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# Research on Identifying Key Elements of Emergency Supply Chain Resilience Based on DEMATEL-ISM and Complex Networks

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**Abstract:** In the context of normalized prevention and control of public emergencies, enhancing the resilience of emergency supply chains holds significant theoretical value and practical implications. To reveal the relative importance of resilience factors, this study establishes an integrated analytical framework for emergency supply chain resilience. First, key resilience factors were extracted through text mining of relevant literature from the China National Knowledge Infrastructure and Web of Science databases. Then, the DEMATEL-ISM method was employed to construct a multi-level hierarchical structure model, clarifying the interrelationships among factors. Finally, based on complex network theory, the comprehensive influence of nodes was evaluated, and the critical elements were identified and analyzed with corresponding recommendations. The results indicate that reserve facility construction efficiency, intelligent early warning and detection capability, accuracy of emergency demand statistics, emergency coordination and cooperation capability, and emergency plan completeness are the key factors of emergency supply chain resilience. The proposed integrated approach of "text mining-system modeling-network analysis" enables the systematic identification of resilience factors and provides a decision-support tool for building resilient supply chain systems.

**One sentence summary:** This study presents a novel approach to enhancing emergency supply chain resilience, showing that five critical factors are key drivers. It innovates the identification of these factors, making it accessible for emergency management practitioners and researchers.

**Keywords:** Emergency supply chain, Resilience, Critical factors identification, DEMATEL-ISM method, Complex network

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# 1 Introduction

In recent years, public emergencies worldwide have exhibited a trend of increasing frequency and complexity, encompassing natural disasters, public health crises, and political conflicts. These diverse and uncertain risks pose significant challenges to the stability and continuity of supply chain systems (Maharjan & Kato, 2022). Within this context, the emergency supply chain, as a core component of national emergency management systems, has a resilience level that directly determines the effectiveness of emergency response and the capacity to mitigate socioeconomic losses. Consequently, systematically analyzing and enhancing the resilience of emergency supply chains has emerged as a critical research priority within academia.

The concept of supply chain resilience was first introduced by Rice and Caniato (Rice & Caniato, 2003), with Christopher and Peck (Christopher & Peck, 2004) providing its formal definition as "the ability of a system (supply chain) to return to its original state or move to a new, more desirable state after being disturbed." Subsequently, scholars have proposed various interpretations of supply chain resilience. The currently prevailing academic definition characterizes it as the adaptive capacity of a supply chain to prepare for unexpected events, respond to disruptions, and recover from them (Ponomarov & Holcomb, 2009).

Identifying key influencing factors and elucidating the complex interrelationships among them is fundamental to strengthening emergency supply chain resilience. In response, numerous studies have investigated the influencing factors and corresponding evaluation systems. Huang et al. (2021) employed the Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Interpretative Structural Modeling (ISM) methods to investigate the influencing factors and underlying mechanisms of urban resilience. By constructing a hierarchical structure model of urban resilience factors, they identified key driving factors and revealed the interrelationships among them, thereby providing a theoretical basis for enhancing urban resilience and optimizing urban governance. Liu et al. (2021) applied a fuzzy DEMATEL-ISM approach to examine the comprehensive influence degrees, causal relationships, and logical hierarchies among factors influencing cross-border e-commerce supply chain resilience. Feyzi (2020) integrated the fuzzy Delphi method with DEMATEL-ISM to identify and analyze the influencing factors and their interdependencies within the automotive industry supply chain, subsequently improving the resilience level of Iran Khodro Company. Lu et al. (2022) adopted a DEMATEL-ISM method incorporating Pythagorean fuzzy sets to assess influencing factors in prefabricated building supply chains, supporting managerial identification of critical aspects and enabling sustainable management. Wang et al. (2023) introduced grey theory to enhance the DEMATEL-ISM method, identifying transmission pathways among factors affecting the resilience of green agricultural product supply chains and offering a theoretical foundation for government and enterprise interventions. Li and Lu (Li & Lu, 2025) integrated DEMATEL, ISM, and the Analytic Network Process (ANP) to analyze the driving factors of smart city resilience. Their study elucidated the interaction pathways and relative importance of various influencing factors and established a resilience-driving mechanism framework, providing valuable references for smart city resilience development and management decision-making.

A review of the extant literature reveals that existing research predominantly utilizes enhanced DEMATEL-ISM methodologies to explore supply chain resilience. These studies typically construct multi-level hierarchical structural models to delineate causal relationships and hierarchical configurations among factors, and assess factor importance through centrality (the sum of influence and influenced degrees) and causality (the difference between influence and influenced degrees). While such approaches emphasize system decomposition and the hierarchical stratification of complex problems, clarifying both the level and causal linkages of each factor, they remain relatively one-dimensional in their evaluation of factor importance. Consequently, they inadequately capture the criticality of specific nodes within the broader network.

In response to this limitation, the present study integrates text mining, complex network theory, and the DEMATEL-ISM analytical framework to develop a comprehensive analytical model for examining the influencing factors of emergency supply chain resilience. This framework employs text mining to extract relevant factors and leverages a complex network integrated with multi-dimensional importance indicators in conjunction with the DEMATEL-ISM model. It elucidates both the interrelationships and hierarchical structures among factors, thereby establishing a more holistic resilience evaluation system. In doing so, it effectively addresses the inherent one-sidedness of traditional methods in the analysis of key influencing factors.

## 2 Methodology and Theoretical Framework

This study adopts a research methodology integrating "text mining-system modeling-network analysis" to systematically identify the key influencing factors of emergency supply chain resilience. The specific implementation process is illustrated in Figure 1.

