Computers & Industrial Engineering 201 (2025) 110897

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Data-driven supply chains mapping and disruption analysis: The case of automotive SoC enterprises in China

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ARTICLE INFO

Keywords:
Supply chain
Complex networks
Interaction disruption models
Cascade failure

ABSTRACT

Effective modeling of modern supply chains is crucial for improving visibility, mitigating systemic risks, and developing resilient strategies. However, data limitations imposed by industry sensitivity and competition have hindered research in this area. Combining big data and complex network theory, this study introduces an Open Supplier Knowledge Extraction and Complement (OSKEC) approach, incorporating cross-domain named entity recognition, firm entity fuzzy matching, and supplier relation inferring, to construct highly reliable supply chain networks from limited information. Applying OSKEC on the Chinese automotive Systems-on-Chips (SoCs) industry approves its effectiveness in enhancing supply chain visibility and resilience. Topological analysis for the built supply chain network reveals a clear scale-free degree distribution, implying a strong heterogeneity for the interdependence of entities in the network. Specifically, NVIDIA, Qualcomm, and Mobileye occupy the majority share of the automotive SoC market in China, while local enterprises only hold a smaller portion. We further develop two interaction disruption models (IDMs) which simulate the impact of various disturbances on firms with different recovery capacities and risk-transfer strategies, and find that a risk-transfer enterprise strategy may lead to a rapid collapse of the network in the early stages of disruptions. In general, the study improves the understanding of modern supply chain dynamics and inform effective risk management strategies in the Chinese automotive SoC sector.

1. Introduction

Supply chain disruptions—events interrupting product or service flow—can lead to severe financial losses, operational inefficiencies, and competitive disadvantages (Berger et al., 2023; Zhao et al., 2019). The disruption and resilience of supply chain networks have gained significant attention and research over the past few decades, and many studies on supply chain resilience have been conducted at the industry level. However, modern supply chain networks exhibit increasing complexity and dynamic inter-firm interactions, and the growing complexity of supply chains hinders visibility into the network structure, necessitating research on overall network resilience (Cao et al., 2019). To mitigate risks from technological obsolescence, natural disasters, and geopolitical tensions, firms seek strategies to enhance supply chain adaptability.

In specific industry sectors such as semiconductors (Malkin & He, 2024), pharmacy (Dosi et al., 2023), and artificial intelligence (Gupta et al., 2023), the presence of monopolistic enterprises is notable. These industries often face high technological barriers to entry. Consequently, the failure or bankruptcy of a dominant firm can have catastrophic consequences for the global supply chain (Sudan et al., 2023). The semiconductor industry, particularly in the realm of Systems-on-Chips (SoCs), is subject to stringent international regulations governing design, production, processing, and raw material sourcing (Cohen, 2024; Mickle et al., 2023). Chinese vehicle manufacturers face significant challenges due to their heavy reliance on foreign SoC monopolies within an imbalanced global trade environment. These automotive SoCs are primarily used for advanced applications such as advanced driver assistance systems (ADAS) and in-vehicle infotainment systems (IVIS). They represent the most concentrated embodiment of cutting-edge technology in EVs. However, the Chinese automotive SoC industry is uniquely characterized by high-tech dependence on specialized suppliers (*e.g.*, Nvidia, Mobileye, and Qualcomm) and significant geopolitical influences. Supply chain disruptions and decoupling exacerbate the difficulties faced by automotive SoC companies in developing effective business continuity strategies (Berger et al., 2023). To assess the resilience and robustness of real-world supply chains, it is imperative to

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https://doi.org/10.1016/j.cie.2025.110897
Received 6 September 2024; Received in revised form 2 January 2025; Accepted 17 January 2025
Available online 25 January 2025

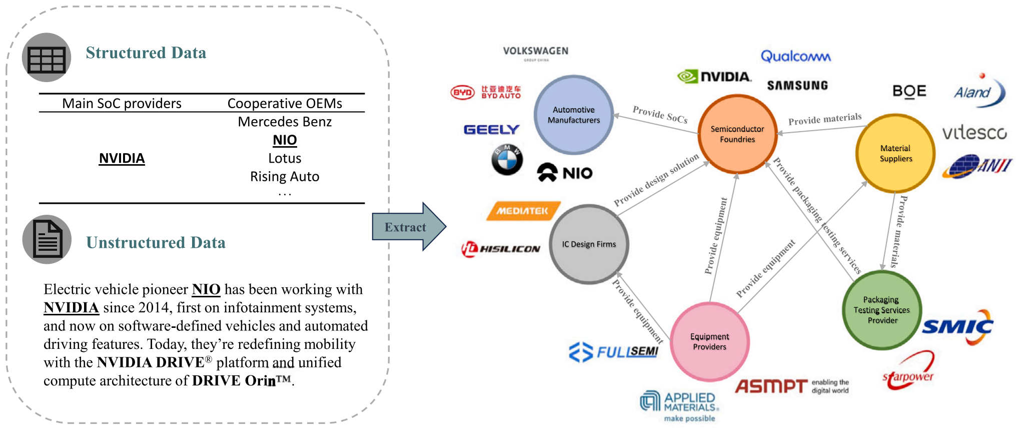

Fig. 1. Examples of constructing a supply chain network at the firm level.

develop a supply chain model that accurately represents the network's layered structure, interactions, and dynamic evolution.

Traditional supply chain network modeling methods, such as mathematical, operational, and agent-based approaches (Fathi et al., 2024; Marra et al., 2012; Reyes et al., 2023), often struggle to capture the dynamic, complex, and real-time nature of modern supply chains. Moreover, the confidential nature of supplier information limits the availability of complete network data. To address these challenges, this study leverages the combined power of knowledge graphs, complex network theory, and big data. By integrating structured and unstructured data, we can comprehensively characterize supply chain heterogeneity and dynamic relationships. Structured data provides precise supplier information, while unstructured data offers rich contextual insights. This integrated approach enhances visibility into deep-level supply chain structures, enabling improved risk perception and resilience. For instance, in the Chinese automotive SoC supply chain (Fig. 1), knowledge graphs can illuminate complex inter-enterprise interactions, supporting the development of robust supply chain strategies.

The scarcity of supply chain data in certain sectors has long been a challenge for supply chain modeling. However, with the rapid development of Chinese EVs in recent years, a vast amount of supplier data available in open-domain provides an opportunity to address this issue. The big data-driven approach has been widely adopted in supply chain network research and demonstrated reliability (Babu et al., 2024; Lamba & Singh, 2018; Zhao et al., 2019). Publicly available information, such as mandatory disclosures and voluntary announcements, as well as information displayed for purposes of transparency, corporate social responsibility (CSR), and open communication, generates vast amounts of supply chain-related data. This creates a rich repository of supplier interactions within the automotive SoC industry. Extracting valuable supplier information from this data requires advanced mining techniques. The challenge lies in effectively handling diverse, large-scale, and heterogeneous datasets to derive actionable insights (Cerchione & Esposito, 2016).

In this paper, we propose an OSKEC-IDM framework, which integrates the Open Supplier Knowledge Extraction and Complement (OSKEC) approach for the supply chain network construction, and Interaction and Disruption Models (IDMs) for risk assessment and resilience analysis, to characterize real-world supply chains and simulate enterprise behaviors under disruptions. The OSKEC extracts and completes cooperative relationships from open-domain and professional databases to construct a real-world supply chain cooperative network at the firm level, while the IDMs model complex enterprise behaviors based on recovery capacity and risk-transfer strategies. To evaluate the framework, we construct the Chinese automotive SoC supply chain network using multi-source heterogeneous data and analyze proactive strategies for enhancing supply chain resilience. Results show that the enterprises within the Chinese automotive SoC supply chain can take proactive measures to mitigate or even halt the spread of disruption in the whole supply chain network. Furthermore, our findings reveal that if an enterprise opts for the risk-transfer strategy instead of undertaking the disruption risk in some cases, the disruption initially slows but accelerates over time. Lastly, we conduct sensitive analysis to validate our conclusions. The primary research questions addressed in this study are: (1) How disruptions in supply chain networks impact the operational efficiency of automotive SoC enterprises in China. (2) What data-driven methodologies can be applied to predict and mitigate these disruptions. These questions guide the investigation of the dynamics of automotive supply chains and the development of potential solutions for enhancing their resilience.

The remainder of this paper is structured as follows. Section 2 reviews existing literature on supply chain network and disruption modeling. Section 3 introduces the OSKEC-IDM framework and its methodology. Section 4 presents empirical results and analysis of the Chinese automotive SoC supply chain network. Finally, Section 5 summarizes key findings, discusses implications, and outlines future research directions.

2. Literature review

2.1. Modeling of supply chain networks

Traditional linear and sequential models which are proposed to illustrate the supply chain as a simple series of nodes, such as suppliers, manufacturers, and retailers, each connected to the next (Sarimveis et al., 2008), typically emphasize linear and local chain structures and focus on direct upstream and downstream relationships. These chain models assume a direct flow of products, information, and finances from one stage to the next without considering the multiple interactions that might occur at each node (Piya et al., 2020), which often leads to the oversimplification of supply chain structures and fails to capture the complexity of modern supply chains and adequately represent the multiple attributes of supply chain nodes and the diverse interactions across different levels of the supply chain network (Piya et al., 2020; Spiegler et al., 2016). Subsequently, network-based approaches including social network analysis (Leon et al., 2024) and complex network approach (Zhang et al., 2023) are widely used to explain the complex interaction behaviors between two parties in the modern supply chain. In these supply chain network models, massive simulation experiments were carried out, providing valuable insights into complex adaptive behaviors under various scenarios. However, simulation models solely based on the supply chain network structure without realistic data show inherent limitations in the lack of real-world complexities consideration, significantly limiting their accuracy and reliability (Helbing et al., 2006; Thadakamaila et al., 2004). These limitations stem from the simplifications and assumptions necessary for computational models and simulated data, which are unable to fully capture the intricate dynamics, unpredictability, and variability from actual supply chains. This results in a gap between the theoretical outcomes produced by simulations and the practical experiences observed in real-world operations.

To address these issues above, researchers are increasingly focusing on real-world supply chain network structures. Pathak et al. described and discussed the features of the American automotive supply chain network (Pathak, Day et al., 2007; Pathak et al., 2009); Kito et al. discussed the realistic structure of automotive supply chain networks by analyzing actual product data (Kito et al., 2015). Subsequently, they analyzed the comprehensive data in the automobile parts supply chain network and clarified the closeness between strategies and enterprise strategies (Brintrup et al., 2017; Kito & Ueda, 2014). Lu et al. and Cai et al. utilized business data from the Chinese National Important Products Traceability System to construct a triple-layer supply chain model encompassing farm, slaughterhouse, and retailer stages (Cai et al., 2020; Lu et al., 2019). Brintrup et al. assembled a large-scale empirical dataset on the supply chain of Airbus and applied the new science of networks to analyze how the industry is structured (Brintrup et al., 2017). Substantial research has shown that employing real-world data enables us to characterize the nodes representing businesses within supply chain networks and the relationships among these enterprises more precisely (Gualandris et al., 2021).

