GEORGE BROWN PRESS
JOURNALS, BOOKS & PROCEEDINGS

Journal of Computer, Signal, and System Research

Article

SR-DTMA: A Digital Twin-Driven LLM Multi-Agent Framework for Systemic Risk Simulation and Coordinated Decision-Making in Supply Chains

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Abstract: Systemic risk in global supply chains has intensified with increasing interdependencies among firms, logistics infrastructure, and financial institutions, where localized disruptions such as port closures, financial crises, or policy shocks can propagate across networks and trigger large-scale cascading failures. Existing supply chain risk management and simulation approaches are limited in their ability to simultaneously capture decentralized agent behavior, dynamic system interactions, and the semantic complexity of real-world risk information expressed in natural language. To address these challenges, this paper proposes SR-DTMA (Systemic Risk-aware Digital Twin Multi-Agent framework), a digital twin-driven simulation and decision-making framework that integrates Large Language Model (LLM)-powered agents with decentralized multi-agent learning for systemic risk analysis in supply chains. In SR-DTMA, heterogeneous supply chain entities-including manufacturers, ports, and financial institutions-are modeled as autonomous agents that perceive local operational states, interpret unstructured risk events from policy announcements and news, and make adaptive decisions under systemic shocks. By embedding LLM-based risk cognition within a digital twin environment, the framework enables large-scale simulation of risk contagion, strategic interactions, and the conflict between locally rational decisions and global system stability. Extensive experiments under port closure and financial tightening scenarios show that conventional rule-based and RL-driven agents exhibit higher systemic loss and deeper risk propagation. In contrast, SR-DTMA, integrating LLM-driven agents with a lightweight coordination mechanism, reduces the cumulative systemic loss ratio from 0.327 to 0.163, decreases risk propagation depth from 4.8 to 2.6, and shortens recovery time from 21 to 9 steps. These results highlight the effectiveness of coordinated LLM-based decision-making in mitigating systemic supply chain risk and enhancing network resilience.

Keywords: Systemic Risk; Digital Twin; Multi-Agent Systems; Large Language Models; Supply Chain Resilience; Risk Contagion

Received: 12 December 2025
Revised: 26 January 2026
Accepted: 06 February 2026
Published: 10 February 2026

1. Introduction

Global supply chains have evolved into highly interconnected and interdependent systems that span manufacturing firms, logistics infrastructure, and financial institutions. While such complexity has significantly improved operational efficiency and global integration, it has also increased exposure to systemic risk, where localized disruptions-such as port closures, financial crises, or policy interventions-can propagate through the network and trigger large-scale cascading failures. Recent real-world events have demonstrated that supply chain disruptions are no longer isolated operational incidents but systemic phenomena with profound economic and societal impacts.

Traditional supply chain risk management approaches primarily rely on centralized optimization models or rule-based simulations. Centralized models typically assume complete information and coordinated control, which are rarely achievable in decentralized, multi-actor supply chains. Rule-based or conventional agent-based models, although capable of representing decentralized interactions, often oversimplify decision-making processes and fail to capture the semantic richness of real-world risk information, such as policy announcements, regulatory changes, and news reports. As a result, existing methods struggle to realistically model how heterogeneous actors perceive, interpret, and respond to systemic risk under uncertainty.

The emergence of Large Language Models (LLMs) offers new opportunities for advancing systemic risk analysis in supply chains. LLMs exhibit strong capabilities in natural language understanding, contextual reasoning, and knowledge integration, making them well suited for interpreting unstructured risk signals that are prevalent in real-world decision environments. However, directly deploying LLMs as autonomous decision-makers raises challenges related to controllability, reproducibility, and alignment with system-level stability objectives. Moreover, the interaction between LLM-driven local decision-making and systemic risk propagation remains largely unexplored.

