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Research on the Impact Factors of New Energy Vehicle Supply Chain Resilience under Industrial Interconnection

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Abstract: With the deepening evolution of industrial internet, the supply chain of new energy vehicles (NEVs) is undergoing a transformation from closed vertical manufacturing to an open, collaborative multidimensional ecosystem. The risk characteristics and resilience demands faced by this sector are being profoundly reshaped. Existing literature predominantly focuses on the general resilience of traditional manufacturing, with limited systematic analysis of resilience influencing factors and transmission mechanisms in the digital interconnection context of NEVs' technology-intensive industry. To address this, this paper proposes an unstructured data mining and analysis framework integrating Latent Dirichlet Allocation (LDA) and Interpreted Structural Model (ISM). Using policy documents and industry reports from 2020 to 2025 as the corpus, the study extracts six core themes influencing systemic resilience through LDA: digital collaboration and platform services, core component supply and R&D, logistics networks and transportation support, risk early warning and emergency response, macro-environment and policy guidance, and partnerships and ecosystem co-construction. Building upon this, DEMATEL and ISM methods are employed to construct a multi-layered structural model revealing the inherent hierarchical logic among elements. Results demonstrate that macro-environment and policy guidance serve as fundamental driving forces; digital platforms and ecosystem co-construction act as pivotal enabling mechanisms; component supply and logistics networks provide intermediate support at the physical entity level; while risk early warning and emergency response directly manifest resilience capabilities at the top tier. This study expands the measurement dimensions of supply chain resilience from the perspective of massive text, providing a solid theoretical basis for leading enterprises in the new energy vehicle industry chain to optimize risk resistance strategies and for policy-making departments to improve top-level design in the digital ecosystem.

Keywords: Influencing factors; New energy vehicle supply chain; Supply chain resilience; LDA model; ISM model

1. Introduction

In the wave of global climate governance actions and energy structure transformation, the new energy vehicle industry, as a core engine driving the green transition and high-quality development of the economy, has become increasingly prominent in strategic terms. China, leveraging policy support and market scale advantages, has already become the global leader in the new energy vehicle industry. However, behind the continuous expansion of the industry, the new energy vehicle supply chain has already faced complex, ever-changing, and unprecedented challenges. In recent years, due to the impact of emergencies such as geopolitical tensions, raw material shortages, and technological blockades, its shortcomings in risk resistance, rapid response, and self-repair capabilities have been exposed. How to effectively cope with and resist such external shocks, and build resilience for the new energy vehicle supply chain, has become a core challenge concerning the future healthy development of the industry.

The Industrial Internet, born from the deep integration of next-generation information technology and manufacturing, is revolutionizing traditional industries by transforming production methods, management models, and collaborative mechanisms [1]. Leveraging technologies like IoT, big data, cloud computing, and AI, it drives digitalization, networking, and intelligence across supply chain segments, enabling real-time data flow and value sharing. This innovation provides new approaches and technical support to enhance supply chain resilience, shifting management from reactive responses to proactive forecasting and intelligent coordination. Against this backdrop of industrial interconnection, systematically investigating the key factors influencing the resilience of new energy vehicle supply chains and their underlying mechanisms has become a pressing theoretical and practical challenge.

Currently, supply chain resilience as a critical research field involves extensive foundational theories such as complex systems and dynamic capabilities [2]. It not only refers to the ability to rapidly recover from sudden disruptions but also encompasses the capacity to continuously adapt and maintain stable operations in uncertain environments [3]. This requires supply chains to evolve beyond simple linear connections into complex networks with high flexibility, collaboration, and redundancy. Related research primarily covers four aspects: strategies for enhancing supply chain resilience, measurement and evaluation of supply chain resilience, influencing factors of supply chain resilience, and studies on its underlying mechanisms [4–6]. Research on influencing factors spans multiple sectors including manufacturing, finance, and emergency response, though existing literature predominantly focuses on general manufacturing or traditional industries, lacking in-depth analysis of specific sectors like new energy vehicles (NEVs), which are technology-intensive, highly globalized, and rapidly iterating [7,8]. With the development of industrial internet, NEVs have transcended being mere transportation tools. They now integrate electrification, connectivity, and intelligent technologies, serving as smart terminals that deeply integrate energy, communication, transportation, electronics, and artificial intelligence industries. This fundamental transformation has completely redefined the boundaries of their supply chains, shifting from relatively closed, vertical manufacturing chains to open, dynamic, and multidimensional integrated ecosystems. The risk sources have expanded from simple parts shortage to new fields such as cross-industry technical barriers, data security and policy compatibility, so the research on its resilience has more urgent practical significance.