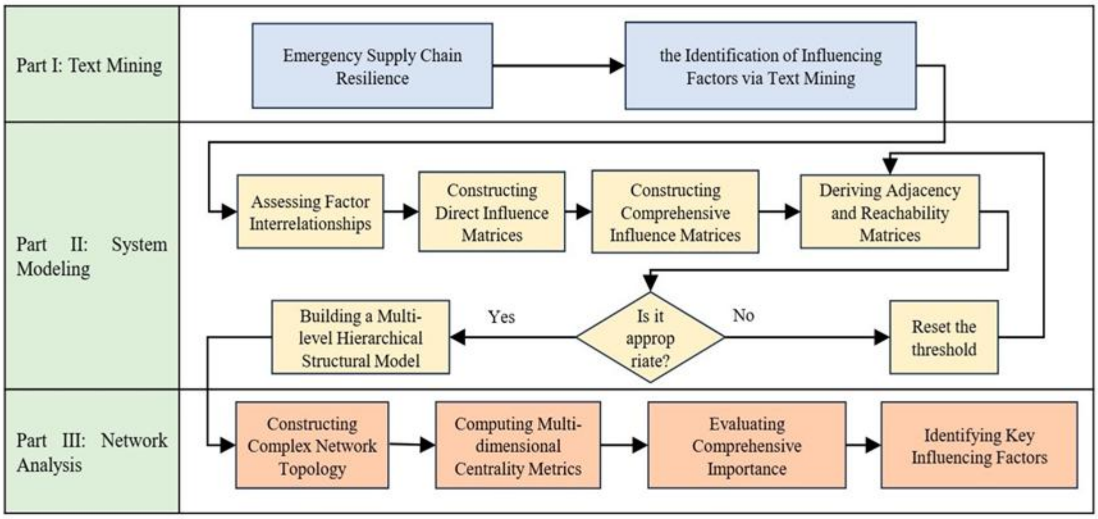


Figure 1. Flowchart of integrated modeling incorporating text mining, the DEMATEL-ISM method, and complex network analysis

### 2.1 Text Mining

Text mining is a technique that involves processing and analyzing textual data to uncover hidden knowledge and patterns. As a branch of data mining, it primarily focuses on various forms of textual data, including text documents, emails, news reports, academic papers, web content, and more. Its ultimate objective is to extract valuable information from large volumes of unstructured text to support decision-making and prediction. The typical procedure includes the following steps: first, relevant content is retrieved from data sources based on predefined keywords; next, the retrieved results are screened to eliminate information unrelated to the research topic; finally, key information is extracted from the highly relevant content (Ge et al, 2025).

## 2.2 The DEMATEL-ISM Method

As a systematic analytical method grounded in graph theory and matrix operations, DEMATEL enables the visualization of complex causal relationships among factors by constructing a direct influence matrix and a comprehensive influence matrix. Furthermore, through the computation of centrality and causality indices, it precisely quantifies the degree of influence and the attributive characteristics of each factor within the system, thereby providing a critical quantitative foundation for subsequent hierarchical decomposition.

ISM, as a classic structural modeling technique, is distinguished by its capacity to convert complex system elements into a hierarchical structural model with clearly defined relational levels. This is achieved through a systematic workflow involving the construction of an adjacency matrix, the derivation of a reachability matrix, and the process of hierarchical decomposition.

Traditional ISM methods often rely on subjective judgment when constructing the adjacency matrix. By utilizing the comprehensive influence matrix generated by DEMATEL as the input for ISM-and setting a scientific threshold to transform continuous influence intensities into binary reachability relationships-the integrated DEMATEL-ISM approach not only preserves the objectivity of causal analysis but also enables the hierarchical representation of system structure (Yang & Chen, 2024). The implementation procedure of the DEMATEL-ISM method is detailed as follows:

(1) Construction of the direct influence matrix. Based on the Delphi method, an expert panel comprising specialists from multiple disciplines is invited to quantitatively assess the pairwise influence relationships among the influencing factors using a 0-3 scale. In this scale, 0, 1, 2, and 3 represent no influence, weak influence, moderate influence, and strong influence, respectively. This process ultimately yields the direct influence matrix $A=(a_{ij})_{n\times n}, a_{ij}=\{0,1,2,3\}$ ,where $n$ denotes the number of influencing factors.

(2) Calculation of the normalized and comprehensive influence matrices. Using the maximum row sum of the direct influence matrix $A$ as the normalization benchmark, the normalized direct influence matrix $B=(b_{ij})_{n\times n}$ is constructed. Its mathematical expression is given as:

$$B=\frac{A}{\max_{1\le i\le n}\sum_{j=1}^{n}a_{ij}} \tag{1}$$

Following this, the comprehensive influence matrix $C$ is derived based on the principle of power series convergence, capturing both the direct and indirect coupling effects among the factors:

$$C=(B+B^2+B^3+\cdots+B^m)=\sum_{\mathrm{m}=1}^{\infty}B^m=B(I-B)^{-1} \tag{2}$$

where $I$ is the identity matrix.

(3) Generation of the adjacency matrix. To mitigate subjective judgment bias, a statistical distribution method is employed to determine the threshold λ for the adjacency matrix:

$$\lambda = \mu + k\sigma \tag{3}$$

Where $\mu$ represents the mean value of the elements in the comprehensive influence matrix, $\sigma$ is the standard deviation, and $k$ is the adjustment coefficient. Based on this, the ISM adjacency matrix $H = (h_{ij})_{n\times n}$ is constructed as follows:

$$h_{ij} = \{^{1, c_{ij} \geq \lambda}_{0, c_{ij} < \lambda} (i = 1, 2, \cdots, n; j = 1, 2, \cdots, n) \tag{4}$$

(4) Reachability matrix and hierarchical topology construction. The transitivity of the adjacency matrix is solved through Boolean matrix operations to obtain the reachability matrix $R$:

$$R = (H + I)^t = (H + I)^{t+1}, t \in N^+ \tag{5}$$

where $t$ is the minimum number of iterations required to satisfy the convergence condition. Based on the reachability matrix $R$, the reachability set $R(S_i)$ and the antecedent set $A(S_i)$ are established for each factor. Hierarchical partitioning is then performed through set operations $R(S_i) \cap A(S_i)$, ultimately forming a multi-level hierarchical structural model.

## 2.3 Complex Network Theory

A complex network is a topological structure composed of a set of nodes and a set of edges, and its essence lies in describing the interactive relationships among the elements of a system (Jiakuan & Haoyu, 2023). The quantitative analysis of node importance is a core focus in the study of network topological characteristics. Key metrics in this domain include Degree Centrality, Closeness Centrality, and Betweenness Centrality, which quantify the topological importance of a node from three dimensions: connection strength, information transmission efficiency, and path control capability, respectively.