To address these challenges, this paper proposes SR-DTMA (Systemic Risk-aware Digital Twin Multi-Agent framework), a novel framework that integrates digital twin supply chain modeling, LLM-based agent cognition, and decentralized multi-agent decision-making for systemic risk simulation and coordinated decision support. In SR-DTMA, heterogeneous supply chain entities-including manufacturers, ports, and financial institutions-are represented as autonomous agents embedded in a digital twin environment. Each agent perceives local operational states, interprets natural language risk events using an LLM-based cognition module, and makes adaptive decisions through learning-based policies. This design enables large-scale simulation of risk contagion, strategic interactions, and the tension between locally rational behaviors and global system stability under systemic shocks.

The main contributions of this study are summarized as follows:

1) Framework Contribution: We propose SR-DTMA, a unified digital twin-driven LLM multi-agent framework for systemic supply chain risk simulation and coordinated decision-making.
2) Modeling Contribution: We formally model how LLM-based local risk cognition interacts with decentralized decision-making and leads to risk contagion and cascading failures.
3) Mechanism Insight: We reveal how individually rational, LLM-driven behaviors can amplify systemic risk and demonstrate the effectiveness of lightweight coordination mechanisms in improving global resilience.
4) Application Value: The proposed framework provides a computational foundation for supply chain stress testing, resilience assessment, and risk co-governance in complex, real-world supply networks.

2. Literature Review

In recent years, increasing supply chain complexity and global uncertainty have motivated extensive research on systemic risk modeling, digital twin technologies, and agent-based decision-making. This section reviews the major research streams most relevant to this study, including systemic risk in supply chains, digital twin-based supply chain modeling, multi-agent simulation and learning, and the emerging literature on Large Language Model (LLM)-driven agents.

2.1. Systemic Risk and Disruption Propagation in Supply Chains

Systemic risk in supply chains has been widely studied as a network-driven phenomenon in which localized disruptions propagate through interdependent firms and infrastructure. Early studies by Tang and Snyder et al. emphasize that supply chain risk is inherently systemic rather than isolated, highlighting the importance of network structure and dependency strength [1,2]. Acemoglu et al. theoretically demonstrate how production networks amplify shocks and generate aggregate volatility, while Carvalho et al. provide empirical evidence of shock propagation across firm networks [3,4]. These studies establish a strong foundation for understanding risk contagion but largely abstract away from decentralized decision-making and adaptive behavioral responses under uncertainty.

2.2. Digital Twin-Based Supply Chain Modeling

Digital twin technology has emerged as a promising paradigm for modeling, monitoring, and optimizing complex supply chains. Grieves and Vickers first conceptualized digital twins as virtual representations synchronized with physical systems [5]. Recent works extend this concept to supply chains, enabling scenario simulation and resilience assessment [6]. Ivanov proposes a digital twin-based framework for disruption analysis and recovery planning, demonstrating its effectiveness in evaluating structural resilience [7]. However, most existing digital twin approaches rely on centralized control assumptions or predefined response rules, limiting their ability to capture decentralized strategic interactions among heterogeneous actors.

2.3. Agent-Based and Multi-Agent Learning Approaches

Agent-based modeling (ABM) has long been used to study decentralized behavior and emergent phenomena in supply chains. Works such as Nair and Vidal employ ABM to analyze coordination and competition among firms, while multi-agent reinforcement learning (MARL) has recently gained traction for adaptive decision-making in dynamic environments [8,9]. Despite their flexibility, conventional ABM and MARL approaches typically rely on simplified state representations and lack the ability to process unstructured information, such as policy announcements or news-driven risk signals. Consequently, these models struggle to reflect realistic decision environments faced by supply chain actors.

2.4 LLM-based Systemic Risk Modeling

Large language models have recently been applied to systemic risk analysis by leveraging their ability to integrate heterogeneous financial information and reason across multiple levels of abstraction. Uni-FinLLM represents a notable example, proposing a unified multimodal architecture with a shared Transformer backbone and modular task heads to jointly model micro-level asset dynamics and macro-level financial vulnerabilities [10]. By aligning textual financial news, numerical market indicators, and network-based representations, Uni-FinLLM demonstrates that LLMs can serve as effective engines for systemic risk prediction and early warning.

