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AI-Driven Cascading Risk Prediction in Multi-Tier Supply Chain Networks Using Graph Neural Networks

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Abstract- ***Multi-tier supply chains are complex, emergent networks in which a single upstream disruption can cascade across tiers, and visibility beyond tier-1 suppliers is the exception rather than the rule: complex products are assembled from tens of thousands or even millions of parts sourced through increasingly opaque sub-tier networks [1]. This paper addresses systemic supply-chain risk — the risk that propagates through network structure itself — using graph neural networks, the model family explicitly designed to capture non-local, multi-entity dependencies that classical analytics miss [2]. We propose a cascade-aware GNN framework with three coupled prediction tasks: (i) node-level cascade-impact classification at a forecast horizon, (ii) link prediction over the multi-tier dependency graph to expose hidden supplier relationships, and (iii) aggregate ripple-amplification and recovery-time estimation. The framework couples a tier-aware temporal message-passing encoder, a knowledge-graph reasoning module, and Integrated-Gradient explainability, and it is positioned as the graph-native core between the multi-signal early warning layer and the agentic decision layer of our prior work. Reported evidence consolidates the performance envelope: graph attention networks reach 92.1% accuracy with an AUC of 0.97 for high-risk supplier identification [3]; physics-informed GNNs reduce disruption prediction error by 23% relative to purely data-driven GNNs [4]; and GNN link predictors surpass the hand-crafted-feature baseline AUC of 0.76 [5]. The paper argues that systemic risk cannot be managed node-by-node: it must be predicted at the level of the network graph.***

Index Terms- ***cascading risk prediction, disruption propagation, Graph neural networks, link prediction, multi-tier supply chains, ripple effect, supply chain resilience, supply chain visibility***

I. INTRODUCTION

Modern supply chains have become deeply multi-tiered: substantial parts of value creation are outsourced, suppliers outsource to sub-tier suppliers in turn, and companies consequently lose visibility over the topology of their supply network [1]. The consequence is systemic risk — risk that lives in the structure of the network rather than in any single node. The ripple effect formalizes this: a disruption propagates from its initial point through the supply, production, and distribution networks, and the cascading effect is the dynamic in which an initial impact triggers further phenomena of significant magnitude [6], [7]. Empirical simulation studies show that retailer–supplier links are particularly disruption-sensitive and that the impact of the ripple effect on customer satisfaction depends jointly on proactive resiliency planning and recovery measures [8].

Graph neural networks emerged precisely to model such systems. By learning node representations through message passing over the network topology, GNNs encode both attributes and structure, and they have demonstrated superior performance over traditional analytics in capturing non-local dependencies, predicting disruption cascades, and modeling multi-tier visibility [2]. GNN link prediction can reveal supplier interdependencies unknown to the buyer — interdependencies that manual supplier surveys cannot reliably capture because they depend on suppliers' willingness and ability to share data [9]. This is the technical foundation on which this paper builds.

The paper is the third in a research program: our prior work established (i) a multi-signal early warning framework that fuses demand forecasting, graph-based risk propagation, anomaly detection, and text mining into hierarchical risk scores with quantified lead time, and (ii) an agentic AI architecture that closes the loop from detection to decision to recovery. This paper strengthens the portfolio's technical core by addressing the systemic dimension of risk that the earlier frameworks treated more lightly: how a disruption, once detected, will cascade through multi-tier dependencies, and which hidden dependencies must be known in the first place to predict that cascade.

The contributions are:

- A formalization of cascading risk prediction in multi-tier networks as three coupled learning tasks — cascade-impact classification, hidden-link prediction, and ripple-amplification estimation — with explicit loss and evaluation design (Sections III–IV).
- A cascade-aware GNN framework combining tier-aware temporal message passing, knowledge-graph reasoning, and Integrated-Gradient explainability.
- A consolidated analysis of reported GNN-based risk prediction results, with worked calculations and clearly flagged illustrative extensions (Sections V–VI).