Degree centrality is the most direct metric for characterizing node centrality in network analysis. A higher node degree indicates greater degree centrality, signifying that the node is more important within the network. This metric is primarily used to assess the extent of a node's connectivity within the network and is calculated as follows:

$$DC_s = \sum_{s=1, s\neq t}^{V} d_{st} \tag{6}$$

Where $d_{st}$ denotes the connection edge between nodes *s* and *t*; *V* is the total number of nodes in the network; and $DC_s$ represents the degree centrality of node *s*.

Betweenness centrality measures a node's capacity to control information flow within a network, evaluating its bridging role by calculating the proportion of shortest paths that pass through the node relative to the total number of shortest paths in the network. Its mathematical expression is given as:

$$BC_o = \sum_{s \neq o \neq t} \frac{v_{st}^{o}}{g_{st}} \tag{7}$$

Where $v_{st}^{o}$ represents the number of shortest paths between nodes *s* and *t* that pass through node *o*; $g_{st}$ denotes the total number of shortest paths between nodes *s* and *t*; $BC_o$ is the betweenness centrality of node *o*.

Closeness centrality evaluates the efficiency of a node's reachability from a global perspective, defined as the normalized value of the reciprocal of the sum of the shortest path distances from the node to all other nodes in the network. Its calculation formula is expressed as:

$$CC_s = \frac{V-1}{\sum_{t=1}^{s} v_{st}} \tag{8}$$

Where $v_{st}$ is the number of edges contained in the shortest path from the initial node *s* to the target node *t*, and $CC_s$ denotes the closeness centrality of node *s*.

Based on historical data and expert opinions, the entropy weight method is employed to objectively assign weights to the three network centrality indicators. Through the construction of a comprehensive node importance evaluation model (Jiakuan & Haoyu, 2023), the integrated computation of multi-dimensional indicators is achieved as follows:

$$Z_s = \sum_{w=1}^{q} E_w \frac{K_{sw}}{G_{w,ave}} \times 100\% \tag{9}$$

where $E_w$ denotes the weight of the w-th evaluation indicator; $q$ is the total number of evaluation indicators; $K_{sw}$ represents the value of the w-th indicator for node s; $G_{w,ave}$ is the mean value of the w-th indicator across all nodes; and $Z_s$ indicates the comprehensive importance of node *s*.

# 3 Case Study

## 3.1 Text Mining of Influencing Factors

This study used the China National Knowledge Infrastructure (CNKI) and the Web of Science (Web of Science Core Collection) as data sources. The retrieval period was set from January 1, 2020, to August 1, 2025. To ensure comprehensive coverage of research on supply chain resilience and emergency supply chain resilience, a subject search was conducted in CNKI, while a Topic search (including title, abstract, and keywords) was performed in the Web of Science database. The search was carried out using combinations of the keywords "supply chain resilience," "supply chain elasticity," "emergency supply chain resilience," "emergency supply chain elasticity," and "influencing factors," along with their Chinese equivalents. A total of 394 records were retrieved, including 148 from CNKI and 246 from Web of Science.

To ensure the relevance and quality of the sample, the retrieved literature was screened according to predefined criteria. First, duplicate records across the two databases were removed. Second, an initial screening was conducted based on titles, abstracts, and keywords to exclude studies not directly related to influencing factors of supply chain resilience. Third, non-academic publications such as conference notices, book reviews, and news reports were excluded, as well as studies that addressed supply chain resilience but did not analyze influencing factors or underlying mechanisms. Finally, full-text review was conducted to determine the final sample. After screening, a total of 29 articles were retained for subsequent analysis.

In the process of factor identification, this study did not employ automated full-text text mining techniques. Instead, it focused on extracting and synthesizing factor-related information from tables, indicator systems, and relevant textual descriptions reported in the selected studies. Based on this, a four-step procedure-factor extraction, open coding, synonym merging, and category mapping-was adopted to construct the influencing factor system. Specifically, relevant factor items were first extracted from factor tables, indicator systems, and associated discussions in the literature. These items were then subjected to open coding to form an initial set of factors. Subsequently, semantically similar or conceptually equivalent factors were merged; for example, "information sharing capability" and "information coordination capability" were consolidated into "government-enterprise information coordination capability," while "disaster monitoring capability" and "risk early-warning capability" were integrated into "intelligent early-warning and detection capability." Finally, the consolidated factors were mapped onto five primary dimensions-prevention capability, response capability, recovery capability, learning capability, and public governance system-based on the theoretical framework of emergency supply chain resilience.

Through this process, an influencing factor system consisting of five primary indicators and 24 secondary indicators was established, as shown in Table 1. Specifically, prevention capability relates to ex-ante risk identification and resource preparedness; response capability reflects rapid reaction and coordinated execution during emergencies; recovery capability focuses on post-disaster restoration and system reconstruction; learning capability captures the organization's dynamic adaptability and continuous improvement; and the public governance system represents the role of institutional support and multi-actor coordination in enhancing emergency supply chain resilience.

Table 1. Influencing factors of emergency supply chain resilience

| Primary indicators | Secondary indicators | Description of Secondary Indicators |
|---|---|---|
| Prevention Capability A | Emergency Material Supply Capability A1 | Suppliers' Capability to Ensure Stable Material Supply |
| | Emergency Material Procurement Capability A2 | Suppliers' Capability to Procure and Allocate Materials |

| | | |
|---|---|---|
| | Emergency Warehousing Capacity A3 | Capacity of Emergency Material Reserve Warehouses |
| | Reserve Facility Construction Efficiency A4 | Site Selection and Construction Speed of Emergency Warehouse |
| | Warehousing Throughput Efficiency A5 | Material Inbound and Outbound Processes and Turnover Efficiency |
| | Material Maintenance and Management Capability A6 | Materials Maintenance and Management Capability |
| | Transportation Network Management Capability A7 | Capability to Optimize Transportation Routes and Scheduling During Emergencies |
| | Material Integrity Assurance Rate A8 | Ratio of Undamaged to Damaged Materials Upon Arrival at Demand Points |
| | Logistics Facility Development Level A9 | Development Level of Transportation Networks and Related Infrastructure |
| | Intelligent Early Warning and Detection Capability A10 | Disaster Risk Forecasting and Early Warning Capability |
| Response Capability B | Accuracy of Emergency Demand Statistics B1 | Suppliers' Capability to Rapidly Analyze and Forecast the Types and Quantities of Emergency Material Demand |
| | Accuracy of Emergency Information Sharing B2 | Level of Information Sharing Among Enterprises Regarding Emergency Events |
| | Emergency Information Acquisition Capability B3 | Capability to Accurately Acquire Information on Disaster-Affected Areas |
| | Transportation Information Tracking Capability B4 | Capability to Acquire Information on Emergencies During Transportation |
| | Emergency Coordination and Cooperation Capability B5 | Capability for Resource Integration and Joint Action Among Suppliers |
| | Logistics and Transport Capability B6 | Capability to Complete Designated Transportation Tasks Within Required Emergency Timelines |
| | Emergency Materials Distribution Capability B7 | Capability for Rational Allocation of Emergency Supplies and Route Planning |
| | Emergency Response Decision-Making Capability B8 | Emergency Response Decision-Making Speed |
| Recovery Capability C | Infrastructure Restoration Capability C1 | Capability for Rapid Restoration of Critical Infrastructure (e.g., Transportation Networks) Following Disasters |
| Learning Capability D | Risk Prevention and Control Culture D1 | Establishment of Suppliers' Internal Safety Management Systems |
| Public Governance System E | Government Governance Capacity E1 | Capability to Integrate and Allocate Human, Financial, and Material Resources |