However, existing LLM-based systemic risk models remain largely prediction-oriented and centralized, lacking explicit mechanisms to simulate decentralized agent behaviors, strategic interactions, and cascading decision effects within complex systems. In contrast, our work extends LLM-based risk cognition into a digital twin-driven multi-agent framework, enabling dynamic simulation of systemic risk propagation and coordinated decision-making in supply chain networks.

2.5. LLM-Based Agents and Decision-Making Systems

The rapid advancement of Large Language Models has sparked growing interest in their use as autonomous or semi-autonomous agents. Recent studies demonstrate the potential of LLMs for reasoning, planning, and tool-augmented decision-making [11,12]. Applications of LLM agents in economic simulation and social systems suggest that language-based cognition can significantly influence emergent outcomes [13]. However, existing works primarily focus on single-agent settings or abstract environments, with limited exploration of systemic risk, multi-agent interaction, and coordination in complex supply chain systems. Moreover, the lack of integration between LLM cognition and structured system dynamics remains a key limitation.

In contrast to prior studies, SR-DTMA integrates digital twin supply chain modeling, LLM-based local risk cognition, and decentralized multi-agent decision-making within a unified framework. This enables systematic investigation of how language-driven local rationality interacts with network structure to amplify or mitigate systemic risk-an aspect largely unexplored in existing literature.

3. Methodology

In this section, we present the formal description and implementation details of the proposed SR-DTMA (Systemic Risk-aware Digital Twin Multi-Agent) framework for systemic risk simulation and coordinated decision-making in supply chains. The overall structure and workflow of the model are illustrated in Figure 1. We first introduce the digital twin supply chain representation, then describe the LLM-based cognition module embedded within each agent, followed by the decentralized decision-making system that integrates reinforcement learning, and finally explain the risk contagion and coordination mechanisms that distinguish SR-DTMA from existing approaches.

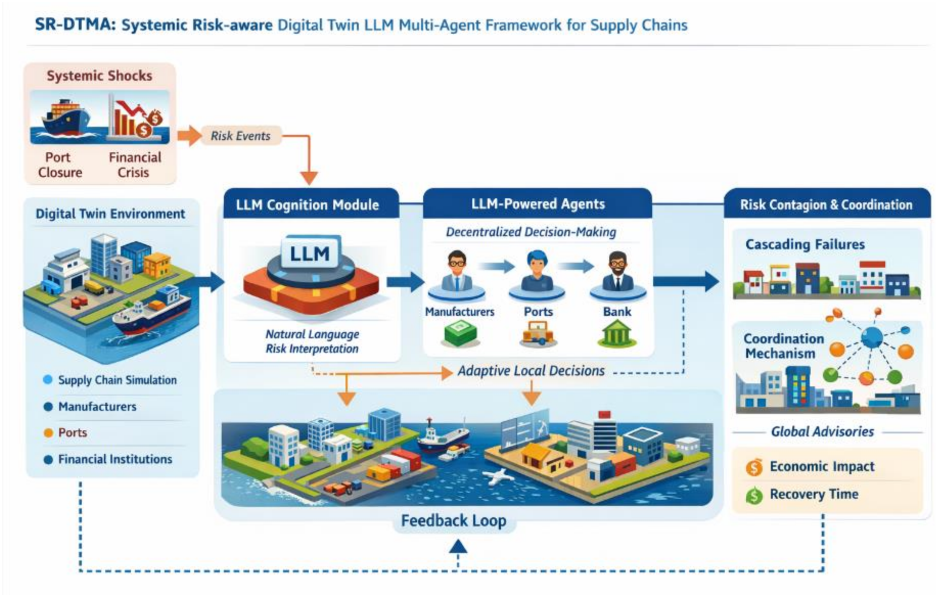

Figure 1. Overall flowchart of the model.