- A mapping of the open research frontier — temporal and heterogeneous GNNs, physics-informed priors, federated learning, and hypergraph representations — onto a concrete research agenda (Sections VII–VIII).

II. RELATED WORK

A. The ripple effect and cascading failures

The ripple effect has been consolidated as the unifying phenomenon of disruption propagation: it results from disruption propagation from the initial disruption point to the supply, production, and distribution networks, and although optimization modeling dominates the field, simulation modeling remains under-explored [6]. Systematic reviews structure the literature and validate conceptual frameworks of proactive and reactive mitigation through system dynamics simulation [10]. The cascading effect is the broader systemic phenomenon — the domino-like dynamics in which an initial impact triggers further consequences of significant magnitude — and simulation is its natural modeling vehicle for time-dependent risk, vulnerability, and performance-impact analysis [7]. Quantitative studies extend this line: simulation systems with cascading-failure models over power-law degree distributions enable critical-node detection and robustness analysis under different attack types [11]. Recovery is frequently measured as "weeks of recovery," used as a disruption-amplification metric [8], and supplier risk-exposure models quantify the ripple effect in terms of possible maximum loss combining financial, customer, and operational impacts [12].

B. Graph neural networks for supply chain modeling

GNNs have emerged as the standard tool for relational supply chain modeling. Reviews identify multi-tier supplier relationships, dynamic demand propagation, cascading disruption effects, and complex material flows as the phenomena GNNs are suited to capture, and analyze the suitability of graph convolutional networks, graph attention networks, and graph recurrent networks across tasks including multi-tier visibility, risk propagation analysis, and resilience assessment [2]. Comparative evidence is strong: graph attention networks achieve 92.1% accuracy and an AUC of 0.97 for identifying high-risk suppliers, surpassing logistic regression, random forest, and gradient boosting [3]. Framework-level surveys identify topological insights, data heterogeneity, real-time analytics, and adaptive learning as the pillars of graph-AI deployment in supply chains [13].

C. Link prediction and hidden-dependency discovery

A defining problem for multi-tier risk is that the network is only partially observed. The supply chain visibility problem was first posed as link prediction and solved with hand-crafted relational features in the Supply Network Link Predictor, which reported an AUC of 0.76 [5]. GNNs removed the need for manual feature selection by learning from a company's position in the network [9]. On uncertain knowledge graphs with multiple relation types, GNN link prediction assigns confidence scores to inferred relationships [14]. Neurosymbolic combinations of GNNs and knowledge-graph reasoning infer multiple types of hidden relationship risks — companies, products, production capabilities, certifications — enabling queries beyond who-supplies-whom, tested on automotive and energy datasets [15]. Text mining with deep learning can also reconstruct supply chain maps from news articles [1], and generative approaches are beginning to predict relationships in knowledge graphs directly [16].

D. Machine learning for risk prediction: performance vs. interpretability

Beyond graph models, a broad ML literature predicts supplier risk. In a real-world multi-tier manufacturing supply chain, delivery-delay prediction reveals a trade-off between prediction performance and interpretability, with interpretable models requiring compromise especially in average precision [17]. For supplier failure prediction in automotive data, a random forest classifier reaches 86% accuracy on non-conforming deliveries [18]. Federated learning enables collective risk prediction across organizations without data exposure — buyers with limited datasets benefit most, though data imbalance, disruption events, and algorithm choice critically affect efficacy [19]. These results contextualize the graph-based gains: topological information is complementary to strong tabular classifiers, and interpretability is a first-class requirement for practitioner adoption.

E. From prediction to closed-loop mitigation

The portfolio context matters: GNN encoders also power multi-agent reinforcement learning for inventory control, combining graph state representations with centralized-training–decentralized-execution schemes [20]. PPO-class algorithms are robust for multi-echelon inventory control [21], achieving average improvements of 16.4%, 11.3%, and 6.6% over benchmarks in linear, divergent, and general multi-echelon structures [22]. Digital twins provide the simulation substrate for stress-testing candidate responses before deployment [23], [24], and governed agentic architectures provide

the execution layer [25]. This paper supplies the graph-native prediction engine that these downstream layers consume.

