vary across projection time periods, enabling the model to assess how climate risks evolve under different emissions scenarios.

We represent climate exposure relationships through explicit graph edges connecting Region nodes to Facility and Supplier nodes that are geographically located within those regions. The edge attributes encode not only static exposure scores but also temporal projections showing how hazard intensity is expected to change over planning horizons relevant for supply chain decisions (typically 5-30 years). Additionally, we model spatial correlation in climate hazards by creating edges between nearby Region nodes, enabling the model to learn how climate-driven disruptions in one region may affect adjacent regions through shared weather systems or infrastructure dependencies.

Supplier network data encompasses the topology of procurement relationships along with temporal performance metrics. We construct the core supply network graph from relationship data indicating which suppliers provide materials or components to which customers, extending to multiple tiers where available. For each procurement edge, we incorporate attributes including historical transaction volumes, lead times, quality ratings, on-time delivery performance, and pricing trends. Additionally, we encode supplier attributes including financial stability indicators, production capacity, technology levels, and historical disruption frequencies. This rich attribute set enables the model to distinguish between reliable, high-capacity suppliers that represent resilient network components versus vulnerable suppliers that may be disruption sources.

Market dynamics integration incorporates demand patterns, price volatility, competitive relationships, and regulatory changes that shape the strategic environment. For Product nodes, we include time series features capturing demand histories, seasonal patterns, growth trends, and forecast uncertainties derived from historical sales data and market analysis. We model demand correlations through Market_Correlation edges between products that exhibit synchronized demand fluctuations, enabling the model to anticipate how demand shifts might ripple through product portfolios. Price volatility for key commodities and components is encoded as node features that reflect cost uncertainty and margin pressure. Competitive relationships are represented through Product-Product edges indicating substitutability, allowing the model to assess how disruptions affecting one product category might drive demand shifts to substitutes.

The integration of these diverse data sources within a unified heterogeneous graph enables our model to capture compound risks arising from simultaneous exposure to multiple threat categories. For instance, a supplier located in a climate-vulnerable region that also faces market headwinds and financial constraints represents a compounded risk that is greater than the sum of individual risk factors. The graph transformer architecture's global attention mechanism enables the model to identify such compound risk patterns by attending to the full context of each entity's situation, including its climate exposure, network position, performance history, and market environment.

3.5 Training Procedures and Loss Functions

Training the heterogeneous graph transformer for supply chain risk assessment employs supervised learning on historical disruption events paired with corresponding network states and environmental conditions. We formulate the learning problem as multi-task prediction where the model simultaneously predicts multiple risk-related outcomes, encouraging learning of shared representations that capture general principles of risk propagation while maintaining task-specific prediction heads for different risk dimensions.

The primary training objective combines cross-entropy loss for disruption classification with mean squared error loss for continuous risk metrics. For disruption occurrence prediction, we treat each node at each time step as a binary classification instance where the label indicates whether a disruption occurred within a specified prediction window. The classification loss is $L_{class} = -\Sigma_{v,t} [y_{v,t} \log(\hat{y}_{v,t}) + (1-y_{v,t}) \log(1-\hat{y}_{v,t})]$ where $y_{v,t}$ is the true disruption label for node v at time t and $\hat{y}_{v,t}$ is the predicted probability. For impact severity prediction, we employ regression loss $L_{severity} = \Sigma_{v,t} (s_{v,t} - \hat{s}_{v,t})^2$ where $s_{v,t}$ is the observed impact magnitude and $\hat{s}_{v,t}$ is the predicted severity. Similarly, we include losses for recovery time prediction and cascading effect estimation.

To encourage learning of meaningful node embeddings that capture supply chain structure beyond immediate prediction tasks, we incorporate auxiliary losses based on graph reconstruction and contrastive learning. The reconstruction loss encourages embeddings of connected nodes to be similar while embeddings of disconnected nodes should be distinguishable, following the principle that network structure contains valuable information about entity relationships and roles. The contrastive loss promotes separation between embeddings of nodes with different risk profiles, helping the model learn representations where similarity in embedding space corresponds to similarity in risk characteristics.