However, the aforementioned studies generally depend on specialized data or assumptions that may not accurately mirror current or future conditions, leading to a discrepancy between the theoretical supply chain structure and the actual structure observed in the real world. Therefore, while these models are useful for understanding general structure and preparing for predictable scenarios, they should be used with caution and supplemented with up-to-date realistic data whenever possible. In addition, the exploration of the real-world structure of supply chain remains limited due to data security concerns and governmental influences in certain industries. In the context of supply chain disruption analysis, particularly in data-sensitive industries like semiconductors, automotive and pharmaceuticals, our OSKEC framework offers transformative advantages over existing methods. Traditional approaches often rely on extensive and specialized datasets, which are not always accessible due to data security concerns, proprietary restrictions, or governmental regulations. OSKEC, by contrast, leverages advanced techniques such as cross-domain named entity recognition, fuzzy matching, and knowledge graph integration to construct comprehensive and reliable supply chain networks from fragmented or incomplete data. This capability allows for a more accurate representation of real-world supply chain structures, even in scenarios with limited data availability. Moreover, OSKEC enhances the scalability and adaptability of disruption analysis by dynamically inferring relationships and identifying critical nodes, enabling a deeper understanding of supply chain vulnerabilities and resilience strategies. These features position OSKEC as a robust and innovative solution, bridging the gap between theoretical models and practical applications in high-stakes, data-restricted industries.

2.2. Supply chain disruption modeling

A disruption of supply chains refers to unexpected events that significantly interrupts the normal flow of products and services within a supply chain network, potentially leading to delays, increased costs, reduced quality, or complete failure in meeting customer demands till bankruptcy (Berger et al., 2023; Cheng et al., 2024; Wang et al., 2023b; Zhao et al., 2019). Supply chain disruptions could arise from natural disasters, geopolitical tensions, economic fluctuations, and technological failures (Son et al., 2021; Wang et al., 2023b). Some Studies analyze how geopolitical tensions and supply–demand imbalances during COVID-19 impacted disruptions in the semiconductor industry, leading to ripple effects in downstream industries like automotive SoCs (Malkin & He, 2024; Ramani et al., 2022). Specifically, U.S.-China trade restrictions significantly constrained semiconductor exports, disrupting the global supply chain and creating bottlenecks in downstream industries like automotive manufacturing (Malkin & He, 2024). Similarly, the systemic nature of disruptions during COVID-19, when semiconductor shortages delayed automotive production, leads to substantial economic losses. These findings highlight the importance of enhancing supply chain recovery capabilities to strengthen resilience of global semiconductor supply chain network (Ramani et al., 2022).

The interconnected nature of modern supply chains makes them susceptible to a wide range of disruptions, which can propagate quickly across the network, affecting multiple entities simultaneously (Brintrup et al., 2017; Son et al., 2021). Studies by Spieske et al. and Sudan et al. explore how the pandemic exposed vulnerabilities in global supply chains and highlight strategies to enhance resilience, such as diversification, digital transformation, and risk pooling (Spieske et al., 2022; Sudan et al., 2023). A lack of preparedness hindered the implementation of certain measures, underscoring the need for enhanced proactive risk management in the aftermath of the pandemic.

Researchers have analyzed the interaction and disruption behaviors within supply chain networks to align them more closely with the principles of Complex Adaptive Systems (CASs) (Lou et al., 2023; Zhao et al., 2019). A CAS is a self-organizing system, and it reconfigures its internal and external linkages to continually evolve (Choi et al., 2001), which is a useful theory in describing supply chain network structures (Kim et al., 2015; Nair et al., 2009). Pathak et al. termed supply networks as a typical case of CAS because a supply chain will adapt and evolve via interactions of nodes within the network (Pathak, Dilts et al., 2007). These interactions are not merely transactional but involve strategic collaboration, information sharing, and mutual dependency among various stakeholders, including suppliers, manufacturers, and customers. Viewing the supply chain network as a CAS provides a valuable approach to studying the effects of disruptions. In the disruption process, a company's behavior is shaped by its specific characteristics, making it intriguing to investigate how a firm's business interaction strategies evolve. For example, Kim et al. found that if a single central node acts as the focal point for aggregating supply and distributing demand, any disruption to this critical node could potentially lead to the complete cessation of operations across the entire supply chain network (Kim et al., 2015). Wang and Zhou et al. investigated the financial repercussions at the firm level resulting from supply chain disruptions during COVID-19. They explored how companies' supply chain diversification strategies—encompassing diversified suppliers, customers, and products—mitigate the adverse impact on firm performance (Wang et al., 2023b).

The impact of company strategies in the field of disruption can be profound, leading to significant market shifts and resilience reduction within the industry supply chain. Moreover, the ripple effects of strategies can extend beyond the immediate supply chain, affecting the entire economy and society. Understanding the mechanisms of interaction and disruption within supply chains is paramount for developing effective strategies to enhance resilience. There are multiple strategies in the field of supply chain resilience, including technological innovation (Sun et al., 2024), supplier redundancy (Kamalahmadi et al., 2022), risk pooling (Hu et al., 2019), prospective supplier visibility (Wang & Webster, 2022), network reconfiguration (Tian & Guo, 2019), and supplier collaboration (Hofman et al., 2020), among others. The IDMs (Interaction Disruption Models) can simulate these resilience strategies and provide a comprehensive understanding of supply chain CASs. It serves as an effective methodology for studying disruption spread across fields such as sociology (Ficara et al., 2023), ecology (Tagliari et al., 2023), and medicine (Ki et al., 2024). By enhancing resilience management capabilities, the IDM enables stakeholders to address and mitigate potential challenges more effectively.

Table 1
Summary of studies on supply chain mapping and disruption analysis.

Reference	Methodology	Resilience evaluation	Industry field	Ripple effect	Neighbor influence	Anti-risk ability	Transfer strategy	Absorption strategy
Choi et al. (2001)	Complex adaptive system	Dimensionality of supply networks	Microprocessor and welding technique	×	✓	×	×	×
Pathak, Dilts et al. (2007)	Supply network evolution	Environmental threshold, and capacity change	U.S. automobile	✓	✓	×	×	×
Kim et al. (2015)	Graph theory	Network structure metrics	Four basic supply network structures	✓	✓	×	×	×
Gualandris et al. (2021)	Network science	Network centrality metric	Airbus supply chain	×	✓	×	×	×
Zhao et al. (2019)	Agent-based modeling	Average number of disrupted firms	Global supply chains across 90 industries	✓	✓	✓	×	×
Tian and Guo (2019)	Graph-based cost model	Reconfiguration cost	Laptop computer assembly	×	×	×	×	×
Rahman et al. (2021)	Agent-based model	Cost	Facemask supply chain	✓	✓	✓	×	×
Ramani et al. (2022)	Stylized supply chain planning model	Demand	Auto industry	✓	✓	×	×	×
Wang et al. (2023b)	Event study	Financial performance	222 publicly traded firms in China	×	✓	✓	×	×
Berger et al. (2023)	Epidemic model	Authority value	21 real-world networks	✓	✓	✓	×	×
Malkin and He (2024)	Case Study	Sales	global semiconductor	×	×	✓	✓	×
This study	Data-driven and Complex Network Simulation	Disruption Percentage	Chinese automotive SoC	✓	✓	✓	✓	✓

The discussion above illustrates the importance of developing appropriate models to capture the interaction and disruption behaviors within the field of supply chain resilience. However, previous models of supply chain networks lack a detailed exploration of the mechanisms of disruption impacts and the global changes across the entire network. Fu et al. provide a cascading failure resilience analysis focused on the automotive manufacturing supply chain. Their study emphasizes the effectiveness of a two-stage recovery strategy, which involves prioritizing under-utilized nodes in the initial phase and subsequently restoring isolated nodes, significantly enhancing network resilience (Fu et al., 2024). Rahman et al. employ an agent-based model to demonstrate the effectiveness of recovery strategies, including emergency stockpiles, increased production capacity, and multi-cooperations, in addressing demand–supply imbalances (Rahman et al., 2021). In this study, we carefully considered the diverse range of enterprise strategies commonly employed to enhance supply chain resilience, aligning them with the unique characteristics of the Chinese automotive SoC industry. Given this sector's reliance on long production cycles, limited domestic technological independence, and significant exposure to geopolitical tensions, we chose to develop models around recovery capacity (RC-IDM) and risk-transfer (RT-IDM) strategies to effectively address the industry's most pressing challenges (see Table 1).

3. Research methodology

3.1. Overall framework

In this paper, we propose an OSKEC-IDM framework based on real-world data to understand the complex adaptive interaction and disruption behaviors in the supply chain network. As shown in Fig. 2, the OSKEC-IDM framework consists of three modules. *Real World Data*: Combining open-domain datasets and professional databases to gather firm entities and their relationships, forming the basis of the supply chain network. *OSKEC Approach*: Processing the extracted data through named entity extraction, relationship complement, and supply chain network construction to create a comprehensive network of firm connections. *IDMs*: Utilizing the Recovery Capacity Model and Risk Transfer Model to simulate supply chain resilience against various disruption scenarios, including high-degree, high-closeness, and high-importance attacks.

The OSKEC module extracts supply chain firms (entities) and their relationships from both open-domain (*e.g.*, research reports, news articles, financial reports) and professional databases (*e.g.*, CSMAR, Wind). To enhance the completeness of the real supply chain network, we employ inference techniques leveraging Large Language Models (LLMs) and Knowledge Graphs (KGs) to expand supply chain relationships. Subsequently, a comprehensive supply chain KG is constructed and analyzed based on the extracted firm entities and relationships.

The IDM module includes two models to simulate enterprise behaviors: the Recovery Capacity-based IDM (RC-IDM) and Risk Transfer-based IDM (RT-IDM). These models analyze the impact of disruptions under various scenarios and inform proactive strategies for enhancing supply chain resilience. Besides, dynamic cross-validation is employed to align simulation results with real-world data, ensuring the OSKEC-IDM framework's accuracy.

3.2. Open Supplier Knowledge Extraction and complement approach

Open-domain sources are freely accessible data resources, such as news media, academic data repositories, and non-profit organizations. In contrast, professional databases are typically proprietary or restricted. Accessing them often requires specialized technical methods or incurs commercial costs.

The OSKEC approach effectively constructs supply chain networks in data-scarce environments. First, it extracts "Open Entities" (firm names) from diverse open-domain datasets using cross-domain transfer learning via GPT-NER (Wang et al., 2023). Simultaneously, partial firm entities and their relationships are collected from professional databases. These are combined with the Open Entities to form the "Basic Triplets" set. Second, fuzzy matching (details in Appendix B) is applied to Basic Entities to rectify naming inconsistencies (*e.g.*, NVIDIA, NVDA, NVIDIA Corporation) to get "Matched Triplets". A triplet is composed of three components: two firm entities and the supply relationship between them. Finally, LLM and KG-based firm relation completion is performed to get the "Integrated Triplets". Fig. 3 illustrates the process of OSKEC approach. *Firm Entity Extraction*: Firm entities are extracted from open domain datasets and professional databases,

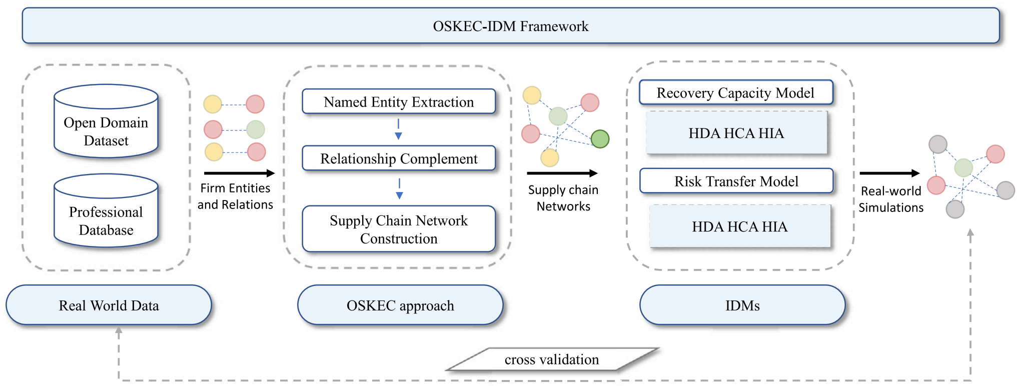

Fig. 2. The architecture of the OSKEC-IDM framework.