| | | |
|---|---|---|
| | Government-Enterprise Information Synergy Capability E2 | Cross-Departmental Information Interoperability Level |
| | Emergency Plan Completeness E3 | Emergency Plan System Development Level for Prevention |
| | Emergency Legal Guarantee System E4 | Completeness of the Emergency Management Legal System |

## 3.2 Hierarchical Partitioning of Influencing Factors

To construct the direct influence matrix of emergency supply chain resilience factors, the Delphi method was employed to solicit expert judgments on the pairwise relationships among the 24 factors listed in Table 1. The expert panel consisted of 10 members from relevant fields, including emergency management, logistics and supply chain management, and emergency material support, encompassing both academic researchers and industry practitioners. The selection criteria required that experts be familiar with theories or practices related to emergency supply chain resilience, possess substantial research or managerial experience, and be able to participate independently and continuously throughout multiple rounds of consultation. The experts' professional or research experience generally ranged from 5 to 8 years, with an average of 5 years.

The Delphi consultation was conducted anonymously. Experts were asked to evaluate the pairwise influence relationships among the 24 factors using a 0-3 scale, where 0, 1, 2, and 3 indicate no influence, weak influence, moderate influence, and strong influence, respectively. Each round of consultation was completed independently to minimize potential bias arising from peer influence. After each round, the evaluation results were aggregated, and feedback on items with substantial disagreement, along with overall statistical summaries, was provided to the experts for reassessment in the subsequent round.

A total of three rounds of Delphi consultation were conducted in this study. To assess the consistency of expert opinions, the dispersion of the evaluation results and the changes across rounds were compared. When the results in subsequent rounds became stable and the level of disagreement among experts was substantially reduced, consensus was considered to have been achieved. Based on the final round of evaluations, the mean values of the expert scores were calculated to construct the direct influence matrix $A=(a_{ij})_{24\times 24}$ of the 24 emergency supply chain resilience factors, as shown in Table 2. The raw data were then normalized using Formula (1) to construct the normalized direct influence matrix $B=(b_{ij})_{24\times 24}$ .Subsequently, the comprehensive influence matrix $C=(c_{ij})_{24\times 24}$ of the factors influencing emergency supply chain resilience was derived by applying Formula (2), thereby systematically reflecting the intensity of effects among the elements, as presented in Table 3.

Table 2. Direct influence matrix *A*

| | A1 | A2 | A3 | A4 | A5 | A6 | ⋯ | C1 | D1 | E1 | E2 | E3 | E4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 0 | 0 | 0 | 0 | 2 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| A2 | 3 | 0 | 0 | 0 | 2 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| A3 | 0 | 0 | 0 | 0 | 2 | 1 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| A4 | 0 | 0 | 3 | 0 | 2 | 0 | ⋯ | 1 | 0 | 0 | 0 | 0 | 0 |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A5 | 0 | 2 | 0 | 0 | 0 | 0 | ⋯ | 2 | 0 | 0 | 0 | 0 | 0 |
| A6 | 1 | 2 | 1 | 0 | 1 | 0 | ⋯ | 0 | 2 | 0 | 0 | 0 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋱ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| C1 | 0 | 2 | 0 | 1 | 2 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| D1 | 1 | 1 | 1 | 0 | 0 | 2 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| E1 | 0 | 2 | 0 | 1 | 0 | 0 | ⋯ | 1 | 2 | 0 | 3 | 3 | 0 |
| E2 | 2 | 0 | 2 | 0 | 0 | 0 | ⋯ | 1 | 0 | 0 | 0 | 3 | 0 |
| E3 | 2 | 1 | 0 | 0 | 0 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| E4 | 1 | 1 | 1 | 0 | 0 | 0 | ⋯ | 1 | 2 | 1 | 1 | 1 | 0 |

Table 3. Comprehensive influence matrix C

| | A1 | A2 | A3 | A4 | A5 | ⋯ | D1 | E1 | E2 | E3 | E4 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 0.009 | 0.012 | 0.009 | 0.004 | 0.080 | ⋯ | 0 | 0 | 0 | 0 | 0 |
| A2 | 0.113 | 0.007 | 0.002 | 0.001 | 0.084 | ⋯ | 0 | 0 | 0 | 0 | 0 |
| A3 | 0.003 | 0.009 | 0.002 | 0.001 | 0.077 | ⋯ | 0 | 0 | 0 | 0 | 0 |
| A4 | 0.002 | 0.010 | 0.115 | 0.002 | 0.087 | ⋯ | 0 | 0 | 0 | 0 | 0 |
| A5 | 0.011 | 0.082 | 0.009 | 0.007 | 0.014 | ⋯ | 0 | 0 | 0 | 0 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋱ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| D1 | 0.050 | 0.050 | 0.042 | 0.001 | 0.017 | ⋯ | 0 | 0 | 0.002 | 0 | 0 |
| E1 | 0.061 | 0.121 | 0.042 | 0.064 | 0.039 | ⋯ | 0.074 | 0 | 0.113 | 0.134 | 0 |
| E2 | 0.107 | 0.033 | 0.099 | 0.004 | 0.029 | ⋯ | 0 | 0 | 0.004 | 0.120 | 0 |
| E3 | 0.085 | 0.044 | 0.011 | 0.001 | 0.011 | ⋯ | 0 | 0 | 0 | 0 | 0 |
| E4 | 0.065 | 0.061 | 0.053 | 0.011 | 0.022 | ⋯ | 0.077 | 0.037 | 0.042 | 0.051 | 0 |

In the threshold determination stage, statistical analysis was performed on the off-diagonal elements of the comprehensive influence matrix based on Equation (3), yielding a mean value of 0.02157 and a standard deviation of 0.03455. On this basis, a statistical distribution method was adopted to determine the threshold for the adjacency matrix, which is defined as $\lambda = \mu + k\sigma$.