In summary, current research on the resilience of new energy vehicle supply chains still has several shortcomings as follows:

(1) In terms of research content, most studies focus on improvement pathways, resilience measurement, or macro policy discussions, lacking systematic and hierarchical exploration of influencing factors;

(2) Regarding research perspectives, current studies lack analysis of new energy vehicle supply chain resilience within the context of industrial internet;

(3) In terms of research methods, most studies primarily collect limited subjective sample data through

questionnaires and interviews to identify influencing factors and evaluation indicators, with few scholars mining structural relationships from massive unstructured data.

Based on this, this paper takes the resilience of new energy vehicle supply chains as its research object under the backdrop of industrial internet. It employs the LDA topic model to identify influencing factors through policy documents, industry reports, and other unstructured data. Then, using the ISM method, it constructs a structural model to reveal hierarchical relationships and logical connections among influencing factors. This systematic approach aims to explore key factors affecting supply chain resilience and their underlying mechanisms.

2. Research process

2.1. Research methods

This study employs the LDA-ISM hybrid methodology to investigate factors influencing the resilience of new energy vehicle supply chains. The LDA model, also known as the Latent Dirichlet Allocation model, serves as a key unsupervised learning framework based on Bayesian principles, playing a pivotal role in unstructured text processing [9]. Distinct from simple word frequency counting, LDA uniquely captures deep semantic connections underlying lexical co-occurrence patterns. This model effectively extracts clear, definable, and traceable latent themes from complex textual data. The ISM approach, developed by American scholars in the 1970s, is a systematic analytical method primarily used to clarify hierarchical relationships and interaction mechanisms within complex systems [10]. Its core concept leverages matrix and graph theory principles to transform empirical judgments and intuitive understanding of complex systems 'internal relationships into logically rigorous directed graph models. Building upon the mining and identification results from the LDA model, this study constructs a hierarchical model of resilience influencing factors in new energy vehicle supply chains. This framework visually represents the system's internal structure while revealing latent relationships and transmission pathways. The specific research methodology is illustrated in **Figure 1**.

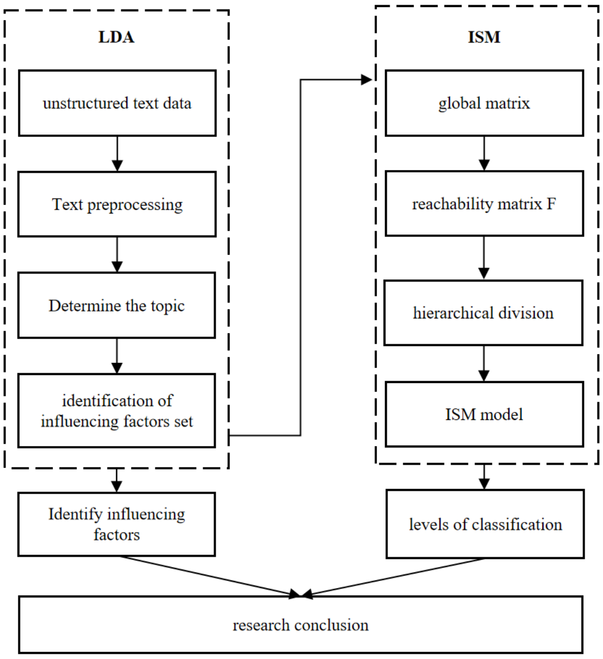

Figure 1. Research path diagram.