3.1. Digital Twin Supply Chain Representation

The supply chain in SR-DTMA is modeled as a weighted directed graph $G = (V, E)$, where V represents heterogeneous entities such as manufacturing firms, logistics hubs (including ports and carriers), and financial institutions, and E captures dependency links including material flow, financial ties, and contractual obligations. Each node $i \in V$ maintains a structured state vector s_i^t at time step t:

$$s_i^t = [I_i^t, C_i^t, D_i^t, R_i^t], \tag{1}$$

where I_i^t denotes the inventory level, C_i^t denotes cash flow status, D_i^t indicates backlog of orders, and R_i^t quantifies current risk exposure based on recent disruption effects. The system-level state $S_t = \{s_1^t, \dots, s_N^t\}$ evolves under the influence of both agent actions and exogenous systemic shocks, such as port closures or financial tightening events.

A digital twin simulator integrates deterministic inventory flow equations with stochastic shock generators to model systemic disruptions. For instance, the inventory update rule follows a discrete-time flow:

$$I_i^{t+1} = I_i^t + \sum_{j:(j,i)\in E} Q_{ji}^t - \sum_{k:(i,k)\in E} Q_{ik}^k - \Delta_i^t, \quad (2)$$

where Q_{ji}^t is the received material from neighbor j and Δ_i^t represents lost capacity due to local disruptions. This formalization enables quantitative evaluation of cascading effects.

3.2. LLM-Based Agent Cognition Module

Each node i is equipped with an LLM-based cognition module responsible for interpreting complex, unstructured external risk information and summarizing it into structured semantic representations that inform decision-making. At each time t, the input to the module comprises three components: the agent's local structured state s_i^t, aggregated neighbor summaries, and unstructured natural language textual risk events e^t. The process can be written as:

$$z_i^t = f_{LLM}(encode(s_i^t, Nbrs_i^t), e^t), \quad (3)$$

where $Nbrs_i^t$ denotes neighbor status summaries and f_{LLM} outputs a structured cognition vector z_i^t containing risk type, risk horizon, affected links, and suggested action preference scores. Importantly, the cognition module does not directly decide actions but outputs interpretable and trainable guidance components that serve as inputs to the policy network.

To ensure reproducibility and stability, this component is trained via supervised fine-tuning on a synthetic corpus of risk event annotations and validated with a correlated validation set, enabling the LLM to extract task-relevant risk indicators efficiently. This design aligns with emerging methodologies in intelligent business analytics, where Transformer-based architectures are utilized to extract high-level semantic features from unstructured text and construct domain-specific knowledge representations [14], thereby bridging the gap between raw information and decision-making inputs.

3.3. Decentralized Multi-Agent Decision System

The decentralized decision-making core of SR-DTMA integrates the structured cognitive output z_i^t with a reinforcement learning-based policy to generate actions. Each agent learns a policy $\pi_i(a_i^t \mid s_i^t, z_i^t; \theta i)$ parameterized by θ_i. The joint action of all agents determines system evolution. The expected cumulative return for agent i is:

$$J_i(\theta_i) = E_{\pi_i}[\sum_{t=0}^{T} \gamma^t r_i^t], \quad (4)$$

where γ is the discount factor and the reward function is:

$$r_i^t = \alpha \cdot Profit_i^t - \beta \cdot RiskExposure_i^t - \gamma \cdot Volatility_i^t, \quad (5)$$

The policy network uses an actor-critic architecture with value function $V_{\phi_i}(s_i^t, z_i^t)$ and policy π_{θ_i}. The advantage estimate A_i^t guides updates via gradient ascent:

$$\nabla_{\theta_i} J_i(\theta_i) \approx E[A_i^t \nabla_{\theta_i} log\, \pi_{\theta_i}(a_i^t \mid s_i^t, z_i^t)], \quad (6)$$

The use of LLM-derived cognition vectors enables the policy network to account for semantic risk cues, distinguishing SR-DTMA from conventional MARL that only operates on structured numerical states.