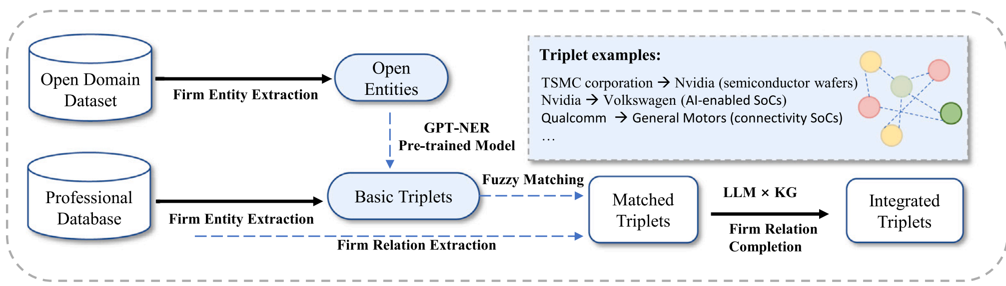

Fig. 3. The process of OSKEC approach.

forming the initial entity set. *Firm Relation Extraction*: Basic triplets are generated using GPT-NER for entity recognition. Fuzzy matching is applied to standardize names and create "Matched Triplets". *Firm Relation Completion*: Large language models (LLM) and knowledge graphs (KG) are used for relation completion, producing the final "Integrated Triplets" set.

3.2.1. Entity extraction

We apply Named Entity Recognition (NER) technology to extract supply chain entities (firm names) from open domain and professional databases. This approach formulate the entity extraction problem as a sequence labeling task.

Given a sentence sequence $X = \{x_1, \ldots, x_n\}$, the NER task assigns an entity type $y \in Y$ to each word x, where Y denotes the set of entity labels and n denotes the length of the given sentence. We utilize the fine-tuned GPT-NER pre-trained model to improve NER performance in the specific industry domain (Wang et al., 2023). Fine-tuning GPT-NER also helps bridge the gap between two tasks: NER and LLM prompt construction. NER is inherently a sequence labeling task, whereas LLM prompt construction involves a text generation model. This approach shows greater ability in low-resource and few-shot setups. When the amount of training data is extremely scarce, GPT-NER performs significantly better than supervised models. This makes it suitable for industry domains that lack extensive supplier information. The process can be decomposed into the following three steps:

(1) Firm datastore construction

To develop a NER model for entity extraction, we construct a training dataset from the open domain. The training dataset contains 8,505 records. It is labeled through automated scripts via the "BIO" labeling method (Wang et al., 2023). The entity types include firms (labeled as F), products (labeled as P), businesses (labeled as B), and locations (labeled as L).

(2) Entity representation extraction

To identify firm entities in the specific field, we adapt fine-tuning pre-trained models for the NER task. This process involves fine-tuning the model to align with specific tasks and domains. By doing so, we enhance the models' performance in recognizing entities within specialized domains.

Representation extraction aims to obtain the high-dimensional vector representation for each token within the input textual sequence. We use BERT (Devlin et al., 2019) as the encoder model to represent the high-dimensional vector of corpus related to supply chain enterprises. The output of BERT is $h_i \in \mathbb{R}^{m \times 1}$, where n denotes the length of the input sentence and m denotes a variable parameter of the dimension of the vector. Then, each embedded high-dimensional vector h is sent to a multi-layer perception (MLP) and then generates the distribution of probability over the named entity vocabulary using the softmax function:

$$p_{\mathrm{NER}} = \mathrm{softmax}\ \mathrm{MLP}\ (h \in \mathbb{R}^{m \times 1}). \tag{1}$$

Based on p_{NER}, the embedded high-dimensional vectors are classified into labels according to a softmax layer.

(3) Few-shot demonstrations for LLM prompt

To guide the LLM's output format and provide task-relevant context, we incorporate few-shot demonstrations into the prompt. By mimicking the provided examples, the LLM generates outputs in a consistent format, facilitating subsequent NER processing. Additionally, the demonstrations offer direct task-related information to enhance prediction accuracy. Entity-level representations are extracted for each firm. Cosine similarity is then used to retrieve K-nearest neighbors (KNNs) from the training set (Torres et al., 2023). This approach surpasses sentence-level KNN methods, which often lack relevant NER information. Semantically similar sentences may not contain the necessary NER tags. For example, "It is a semiconductor company" lacks explicit entities, whereas "NVIDIA is a semiconductor company" includes them. Entity-level representations focus on local evidence, which

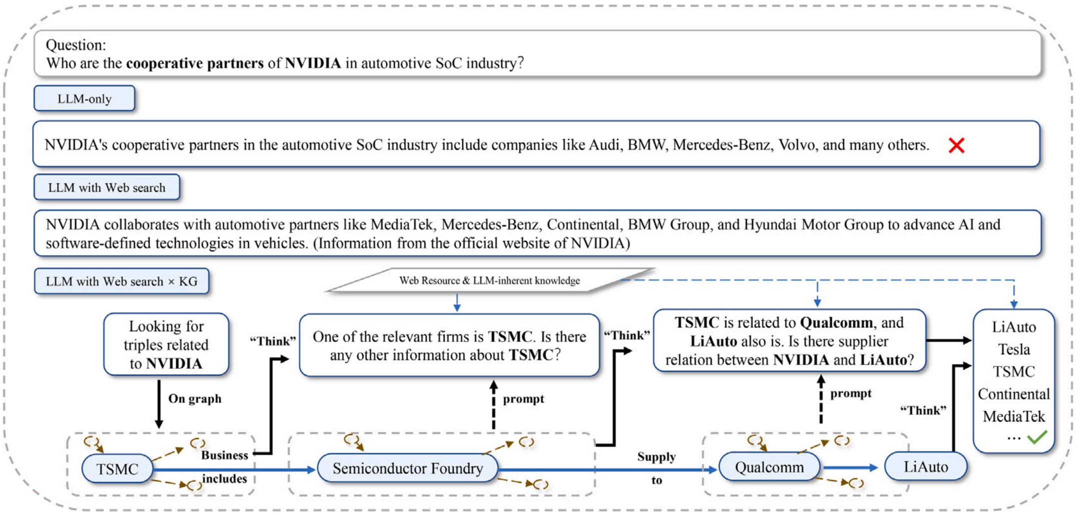

Fig. 4. An example of relation completion using LLM and KG.

better supports the token-level NER task.

To resolve the issue above, we need to retrieve kNN examples based on entity-level representations rather than sentence-level representations. For a given input sequence with N entities, we iterate over all tokens within the sequence to find kNNs for each entity firstly, obtaining $K \times N$ retrieved tokens. Next, we select the top k tokens from the $K \times N$ retrieved tokens and use their associated sentences as demonstrations.

The demonstration sequentially packs a list of examples, where each example consists of both the input sequence X and the output sequence W:

Input: [Example Sentence]$_1$
Output: [Labeled Sentence]$_1$
…
Input: [Example Sentence]$_k$
Output: [Labeled Sentence]$_k$,

where k denotes the number of demonstrations. A real-world example is shown in Table A.1 in Appendix A.

3.2.2. Relation completion

A KG is a directed graph where vertices represent entities, and each edge can be represented as a triplet (h, r, t) with h, r, and t representing to the head entity, relation, and tail entity, respectively. The relation completion task aims to infer missing triplets given an incomplete knowledge graph G. Under the standard entity ranking evaluation, both tail entity prediction $(h, r, ?)$ and head entity prediction $(?, r, t)$ require ranking all potential entities given the known components of the triple. In this study, for each triplet (h, r, t), we add an inverse triplet (t, r^{-1}, t), where r^{-1} is the inverse relation of r. By doing so, we only need to address the tail entity prediction problem (Wang et al., 2022).

LLMs often demonstrate certain limitations in their ability to absorb new information in generating hallucinations and in the transparency of their decision-making processes (Sun et al., 2023). To resolve this issue, we integrate specific supply chain KG into LLMs, thereby expanding our acquired triplets, as shown in Fig. 4. The steps are as follows: (1) Traverse the representative firm entities identified in the acquired triplets and integrate them into the prompt; (2) Search for entities related to these representative firms and integrate them into the prompt. Then, generate answers using the prompt, web resources, and the inherent knowledge of large language models (LLMs); (3) Continue the process in step two until a sufficient number of firms with supply relationships to the representative firms have been identified.

3.3. Supply chain network construction and analysis

Triplets within the knowledge graph are naturally converted into a supply chain network. In this network, nodes and relationships directly map to network components. Beyond standard network metrics, we incorporate the Tianyan Score (TYS), which is a comprehensive indicator of a company's influence, derived from organizational background, operational status, credit rating, innovation, and development trends (Tianyancha, 2024). It is widely used in business research (Hao et al., 2024; Shi & Liu, 2024; Wu et al., 2020). TYS enhances our understanding of a company's position within the supply chain. Then, we calculated various centrality metrics and compared their correlations.

3.3.1. Network construction

The OSKEC approach receives supply chain knowledge and outputs integrated triples. The triplets in knowledge are primitive to be transformed into edges and nodes within a complex network. For a triplet (h, r, t), the head entity and tail entity can be represented as firm nodes v_i and v_j, and r is represented as supply relation e_{ij}.

Due to the difficulty in determining which company is the upstream supplier according to the unstructured data, we only maintain a single fundamental supply relationship between two supplier entities (*e.g.*, the supply relationship between TSMC and NVIDIA). Furthermore, the supply chain network is represented as a network model denoted by $G(V, E)$. In this network, v_i and v_j denote the firm nodes i and j of firms, respectively. $e_{ij} = e_{ji} = 1$ denotes that there is a supply relationship between firm i and firm j. Otherwise, there is no supply relationship between them.

3.3.2. Network analysis

Network science provides comprehensive metrics for investigating the complex structure of supply chains. For example, the average path length in networks denotes the average number of steps along the shortest paths for all possible node pairs. Shorter average path lengths typically suggest a more efficient and responsive supply chain. Moreover, a smaller network diameter might indicate a compact network where suppliers and manufacturers are closely linked, potentially reducing transport times and costs but perhaps increasing vulnerability to localized disruptions. From a community partition perspective, a higher modularity Q indicates a stronger community structure. This means that entities within the same community have tighter cooperative relationships within the supply chain network. The modularity of the Louvain algorithm is defined as:

$$Q = \frac{1}{2m} \sum_{ij} (S_{ij} - \frac{k_i k_j}{2m}) \cdot \delta(C_i, C_j), \tag{2}$$

where m denotes the total number of edges within the network, S_{ij} indicates whether there is an edge between node i and j, with 1 for an edge present and 0 for otherwise. Furthermore, k_i represents the aggregated count of edges connected to node i. C_i and C_j represent the community affiliations of nodes i and j belong to, respectively. In instances where both nodes are members of the identical community, $\delta(C_i, C_j)$ is assigned a value of i; conversely, it is set to 0 (Blondel et al., 2008).

Further, we compare a set of centrality metrics of the supply chain network in Section 4.3. Firm nodes with higher PageRank values within a supply chain are key influencers or critical suppliers, pivotal in maintaining the flow of products and information across the network. The PageRank formula is:

$$PR(i) = \frac{1-d}{N} + d \sum_{j \in M(i)} \frac{PR(j)}{L(j)}, \tag{3}$$

where $PR(i)$ is the PageRank of node i, d is the damping factor, N is the total number of nodes, $M(i)$ is the set of nodes linking to node i, and $L(j)$ is the number of outbound links from node j (Gleich, 2015).