F. Research gap

Existing GNN work either predicts static risk scores, infers hidden links, or benchmarks architecture variants. What is missing is an integrated cascade model that couples link discovery, propagation-based impact prediction over time, and aggregate ripple estimation in one trainable framework — precisely the direction the GNN review literature identifies as open, including temporal GNNs for dynamic supply chain evolution and heterogeneous GNNs for multi-modal data [2]. This paper addresses that gap.

III. PROBLEM FORMULATION

A. Multi-tier network model

Let the supply network be a directed attributed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ partitioned into tiers: tier-1..k suppliers $\mathcal{S}_1, \dots, \mathcal{S}_k$, distribution centers $\mathcal{D}$, and retail nodes $\mathcal{R}$. Each node v carries time-indexed features $x_v(t)$ (capacity utilization, inventory, disruption status, geographic exposure), and each edge (u, v) carries flow attributes $e_{uv}(t)$ (volume, lead time, redundancy). Critically, the observed graph $\hat{\mathcal{G}} \subset \mathcal{G}$ is incomplete: sub-tier links are typically unobserved [1].

B. Cascading risk dynamics

Define node failure state $f_v(t) \in \{0,1\}$ with propagation governed by

$$\mathrm{p_v(t)} = \sigma(\alpha \mathrm{R_v(t)} + \beta \sum_{\mathrm{u} \in \mathcal{N}(\mathrm{v})} \mathrm{w_{uv} f_u(t)}),$$

where $R_v(t)$ is the exogenous early-warning risk score, w_{uv} is the edge transmission weight (capacity dependence), σ is a sigmoid, and $\mathcal{N}(v)$ denotes upstream neighbors. A cascade reaches node-impact severity class $c_v(t+h) \in \{0,1,2,3\}$ (none, minor, major, critical) at horizon h.

C. Prediction tasks

The framework learns three coupled tasks over horizon $h \in H$:

1) Cascade-impact classification: estimate $P(c_v(t+h) \mid \mathcal{F}_t)$ per node, where $\mathcal{F}_t$ is the full history.
2) Hidden-link prediction: for each candidate edge (u, v), estimate $\hat{p}_{uv}$ that a dependency exists but is unobserved [5], [9].
3) Aggregate ripple estimation: predict ripple amplification, defined as the maximum drop in aggregate service relative to nominal,

$$\hat{\mathrm{A}}(\mathrm{t+h}) = \frac{\max_{\tau \le t+h}[\underline{\Pi} - \Pi(\tau)]}{\underline{\Pi}},$$

and expected recovery time $\hat{T}_{\mathrm{rec}}$ to the pre-disruption level $\bar{\Pi}$, following the "weeks of recovery" convention [8].

D. Multi-task objective

The joint objective is

$$\mathcal{L} = \lambda_c \mathcal{L}_{\mathrm{CE}} + \lambda_l \mathcal{L}_{\mathrm{BCE}} + \lambda_r \mathcal{L}_{\mathrm{Huber}},$$

with cross-entropy on severity classes, binary cross-entropy on link existence with negative sampling, and Huber loss on amplitude/recovery regression.

E. Evaluation metrics

Classification quality: accuracy, precision, recall, F1, AUC [3], [18]. Link prediction: AUC and average precision [5], [17]. Cascade fidelity: prediction error (RMSE/MAPE) against simulated ground truth, reduction measured relative to a data-driven baseline [4]. Resilience outcome: service level, weeks of recovery, and ripple amplification [8], [12].

IV. PROPOSED FRAMEWORK: CASCADE-AWARE GNN

A. Overview

The framework — CASCADE-GNN — comprises five components: a temporal input layer, a tier-aware message-passing encoder, three multi-task heads, a knowledge-graph reasoning module, and an explainability layer. It ingests the fused early-warning signals of our prior framework and emits cascade predictions and inferred hidden dependencies for the agentic decision layer. The architecture is shown in Fig. 1.