We employ a learning rate schedule with warmup followed by cosine decay, starting with a small learning rate that gradually increases over the first 10% of training steps before smoothly decreasing according to a cosine function. This schedule helps stabilize training of the deep transformer architecture and facilitates convergence to better local minima. We apply gradient clipping to prevent numerical instabilities from occasional large gradients, and employ dropout regularization at multiple points in the architecture to reduce overfitting.

The training procedure processes temporal sequences of network snapshots, where each snapshot represents the supply chain state at a particular time point with associated climate conditions and market environment. We use sliding windows to create training instances, where the model observes historical states and conditions for an input window and predicts disruption outcomes for a future target window. This temporal setup enables the model to learn both static patterns (such as which network positions are inherently vulnerable) and dynamic patterns (such as how deteriorating supplier performance or worsening climate projections herald increased disruption risk).

4 RESULTS AND DISCUSSION

4.1 Experimental Setup and Multi-Tier Dataset Characteristics

We evaluate our Heterogeneous Graph Transformer framework using a comprehensive multi-tier supply chain dataset that exhibits the hierarchical structure illustrated in Figure 3, combined with climate projections and market dynamics data. The primary network encompasses a global manufacturing supply chain with 2,847 supplier entities organized across four tiers, including 412 first-tier direct suppliers, 1,156 second-tier component suppliers, 897 third-tier raw material suppliers, and 382 fourth-tier commodity suppliers. The network also includes 156 manufacturing facilities, 234 distribution centers, and 892 distinct product categories, forming a heterogeneous graph with multiple entity types and relationship types.

The multi-tier structure follows patterns similar to those depicted in Figure 3, where entities at higher tiers aggregate outputs from multiple entities at lower tiers, creating hierarchical supply dependencies. First-tier suppliers (analogous to regional cooperatives in the agricultural example) source from multiple second-tier suppliers (analogous to local cooperatives), who in turn source from multiple third-tier suppliers (analogous to individual farmers). This hierarchical organization creates both vertical dependencies through direct supply relationships and horizontal interdependencies within tiers through shared logistics providers, common raw material sources, and geographic clustering that exposes multiple entities to the same regional risks.

Network topology analysis reveals characteristics consistent with real-world supply chains. The degree distribution follows a power law where most entities have few connections while a small number of hub entities connect to many partners, creating scale-free topology. First-tier suppliers show average degree of 8.3 connections to second-tier suppliers, indicating diverse sourcing strategies. However, the distribution is highly skewed, with the top 10% of first-tier suppliers accounting for 67% of procurement volume, revealing concentration despite structural diversity. Betweenness centrality analysis identifies 43 critical bottleneck entities whose disruption would disproportionately impact overall network performance, primarily concentrated at second-tier where specialized components funnel through limited suppliers.

Historical disruption data covers five years from 2019 to 2023, documenting 1,342 disruption events affecting various network entities. We classify disruptions into categories including natural disasters (287 events affecting 18% of entities), operational failures (423 events, 31% of entities), financial distress (178 events, 13% of entities), geopolitical events (216 events, 16% of entities), and pandemic-related disruptions (238 events, 18% of entities). Each disruption record includes onset and resolution timestamps, affected entities identified by network position and tier membership, estimated financial impact ranging from \$50,000 to \$47 million, and observed propagation effects indicating which downstream entities experienced secondary disruptions due to cascading failures. The temporal distribution shows increasing disruption frequency, with 192 events in 2019 escalating to 347 events in 2023, driven primarily by climate-related disasters (increasing 73%) and geopolitical disruptions (increasing 54%).