2.2. Impact factor mining and identification based on LDA topic model

This study focused its data collection on the critical period from 2020 to 2025, when China's NEV industry experienced rapid growth and deep integration with industrial internet. Data sources primarily included authoritative national institutions such as the China Association of Automobile Manufacturers (CAAM) website, the Chinese government website, and the official website of the Ministry of Industry and Information Technology, as well as local government platforms. During the search, a series of keyword combinations were employed, including "industrial internet," "NEV," "NEV supply chain," and "smart manufacturing," to maximize coverage of the research topics. Subsequently, a raw corpus was successfully constructed through a combination of web crawling technology and manual screening. The corpus comprised 129 national and local policy documents, 136 industry news articles, and 84 industry reports, totaling 349 pieces. However, the raw text data contained substantial interference information, which would significantly impact the accuracy of topic recognition if directly used for model training.

Therefore, a series of rigorous preprocessing steps are required to ensure corpus accuracy and standardization. First, the text content undergoes basic cleaning to eliminate noise such as punctuation, numbers, and conversion symbols. After that, to enhance model accuracy, the cleaned text data is segmented using the Chinese word segmentation library Jieba in Python. This is followed by stopword processing through a custom vocabulary and the HIT (Harbin Institute of Technology) stopword list, resulting in a lexical set for each document. The final preprocessing yields multiple valid words, with the top 20 word frequency statistics presented in **Table 1**.

Table 1. Word frequency statistics (Top 20)

Keywords	Word frequency
Automobile	9348
New energy	7967
Industry	5343
Develop	4682
Enterprise	4096
Internet	3724
China	2957
Market house	2943
Technology	2829
Trade	2180
Charge	2039
Intelligence	2030
Build	2018
Terrace	2017
Data	2012
Serve	1961
Cell	1895
Product	1797
Promote	1790
Estate	1736

The preceding section outlines the text preprocessing process. Following these operations, the corpus content has been transformed into a substantial vocabulary set, necessitating feature extraction for subsequent analysis. This study employs the TF-IDF method, which effectively shifts the focus of text features from generic high-frequency words to core vocabulary with semantic distinctiveness. This approach provides higher-quality input for the LDA topic model, as detailed in **Equation (1)**:

$$TF-IDF_{i,j} = TF_{i,j} \times IDF_j = \frac{n_{ij}}{\sum_k n_{k,j}} \times \log \frac{|D|}{\left|\{j: t_i \in d_j\}\right|} \tag{1}$$

TF-IDF is the product of the term frequency (TF) and the inverse document frequency (IDF). Here, $TF_{i,j}$ represents the normalized frequency of a feature word i appearing in document j, $n_{i,j}$ represents the number of occurrences of the feature word i in document j, $\sum kn_{i,j}$ represents the total number of occurrences of all feature words in document j, N represents the total number of documents in the corpus, and DF_i represents the number of documents containing the specific feature word i.

Next, we determine the optimal number of topics (K) for this study. Selecting the right K value is crucial for ensuring model quality and result usability. An excessively small K may result in overly broad topics that fail to distinguish subtle textual differences, while an overly large K could lead to fragmented topics with significant semantic overlap or meaningless categories, complicating interpretation. To scientifically and objectively identify the optimal topic count, this study combines two widely recognized quantitative evaluation metrics: perplexity and topic coherence. Perplexity measures a model's predictive accuracy for documents, reflecting its uncertainty or confusion when predicting subsequent word pairs. Lower perplexity values indicate better model fit to the corpus and stronger generalization capabilities, calculated as shown in **Equation (2)**:

$$Perplexity(D) = exp\left\{-\frac{\sum_{d=1}^{M}\log P(D_d)}{\sum_{d=1}^{M}N_d}\right\} \tag{2}$$

Here, M denotes the total number of documents $\mathrm{N_d D_d} \sum_{d=1}^{M} \mathrm{N_d} \log \mathrm{P(D_d)}\ \mathrm{D_d D_d}$ in the test corpus, while the total number of words in a document (i.e., document length) is represented by another variable. The sum of all words in the test corpus is indicated by a third variable. The document's log-likelihood function under the topic model quantifies the probability of the model generating the document.