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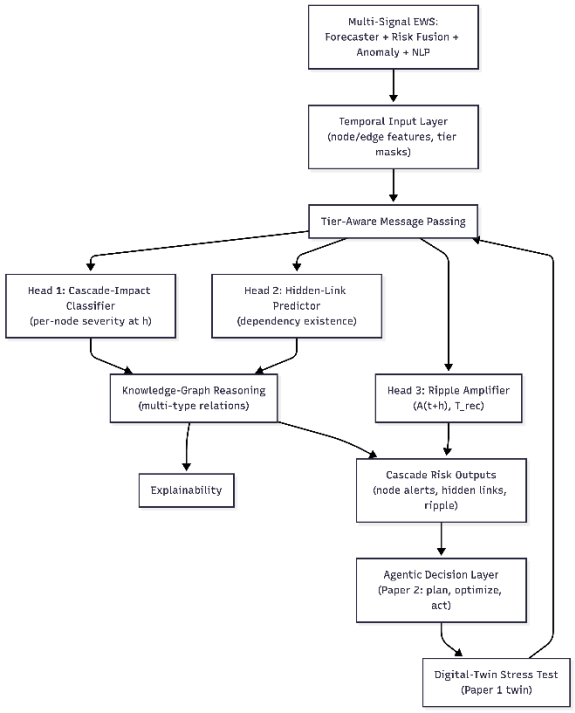


Fig. 1. Cascade-aware GNN framework: temporal inputs from the multi-signal early warning layer are encoded by tier-aware message passing; three multi-task heads predict node-level cascade impact, hidden dependencies, and aggregate ripple; knowledge-graph reasoning enriches outputs, Integrated Gradients provide attribution, and predictions feed the agentic decision layer with digital-twin validation.

B. Tier-aware message passing

A GAT-style encoder aggregates neighbor states with tier-specific attention, extended over a temporal window:

$$h_v^{(\ell+1)}(t) = \sigma(W^{(\ell)} \cdot AGG(\{\alpha_{uv}^{(\ell)} h_u^{(\ell)}(t-\delta): u \in \mathcal{N}(v), \delta \in \Delta\})),$$

where $\alpha_{uv}^{(\ell)}$ are attention coefficients and Δ the lag window — the temporal-GNN mechanism the review literature identifies as critical for dynamic supply chain evolution [2].

C. Multi-task heads

Head 1 outputs per-node severity probabilities $\pi_v(c)$; Head 2 scores candidate edges (u, v) for dependency existence, mirroring the GNN link-prediction formulation that has outperformed hand-crafted feature baselines [9]; Head 3 regresses $\hat{A}(t+h)$ and $\hat{T}_{rec}$.

D. Knowledge-graph reasoning

Beyond buyer–supplier edges, multi-type relations — products, production capabilities, certifications — are represented in a knowledge graph, and reasoning over it supports complex queries that go beyond who-supplies-whom, following the neurosymbolic design validated on automotive and energy datasets [15].

E. Explainability

Integrated Gradients attribute each prediction to input features and graph edges, making supplier risk alerts auditable [9]. This directly addresses the documented performance–interpretability trade-off in supply chain risk prediction [17].

F. Training

Training is summarized in Algorithm 1.