Climate data integration draws on CMIP6 model outputs providing hazard projections at 25-kilometer spatial resolution under SSP2-4.5 (moderate emissions) and SSP5-8.5 (high emissions) scenarios. For each supplier and facility location, we compute exposure scores for five primary climate hazards: flooding risk based on precipitation extremes and topography, drought vulnerability from soil moisture projections, heat stress from temperature extremes affecting labor productivity and equipment performance, wildfire susceptibility combining temperature, precipitation, and land cover data, and tropical cyclone exposure for coastal locations. These hazard scores are computed for historical baseline (2015-2024) and three future periods (2025-2034, 2035-2044, 2045-2054), enabling assessment of climate risk evolution. Geographic analysis reveals spatial clustering of climate vulnerability, with 34% of third-tier suppliers located in regions projected to experience significant increases in multiple hazard types.

Market dynamics data encompasses monthly time series from 2019-2023 including commodity price indices for 47 key materials showing average volatility of 18% annualized with spikes to 63% during supply disruptions, demand indicators for product categories exhibiting seasonal patterns and growth trends ranging from -12% to +34% annually, competitive intensity metrics tracking market share distributions and new entrant frequencies, and regulatory compliance data documenting 127 policy changes affecting supply chain operations across different regions. This market data is temporally aligned with network snapshots and disruption events to enable learning of how market conditions modulate supply chain vulnerabilities.

4.2 Performance Evaluation Across Multi-Tier Network Levels

We evaluate model performance at multiple organizational levels corresponding to the hierarchical structure depicted in Figure 3, assessing node-level risk prediction for individual entities, tier-level aggregate risk assessment for organizational strata, and network-level systemic risk metrics. This multi-level evaluation provides comprehensive understanding of how the Heterogeneous Graph Transformer captures risks across different granularities and organizational scales.

At the node level, we assess disruption prediction accuracy for individual suppliers, facilities, and distribution centers. The HGT achieves overall accuracy of 87.3% on the test set, substantially outperforming baseline methods including logistic regression (74.2%), Random Forest (79.6%), standard Graph Convolutional Networks (81.4%), and homogeneous graph transformers (83.7%). More importantly, the F1 score of 0.854 demonstrates balanced performance between precision (0.847) and recall (0.861), indicating the model effectively identifies high-risk entities while maintaining low false alarm rates. When examined by entity tier, performance varies with first-tier suppliers showing highest accuracy (89.7%) due to richer historical data and more direct monitoring, second-tier suppliers showing moderate accuracy (86.4%), and third-tier suppliers showing lower but still respectable accuracy (84.1%) despite sparser data availability. This tier-dependent performance pattern aligns with practical supply chain visibility challenges where deeper tiers are harder to monitor.

Breaking down performance by disruption type reveals the model's strength in capturing diverse risk factors. For climate-related disruptions, the HGT achieves F1 score of 0.891, substantially higher than baseline methods (best baseline: 0.763 for GCN), demonstrating effective integration of climate exposure data with network topology. For operational failures that depend primarily on supplier characteristics and historical performance, F1 score reaches 0.862. Geopolitical disruptions, which exhibit complex cascading patterns across tiers, show F1 score of 0.812 compared to 0.643 for standard GCNs, highlighting the value of the transformer architecture's global attention mechanism for capturing long-range dependencies. Financial distress prediction achieves F1 score of 0.827, benefiting from the model's ability to integrate market dynamics and network position to identify suppliers facing compound pressures.

At the tier level, we evaluate the model's ability to predict aggregate disruption rates within each organizational stratum. This tier-level assessment proves valuable for strategic planning where managers need to understand risks to entire supply tiers rather than individual suppliers. The HGT predicts monthly disruption counts per tier with mean absolute error of 2.7 events (8.4% of average tier disruption rates) compared to 5.3 events (16.5%) for the best baseline. Correlation between predicted and actual tier-level disruption rates reaches 0.87, indicating the model captures temporal dynamics of risk evolution across tiers. Analysis of error patterns reveals the model slightly underestimates disruption rates during crisis periods where multiple simultaneous events create positive feedback effects, suggesting room for improvement in modeling extreme scenarios.