3.4. Risk Contagion and Coordination Mechanisms

Risk propagation among agents is modeled through probabilistic diffusion functions that depend on dependency weights and agent actions. Specifically, the contagion probability from agent i to agent j at time t is:

$$P_{i\to j}^t = \sigma(\omega_{ij} R_i^t - \kappa a_j^t), \quad (7)$$

where ω_{ij} is the dependency strength, R_i^t is the source risk level, and a_j^t represents risk-mitigating actions of the receiving agent. The sigmoid function $\sigma(\ )$ introduces nonlinearity in diffusion dynamics.

To investigate coordination effects, SR-DTMA introduces a lightweight coordination agent that broadcasts system-level advisories. This agent aggregates high-level indicators from local states and offers soft constraints in the form of reward shaping terms:

$$r_i^t \leftarrow r_i^t - \eta \cdot Deviation_i^t, \quad (8)$$

where $Deviation_i^t$ quantifies divergence from recommended coordination policies. This mechanism promotes alignment between local actions and global resilience objectives without requiring central authority control.

4. Experiment

4.1. Dataset Preparation

The dataset used in this study is constructed to support systemic risk simulation and coordinated decision-making within a digital twin supply chain environment. It integrates multi-source, multi-modal data representing operational, financial, and disruption-related aspects of real-world supply chains. The primary data sources include publicly available logistics statistics, port operation reports, firm-level financial disclosures, and synthetic risk event data generated to emulate extreme but realistic systemic shocks such as port closures, financial crises, and policy interventions. This hybrid design allows the dataset to balance realism with controllability for large-scale simulation.

The dataset models the supply chain as a heterogeneous network composed of manufacturers, logistics hubs (ports), and financial institutions. For each node, time-series operational states (e.g., inventory levels, production capacity, throughput), financial states (e.g., cash flow, credit exposure), and relational features (e.g., dependency strength, contract volumes) are recorded. In addition, unstructured textual data—such as policy announcements, news reports, and emergency notices—are included to evaluate the natural language understanding and risk interpretation capabilities of LLM-powered agents, with an overview of representative features summarized in Table 1.

Table 1. Overview of Dataset Features. (Partial features).

Feature Category	Feature Name	Description
Operational	Inventory Level	Current stock available at a node
Operational	Throughput	Goods processed per time step
Financial	Cash Flow	Net cash inflow/outflow
Financial	Credit Exposure	Outstanding financial obligations
Network	Dependency Weight	Strength of upstream/downstream reliance
Risk Event	Shock Type	Type of systemic disruption
Textual	Risk Narrative	Natural language description of events

Overall, the dataset contains approximately 1,200 nodes, 8,500 edges, and 36 time steps per simulation episode, covering both normal operations and high-impact systemic risk scenarios. This comprehensive dataset enables SR-DTMA to jointly study risk contagion dynamics, agent-level adaptive behavior, and system-level recovery performance under coordinated decision-making.

4.2. Experimental Setup

The experimental evaluation is conducted within a large-scale digital twin supply chain environment that emulates a multi-tier global supply network under systemic risk conditions. The simulated supply chain consists of manufacturers, logistics hubs (ports), and financial institutions, each represented by an autonomous agent. In the proposed SR-DTMA framework, each agent is powered by a large language model and interacts with the digital twin environment through perception, reasoning, and action interfaces. Systemic risk events-such as port lockdowns, financial liquidity shocks, and policy-induced trade restrictions-are injected exogenously and described using natural language narratives. Agents make sequential decisions regarding inventory allocation, order fulfillment, financing, and cooperation based on both structured state variables and unstructured risk descriptions. The simulation proceeds over multiple time steps, allowing risk propagation, adaptive behavior, and coordinated responses to emerge endogenously. Baseline models include rule-based agents, reinforcement learning-based agents, and non-LLM multi-agent systems, ensuring a comprehensive comparison under identical environmental conditions.