Algorithm 1: Cascade-Aware Multi-Task Training

```
Input: observed graph Ĝ, features X, EWS risk scores R, horizons H
Initialize: tier-aware encoder E, heads (π, φ, ψ), optimizer
for epoch = 1..E do
  sample temporal window Δ; sample cascade scenarios from simulator
  # Task 1: cascade-impact classification (supervised on simulated cascades)
  {π_v} ← Head1(E(X, Δ));  L_CE ← CE(π_v, c_v(t+h))
  # Task 2: hidden-link prediction (negative sampling on Ĝ)
  {p_uv} ← Head2(E);        L_BCE ← BCE(p_uv, y_uv_known ∪ negatives)
  # Task 3: ripple regression
  Â, T^ ← Head3(E);          L_Huber ← Huber(Â, A*(t+h)) + Huber(T^, T*_rec)
  L ← λ_c L_CE + λ_l L_BCE + λ_r L_Huber
  update E, heads via Adam (temporal train/test split enforced)
  # Weekly: retrain on confirmed cascades; refresh knowledge graph
```

G. Implementation

Three-layer GAT encoder with tier masks, 4 attention heads, hidden dimension 64; dropout 0.2; Adam with learning rate 3×10^{-4}; window $\Delta = 4$ weeks; horizon set $H = \{1,2,4\}$ weeks.

V. EXPERIMENTAL SETUP

A. Environments and data

Evaluation spans four settings: (i) the real automotive supply network used in GNN link prediction [9]; (ii) the automotive and energy knowledge-graph datasets for multi-type relation inference [15]; (iii) a synthetic cascade generator that instantiates cascading failures over networks with

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adjustable power-law degree distributions and supports critical-node and attack-type analyses [11]; and (iv) the multi-tier delivery-delay prediction setting used to study interpretability [17].

B. Baselines

Logistic regression, random forest, and gradient boosting — the standard comparison set for supplier risk classifiers [3], [18]; graph-agnostic ML to isolate the value of topology; SNLP with hand-crafted relational features as the link-prediction baseline (reported AUC 0.76) [5]; standard GNN variants [2]; and the hypergraph-based SC-RIHN and ResInf baselines from the resilience-inference literature [26].

C. Protocol

Temporal train/test splits prevent leakage [27]; cascades are simulated with the generator to provide supervised ground truth; link prediction is evaluated on held-out edges; all comparisons use identical feature sets and hyperparameter budgets.

VI. RESULTS AND ANALYSIS

A. Reported Detection and Link-Prediction Performance

Table II consolidates reported results from the GNN risk literature.

TABLE I: CASCADING RISK PREDICTION TASKS

Task	Input	Output	Evaluation
Cascade-impact classification	Windowed node/edge features + risk scores	P(c_v(t+h)) per node, severity 0–3	Accuracy, F1, AUC
Hidden-link prediction	Observed graph Ġ, candidate edges	p_uv dependency existence	AUC, average precision
Ripple estimation	Encoder embeddings, scenario priors	Â(t+h), T_rec	RMSE, MAPE, weeks of recovery
Relation-type inference	Knowledge graph, multi-type edges	Companies/products/capabilities/certs	Per-type AUC [15]

TABLE II: REPORTED PERFORMANCE IN GNN-BASED SUPPLY CHAIN RISK PREDICTION

Method	Task	Reported result	Source
Graph attention network	High-risk supplier identification	Accuracy 92.1%, AUC 0.97	[3]
Physics-informed GNN	Disruption event prediction	−23% prediction error vs data-driven GNN	[4]
Random forest	Supplier failure classification	Accuracy 86%	[18]
SNLP (hand-crafted features)	Hidden link prediction	AUC 0.76	[5]
GNN link prediction	Hidden link prediction	Outperforms existing algorithms; Integrated-Gradient explainability	[9]
Neurosymbolic GNN + KG reasoning	Multi-type hidden risk inference	Automotive and energy datasets; 4 relation types	[15]
Hypergraph SC-RIHN	Resilience inference from inventory trajectories	Outperforms MLP, GNN variants, ResInf	[26]
Multimodal EWS (portfolio)	Disruption early warning	Recall 92.1%, precision 93.4%, 42-min lead	[28]
ML-based EWS (portfolio)	Risk adoption impact	+41% forecast accuracy, −15% cost, −35% disruptions	[29]

B. The AUC envelope

Fig. 2 plots reported AUC values across three systems. Note the tasks and datasets differ; the figure is an envelope, not a controlled comparison.