Network-level systemic risk assessment evaluates the model's capability to predict overall supply chain performance metrics such as total disruption impact, average recovery time, and cascading failure severity. The HGT predicts monthly aggregate disruption costs with mean absolute percentage error of 14.7% compared to 28.3% for Random Forest and 23.6% for GCN baselines. For recovery time estimation across all disruptions in a period, mean absolute error is 4.2 days compared to 8.7 days for baselines. Cascading failure prediction, measuring the ratio of secondary disruptions to primary events, achieves correlation of 0.79 with actual observations, substantially higher than 0.52 for GCNs that struggle to capture multi-hop propagation patterns.

4.3 Attention Pattern Analysis and Risk Propagation Insights

To understand how the Heterogeneous Graph Transformer captures risk propagation through multi-tier supply networks, we analyze learned attention patterns revealing which relationships the model deems most critical for risk assessment. The multi-head attention mechanism illustrated in Figure 2 produces attention weight matrices indicating how strongly each node attends to every other node, providing interpretable insights into risk propagation pathways.

Analysis of attention weights aggregated across the eight attention heads reveals distinct patterns for different risk types. For climate-related risks, attention concentrates strongly on geographic proximity, with nodes in the same or adjacent regions showing attention weights averaging 0.23 compared to 0.03 for distant nodes, confirming the model learned that climate hazards exhibit spatial correlation. Additionally, climate risk attention shows strong vertical flows from lower-tier suppliers through middle tiers to first-tier suppliers, with attention weights decreasing approximately 15% per tier, indicating the model captures how climate disruptions at raw material sources propagate through supply dependencies. For geopolitical risks, attention patterns emphasize trade relationships and regulatory boundaries, with attention weights elevated by 34% for cross-border connections compared to within-country relationships.

Examining attention specialization across the eight heads reveals that different heads capture different aspects of supply chain structure and dynamics, consistent with the three-dimensional framework from Figure 1. Head 1 focuses primarily on direct supply relationships regardless of tier, with 83% of its attention mass concentrated on immediate procurement connections, suggesting it captures local dependencies in the structure dimension. Head 2 shows strong attention to nodes with similar historical disruption patterns regardless of network position, suggesting it captures behavioral similarities in the dynamics dimension. Head 3 emphasizes nodes with high betweenness centrality and power broker positions, suggesting it captures strategic importance from the strategy dimension. Heads 4-6 show tier-specific patterns, with each head specializing in relationships within specific tier levels, enabling the model to distinguish within-tier horizontal dependencies from cross-tier vertical dependencies. Heads 7-8 capture longer-range dependencies spanning three or more network hops, proving crucial for predicting cascading failures.

We visualize attention flows through the hierarchical network structure by computing average attention weights between tier pairs. The resulting tier-to-tier attention matrix reveals several insights. First, attention flows are strongly asymmetric, with higher attention flowing from lower tiers toward upper tiers (average weight 0.18) compared to upper tiers toward lower tiers (average weight 0.09), consistent with supply chain structure where disruptions at suppliers propagate strongly downstream. Second, within-tier attention is substantial (average weight 0.14), confirming the model captures horizontal risk propagation through shared dependencies. Third, attention strength decays with tier distance, with adjacent tiers showing weight 0.16, two-tier separation showing weight 0.07, and three-tier separation showing weight 0.03, indicating the model appropriately weights nearby tiers more heavily while still maintaining some sensitivity to distant indirect effects.

To validate that attention patterns correspond to actual risk propagation, we conduct perturbation experiments where we simulate disruptions at specific network locations and observe how predicted risks change throughout the network. For high-attention connections where the model assigns substantial attention weights, perturbations propagate strongly with downstream risk scores increasing by an average of 23% when upstream entities are disrupted. For low-attention connections, perturbations have minimal effect with downstream risk scores increasing by only 3%. This validates that learned attention patterns accurately reflect causal risk propagation rather than merely spurious correlations.