To verify the rationality of the threshold selection, a sensitivity analysis was conducted by examining the threshold segmentation results under different values of k, specifically $k$ = 0.5, 1, and 2. The results indicate that when $k$ = 0.5, the threshold is relatively low, resulting in the retention of a large number of weak relationships and leading to structural redundancy. When $k$ = 2, the threshold becomes relatively high, causing some important relationships to be eliminated and yielding an overly sparse network structure. In contrast, when $k$ = 1, the corresponding threshold is 0.05612, and the resulting adjacency matrix achieves a better balance between relationship filtering and structural interpretability.

Based on this threshold, the adjacency matrix was constructed using Equation (4), as shown in Table 4. Subsequently, Boolean operations were applied according to Equation (5) to derive the reachability matrix, as presented in Table 5.

Table 4. Adjacency matrix *H*

| | A1 | A2 | A3 | A4 | A5 | A6 | ⋯ | C1 | D1 | E1 | E2 | E3 | E4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 0 | 0 | 0 | 0 | 1 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| A2 | 1 | 0 | 0 | 0 | 1 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| A3 | 0 | 0 | 0 | 0 | 1 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| A4 | 0 | 0 | 1 | 0 | 1 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| A5 | 0 | 1 | 0 | 0 | 0 | 0 | ⋯ | 1 | 0 | 0 | 0 | 0 | 0 |
| A6 | 0 | 1 | 0 | 0 | 0 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋱ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| C1 | 0 | 1 | 0 | 0 | 1 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| D1 | 0 | 0 | 0 | 0 | 0 | 1 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| E1 | 1 | 1 | 0 | 1 | 0 | 0 | ⋯ | 1 | 1 | 0 | 1 | 1 | 0 |
| E2 | 1 | 0 | 1 | 0 | 0 | 0 | ⋯ | 0 | 0 | 0 | 0 | 1 | 0 |
| E3 | 1 | 0 | 0 | 0 | 0 | 0 | ⋯ | 0 | 0 | 0 | 0 | 0 | 0 |
| E4 | 1 | 1 | 0 | 0 | 0 | 0 | ⋯ | 0 | 1 | 0 | 0 | 0 | 0 |

Table 5. Reachability matrix *R*

| | A1 | A2 | A3 | A4 | A5 | A6 | ⋯ | C1 | D1 | E1 | E2 | E3 | E4 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| A1 | 1 | 1 | 1 | 0 | 1 | 0 | ⋯ | 1 | 0 | 0 | 0 | 0 | 0 |
| A2 | 1 | 1 | 1 | 0 | 1 | 0 | ⋯ | 1 | 0 | 0 | 0 | 0 | 0 |
| A3 | 1 | 1 | 1 | 0 | 1 | 0 | ⋯ | 1 | 0 | 0 | 0 | 0 | 0 |
| A4 | 1 | 1 | 1 | 1 | 1 | 0 | ⋯ | 1 | 0 | 0 | 0 | 0 | 0 |
| A5 | 1 | 1 | 1 | 0 | 1 | 0 | ⋯ | 1 | 0 | 0 | 0 | 0 | 0 |
| A6 | 1 | 1 | 1 | 0 | 1 | 1 | ⋯ | 1 | 0 | 0 | 0 | 0 | 0 |
| ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋱ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ | ⋮ |
| C1 | 1 | 1 | 1 | 0 | 1 | 0 | ⋯ | 1 | 0 | 0 | 0 | 0 | 0 |
| D1 | 1 | 1 | 1 | 1 | 1 | 1 | ⋯ | 1 | 1 | 0 | 0 | 0 | 0 |
| E1 | 1 | 1 | 1 | 1 | 1 | 1 | ⋯ | 1 | 1 | 1 | 1 | 1 | 0 |
| E2 | 1 | 1 | 1 | 1 | 1 | 0 | ⋯ | 1 | 0 | 0 | 1 | 1 | 0 |
| E3 | 1 | 1 | 1 | 0 | 1 | 0 | ⋯ | 1 | 0 | 0 | 0 | 1 | 0 |
| E4 | 1 | 1 | 1 | 1 | 1 | 1 | ⋯ | 1 | 1 | 0 | 1 | 0 | 1 |

Through topological analysis of the reachability matrix, the reachability set $R(S_i)$ and antecedent set $A(S_i)$ for each influencing factor were systematically constructed. Hierarchical partitioning was achieved via set intersection operation $R(S_i) \cap A(S_i)$ ,establishing the multi-level hierarchical relationships among the elements. The resulting hierarchical model of factors influencing emergency supply chain resilience is shown in Figure 2.