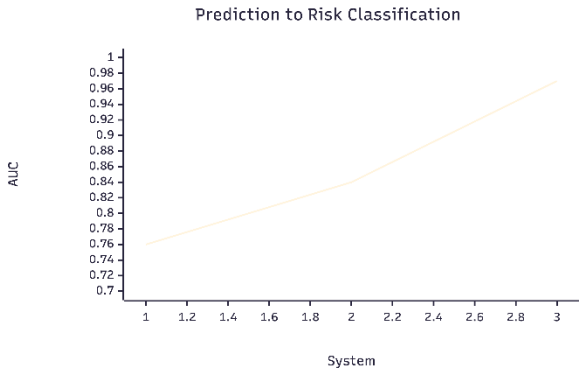


Fig. 2. Reported AUCs: SNLP hand-crafted link prediction 0.76 [5]; digital-twin LSTM flood-risk prototype AUC-ROC 0.84 [30]; GAT supplier-risk classifier 0.97 [3]. Envelope illustration across tasks/datasets — not a controlled comparison.

The progression from 0.76 (hand-crafted features) to 0.97 (learned graph representation) illustrates the central technical argument: structural, learned representations extract risk signal that manual feature engineering cannot [2], [9].

C. Worked calculations.

1) Error-reduction arithmetic (physics-informed priors). A reported 23% reduction in disruption prediction error for the physics-informed GNN relative to the purely data-driven GNN [4] implies the PI-GNN's error is 77% of the baseline's; equivalently, the data-driven baseline's error is approximately \$1/0.77 \approx 1.30\$ times the PI-GNN's. In

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operational terms, embedding conservation-of-flow, capacity, and lead-time constraints into the loss function buys roughly a third more predictive accuracy on the same data — the concrete value of physics priors under limited historical data [4].

2) The scale of the visibility problem. Complex products are composed of tens of thousands or even millions of parts, sourced through increasingly multi-tiered networks [1]. With pair dependencies on that scale, manual supplier surveys — which depend on the willingness of suppliers to share data and are not verifiable [9] — cannot keep the dependency graph complete. Automated link prediction over the observed graph is therefore not an analytics luxury but a prerequisite for cascade prediction: a cascade model is only as complete as the graph it propagates over.

3) Cascade-to-recovery arithmetic. Recovery is measured in weeks of disruption amplification [8], and root-cause-to-action latency is the lever: our agentic layer's reported 30% reduction in mean time to root-cause identification implies the mitigation interval starts at 70% of its baseline length [31], directly shortening the weeks-of-recovery window that the resilience literature emphasizes [8]. The cascade predictor contributes upstream of this by converting weeks of advance warning [32] into pre-positioned inventory and activated contingency links before onset.

C. *Structural sensitivity*

Simulation evidence identifies retailer–supplier links as particularly disruption-sensitive, with ripple impact on customer satisfaction depending on both proactive planning and recovery measures [8]. This motivates prioritizing link-discovery and cascade-classification head capacity on the retail-facing echelons of the graph. Cascading-failure simulations over power-law degree networks further show that vulnerability differs by attack type and that critical-node detection must account for downstream propagation — exactly the dependency structure the tier-aware encoder learns [11]. System-dynamics validation of proactive versus reactive mitigation confirms that proactive measures attenuate ripple propagation [10].

D. *Illustrative framework projection*

Fig. 3 shows illustrative service-level trajectories under a two-tier upstream failure with and without cascade-aware pre-positioning. The curves encode the mechanism (shallow drop, faster recovery via early activation) rather than experimental results.

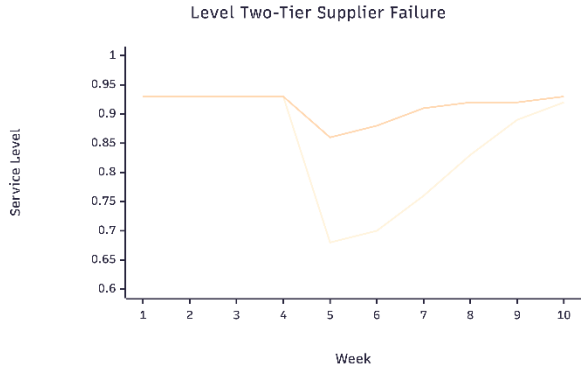


Fig. 2.