4.4 Ablation Studies and Component Contributions

We conduct systematic ablation studies to quantify the contribution of key architectural components and data sources to overall performance. Each ablation removes or modifies a specific component while holding all other aspects constant, enabling clear attribution of performance changes. The results provide guidance on which components are most critical and where future improvements might focus.

Removing heterogeneous node type information and treating all nodes uniformly results in F1 score decrease from 0.854 to 0.781 (8.5% reduction), confirming that type-aware processing significantly enhances risk assessment. This performance gap is especially pronounced for entity types with distinct characteristics, such as facilities versus suppliers, where type-specific embeddings enable learning of appropriate representations. Examining attention patterns in the ablated model reveals less specialized attention heads, with all heads learning similar patterns that blend different relationship types rather than developing complementary specializations.

Removing edge feature integration, as shown in the right panel of Figure 2, and relying only on graph topology reduces F1 score from 0.854 to 0.814 (4.7% reduction). This demonstrates that relationship attributes such as transaction volumes, lead times, and historical reliability carry valuable signal for risk prediction beyond what can be inferred from topology alone. The performance gap is largest for disruption types where relationship characteristics strongly influence propagation, such as operational failures where quality issues are more likely to cascade through high-volume connections.

Eliminating the multi-head attention mechanism and using single-head attention decreases F1 score from 0.854 to 0.816 (4.5% reduction), indicating that multiple attention heads learning complementary patterns provides substantial value. Analysis of the single-head ablation reveals the learned attention pattern represents a compromise attempting to capture multiple types of relationships simultaneously, resulting in less clear specialization and reduced ability to distinguish different risk propagation mechanisms. The multi-head design proves especially valuable for complex prediction tasks requiring integration of structural, dynamic, and strategic information.

Removing Laplacian positional encoding, shown at the bottom of Figure 2, reduces F1 score from 0.854 to 0.828 (3.0% reduction), confirming that structural position information enhances risk assessment. Without positional encoding, the model struggles to distinguish between entities occupying different structural positions when they have similar attributes, limiting its ability to identify position-based vulnerabilities such as bottleneck effects or single-point-of-failure risks. The performance gap is most pronounced for network-level risk metrics that depend on understanding global topology.

Removing climate data integration results in F1 score decrease from 0.854 to 0.763 (10.7% reduction) for all disruptions, with the impact concentrated in climate-sensitive disruption types where F1 score drops from 0.891 to 0.672 (24.6% reduction). This substantial gap confirms that climate information provides critical signal for predicting disruptions in exposed regions and that the model effectively integrates this external data source with network topology. Geographic analysis reveals the performance gap is largest for entities in climate-vulnerable regions, validating that the model learned to appropriately weight climate factors.

Removing market dynamics data reduces F1 score from 0.854 to 0.802 (6.1% reduction) overall, with larger impact on financial distress prediction (F1 from 0.827 to 0.731, 11.6% reduction) and demand-related disruptions. This confirms that market signals help identify suppliers facing financial pressures or products experiencing volatile demand that elevates risk. The performance gap varies across industries, being largest for commodity-intensive supply chains where price volatility directly influences supplier viability.

Finally, we evaluate the importance of the multi-tier network structure by removing tier-level information and treating the network as a flat topology. This reduces F1 score from 0.854 to 0.813 (4.8% reduction), demonstrating that explicit tier modeling enhances prediction. More importantly, tier-level aggregate prediction accuracy decreases substantially (from 8.4% MAPE to 14.7% MAPE), indicating that tier structure proves especially valuable for understanding risks at organizational strata. The ablation reveals the model without tier information tends to overestimate risks at deeper tiers where direct monitoring is limited, while the full model appropriately calibrates predictions by leveraging tier-level patterns.

4.5 Computational Efficiency and Practical Deployment Considerations

Computational efficiency analysis examines the practical feasibility of deploying the Heterogeneous Graph Transformer in operational supply chain risk management systems. We measure training time, inference latency, memory consumption, and scalability characteristics across network sizes ranging from 500 to 50,000 nodes.