The clustering coefficient and triangles describe local connection features, indicating the degree to which companies cluster around key players. The clustering coefficient is given by:

$$C_i = \frac{2e_i}{k_i(k_i - 1)}, \tag{4}$$

where C_i is the clustering coefficient of node i, e_i is the number of connections between the neighbors of node i, and k_i is the number of neighbors of node i (Luce & Perry, 1949). The number of triangles is:

$$T_i = \frac{1}{2} \sum_{j,k} (a_{ij} a_{jk} a_{ki}), \tag{5}$$

where T_i is the number of triangles node i is part of, and a_{ij} is the adjacency matrix element between nodes i and j (Watts & Strogatz, 1998).

Nodes with high eigenvector centrality are well-connected and linked to other well-connected nodes. The eigenvector centrality is defined as:

$$EC(i) = \frac{1}{\lambda} \sum_{j \in N(i)} a_{ij} EC(j), \tag{6}$$

where $EC(i)$ is the eigenvector centrality of node i, λ is a constant, a_{ij} is the adjacency matrix element between nodes i and j, and $N(i)$ is the set of neighbors of node i (Bonacich, 1972).

High closeness centrality means firm nodes can quickly interact with all other nodes, making them efficient for roles like centralized manufacturers or distribution centers. The closeness centrality is:

$$C_C(i) = \frac{1}{\sum_j d(i,j)}, \tag{7}$$

where $C_C(i)$ is the closeness centrality of node i, and $d(i,j)$ is the shortest path distance between nodes i and j (Freeman, 2002).

High betweenness centrality indicates nodes that frequently occur on the shortest paths between other nodes, holding strategic importance as control points for the flow of products and information. The betweenness centrality is:

$$BC(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}, \tag{8}$$

where $BC(i)$ is the betweenness centrality of node i, σ_{st} is the total number of shortest paths from node s to node t, and $\sigma_{st}(i)$ is the number of those paths that pass through node i (Brandes, 2001).

3.4. The interaction and disruption model

3.4.1. Interaction behavior

As previously mentioned, there are plenty of studies that view supply chains as complex adaptive systems for analysis (Choi et al., 2001; Kim et al., 2015; Nair et al., 2009; Pathak, Dilts et al., 2007). Therefore, we constructed two IDMs to explore the propagation of supply chain disruptions across the network and their overall impact on the supply chain network. Both the interaction behaviors and disruption methods in this research are based on the following assumptions: (1) In a supply chain network, undirected edges represent bilateral cooperation between firm nodes, including upstream and downstream collaboration. Hence, any business action by one firm could influence its connected firms. Without remedial measures, disruptions can spread through these bilateral cooperations until the entire supply chain network is destroyed; (2) TYS integrates parameters such as creditworthiness, historical performance, and market positioning, providing a comprehensive measure of a firm's financial and operational stability. This makes TYS an effective indicator of the firm's risk-taking capacity, as it reflects the ability to absorb financial shocks and sustain operations under adverse conditions. We define TYS as the risk-taking capacity c_i of the firm node i; (3) The risk propagation in the supply chain is sequential, that is, the state of an enterprise at a certain moment is determined by the state of its neighbor nodes and the state of the enterprise itself at the previous moment.

An enterprise seeks the optimal strategy to ensure its safety during disruption propagation in the supply chain. It must decide whether to offload risk to its suppliers, with whom it shares interests. Transferring risk can initially enhance the enterprise's survival prospects. However, it also increases vulnerability if neighboring suppliers sustain damage. Therefore, selecting the appropriate strategy is crucial. Our research models the risk propagation process and assesses whether enterprises should transfer risk to their supply partners during supply chain disruptions.

3.4.2. Disruption model

We use the largest connected component (LCC) to represent the entire supply chain features, ignoring some boundary firm nodes. Enterprises with significant influence within the LCC often play a crucial role in supply chain disruptions. We use degree, closeness centrality, and risk-taking capacity as indexes to measure their influence and select the initial attacked firm nodes. The three attack strategies are as follows:

- High-degree attack (HDA): targeting nodes with the most connections to quickly dismantle the network's most interconnected components.
- High-closeness centrality attack (HCA): focusing on nodes that have minimized distances to all other nodes due to their strategic positions, thereby probably disrupting the network structure fast.
- High-importance attack (HIA): selecting nodes based on their risk-taking capacity, aiming to maximize the impact of their removal.

Building on various network attack strategies, we assess the risk of cascading failures in the supply chain influenced by multiple external coupling factors. These risks are designed to simulate how external events impact key nodes with distinct characteristics within the supply chain network. Subsequently, we develop the following two Interaction and Disruption Models (IDMs) to simulate how risk propagates throughout the entire supply chain network. Specifically, the disturbances focus on operational risks, which are indirectly incorporated through the concepts of "recovery capacity" and "risk-taking ability".

(1) Recovery Capacity-Interaction Disruption Model (RC-IDM)

In the process of disruption spread, the enterprise would locate between the state of operation and disruption. We define that the state of enterprise ranges from 0 to 1, where 1 denotes that the firm has absolutely failed and 0 denotes the firm is operating normally.

We define the following formula to update the state of enterprises:

$$s_i(t) = s_i(t-\tau) + \lambda(1 - s_i(t-\tau)) \sum_j \beta_j s_j(t-\tau) - \mu s_i(t-\tau), \tag{9}$$

where $s_i(t)$ denotes the state of the firm i and ranges from 0 to 1; λ denotes the influenced coefficient of all neighbor firm nodes; μ denotes the anti-risk coefficient of the firm node i; τ denotes the delay operator, normally is 1. β_j denotes the influence from a single neighborhood, which is a piecewise function based on $s_j(t-\tau)$:

$$\beta_j = \begin{cases} \beta_1 & s_1 < s_j(t-\tau) \le 1, \\ \beta_2 & s_0 < s_j(t-\tau) \le s_1, \\ \beta_3 & 0 \le s_j(t-\tau) \le s_0. \end{cases} \tag{10}$$

where s_0 represents the critical threshold between normal operation and minor anomalies, while s_1 indicates the critical threshold between minor anomalies and near failure.

(2) Risk Transfer-Interaction Disruption Model (RT-IDM)

In the real world, enterprises typically have two strategies when faced the business risk: (1) transfer strategy: transferring the risk to its neighbor firm nodes; (2) absorption strategy: undertaking the risk by themselves. The enterprise will experience short-term stability once it chooses the transfer strategy; however, the disruption risk will rapidly increase in the next phase because its viability is closely tied to the performance of its neighboring firm nodes.

The failure possibility of the enterprise at time t is defined as:

$$p_i(t) = \frac{\sum s_j(t-\tau)}{n} + \Delta r \cdot p_a, \tag{11}$$

where $s_j(t-\tau)$ denotes the firm node's state at the time of $t-\tau$, and n denotes the number of the neighbor firm nodes of firm node i. p_a and Δr denotes the possibility that firm node i chooses the absorption strategy and the corresponding increase in risk probability, respectively.

The risk-taking capacity is reset as:

$$c_i(t) = \max(c_\Delta, c_i(t-\tau) - \eta_j \Delta c), \tag{12}$$

where $c_i(t)$ denotes the risk-taking capacity of firm node i at the time of t; c_Δ denotes the minimum capacity; Δc is the decrement of risk-taking capacity. If a firm node chooses the transfer strategy, $\eta_j = 0$; otherwise, η_j denotes the attenuation coefficient for neighbor firm nodes.

RC-IDM and RT-IDM focus on the most pressing challenges in the context of Chinese automotive SoC industry. Recovery capacities address the internal resilience of enterprises, focusing on their ability to restore operations and minimize downtime during disruptions. This is particularly crucial in industries like Chinese automotive SoCs, where long production cycles and high technological dependencies make swift recovery challenging. Conversely, risk-transfer strategies are designed to manage external risk redistribution, allowing enterprises to mitigate the operational impacts of disruptions by sharing risks with suppliers or other partners.

4. Empirical results and analysis

In this section, we take the SoC supply chain in China as an example to illustrate the application of the OSKEC-IDM framework in the model construction, typological analysis, and disruption simulation of the supply chain network.

4.1. Data sources

The open domain data, which includes extensive and relevant text information about the Chinese automotive SoC industry, was collected from business research reports and websites as of February 2023. The primary sources we targeted include two leading websites within the Chinese automotive industry: (1) AutoHome (https://www.autohome.com.cn), which is one of the most influential and comprehensive automotive websites in China. AutoHome boasts over 40 million registered users and attracts more than 30 million unique visitors per day, offering extensive coverage of automotive trends and consumer insights. (2) Gasgoo (https://auto.gasgoo.com) is another major website in the Chinese automotive sector, focusing on industry news, market analysis, and professional insights. It serves a diverse audience, including industry professionals, manufacturers, and car enthusiasts. Gasgoo has a significant influence with a monthly user base exceeding 3 million, providing valuable information to both industry insiders and the general public.

The professional data was collected from the China Stock Market & Accounting Research (CSMAR) database and Wind database. CSMAR database provides comprehensive and reliable data on the top 5 suppliers and clients of Chinese listed companies in the Chinese SoC industry from 2002 to 2020, and Wind database provides customer and supplier data disclosed by more than 20,000 companies in the A-share and Hong Kong stock markets; then we use the data related to Chinese automotive SoC from 2002 to 2020.

Table 2
Empirical network statistics.

	N	E	L	D	Q
Basic triples	1,352	1,994	5.10	17	0.72
Matched triplets	1,239	1,982	4.99	14	0.68
Integrated triples	1,627	2,463	4.73	13	0.71

4.2. Empirical network

We adopted the OSKEC approach to combine open domain information with professional databases in the Chinese automotive SoC industry, confronting the challenge of limited access to supplier information. Each triplet represents a cooperative relationship between two firm entities, which lays a solid foundation for supply chain network construction and analysis. Fig. 3 demonstrates the detailed evolution process of triplets, while Table 2 summarizes the basic statistics of these triplets that construct the empirical networks. These statistics include the number of nodes (N) and edges (E), reflecting the overall scale of the supply chain network. With a given number of nodes, a higher number of edges generally indicates greater resilience, as it suggests more alternative pathways for maintaining connectivity. The characteristic path length (L) represents the average shortest path length between pairs of nodes, where a shorter average path length suggests a more efficient network with lower delays in risk transmission. The diameter (D) is the maximum shortest path length between any two nodes. A smaller diameter indicates that disruptions have limited reach, thus contributing to resilience by containing potential disruption risks. Modularity (Q) measures the strength of community structure within the supply chain network. Higher modularity indicates well-defined communities, which can improve resilience by isolating risks within specific parts of the network, reducing the chance of disruptions spreading widely.

To investigate the dynamics of interaction and disruption within the automotive SoC supply chain, focusing on the network's largest connected component effectively isolates and disregards solitary nodes (*i.e.*, suppliers or entities) characterized by limited interconnections within the network. Consequently, it accentuates the supply chain network's core features, which are paramount for supply chain operational dynamic analysis. Moreover, it simplifies the supply chain's complexity, facilitating the identification of opportunities for enhancement, risk reduction, and optimization (Guntuka et al., 2023; Saisridhar et al., 2024). Therefore, the supply chain network within the subsequent discussion denotes the largest connected sub-network identified within the integrated triplet network, which contains 1,355 nodes and 2,230 edges.