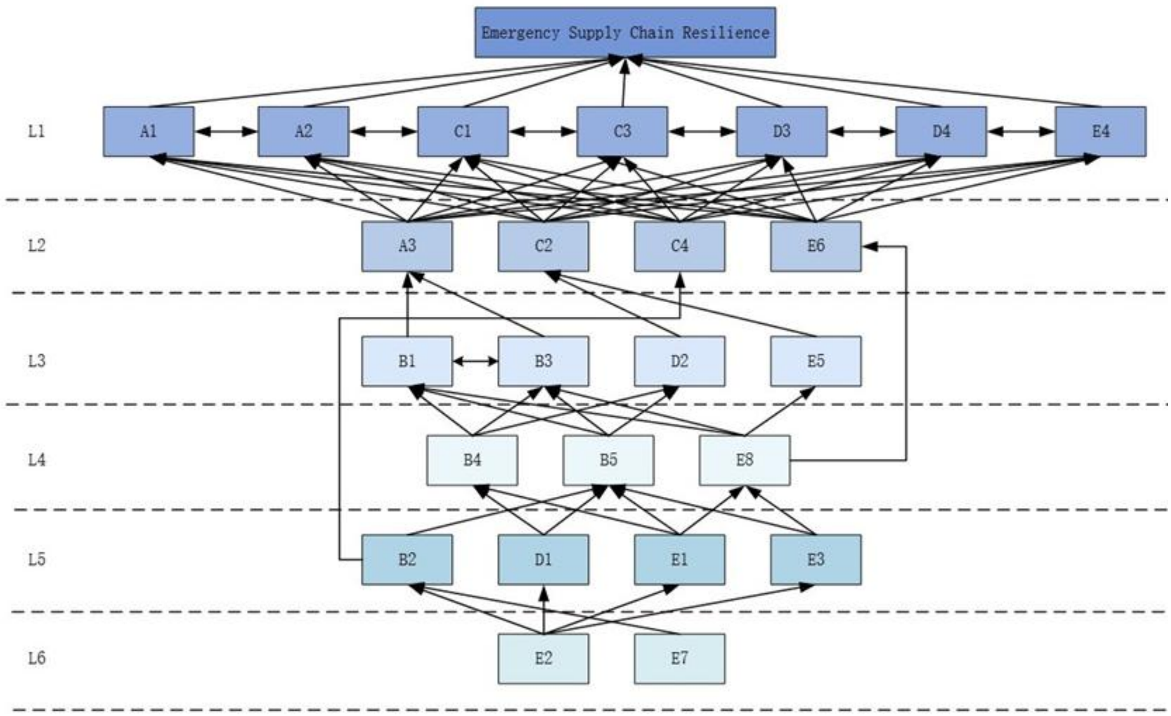


Figure 2. Multi-level hierarchical structure of factors influencing emergency supply chain resilience

The multi-level hierarchical structure of factors influencing emergency supply chain resilience, as shown in Figure 2, reveals the hierarchical dependencies and causal transmission paths among the factors. This structure provides the complex network with refined and validated nodes, directed relational edges, and a framework for hierarchical analysis, significantly empowering complex network analysis and enabling more precise and in-depth interpretations that incorporate causal properties.

## 3.3 Complex Network-Based Characteristic Analysis

The influencing factors of emergency supply chain resilience were abstracted as network nodes, and the relationships among these factors were defined as network edges. A directed network structure was constructed based on the accessibility matrix. Specifically, when factor $i$ exerts a significant influence on factor $j$, a directed link is established from node $i$ to node $j$, thereby forming a complex network model of emergency supply chain resilience factors. Based on this model, Gephi software was employed to visualize the network structure and perform topological analysis, and the resulting network is shown in Figure 3.

On this basis, the degree centrality, betweenness centrality, and closeness centrality of each node were calculated according to Equations (6)-(8). Degree centrality reflects the direct connectivity of a node and indicates its local influence within the network. Betweenness centrality measures the extent to which a node acts as an intermediary along the shortest paths, reflecting its control over information flow. Closeness centrality captures the relative distance from a node to all other nodes, indicating its overall accessibility within the network. Based on these metrics, the influencing factor nodes were ranked, and the distribution of their centrality values in descending order is presented in Figure 4.

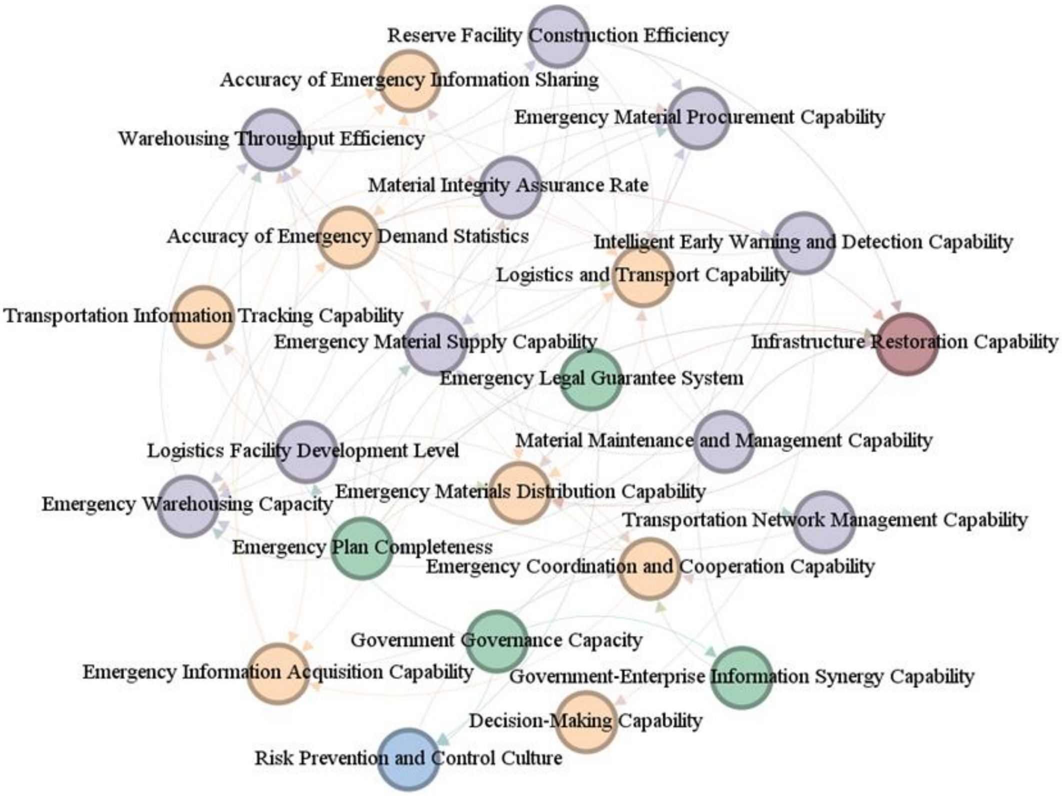


Figure 3. Complex network topology of factors influencing emergency supply chain resilience