Topic consistency measures the semantic relevance between words within a topic. Generally, higher consistency scores indicate better topic quality and easier human comprehension [11]. Its calculation is relatively complex, as it involves a series of computational steps rather than a single mathematical formula. The core methodology employs normalized pointwise mutual (ti,tj) information (NPMI) and a sliding window to calculate the relevance between high-frequency words within a topic. Simply put, it computes the NPMI score between any two words in the top N words of a topic, then averages the scores across all word pairs. Higher NPMI scores indicate greater probability of co-occurrence between the words in the document and stronger semantic relevance. This study conducted experiments with K values ranging from other studies, calculating the model's confusion score and topic consistency score for each K value [2,11]. The results are presented in **Figure 2** and **Figure 3**.

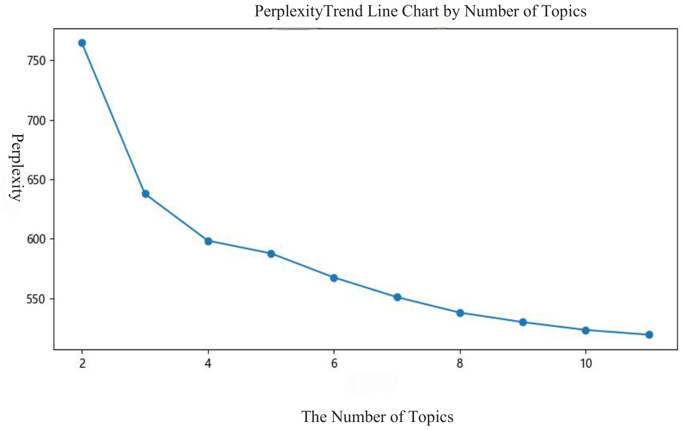

Figure 2. Difficulty curve.

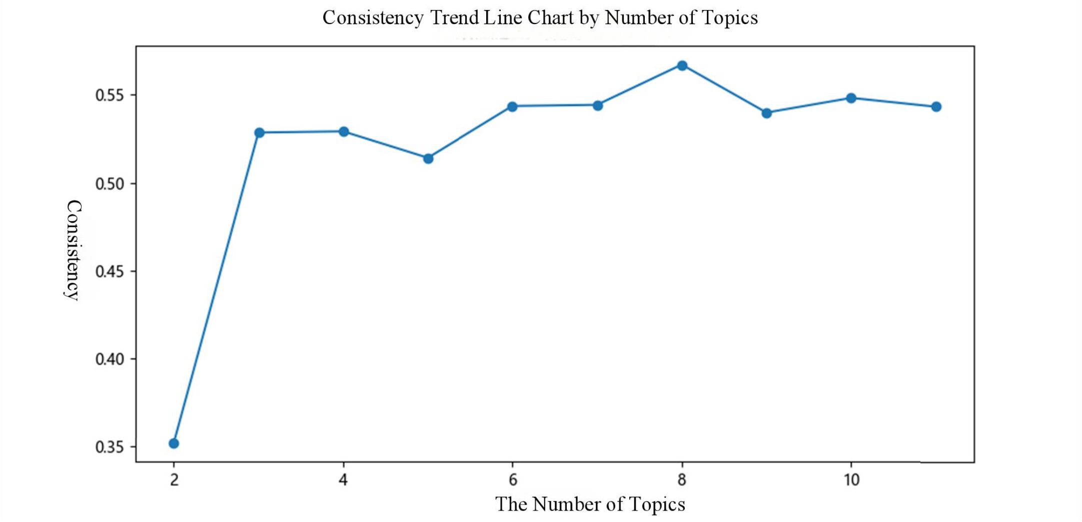

Figure 3. Consistency curve.