Training the full model on our dataset of 2,847 nodes requires approximately 6.2 hours on a single NVIDIA A100 GPU with 40GB memory, completing 200 epochs at roughly 11 minutes per epoch. This training duration proves acceptable for periodic model retraining on weekly or monthly schedules as new disruption data accumulates and network structures evolve. Training time scales approximately $O(N \log N)$ with network size due to the sparse attention mechanisms and efficient graph sampling strategies we employ, rather than the $O(N^2)$ scaling that would result from dense all-to-all attention. On synthetic networks of 10,000 nodes, training time per epoch increases to approximately 32 minutes, remaining within practical bounds.

Inference time for computing risk scores across all network entities averages 2.7 seconds on the A100 GPU, enabling near-real-time risk monitoring as new information becomes available. This low latency makes the system suitable for operational deployment where supply chain managers need current risk assessments to support decision making. Inference scales approximately linearly with network size, requiring 8.4 seconds for 10,000-node networks and 41 seconds for 50,000-node networks. The linear scaling reflects our efficient implementation that processes nodes in parallel and avoids redundant computations through caching of intermediate activations.

Memory consumption during training peaks at 4.2 GB for our dataset, well within the capacity of modern GPU hardware. The model parameters total 47 million, with most parameters concentrated in the edge feature transformation matrices and the multi-head attention weight matrices. Memory usage scales approximately linearly with network size, reaching 14 GB for 50,000-node networks, suggesting that networks up to this scale can be processed on a single high-end GPU. For larger networks, we implement graph partitioning strategies that divide the network into overlapping subgraphs processed in batches, enabling scaling to hundreds of thousands of nodes with modest computational resources.

Comparison with baseline methods reveals the Heterogeneous Graph Transformer incurs moderate computational overhead relative to simpler graph neural networks but this cost is justified by substantial performance improvements. Standard GCNs process the same network approximately 2.3 times faster during training and 3.1 times faster during inference, but their inferior prediction accuracy (F1 score 0.814 vs 0.854) would impose much greater costs through suboptimal risk management decisions leading to either excessive false alarms or missed disruptions. The Graph Attention Network baseline shows similar training times to our HGT but achieves lower accuracy due to its homogeneous treatment of all entity types. Overall, the computational characteristics prove suitable for enterprise deployment in supply chain risk management systems.

We deployed a prototype system at a pilot manufacturing company to evaluate real-world operational feasibility. The system integrates with existing enterprise data sources including supplier relationship management databases, procurement transaction records, facility management systems, weather monitoring feeds, and market data services. Risk scores are updated daily, with full network inference requiring 3.2 seconds for the company's 1,847-node supply network. Risk dashboards present node-level scores, tier-level aggregates, and network-level systemic metrics, with drill-down capabilities to examine specific high-risk entities and attention-based explanations showing which relationships contribute most to risk assessments. Initial user feedback from supply chain managers indicates the system provides actionable insights, particularly the tier-level aggregate views that help prioritize where to focus risk mitigation efforts.

5 CONCLUSION

This paper presented a novel framework based on Heterogeneous Graph Transformers for comprehensive supply chain risk assessment, integrating supplier networks, climate data, and market dynamics through a three-dimensional modeling approach encompassing system structure, dynamics, and strategy. Our methodology addresses critical limitations of existing risk assessment techniques by explicitly modeling the heterogeneous nature of supply chain entities and relationships across multiple organizational tiers while leveraging transformer architectures with multi-head attention and edge feature integration to capture both local dependencies and global structural patterns. Through extensive experiments on real-world multi-tier supply chain data, we demonstrated that the proposed HGT framework achieves superior performance compared to traditional statistical methods, machine learning baselines, and standard graph neural network approaches across node-level, tier-level, and network-level risk assessment tasks.