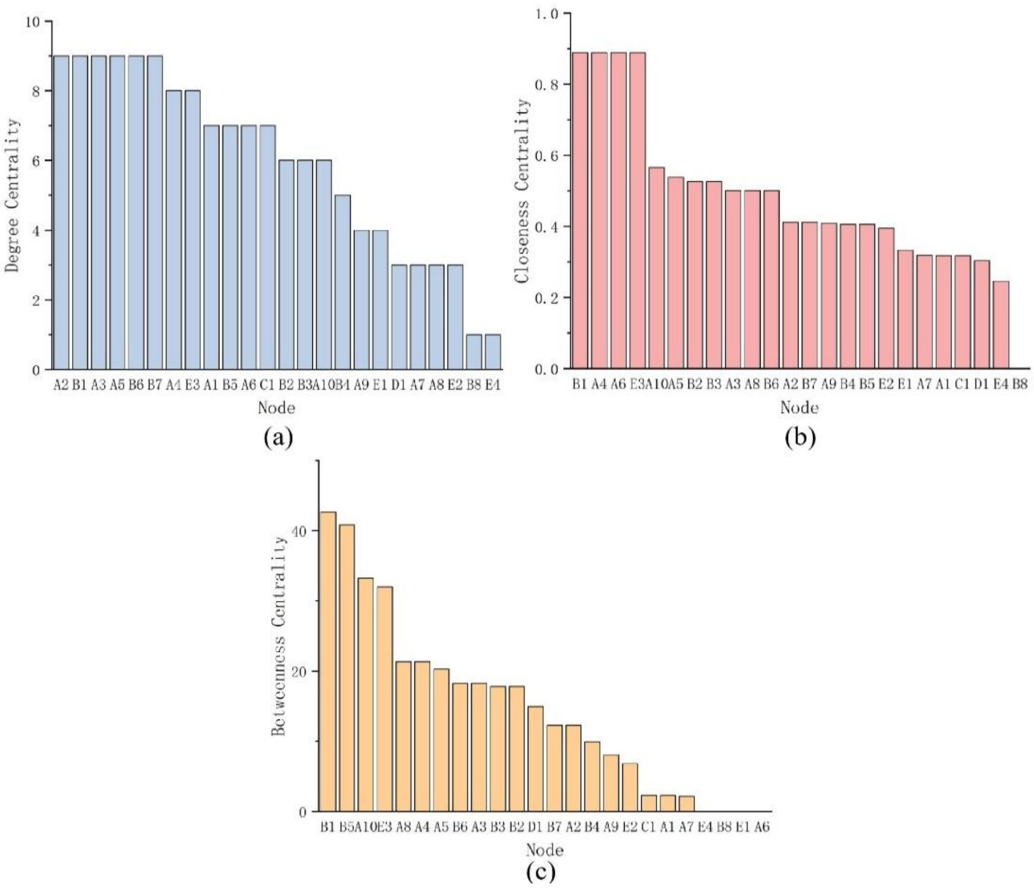


Figure 4. Distribution of node centrality metrics

As shown in the degree centrality analysis results in Figure 4(a), emergency material procurement capability (A2), emergency warehousing capacity (A3), warehousing throughput efficiency (A5), accuracy of emergency demand statistics (B1), logistics and transport capability (B6), and emergency materials distribution capability (B7) exhibit the highest degree centrality values, indicating that they serve as the most densely connected core hubs within the network. This suggests that these nodes occupy critical positions in the topological structure, functioning as key junctions for information flow and possessing the most extensive direct connections.

Figure 4(b) reveals that intelligent early warning and detection capability (A10), accuracy of emergency demand statistics (B1), emergency coordination and cooperation capability (B5), and emergency plan completeness (E3) have significant betweenness centrality within the network, indicating that they occupy critical paths controlling information flow and act as bridges connecting different nodes. These nodes directly influence the overall smoothness of network operation.

Analysis of data presented in Figure 4(c) demonstrates that reserve facility construction efficiency (A4), material maintenance and management capability (A6), and accuracy of emergency demand statistics (B1) possess prominent closeness centrality, signifying that they are situated in relatively central positions within the network topological structure. These nodes exhibit the structural advantage of the shortest average paths to reach other nodes, positioning them as core locations for information dissemination.

Building upon this analysis, the evaluation results of node importance in the complex network were calculated using Formula (9), as presented in Table 6.

Table 6. Comprehensive importance evaluation of nodes

| Node | Closeness Centrality | Betweenness Centrality | Degree Centrality | Comprehensive Importance |
|---|---|---|---|---|
| A1 | 0.318 | 2.286 | 7 | 0.575 |
| A2 | 0.412 | 12.286 | 9 | 1.004 |
| A3 | 0.500 | 18.286 | 9 | 1.250 |
| A4 | 0.889 | 21.333 | 8 | 1.641 |
| A5 | 0.538 | 20.286 | 9 | 1.340 |
| A6 | 0.889 | 0 | 7 | 1.007 |
| A7 | 0.319 | 2.167 | 3 | 0.439 |
| A8 | 0.500 | 21.333 | 3 | 1.136 |
| A9 | 0.409 | 8.042 | 4 | 0.716 |
| A10 | 0.565 | 33.250 | 6 | 1.628 |
| B1 | 0.889 | 42.667 | 9 | 2.275 |
| B2 | 0.526 | 17.833 | 6 | 1.160 |
| B3 | 0.526 | 17.833 | 6 | 1.160 |
| B4 | 0.406 | 9.917 | 5 | 0.800 |
| B5 | 0.406 | 40.833 | 7 | 1.737 |
| B6 | 0.500 | 18.286 | 9 | 1.250 |

| | | | | |
|---|---|---|---|---|
| B7 | 0.412 | 12.286 | 9 | 1.004 |
| B8 | 0 | 0 | 1 | 0.033 |
| C1 | 0.318 | 2.286 | 7 | 0.575 |
| D1 | 0.304 | 14.958 | 3 | 0.786 |
| E1 | 0.333 | 0 | 4 | 0.423 |
| E2 | 0.395 | 6.833 | 3 | 0.637 |
| E3 | 0.889 | 32 | 8 | 1.942 |
| E4 | 0.246 | 0 | 1 | 0.247 |

Based on the data in Table 6, the complex network topology of factors influencing emergency supply chain resilience was reconstructed using Gephi software, in which node size is proportional to its comprehensive importance. The resulting visualization is presented in Figure 5.