The confusion curve reveals that when K exceeds 8, the slope of the curve significantly flattens. Examining the consistency curve, we observe it peaks at K = 8, indicating this value represents the potential optimal choice. However, an excellent LDA model should not only demonstrate strong data fit but also feature highly discriminative and interpretable topics. To further evaluate topic quality, we conducted visual analysis using the pyLDAvis tool for topic models across different K values. The visualization results are presented in **Figure 4** and **Figure 5**.

Figure 4. Distance map between topics at K = 8.

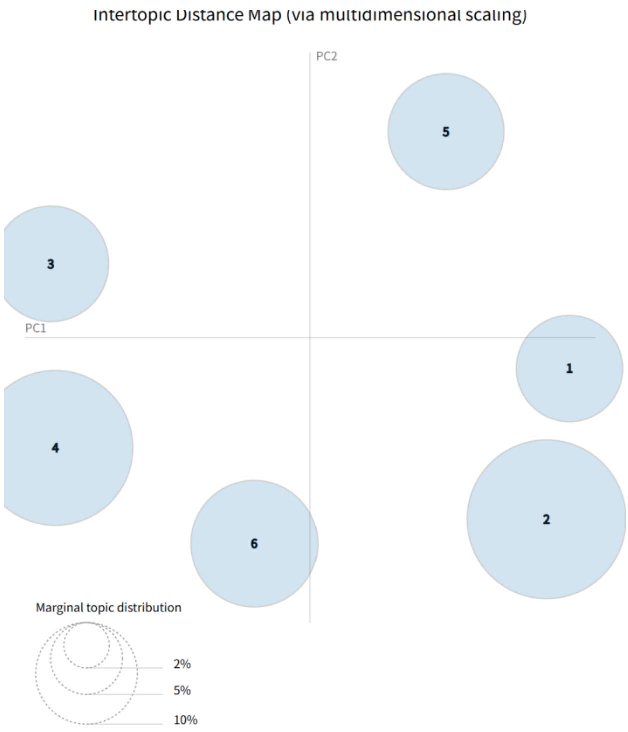

Figure 5. Distance between topics at K = 6.

The analysis revealed that while K = 8 achieved the highest consistency score, it exhibited significant overlapping between themes, indicating blurred boundaries and poor differentiation among multiple themes, which hinders subsequent interpretation and practical application. In contrast, K = 6 resulted in more independent theme distributions in the visualization, with significantly reduced overlap, demonstrating stronger thematic independence. After comprehensively evaluating model fit and thematic interpretability, this study ultimately selected K = 6 as the optimal theme count. This choice optimizes theme differentiation and practical value while maintaining high consistency scores, thereby constructing a more robust and interpretable thematic model.

By summarizing the semantic meanings of high-frequency feature words under each theme, we identified six themes with significant discriminative power and practical explanatory value, resulting in a “theme-lexical” table for each of the six themes, as shown in **Table 2**.

Table 2. Topic-glossary

Theme	Topic name	High-frequency vocabulary
1	Digital Collaboration and Platform Services	Service, Information, User, Platform, Network, Data, Interconnection, Algorithm, Sharing, Cloud
2	Supply and R&D of Core Components	battery, chip, component, manufacturing, capacity, technology, R&D, supplier, quality, alternative
3	Logistics Network and Transportation Guarantee	Storage, Transportation, Node, Distribution, Inventory, Scheduling, Hub, Delay, Route, Capacity
4	Risk Early Warning and Emergency Response	Risk, Disruption, Shock, Recovery, Agility, Redundancy, Early Warning, Assessment, Resilience, Dynamic
5	Macro environment and policy orientation	policy, subsidy, carbon peak and carbon neutrality, environmental protection, market, regulation, standard, supervision, green, access
6	Partnership and Ecological Co-construction	cooperation, partner, trust, contract, alliance, interest, cooperation, ecology, communication, reconstruction

2.3.1. Theme 1: Digital collaboration and platform services

The high-frequency terms in this theme are predominantly centered around concepts like “platform,” “data,” “network,” and “service.” In the context of industrial internet, the physical boundaries of supply chains are being dismantled, replaced by cloud-based and algorithm-driven supply-demand matching. These terms not only reflect the industrial internet’s role as foundational infrastructure but also highlight the pivotal role of data elements in breaking down information silos and enhancing visibility across the entire supply chain. Consequently, this set of terms is categorized as “digital collaboration and platform services,” underscoring how technological empowerment directly enhances supply chain transparency and responsiveness.