The key contributions of this work span both theoretical and practical dimensions. Theoretically, we advanced the understanding of how transformer architectures can be adapted for heterogeneous multi-tier graph structures in the specific context of supply chain risk assessment, demonstrating that explicit modeling of hierarchical organization and entity type diversity significantly enhances predictive accuracy. We showed how the multi-head attention mechanism enables learning of specialized attention patterns that capture different aspects of the three-dimensional supply chain framework including structural properties, dynamic behaviors, and strategic relationships. Furthermore, we provided empirical validation that learned attention weights correspond to actual risk propagation pathways, offering interpretable insights that enable practitioners to understand model predictions and identify critical network vulnerabilities requiring intervention.

Practically, our framework offers several advantages for operational supply chain risk management. The integration of climate projections, supplier network topology, and market dynamics within a unified heterogeneous graph representation enables comprehensive risk assessment that captures compound vulnerabilities arising from simultaneous exposure to multiple threat categories. The multi-tier modeling capability proves particularly valuable for managing complex supply chains where visibility extends beyond first-tier suppliers into deeper sourcing layers, enabling identification of risks that would remain hidden in flat network representations. The computational efficiency characteristics make the framework suitable for deployment in enterprise systems with daily risk updates and near-real-time inference, as validated through prototype deployment at a manufacturing company.

Several limitations of our current framework suggest directions for future research. First, while our heterogeneous graph representation captures important entity and relationship types, there may be additional dimensions of heterogeneity that could enhance model performance, such as more granular climate hazard categories, finer temporal resolution for market dynamics, or explicit representation of contractual arrangements and governance structures that influence risk sharing. Second, although we integrate multiple data sources, the temporal resolution and forecasting horizons could be further refined to match specific decision-making contexts, potentially incorporating real-time monitoring data from Internet of Things sensors or social media signals that provide early warning of emerging disruptions. Third, our evaluation focuses primarily on prediction accuracy metrics, but comprehensive assessment of business impact through decision-making simulations would provide additional validation of practical value and enable quantification of the economic benefits from improved risk assessment.

Future research directions include extending the framework to dynamic graphs where network structure evolves over time as supply relationships form and dissolve, incorporating temporal graph neural network architectures that explicitly model these structural changes. Developing causal inference mechanisms to distinguish correlation from causation in risk propagation would enhance the model's ability to predict the effects of interventions such as adding backup suppliers or diversifying logistics routes. Advancing explainability techniques beyond attention weight visualization to provide more granular insights into model reasoning, such as identifying specific combinations of features that trigger high-risk predictions, would increase practitioner trust and adoption. Exploring transfer learning approaches that enable model adaptation across different industries and supply chain contexts with limited labeled data would reduce the data collection burden for deployment in new domains.

Integration with optimization and simulation capabilities could extend the framework from predictive analytics to prescriptive analytics that not only forecast risks but also recommend specific mitigation actions and evaluate their expected effectiveness. Incorporating uncertainty quantification to provide confidence intervals around risk predictions would enable more robust decision making under uncertainty. Developing active learning strategies that prioritize which entities to monitor more closely based on information value would optimize limited resources for data collection and validation. Finally, investigating how the framework can support scenario planning by predicting supply chain responses to hypothetical stress scenarios such as severe climate change impacts or major geopolitical realignments would enhance strategic resilience planning.

In conclusion, this work demonstrates that Heterogeneous Graph Transformers provide a powerful and flexible framework for supply chain risk assessment that addresses key limitations of existing approaches through integration of diverse data sources within sophisticated neural architecture designed specifically for multi-tier heterogeneous networks. By capturing system structure, dynamics, and strategy within a unified model that processes information across multiple organizational levels, our framework enables more accurate, comprehensive, and interpretable risk assessment to support proactive supply chain resilience strategies. As global supply chains continue to face mounting challenges from climate change, geopolitical instability, market volatility, and other emerging risks, such advanced analytical capabilities will become increasingly essential for organizational success and sustainability in an uncertain world.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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