Visualization of the supply chain network is shown in Fig. 5. The size of each node is proportional to its degree, indicating the number of connections each enterprise has within the network. The color represents the network cluster to which the node belongs, showing different communities within the supply chain. The insets show the main clients for Qualcomm, NVIDIA, and Mobileye, highlighting their cooperative partners within the automotive SoC industry. The color

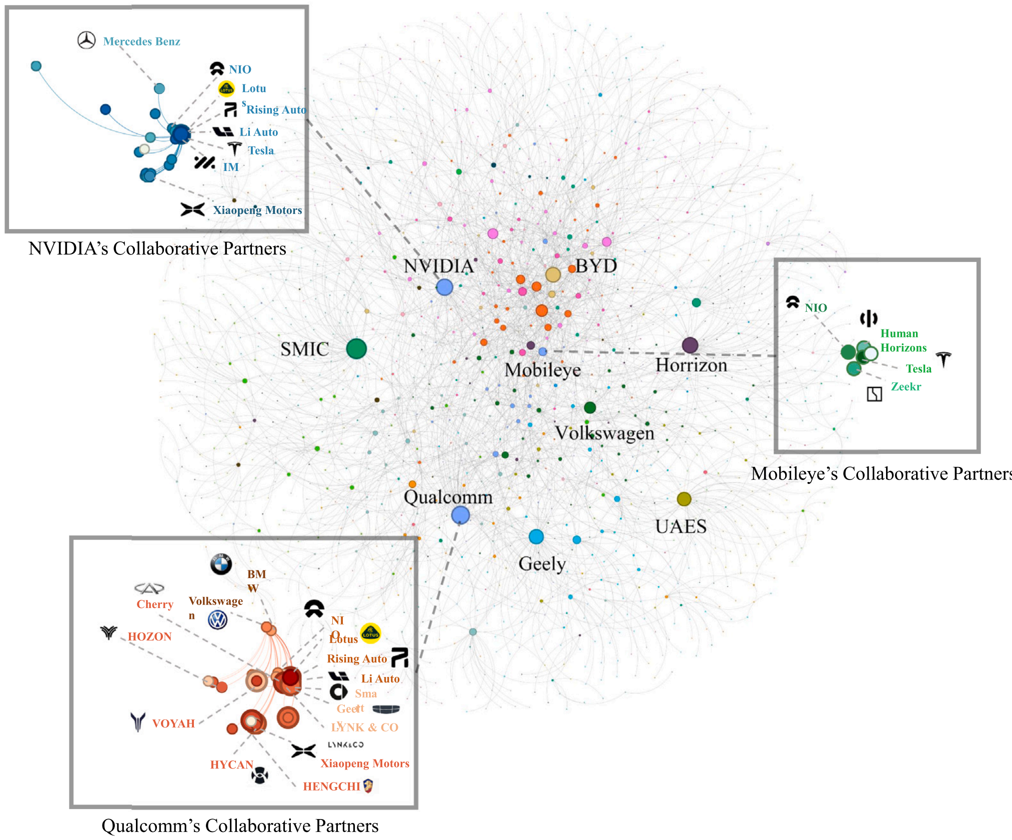

Fig. 5. Automotive SoC supply chain network in the Chinese market.

of the nodes in each inset reflects the geographical location of first-tier cooperative enterprises, and the size of the circles indicates the clustering coefficient of the enterprise nodes. Utilizing the Louvain algorithm (Blondel et al., 2008), each firm within the automotive SoC supply chain network is allocated to its corresponding community. This method facilitates the identification of modular structures within the supply chain, enhancing our understanding of the intricate relationships and interdependencies among firms in the automotive SoC ecosystem. In the Chinese market, Qualcomm, NVIDIA, and Mobileye are the primary suppliers of ADAS (Advanced Driver Assistance Systems) and in-vehicle infotainment chips. Qualcomm's clients are widely distributed across Beijing, the Yangtze River Delta, and the Pearl River Delta. NVIDIA's clients are dispersed, mainly in Shanghai, Beijing, and Guangzhou. Mobileye's clients are concentrated in the Yangtze River Delta, including Anhui, Shanghai, and Zhejiang. Automakers are often interconnected through one or several intermediary companies, and the relationships between chip manufacturers and their material or equipment suppliers are particularly evident.

4.3. Topological analyses

The automotive SoC supply chain exhibits scale-free characteristics, resembling patterns observed in global trade, social, disease, and internet networks (Alexander et al., 2022; Barabási, 2005; Elsler et al., 2023; Goh et al., 2007). A small number of high-degree firms dominate the network, while most firms have few connections. This indicates a hierarchical structure with influential core firms and a periphery of less central players. The Tianyan Score (TYS) is employed to quantify firm influence within the supply chain, aligning with previous research (Hao et al., 2024; Shi & Liu, 2024; Wu et al., 2020). Fig. 6 visually represents the scale-free degree distribution and the correlation between network centrality. The Chinese automotive SoC supply chain network exhibits scale-free characteristics, where a small number of firms (nodes) have a disproportionately high number of connections. Prior studies have demonstrated the vulnerability of scale-free networks to targeted attacks on high-degree nodes (Berger et al., 2023; Thadakamaila et al., 2004), a finding we will explore further in our simulation analysis.

The topological structure of the supply chain significantly influences the process of risk propagation; therefore, supply chain structure parameters are considered to have a crucial impact on the resilience of the entire supply chain (Ivanov, 2018; Ivanov et al., 2017; Pavlov et al., 2018). In Fig. 6, nodes with extensive connections tend to have high betweenness centrality, PageRank, and eigenvector centrality scores. Betweenness centrality measures a node's role in connecting other nodes through shortest paths, while eigenvector centrality highlights the importance of nodes connected to other influential nodes, reinforcing their central role in the supply chain network. The intertwined nature of metrics such as degree, PageRank value, betweenness centrality, and eigenvector centrality intimates that the most central nodes wield considerable influence over the interaction behavior and disruption process. These central nodes emerge as vital cogs within the supply chain network, indispensable to the supply chain's operational efficiency and resilience. The observed positive correlations between local clustering indicators (Clustering, Triangles) and overarching centrality metrics (Betweenness Centrality) suggest that nodes embedded within densely interconnected groups can assume significant roles on a broader network scale. Companies with substantial capital may provide services or products to a select group of enterprises consistently, while the majority of nodes with numerous connections might possess only moderate resources. This phenomenon suggests a strategic distribution of resources or a balancing mechanism within the network, where nodes positioned less centrally hold significant resources, which helps mitigate risks or decentralize control.

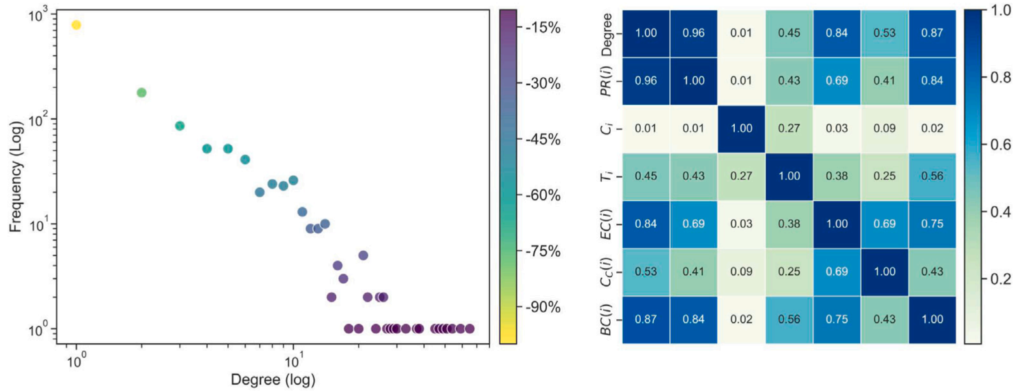

Fig. 6. Degree distribution and correlation of network features.

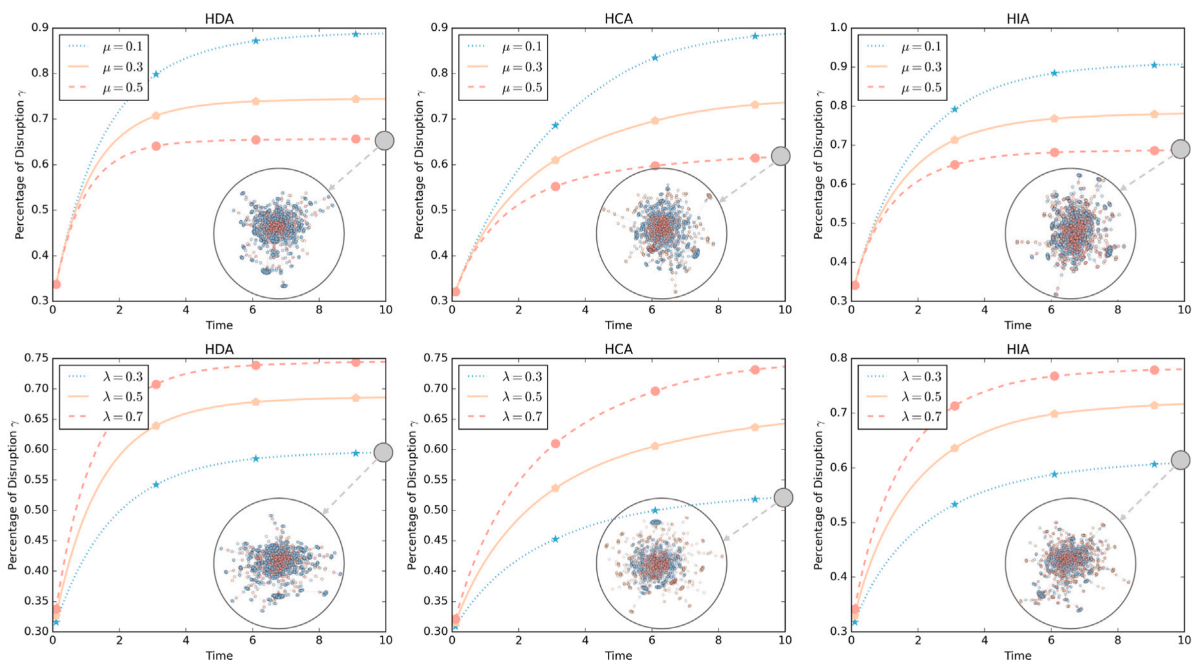

Fig. 7. The change of γ under HDA, HCA, and HIA strategies in RC-IDM.

4.4. Disruption simulation

In the real world, it is extremely detrimental for firms when their capacity falls below 30%. Therefore, we designate 0.3 and 0.7 as s_0 and s_1, respectively. The first stage of failure is defined as 0 to s_0, the second stage as s_0 to s_1, and the third stage as s_1 to 1. Besides, we use γ and c to represent the global percentage of disruption and risk-taking capacity, respectively.

Fig. 7 illustrates the percentage of disruption (γ) over time for different attack strategies: High-degree attack (HDA), High-closeness centrality attack (HCA), and High-importance attack (HIA) in RC-IDM. In the sub-graphs, light brown nodes signify enterprises in the first stage of failure, blue nodes denote enterprises in the second stage, and pink nodes indicate enterprises in the third stage.