2.3.2. Theme 2: Supply and R&D of core components

Terms like “battery”, “chip”, “production capacity”, and “alternative solutions” directly address the core pain points of the NEV industry. Unlike traditional fuel-powered vehicles, NEVs heavily rely on the “three-electric” system and automotive-grade semiconductors. Disruptions in these high-tech bottleneck components often trigger severe supply chain reactions. This theme highlights the vulnerability in material composition within the supply chain, termed “core component supply and R&D”, underscoring that self-reliance in key technologies and multi-source supplier substitution strategies form the foundation for building structural resilience.

2.3.3. Theme 3: Logistics network and transportation guarantee

Terms like “warehouse”, “node”, “hub”, and “route” vividly characterize the physical spatial dynamics of supply chains. When external shocks occur, the paralysis of logistics network nodes or sudden capacity drops may cause vehicle delivery delays or even production halts. From a logistics engineering and management perspective, these terms underscore the critical importance of buffer stock allocation, dynamic route scheduling, and hub resilience. Hence, they are distilled into “logistics network and transportation assurance” to emphasize supply chain robustness at the physical spatial level.

2.3.4. Theme 4: Risk early warning and emergency response

The theme is primarily characterized by dynamic resilience features such as “disruption”, “agility”, “early warning”, and “redundancy”. The core of supply chain resilience lies not only in resisting known risks but also in rapid state recovery and adaptation during emergencies. These terms encompass the entire process from situational awareness during the risk incubation phase, through absorption and buffering during the outbreak phase, to structural reorganization during the recession phase. Accordingly, the title “risk early warning and emergency response” is proposed, directly aligning with the capability evolution closed loop in resilience theory.

2.3.5. Theme 5: Macro environment and policy orientation

Terms like “dual carbon goals”, “subsidies”, “environmental protection”, and “regulations” reflect external environmental constraints and driving forces that transcend the micro-level of enterprises. As a quintessential policy-driven pioneering industry, the new energy vehicle sector sees emission standard upgrades, access threshold adjustments, or subsidy reductions all reshape supply chain competition patterns and compliance costs at the macro level. This framework, termed “macro-environment and policy orientation”, highlights how policy frameworks as external regulatory variables exert profound influence on the medium-to-long-term evolution of supply chains.

2.3.6. Theme 6: Partnership and ecological co-construction

The final set of high-frequency terms, such as “trust”, “contract”, “alliance” and “ecosystem”, explores the interaction logic among on-chain entities through the lens of social network theory. In the highly complex ecosystem of new energy vehicles, the isolated efforts of individual enterprises can no longer withstand systemic risks. Cross-border alliances, built on implicit contracts, information sharing, and shared interests, have emerged as a new competitive paradigm. Dubbed “partnership and ecosystem co-construction,” this concept underscores that supply chain resilience is not merely an engineering challenge but a collaborative evolutionary process rooted in relational capital.

2.3. ISM analysis

This study defines the six themes identified by LDA as the core elements of a supply chain resilience system, S={S1, S2,…,S6}, which are as follows:

S1:Digital Collaboration and Platform Services;
S2:Core Component Supply and R&D;
S3:Logistics Networks and Transportation Assurance;
S4:Risk Early Warning and Emergency Response;
S5:Macro Environment and Policy Guidance;
S6:Partnerships and Ecosystem Co-construction.