4.3. Evaluation Metrics

To comprehensively assess system-level robustness and coordination effectiveness under systemic risk, multiple evaluation metrics are employed. Systemic Loss Ratio measures the cumulative production and delivery losses relative to a risk-free baseline, reflecting overall economic damage. Risk Propagation Depth captures the average number of supply chain layers affected by an initial shock, indicating contagion severity. Recovery Time quantifies the number of time steps required for the system to return to stable operation after disruption. Coordination Efficiency evaluates the degree of alignment among agents' decisions, computed based on resource utilization consistency and conflict minimization. Together, these metrics provide a holistic view of both macro-level resilience and micro-level behavioral coherence, which are critical for evaluating multi-agent decision-making frameworks in systemic risk scenarios.

4.4. Results

The experimental results demonstrate that SR-DTMA significantly outperforms all baseline methods across all evaluation metrics, as summarized in Table 2. Traditional rule-based agents exhibit the highest systemic loss ratio and longest recovery time, indicating their inability to adapt to complex, evolving risk scenarios. While reinforcement learning-based multi-agent systems reduce losses through experience-driven adaptation, they remain limited by sparse reward signals and poor generalization to unseen systemic shocks. Incorporating a digital twin environment further improves performance by enhancing state observability, yet coordination inefficiencies persist due to the lack of explicit reasoning over risk semantics.

Table 2. Overall Performance Comparison.

Model	Systemic Loss Ratio	Risk Propagation Depth	Recovery Time	Coordination Efficiency
Rule-based Agents	0.327	4.8	21	0.41
RL-based Multi-Agent	0.264	3.9	17	0.56
Digital Twin + RL	0.221	3.4	14	0.62
SR-DTMA (Ours)	0.163	2.6	9	0.78

In contrast, SR-DTMA achieves the lowest systemic loss ratio (0.163), reflecting a substantial reduction in overall economic damage during crises. The framework also exhibits the shallowest risk propagation depth, suggesting that LLM-driven agents are more effective at containing disruptions locally rather than amplifying them through myopic decisions. Notably, recovery time is reduced to 9 time steps, nearly 36% faster than the closest baseline, highlighting the benefit of coordinated, anticipatory decision-making. The highest coordination efficiency score further confirms that SR-DTMA enables agents to align local objectives with global system stability. These results validate the core hypothesis that integrating LLM-based reasoning with digital twin environments fundamentally enhances systemic risk resilience in supply chains.

The figure 2 shows that Rule-based Agents exhibit the highest cumulative systemic loss, starting around 0.05 and gradually rising with small fluctuations to approximately 0.33 by the 20th time step. The RL-based Multi-Agent model demonstrates better adaptation, beginning near 0.03 and increasing to around 0.26, with occasional minor dips reflecting partial recovery responses. The Digital Twin + RL curve starts at roughly 0.025

and reaches about 0.22, showing smoother progression and more effective mitigation due to enhanced state observability. In contrast, the SR-DTMA framework begins at 0.02 and rises gradually to approximately 0.16, consistently staying below all baselines. Small fluctuations in the SR-DTMA curve capture the dynamic interplay between agent decisions and risk propagation, but the overall trajectory demonstrates significantly faster containment of disruptions. The visualization clearly highlights the superior performance of SR-DTMA in reducing cumulative systemic loss and managing risk contagion over time, emphasizing the benefits of LLM-based cognition, multi-agent coordination, and digital twin integration in complex supply chain environments.