For all three attack strategies, higher values of μ lead to lower disruption levels over time. Notably, for $\mu = 0.5$, the disruption curves plateau at much lower levels compared to $\mu = 0.1$. This plateau effect indicates a threshold beyond which further increases in recovery capacity may yield diminishing returns, which is a crucial consideration for resource allocation in disruption management. The diminishing returns observed for μ beyond certain thresholds imply that while investing in recovery capabilities is essential, there should be a balanced approach that also considers propagation control (λ). Recovery capacity (μ) plays a crucial role in mitigating disruption, while the HCA strategy amplifies it. For $\lambda = 0.7$, the disruption curves reach higher levels more quickly, indicating a rapid escalation in network disruption. This rapid escalation phase is critical for early intervention and underscores the need for real-time monitoring and response mechanisms in the Chinese automotive SoC supply chain.

HDA consistently results in higher disruption levels compared to HCA and HIA for the same parameter settings. This suggests that targeting the most connected nodes is the most effective strategy for causing maximum disruption. While strategic node positioning (HCA) and risk-taking capacity (HIA) are important, they are less critical than sheer connectivity in immediate disruption scenarios. For HDA, rapid transitions from light brown to pink nodes indicate the need for immediate interventions on the most connected nodes to prevent fast-spreading disruptions. Recovery should prioritize pink nodes to restore critical functions, followed by blue nodes. In contrast, HCA and HIA allow for phased responses with early detection and gradual mitigation focusing on nodes in the first and second stages. Balanced recovery efforts across light brown and blue nodes are essential to prevent escalation. The findings highlight the importance of designing networks with resilience against high-degree attacks. This can involve

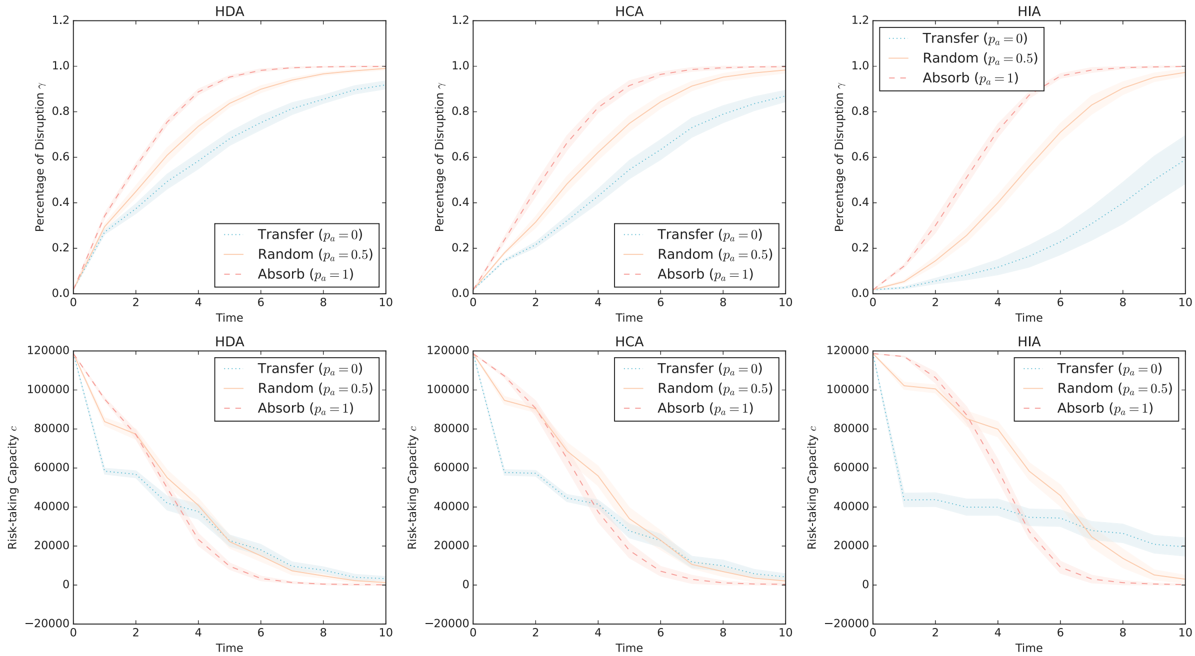

Fig. 8. The change of γ and c under community leader HDA, HCA, and HIA in RT-IDM.

distributing connectivity more evenly and avoiding the formation of overly critical firm hubs. Policymakers and enterprises should prioritize investments in both recovery and disruption control to achieve optimal resilience.

In RT-IDM, we find that when enterprises adopt the absorption strategy — actively managing risk from supply chain partners rather than dispersing it among the remaining partners — the disruption process within the entire supply chain slowly reaches a state of paralysis, as shown in Fig. 8. The first-row graphs demonstrate that the transfer strategy ($p_a = 0$) causes the least damage. The second-row graphs show that the overall risk-taking capacity decreases rapidly initially but stabilizes over time under the transfer strategy. In contrast, under the absorb strategy ($p_a = 1$), the initial decrease is slower but accelerates significantly in the mid-term, indicating a rapid collapse of risk-taking capacity as cascading risks propagate. Conversely, if the enterprise transfers risk to its partners, the disruption spreads quickly at the early stage but the speed of disruption slows down over time. Under a random strategy, where each surviving enterprise has a 50% chance of choosing the absorption strategy and the remaining probability of choosing the transfer strategy, the speed of disruption in the supply chain network is relatively mitigated.

When we focus on the changes in the risk-taking capacity of all firm nodes within the supply chain network, some interesting phenomena emerge, as shown in Fig. 8. As cascading risks propagate, the collapse speed of the risk-taking capacity of the entire supply chain network decreases with the risk-transfer strategy. Enterprises in the empirical network should consider absorbing a portion of the risks themselves rather than simply transferring them to other supply chain partners under specific situations. This approach can enhance the inherent resilience and stability of the entire supply chain, thereby reducing the risk of disruptions when external shocks happen.

Traditional spreading models, such as the SIR (Susceptible–Infectious–Recovery) and SIS (Susceptible–Infectious–Susceptible) models, have been widely applied to simulate disruption propagation within supply chain networks (Lei et al., 2021; Shi & Liu, 2024). The SIR model assumes that enterprises recover from disruptions and gain immunity to future risks, while the SIS model captures the recurring nature of risks by allowing enterprises to remain susceptible to the same disruptions after recovery. However, these models exhibit limitations when applied to real-world supply chain networks, particularly in dynamic and complex industries such as the Chinese automotive SoC sector. In Fig. E.2, which depicts the SIR model under different attack strategies (HDA, HCA, and HIA), we observe a characteristic initial spike in percentage of disruption, followed by a rapid decline as nodes transition to the "recovered" state and gain immunity. For instance, under the HDA attack strategy, disruption peaks early, especially when recovery rates (μ) are high ($\mu = 0.5$). However, as time goes on, there is a sharp decline in percentage of disruption. This decline fails to reflect the persistent vulnerabilities of real-world supply chains, where interconnected dependencies often lead to ongoing risks. Fig. E.3, illustrating the SIS model, demonstrates a gradual increase in disruption levels that eventually stabilize at a high plateau. Under the HDA attack, higher infection rates ($\lambda = 0.7$) lead to consistently higher levels of disruption ($\gamma > 0.7$), even at later time steps, as nodes repeatedly become infected. While this better captures the ongoing risks inherent in supply chain networks, it does not account for the compounded effects of cascading failures and differences in node-specific dynamics.

Our RC-IDM and RT-IDM models address the limitations of SIR and SIS by incorporating accumulated disruption effects, dynamic decision mechanisms, and interdependencies among nodes. RC-IDM integrates firm node-specific attributes, such as recovery capacity and operational status, to prioritize recovery efforts, while RT-IDM adds risk-transfer strategies to provide insights into mitigating the initial cascading failures. Unlike traditional models, RC-IDM and RT-IDM reflect the cumulative nature of disruptions and dynamic interplay between nodes, providing a more nuanced understanding of disruption propagation and recovery. Tailored to the Chinese automotive SoC sector, these models are better suited for addressing complex dependencies and frequent disruptions, offering actionable insights for improving resilience and recovery in modern supply chains.

4.5. Sensitivity analysis

In this section, we perform sensitivity analysis for both RC-IDM and RT-IDM using various parameters.

First, we analyze the impact of the influenced coefficient of all neighbor firm nodes (λ) and the anti-risk coefficient of the firm node (μ) on the percentage of disruption (γ) under HDA, HCA, and HIA

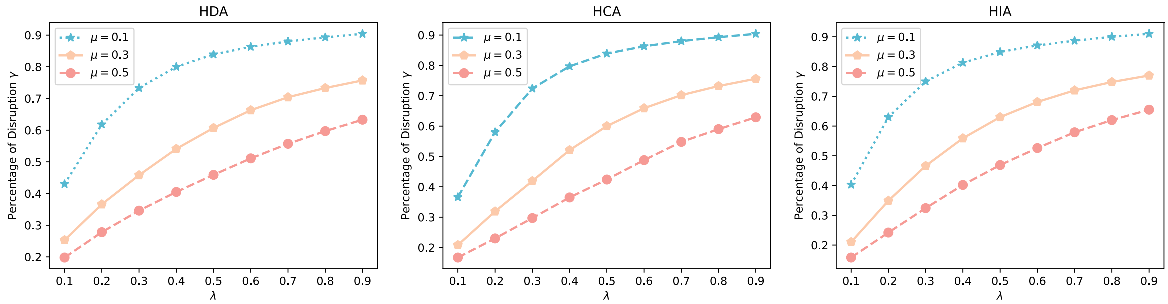

Fig. 9. The impacts of μ and λ on the percentage of disruption under the HDA, HCA, and HIA strategies in RC-IDM.

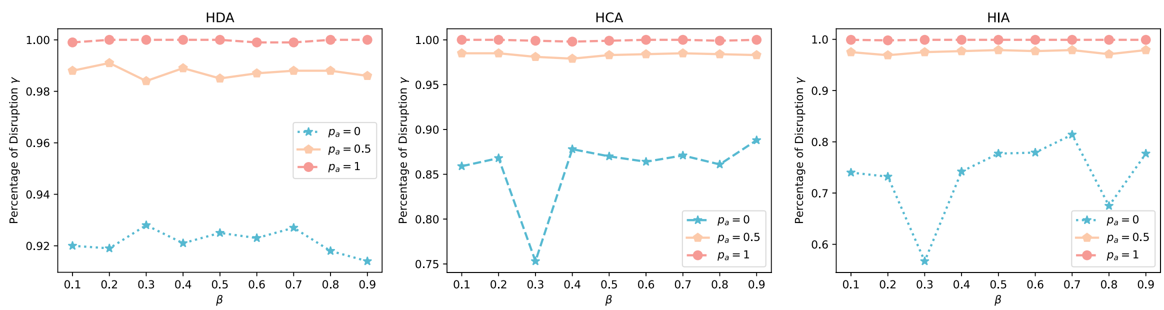

Fig. 10. The impacts of β and p on the percentage of disruption under the HDA, HCA, and HIA strategies in RT-IDM.

strategies in RC-IDM. These parameters are changed for each analysis, varying λ from 0.1 to 0.9 and μ from 0.1 to 0.5, with the same setting of parameters as in Section 4.4. Fig. 9 compares the relationships between the percentage of disruption and parameters under different strategies.

From Fig. 9, we can see that as λ increases, the percentage of disruption of all three strategies will rise. However, as μ increases, the percentage of disruption of all three strategies will decline. The results validate the robustness of the RC-IDM we proposed, which verifies that our model is reliable. Besides, the results show that there is a plateau effect when μ equals 0.1, and the percentage of disruption under the HDA, HCA, and HIA strategies in RC-IDM increases rapidly with λ lower than 0.4; however, the increasing rate significantly drops and becomes constant with λ greater than 0.4. When μ equals 0.3 or 0.5, the percentage of disruption under the HDA, HCA, and HIA strategies in RC-IDM exhibits a nearly linear increase with λ. These results suggest that supply chain managers should seize the opportunity to address disruptions when the influence from other firms is minor or the recovery capacity is sufficiently high; otherwise, when other firms have a strong impact or the recovery capacity is relatively low, the percentage of disruption will increase rapidly.