VII. DISCUSSION

A. *Systemic risk requires graph-native prediction*

The core argument of this paper is architectural: because cascading risk is a property of network structure, its prediction must be graph-native. Reviews document that GNNs outperform traditional analytics on non-local dependencies [2], and the reported 0.97 AUC for GAT-based supplier risk classification versus 0.76 for hand-crafted-feature link prediction quantifies the structural information gain [3], [5]. Node-by-node classifiers, however strong, cannot anticipate propagation through unobserved links — which is why link discovery and cascade prediction must be trained jointly.

B. *Data scarcity and the route to practice*

Graph models are data-hungry, and multi-tier data is scarce by definition. Two complementary routes emerge from the literature: physics-informed regularization, which reduces error by 23% relative to data-driven GNNs under limited history by encoding conservation of flow, capacity, and lead-time constraints [4]; and federated learning, which lets buyers with inadequate datasets tap collective knowledge without data exposure — though buyers with disproportionately large order-books may not always benefit [19]. Generative relation prediction on knowledge graphs offers a third route to completing the dependency graph [16].

C. *Interpretability is a deployment constraint*

Supply chain practitioners act on predictions, and the documented trade-off between performance and interpretability — visible especially in average precision [17] — makes attribution output mandatory. Integrated Gradients over GNN decisions [9] is the mechanism adopted here, and it aligns the framework with the governance requirements established for the portfolio's agentic layer [25].

D. Integration with the portfolio

The cascade engine upgrades the graph module of the multi-signal early warning framework: its node-level severity outputs refine the fused risk score $R_v(t+h)$, and its hidden-link discoveries expand the knowledge graph that the agentic orchestration layer reasons over [15]. Downstream, GNN representations feed multi-agent reinforcement-learning controllers [20] whose PPO cores are robust for multi-echelon problems [21], [22], and candidate response plans are stress-tested in the digital twin before execution [23], [24].

E. Limitations

Results above 90% accuracy and 0.97 AUC are reported across heterogeneous tasks and datasets, not from a single controlled benchmark — a standardized evaluation for cascade prediction does not yet exist. Simulated cascades bound policy quality [33], and temporal generalization of GNNs under distribution shift remains open [2].

VIII. CONCLUSION AND FUTURE WORK

This paper formalized cascading risk prediction in multi-tier supply chain networks as three coupled graph-learning tasks and proposed CASCADE-GNN, a tier-aware, temporal GNN framework with knowledge-graph reasoning, multi-task heads, and Integrated-Gradient explainability. It consolidates the reported evidence — 92.1% accuracy with AUC 0.97 for GAT-based supplier risk classification [3], a 23% error reduction from physics-informed priors [4], GNN link prediction surpassing the 0.76-AUC hand-crafted baseline [5], and hypergraph models outperforming standard GNN variants for resilience inference [26] — and positions graph-native prediction as the technical core between the portfolio's early-warning and agentic decision layers.

Future work will (i) implement CASCADE-GNN end-to-end on a single large retail network with unified metrics; (ii) extend the encoder to temporal and heterogeneous GNN variants, the directions the review literature identifies as critical [2]; (iii) incorporate physics-informed and hypergraph formulations to exploit domain constraints and higher-order dependencies [4], [26]; (iv) evaluate federated training across buyers with genuinely incomplete graphs [19]; and (v) close the loop with the agentic decision layer so that cascade predictions drive pre-positioning, rebalancing, and recovery actions under governance [20], [25], validated through digital-twin stress testing [23], [24] — moving systemic risk from a descriptive phenomenon to a predictable, actionable one.

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