After establishing these six key systemic elements for new energy vehicle supply chain resilience, the Delphi Method was employed to conduct back-to-back multi-round discussions and evaluations of direct impact relationships among the elements through expert consultations. When element Si has a direct and significant impact on Sj, aij=1 is assigned; otherwise, aij=0 is assigned if there is no direct impact or the impact is minimal. This process resulted in constructing a 6×6 adjacency matrix A (**Table 3**).

Table 3. Adjacency matrix A

Factor	S1	S2	S3	S4	S5	S6
S1	0	1	1	1	0	1
S2	0	0	1	1	0	0
S3	0	1	0	1	0	0
S4	0	0	0	0	0	0
S5	1	0	0	0	0	1
S6	1	1	1	0	0	0

The adjacency matrix A is a Boolean matrix that follows Boolean algebraic operations: 0+0=0, 0+1=1, 1+1=1, 1×0=0, 0×1=0, and 1×1=1. According to these rules, if matrix M satisfies conditions (4) and (5), it is termed the reachable matrix of A. A reachable matrix describes any transitive relationship between core categories, indicating whether all constituent elements have influence relationships.

$$(A+I) \neq (A+I)^2 \neq \ldots \neq (A+I)^k = (A+I)^{k+1} \tag{3}$$

$$k \leq n-1 \tag{4}$$

$$R = (A+I)^k \tag{5}$$

Here, I denotes the identity matrix; k represents the transformation order of the reachability matrix; and n is the matrix order.

This study utilized the mathematical software Matlab R2020a to derive the reachability matrix M, as shown in **Table 4**.

Table 4. Reachable matrix M

Factor	S1	S2	S3	S4	S5	S6
S1	1	1	1	1	0	1
S2	0	1	1	1	0	0
S3	0	1	1	1	0	0
S4	0	0	0	1	0	0
S5	1	1	1	1	1	1
S6	1	1	1	1	0	1

The hierarchical structure model is constructed by categorizing the influencing factors in the reachability matrix M. The factor decomposition and extraction criteria are defined as: R(Si) ∩ A(Si) = R(Si), where R(Si) denotes the set of all factors reachable from factor Si in the reachability matrix M, and A(Si) represents the set of all factors reachable from factor Si. Based on these conditions and the reachability matrix, the reachability sets, antecedent sets, and intersections of each factor are presented in Table 5. Through computation, the sets are determined as L1 = {S4}, L2 = {S2, S3}, L3 = {S1, S6}, and L4 = {S5}. This completes the hierarchical classification of the reachability matrix M (**Table 5**).

Table 5. Reachable sets, antecedent sets, and intersection table

Factor	Reachable set	Prior set	Be mixed
S1	1,2,3,4,6	1,5,6	1,6
S2	2,3,4	1,2,3,5,6	2,3
S3	2,3,4	1,2,3,5,6	2,3
S4	4	1,2,3,4,5,6	4
S5	1,2,3,4,5,6	5	5
S6	1,2,3,4,6	1,5,6	1,6

Based on the aforementioned conclusions, after completing the hierarchical division, a directed connection graph is constructed to visually represent the model's structural hierarchy. Factors at the same level are represented by boxes at identical horizontal positions, while their logical relationships are connected through directed lines. Finally, the definitions of symbolic symbols are substituted to obtain the ISM model diagram of resilience influencing factors in the new energy vehicle supply chain under industrial interconnection, as shown in **Figure 6**.