Next, we perform sensitivity analysis to analyze the impact of the parameters on the percentage of disruption (γ) and risk-taking capacity (c) for HDA, HCA, and HIA strategies in RT-IDM. Let the attenuation coefficient for the neighbor firm node (β), vary from 0.1 to 0.9, and the probability of choosing the transfer strategy, p, vary from 0 to 1, with the same setting of parameters as in Section 4.4. To compare the impacts of parameters on the percentage of disruption and risk-taking capacity under different strategies more visually, we plot Figs. 10 and 11.

From Figs. 10 and 11, we can see that as p increases, the percentage of disruption of all three strategies will rise while the risk-taking capacity of these strategies will decline. However, β does not have a significant linear effect on the percentage of disruption or the risk-taking capacity of all three strategies. The results validate the robustness of the RT-IDM we proposed, which verifies that our model is reliable.

Fig. 10 shows a stable pattern in the percentage of disruption under the HDA, HCA, and HIA strategies in RT-IDM when p_a equals 0.5 or 1; however, there is a fluctuation in the percentage of disruption when p equals 0, especially under the HCA and HIA strategies in RT-IDM. Specifically, when p_a equals 0 and β equals 0.3, the percentage of disruption under the HCA and HIA strategies is the lowest compared to other conditions. Additionally, the HDA strategy leads to the highest percentage of disruption, while the HIA strategy incurs the lowest percentage of disruption when p_a and β are equal. As a result, to mitigate the detrimental impact of disruption, supply chain managers should choose the transfer strategy and HIA strategy in RT-IDM.

Fig. 11 indicates a stable pattern in the risk-taking capacity under the HDA, HCA, and HIA strategies in RT-IDM when p_a equals 1; however, there is a fluctuation in the risk-taking capacity when p_a equals 0 or 0.5. Furthermore, the HDA strategy results in the lowest risk-taking capacity, while the HIA strategy induces the highest risk-taking capacity when p and β are equal. Hence, supply chain managers should choose the transfer strategy and HIA strategy in RT-IDM to enhance their risk-taking capacity.

4.6. Managerial implications

Real-world supply chains are dynamic, hierarchical, and complicated, with multiple layers of interdependent relationships. Effectively capturing and managing this intricate structure is significant for optimizing overall supply chain performance and mitigating disruption risks. The OSKEC-IDM framework provides a powerful tool to visualize these complex interconnections, extracting key topology features from the supply chain network structure. It empowers policymakers and company managers to identify critical firm nodes, assess potential vulnerabilities, and understand how disruptions may propagate through the supply chain network, enabling them to implement targeted strategies to reinforce the most vulnerable areas of the supply chain.

In the RC-IDM, among the three attack strategies (HDA, HCA, HIA), when the recovery capacity (μ) is reduced from 0.5 to 0.3, the overall

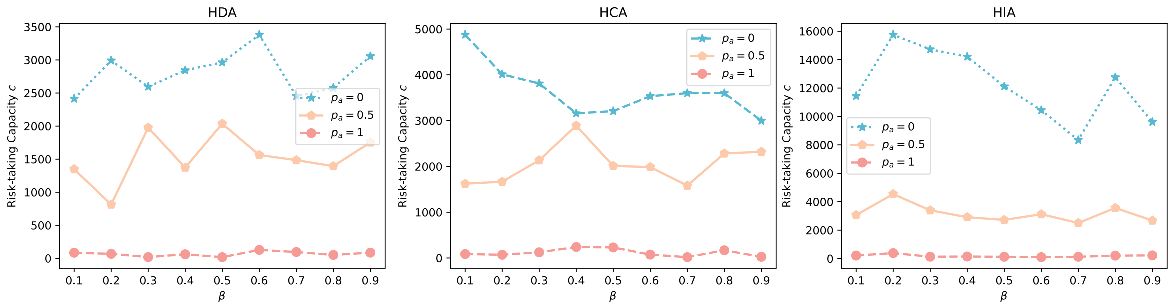

Fig. 11. The impacts of β and p on risk-taking capacity under the HDA, HCA, and HIA strategies in RT-IDM.

percentage of disruption (γ) of the supply chain increases by approximately 20%. This demonstrates that in the face of disruptions, timely investment in improving the ability to recover can bring significant benefits to the business. This trend is even more pronounced when the recovery capacity is already weak. If μ is reduced from 0.3 to 0.1, γ increases by about 30%. While the reduction in μ is the same, the γ across the entire network increases dramatically (by approximately 10%) when the overall resilience of the supply chain in the automotive SoC industry is weak. When we examine the impact of the influence of neighbor firm nodes, we find that the HCA strategy has the greatest variation in the influence of neighbor nodes. When the influence of neighbor nodes increases from 0.3 to 0.5, γ increases by approximately 30%. In contrast, under the HDA and HIA strategies, γ increases by only about 23% under the same conditions. This indicates the significant impact of network topology on disruption. Networks where most nodes are closer have a greater impact on the overall disruption than networks where more connections are concentrated in certain nodes. In our simulation of the Chinese automotive SoC industry, we found that about 114 firms were affected by this network topology. For managers, this highlights the importance of reducing dependence on neighbor nodes and integrating upstream and downstream supply chains to minimize exposure to large-scale disruptions.

Turning to the RT-IDM, we find that γ is significantly slowed under the same conditions when firms adopt a complete risk transfer strategy. For instance, when risk propagation reaches the fourth step, γ under an absorption strategy exceeds 80%, while γ under a transfer strategy remains below 50%. In the HIA strategy, the percentage of disruption in the fourth step is about 65% higher under the absorption strategy than under the transfer strategy. This suggests that when disruption risks arise, enterprises across the entire supply chain network should collaborate to address the disruption collectively, rather than confronting it in isolation, as this approach more effectively curtails its further spread. This is particularly important for managing global supply chain risks in a more interconnected world.

When examining the overall risk-taking capacity c of the entire supply chain network, we found that when the network's risk-taking ability is below 30%, the absorption strategy accelerates the collapse of the network. However, when c is higher than 30%, the absorption strategy significantly slows down the network's collapse. It is valuable for policymakers in managing the overall resilience of supply chain networks. For instance, when a country's innovative enterprises face large-scale sanctions, it is beneficial for firms with higher risk-taking ability to absorb the risk rather than transferring it to smaller firms, thus enhancing the resilience of the entire national supply chain network. These findings above highlight the profound impact of strategic investments in network resilience and provide a clear path for managers to optimize operations, mitigate risk, and realize significant cost savings.

5. Conclusion and discussion

Effective supply chain information sharing is crucial for enhancing decision-making and collaboration, particularly in sectors like SoC manufacturing. While research on supply chain networks has grown, challenges persist in data acquisition and modeling. Limited access to comprehensive supply chain data, often restricted to professional databases with data scarcity and anonymity issues, has hindered the development of accurate and dynamic models. Consequently, many studies rely on simplified simulations that fail to capture real-world complexities. To address these limitations, this study leverages both open-domain and professional databases to extract and integrate supply chain information. By combining these data sources, we aim to construct a more comprehensive and realistic representation of the supply chain network.

This study has introduced an OSKEC-IDM framework for supply chain network construction and cascade failure simulation amidst limited information availability. We integrate both open-domain and professional databases to empirically construct Chinese automotive SoC supply chain triplets to maximize the effectiveness of the multiple data sources. In detail, we utilize NER to gather crucial data from industry-leading websites, the CSMAR database, and the Wind database. This data is used to create a foundational dataset of firm entities. Then, cross-domain transfer learning is used to mitigate data scarcity in KG and Levenshtein distance calculations for relationship mapping and entity similarity assessments. The connections between these entities are enhanced using inference technology, which aids in expanding the network scale of the supply chain. The characteristics of the supply chain network are then analyzed, followed by the implementation of two interaction models, namely the RC-IDM and RT-IDM, to simulate cascade failures.

Our analysis of the Chinese automotive SoC supply chain reveals a scale-free topology, a characteristic commonly found in complex systems. By examining the correlation between network indices and exploring underlying structural dynamics, we gain deeper insights into the supply chain's behavior. The RC-IDM model assesses the impact of enhancing a firm's anti-risk capabilities on overall network stability. Our findings suggest that bolstering resilience can mitigate disruption spread. To explore risk management strategies, we compare risk absorption and risk transfer approaches. Risk absorption initially protects the network but leads to a faster decline in risk-taking capacity. Conversely, risk transfer accelerates initial risk spreading but ultimately results in slower network paralysis.

These findings underscore the importance of understanding network structure and dynamics. The OSKEC framework provides a general and effective tool to construct realistic supply chain networks. This feature makes it well-suited for extension to other industries such as pharmaceuticals, electronics, and aerospace, where supplier information is scarce and highly valuable. Applying the framework to different sectors can demonstrate its universality and robustness. Moreover, incorporating a wider range of potential disruptions into the IDMs, including

Table A.1
Instructions and Labeled examples for firm entity recognition.

Category	Text
Instruction	You are a developer of a named entity recognition tool, and you need to mark the name of the enterprise, which provides automotive-related components. Here are some examples I have provided.
Example 1	The given sentence: Xi'an Taikun Plastic Co., Ltd. is a supplier with a good reputation in the semiconductor industry, headquartered in Xi'an, Shaanxi Province. The company has a certain market share with high-quality products and services.
Labeled Entity 1	@@Xi'an Taikun Plastic Co., Ltd.@@
Example 2	The given sentence: Ji'an Hongkun Technology Co., Ltd. is a company dedicated to research and manufacturing, mainly providing electronic components and related electronic equipment. The company takes innovation and quality as its core values, actively promoting and facilitating progress, and providing customers with high-quality supply services.
Labeled Entity 2	@@Ji'an Hongkun Technology Co., Ltd.@@
Result	Input: Xi'an CRRC Yongdian Electric Co., Ltd. was established in 2005 and is headquartered in Xi'an, Shaanxi Province. As a supplier, the company focuses on the research and development, manufacturing, and sales of electrical equipment in the automotive industry. Output: @@Xi'an CRRC Yongdian Electric Co., Ltd. @@

geopolitical tensions, natural disasters, and technological disruptions, could further enrich our understanding of resilience in modern supply chains. Building on these scenarios, integrating proactive and reactive strategies within the IDMs could provide a more balanced approach to managing disruptions. Proactive measures focus on preparation and prevention, while reactive measures ensure timely responses. Exploring these risks and combining these strategies will allow for more comprehensive risk mitigation frameworks that enhance supply chain network stability across various and complex environments. While this study advances our understanding of supply chain networks, further exploration of real-world scenarios and the development of more sophisticated models that consider both recovery-ability and risk-transfer strategies are necessary. Ultimately, this research provides a foundation for building resilient supply chains capable of withstanding complex risks in an increasingly interconnected global economy.