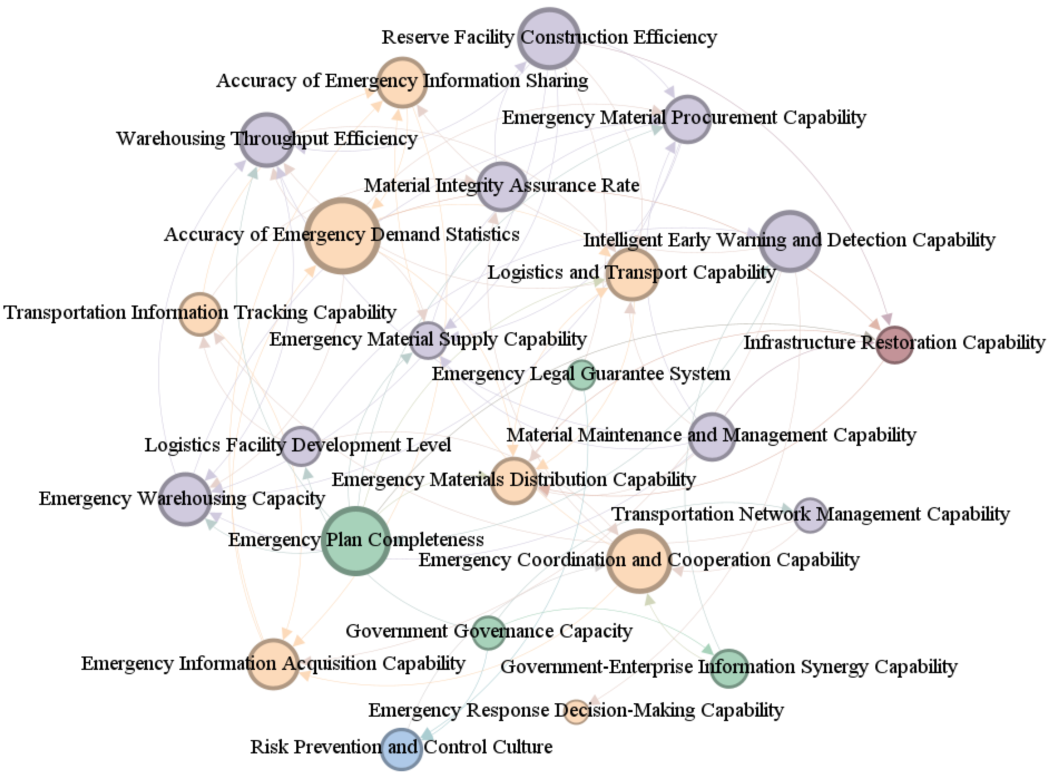


Figure 5. Complex network topology of factors influencing emergency supply chain resilience based on multi-centrality comprehensive weights

As shown in Table 6 and Figure 5, among the factors influencing emergency supply chain resilience, reserve facility construction efficiency (A4), intelligent early warning and detection capability (A10), accuracy of emergency demand statistics (B1), emergency coordination and cooperation capability (B5), and emergency plan completeness (E3) exhibit relatively high comprehensive importance.

Specifically, reserve facility construction efficiency requires enterprises to accelerate the construction of emergency warehouses, strategically position these facilities in critical locations, and optimize inventory management strategies to ensure rapid response and the capacity to meet material demands in surrounding areas upon the occurrence of emergencies. Intelligent early warning and detection capability necessitates the improvement of disaster monitoring networks, the integration of multi-source data-including meteorological, geological, and transportation information and the establishment of intelligent early warning systems to enable early identification and risk assessment of emergencies, thereby securing valuable time for emergency decision-making. Accuracy of emergency demand statistics calls for enterprises to integrate historical disaster data, market demand, regional population information, and other relevant data to construct demand forecasting models for emergency materials, thus enabling precise material estimation. Emergency coordination and cooperation capability emphasizes active collaboration and resource integration among enterprises to enhance the efficiency of material allocation. emergency plan completeness requires that, in the aftermath of a crisis, government organizations promptly assemble expert teams to formulate scientifically sound and context-responsive emergency plans, clearly delineate departmental responsibilities and coordination procedures, and thereby improve the effectiveness and efficiency of emergency response.

# 4 Discussions

This study developed an integrated analytical framework incorporating “text mining-system modeling-network analysis” to identify the key factors influencing emergency supply chain resilience in the context of public emergency prevention and control. The main conclusions are as follows:

1. The text mining approach based on the CNKI and Web of Science databases demonstrates higher analytical efficiency compared to traditional literature review methods.

2. The integrated DEMATEL-ISM method not only quantifies the complex causal influence relationships among factors but also constructs a clear multi-level hierarchical structural model, intuitively revealing the hierarchical structure of factors influencing emergency supply chain resilience.

3. Drawing on complex network theory, this study comprehensively employs degree centrality, betweenness centrality, and closeness centrality metrics to evaluate node influence and achieve topological visualization. This approach enhances both the scientific rigor and intuitive clarity of identifying key factors and assessing their importance within the global network. Finally, five key nodes-reserve facility construction efficiency, intelligent early warning and detection capability, accuracy of emergency demand statistics, emergency coordination and cooperation capability, and emergency plan completeness-are analyzed, with corresponding recommendations proposed for government and enterprises.

This research provides scientific and effective decision support for emergency management under crisis conditions, assisting managers in improving the effectiveness and operational efficiency of emergency response processes. As emergency management theory and practice continue to evolve, future research should further develop more comprehensive analytical frameworks and adopt mixed-method approaches combining qualitative and quantitative analyses. Such efforts will enable a more systematic exploration of the critical influencing factors of emergency supply chain resilience, thereby providing more reliable theoretical foundations and practical guidance for enhancing resilience levels in emergency supply chains.

## CRediT authorship contribution statement

Conceptualization: H. Sun and F. Wang; Methodology: H. Sun and J. Li; Formal analysis: H. Sun and F. Wang; Writing: H. Sun and J. Li; Visualization: H. Sun, J. Li and F. Wang; Review: H. Sun and F. Wang; Editing: H. Sun and J. Li; All authors have read and agreed to the published version of the manuscript.

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## Use of AI

In the preparation of this work, the authors did not use any artificial intelligence tools or services to complete the tasks, including writing, data analysis, or content generation. The entire manuscript was produced through the authors' original research, critical thinking, and writing. All content has been reviewed, edited, and verified by the authors, who accept full responsibility for the accuracy and integrity of the publication.

## Declaration of competing interests

There is no conflict of interest.

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