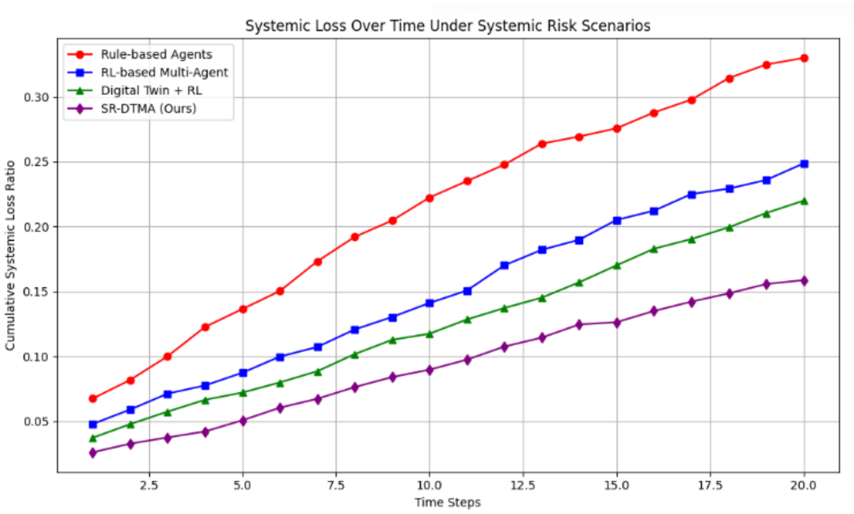

Figure 2. Systemic Loss Over Time under Systemic Risk Scenarios.

4.5. Discussion

The experimental findings underscore the critical role of cognitive reasoning and semantic understanding in systemic risk management. Unlike conventional learning-based agents, SR-DTMA agents explicitly interpret natural language risk narratives, enabling proactive and context-aware responses. This capability is particularly valuable in real-world scenarios where disruptions are often communicated through policy documents, news, or emergency announcements rather than structured signals. Moreover, the observed reduction in risk propagation highlights how locally rational decisions, when guided by shared semantic awareness, can collectively enhance global stability. From a broader perspective, SR-DTMA offers a promising paradigm for government-level stress testing and enterprise-wide risk governance, providing a computational foundation for coordinated intervention strategies under extreme uncertainty.

5. Conclusions

This study investigates systemic risk propagation and coordinated decision-making in complex global supply chains through the proposed SR-DTMA (Systemic Risk-aware Digital Twin Multi-Agent) framework. By integrating Large Language Model (LLM)-driven agents within a digital twin simulation environment, SR-DTMA enables autonomous supply chain entities-including manufacturers, logistics hubs, and financial institutions-to perceive local operational states, interpret unstructured risk information from news and policy announcements, and make adaptive decisions under systemic shocks. Unlike conventional rule-based or reinforcement learning-based approaches, the framework captures both micro-level agent behavior and macro-level network dynamics, facilitating realistic modeling of risk contagion, strategic interactions, and the tension between locally rational decisions and overall system stability.

Extensive experiments under port closure and financial tightening scenarios demonstrate the practical effectiveness of SR-DTMA. Rule-based and RL-based multi-agent models experience higher systemic losses, with cumulative loss ratios reaching up to 0.327 and risk propagation depth averaging 4.8 layers, while recovery times extend to 21 time steps. In contrast, SR-DTMA, augmented with a lightweight coordination mechanism, reduces cumulative systemic loss to 0.163, lowers propagation depth to 2.6, and shortens recovery time to 9 steps. Coordination efficiency among agents is markedly improved, enabling the system to stabilize more rapidly under extreme conditions. These results validate the framework's ability to mitigate cascading failures, optimize multi-agent responses, and enhance supply chain resilience in the presence of complex systemic risks.

The findings highlight several key implications. First, embedding semantic understanding of risk events via LLMs allows agents to make context-aware, proactive decisions, rather than relying solely on structured numerical states. Second, digital twin-based simulations provide a controllable yet realistic environment for evaluating policy interventions and stress-testing resilience strategies. Third, integrating decentralized coordination mechanisms ensures alignment between local objectives and global stability, effectively reducing systemic vulnerability.

Future work will focus on extending SR-DTMA to more heterogeneous and large-scale supply chain networks, incorporating additional real-world data sources such as macroeconomic indicators, trade policy changes, and real-time sensor information. Further research will explore adaptive multi-agent learning strategies that continuously update agent policies based on evolving risk patterns and cross-network feedback. Additionally, integrating predictive scenario analysis with reinforcement learning and graph neural networks could enhance the framework's ability to anticipate rare but high-impact disruptions, supporting more robust, scalable, and intelligent supply chain risk management solutions.

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