CRediT authorship contribution statement

Jiawei Feng: Writing – original draft, Visualization, Software, Resources, Methodology, Investigation, Data curation, Conceptualization. **Mengsi Cai:** Writing – review & editing. **Fangze Dai:** Resources, Methodology, Investigation, Data curation. **Shuo Liu:** Methodology. **Tianci Bu:** Formal analysis. **Xiaoyu Zhang:** Conceptualization. **Huijun Zheng:** Investigation. **Xin Lu:** Writing – review & editing, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

We sincerely thank Gabi for her support and care provided during the Volkswagen internship, helping us to deepen our knowledge in the field of Chinese automotive SoCs. We are also grateful to Wanqiu Cheng, Xiaopeng Li, and Xiangyun Meng for their assistance in developing the OSKEC approach. This work was supported by the National Natural Science Foundation of China (92467302, 72025405, 72421002, 72301285, 72401289, 72474223), the National Social Science Foundation of China (22ZDA102), the Major Consulting Projects of the Chinese Academy of Engineering, China (2022-JB-01), the Natural Science Foundation of Hunan Province, China (2023JJ40685), the National Postdoctoral Program for Innovative Talents of China (BX20230475), and the Postgraduate Scientific Research Innovation Project of Hunan Province, China (XJCX2023163). The authors declare that they have no conflict of interest.

Appendix A. A real-world firm NER example

See Table A.1.

Appendix B. Cross-domain transfer learning & fuzzy matching

To overcome the difficulties and compensate for the lack of high-quality data from real-world operations, cross-domain transfer training has been utilized in NER tasks, as shown in Fig. B.1. Integrating external knowledge sources, such as financial databases, stock information, and marketing data, could further improve NER performance by supplying extra context for named entities not covered in the training dataset. Utilizing information across various domains significantly improves entity classification in languages with scarce resources. However, transfer learning introduces the challenge where a single firm entity may have different names across various fields. The fuzzy matching technique is employed to address this issue.

We use the Levenshtein distance, also known as the edit distance, to measure the difference between pre-processed similar firm entities. The Levenshtein distance (represented as L) between two firm strings a and b is calculated using a dynamic programming approach. Then, the similarity S of these two firm strings is represented as

$$S = \left(1 - \frac{L}{\max(|a|, |b|)}\right), \tag{B.1}$$

where $|a|$ and $|b|$ represent the length of firm strings a and b, respectively. For example, we calculate S between NVIDIA and NVDA and then get S as 0.8. The higher the similarity score between firm entities is, the more similar the two entities are. Then, we group all firms with a similarity score above 0.6 as the same firm. Next, we concentrate on completing supply relations between different companies.

Appendix C. Definition of variables and parameters

See Table C.2.

Appendix D. Pseudo-code of IDMs

See Algorithms 1 and 2.

Appendix E. Disruption simulation of SIR & SIS models

See Figs. E.2 and E.3.

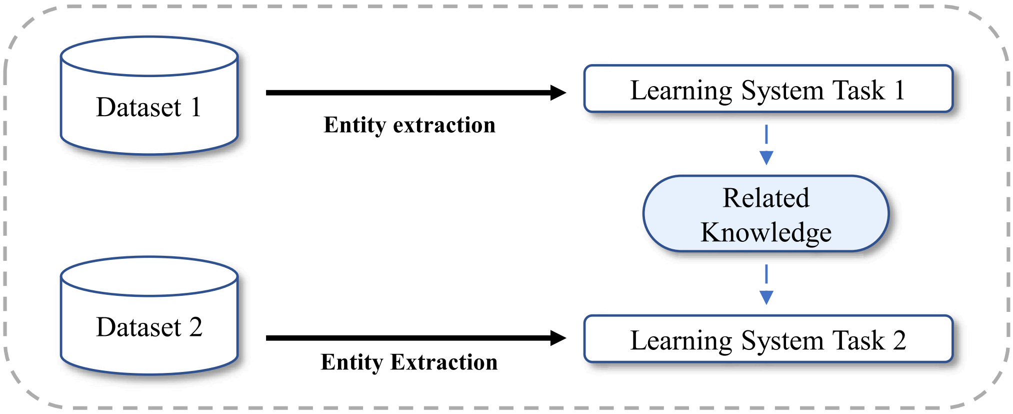

Fig. B.1. Cross-domain transfer learning.

Table C.2
Definitions of Variables and Parameters.

Formula	Variable/ Parameter	Definition
$s_i(t) = s_i(t-\tau)+$ $\lambda(1-s_i(t-\tau))\sum_j \beta_j s_j(t-\tau)$ $-\mu s_i(t-\tau)$	$s_i(t)$	The state of firm node i at time t, ranging from 0 to 1.
	τ	The delay operator, normally set to 1.
	λ	The influence coefficient of all neighbor firm nodes.
	μ	The anti-risk coefficient of the firm node i.
	β_j	The influence from single neighbor firm node j.
$p_i(t) = \frac{\sum s_j(t-\tau)}{n} + \Delta r \cdot p_a$	$p_i(t)$	The failure probability of firm node i at time t, ranging from 0 to 1.
	n	The number of all neighbor firm nodes.
	Δr	The increase in risk probability when the absorption strategy is chosen.
	p_a	The probability that firm node i chooses the absorption strategy.
$c_i(t) = \max(c_\triangle, c_i(t-\tau) - \eta_j \Delta c)$	$c_i(t)$	The risk-taking capacity of firm node i at time t.
	$c_\triangle$	The minimum risk-taking capacity.
	η_j	The attenuation coefficient for neighbor firm node j; if the transfer strategy is chosen, $\eta_j = 0$.
	Δc	The decrement of risk-taking capacity.

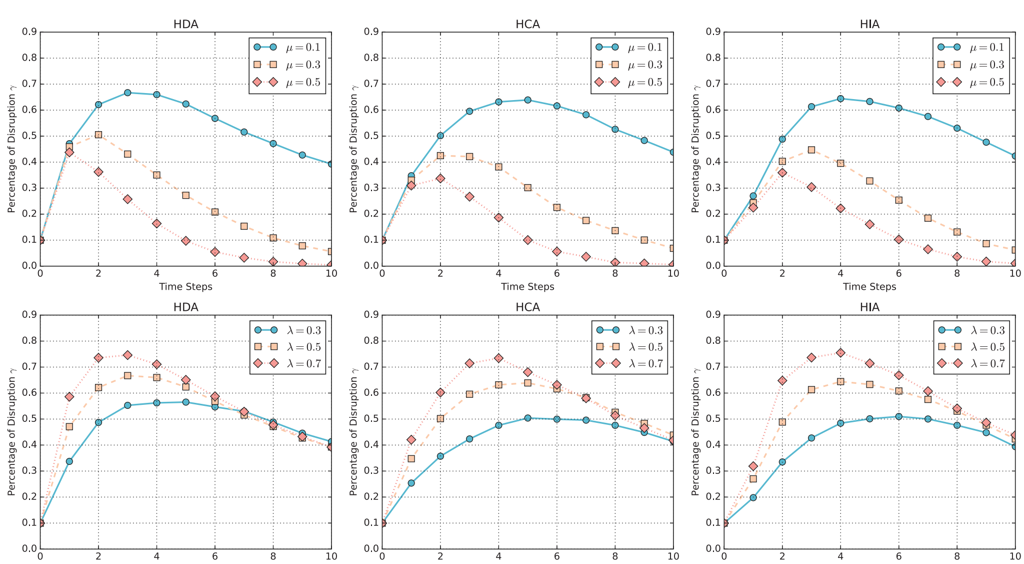

Fig. E.2. The change of γ under HDA, HCA, and HIA in SIR model.

Algorithm 1: Recovery Capacity-IDM

Input: Network $< V, E >$, influence coefficient λ, anti-risk coefficient μ, delay operator τ, thresholds s_0, s_1, time steps T

Output: State $s_i(t)$ for all firm nodes at each time step t

```
Initialize(State s_i(0) ← 0 for all firm nodes);
for t = 1 to T do
    foreach firm node i do
        Compute( if s_j(t − τ) > s_1 then
                β_j ← β_1;
            else if s_0 < s_j(t − τ) ≤ s_1 then
                β_j ← β_2;
            else
                β_j ← β_3;
        ) s_i(t) ← s_i(t − τ) + λ(1 − s_i(t − τ)) Σ_j β_j s_j(t − τ) − μ s_i(t − τ);
    Update(state of all firm nodes);
```

Algorithm 2: Risk Transfer-IDM

Input: Network $< V, E >$, transfer probability p_t, risk-taking capacity $c_i(0)$, influence coefficient β_j, minimum capacity $c_{\triangle}$, decrement of risk-taking capacity Δc, absorption possibility p_r, lifting risk probability Δr, delay operator τ, time steps T

Output: State $s_i(t)$ and risk-taking capacity $c_i(t)$ for all firm nodes at each time step t

```
Initialize(State s_i(0) ← 0 and c_i(0) ← c_i for all firm nodes);
for t = 1 to T do
    foreach firm node i do
        if s_i(t − τ) = 1 then
            s_i(t) ← 1;
        else
            p_failure ← (Σ_j s_j(t−1)) / (number of neighbors) + Δr · p_a;
            if The firm node chooses transfer strategy then
                η_j ← 0;
                Transfer risk to neighbors, update their states;
            else
                η_j ← attenuation coefficient;
                Update the state s_i(t) based on p_failure
            Update the risk-taking capacity of neighbors
            c_i(t) ← max(c_△, c_i(t − τ) − η_j Δc);
```

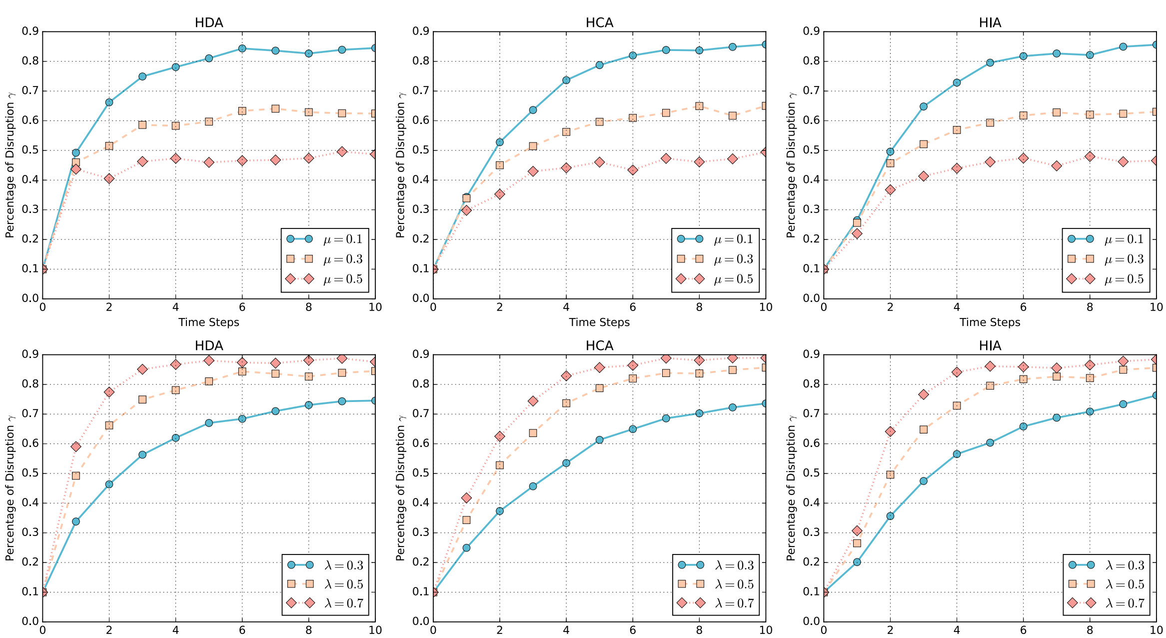

Fig. E.3. The change of γ under HDA, HCA, and HIA in SIS model.

Data availability

The authors do not have permission to share data.

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