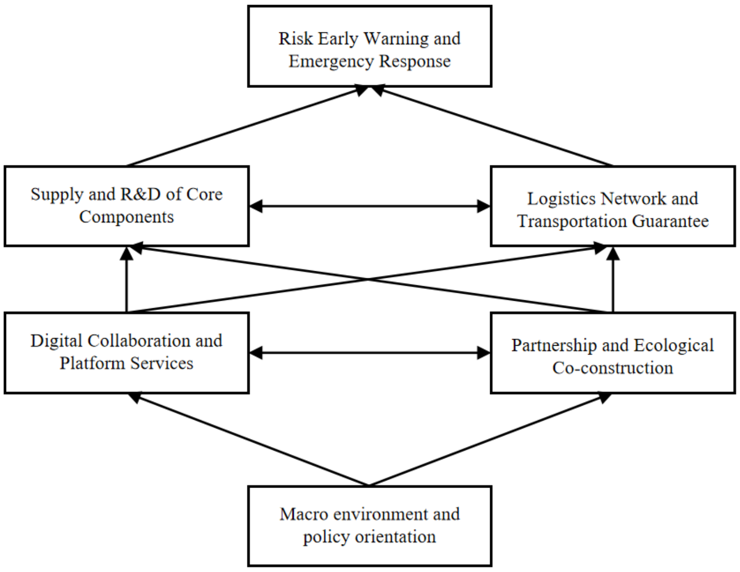

Figure 6. ISM influencing factors model.

3. Discussion

Through constructing an ISM framework and hierarchical categorization of LDA topic mining results, this study systematically elucidates the transmission pathways and hierarchical distribution of factors influencing the resilience of new energy vehicle supply chains from an industrial interconnection perspective. The six core elements are systematically organized into four progressive tiers, demonstrating an inherent progression from macro to micro levels and from ecological foundations to capability manifestations. The key findings are as follows:

The macro-environment and policy orientation (S5) serve as the fundamental drivers for building supply chain resilience. Positioned at the fourth and foundational layer of the ISM model, this factor constitutes the bedrock of the entire system. As a quintessential policy-driven pioneer industry, the supply chain evolution of new energy vehicles is profoundly shaped by external institutional environments. The evolution of environmental regulations, the advancement of the dual-carbon strategy, and adjustments to industry entry thresholds collectively establish compliance boundaries and developmental frameworks for the ecosystem at the macro level. Steady and forward-looking policy guidance continuously provides external dividends and directional guidance for cultivating mid-to-high-level elements.

Digital collaboration and platform services (S1) and partnership and ecosystem co-construction (S6) form the foundational hub. These two elements, positioned at the third tier of the model, serve as pivotal “soft power” components bridging upper and lower levels within the system. Within the industrial internet framework, they are interdependent: digital tools dismantle traditional physical silos, enabling data to flow seamlessly across supply chain nodes; meanwhile, trust-based and contract-driven ecosystem alliances redefine interaction rules among nodes, empowering enterprises to mitigate risks through social networks. This deep integration of data flows and relational flows directly enhances the operational efficiency of physical supply chains.

The supply and R&D of core components (S2) and the logistics network and transportation support (S3) serve as the backbone of resilience transmission. These two elements at the model’s second tier form the “tough nuts to crack” in supply chain resilience. The degree of self-sufficiency in critical materials like the “three-electric” systems and automotive-grade semiconductors, along with the scheduling and redundancy capabilities of physical logistics hubs when facing disruptions, determine the physical space’s maximum damage tolerance. The underlying data platforms and macro policy dividends must be effectively transformed into flexible buffer zones for these two key physical nodes to effectively break the chain of risk propagation.

Risk early warning and emergency response (S4) serve as the visible manifestation of system resilience. The emergency response capability at the model’s first layer (topmost) acts as the frontline defense against external disruptions, while also being the ultimate outcome of all underlying structural elements. It relies heavily on policy guidance from the base layer, real-time information capture through deep digital networks, and robust support from mid-level material and transportation infrastructure. Only when the system foundation is solidified can the supply chain detect potential crises during their latent phase and swiftly activate redundant resources and agile recovery during shock events.

4. Conclusion

In conclusion, within the highly open industrial internet ecosystem, enhancing the resilience of new energy vehicle supply chains requires more than isolated improvements at individual nodes. It constitutes a systemic endeavor that integrates macro-level institutional frameworks, relational networks, physical infrastructure, and dynamic capabilities. Managers must align with fundamental policy logic, strengthen the foundation of digital platforms and relational capital, reinforce defenses for critical components and logistics networks, and ultimately establish a modern, flexible supply chain system with comprehensive domain awareness and self-healing capabilities.

Disclosure statement

The author declares no conflict of interest.

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