

Article

Evaluation and Obstacle Diagnosis of International Supply Chain Resilience for New Energy Vehicles: An Integrated AHP–Entropy–TOPSIS and fsQCA Approach from Hubei, China

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Abstract

Under the “dual carbon” goals (carbon peak and carbon neutrality), the new energy vehicle (NEV) industry has become a strategic focus of great-power competition, and the resilience of its international supply chain is critical to industrial security and development initiatives. As a traditional automobile manufacturing hub in China, Hubei Province faces increasingly prominent global risks in its supply chain during the transition to NEVs; scientifically evaluating and enhancing its international supply chain resilience is therefore of great practical significance. Drawing on supply chain resilience theory, this paper constructs an evaluation index system comprising 18 specific indicators across four dimensions: robustness, redundancy, agility, and innovativeness. To overcome the limitations of a single weighting method, a combined subjective and objective weighting approach that integrates the Analytic Hierarchy Process (AHP) and the entropy weight method was employed to determine indicator weights. Subsequently, the TOPSIS model was applied to measure the supply chain resilience level of Hubei Province from 2018 to 2025, with horizontal comparisons conducted against Shanghai and Guangdong. Finally, an obstacle degree model was introduced to quantitatively diagnose the key factors constraining resilience improvement. The results indicate that the international supply chain resilience of Hubei’s NEV industry has shown a continuous upward trend. By 2025, it ranks in the first tier alongside Guangdong (with closeness coefficients of 0.8180 and 0.8181, respectively), approaching the level of Shanghai. Weaknesses are concentrated primarily in the agility dimension, while upstream resource dependence remains a salient issue within the robustness dimension. “External dependence on key raw materials,” “average recovery time from logistics disruptions,” and “level of supply chain information sharing” are still the top three obstacle factors. Fuzzy-set qualitative comparative analysis (fsQCA) further reveals that low resource autonomy and slow logistics recovery are core conditions leading to low resilience, and the coupling of multiple obstacle factors amplifies the risk transmission effect. Based on this, this study proposes optimization recommendations focusing on foundation strengthening and chain consolidation, digital chain connectivity, and innovation–chain integration, in order to enhance the resilience of the international supply chain for new energy vehicles in Hubei. This research provides a methodological reference for evaluating the supply chain resilience of regionally distinctive industries and offers a quantitative basis for Hubei Province and related enterprises to formulate targeted improvement strategies.

Academic Editor: Joeri Van Mierlo

Received: 20 May 2026

Revised: 4 July 2026

Accepted: 7 July 2026

Published: 15 July 2026

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Keywords: new energy vehicles (NEVs); international supply chain; supply chain resilience

1. Introduction

Within the grand narrative of global proactive responses to climate change and the pursuit of green and low-carbon transitions, developing new energy vehicles (NEVs) has become a strategic consensus among the world's major economies for building new competitive advantages in future industries [1]. China has positioned NEV development as a critical pathway to achieving its “dual carbon” goals and transitioning from a major automobile country to an automobile powerhouse, with its industrial scale and market penetration rate consistently leading the world. However, the highly complex global division of the labor system in the NEV industry, while delivering efficiency gains, also exposes its supply chain to multiple risks, including geopolitical conflicts, trade barriers, technology blockades, and sudden public events [2]. In recent years, a series of shocks, ranging from chip shortages to drastic fluctuations in battery raw material prices, have revealed the vulnerability of global supply chains. Supply chain resilience—defined as the capacity of a supply chain to prevent disruptions before they occur, adapt during shocks, and rapidly recover and evolve in their aftermath—has thus evolved from an academic concept into a core practical issue bearing on industrial security and development initiatives [3].

Enhancing the resilience and security of industrial and supply chains has become one of the core strategic tasks for China in fostering a new development paradigm and promoting high-quality development. Under this strategic guidance, the academic community has conducted multi-dimensional research on the supply chain resilience of new energy vehicles.

In terms of influencing factors and driving mechanisms of resilience, Fan and Lu [4] constructed an evaluation system encompassing capabilities such as risk resistance, recovery, and innovation to assess the supply chain resilience of automotive enterprises. Li and Sukhotu [5] identified key driving factors of electric vehicle supply chain resilience, categorizing them into five types—visibility, flexibility, collaboration, redundancy, and robustness—and pointed out that the synergistic effects among these factors constitute the key mechanism through which resilience is formed. Regarding supply chain structure and risk propagation, Wu and Li [6] focused on the dual impact of internationalization and supply chain complexity on resilience, indicating that overly complex global networks may amplify risk propagation. Huang et al. [7] employed a complex network analysis approach to simulate the resilience performance of China's electric vehicle supply chain under different attack strategies, identifying critical nodes and vulnerable paths.

In terms of critical resource supply chain security, the supply risks of upstream mineral resources have attracted considerable research attention. Lou et al. [8] assessed the resilience of the electric vehicle lithium-ion battery supply chain from the perspective of supply shortages at upstream mineral enterprises. Shao and Jin [9] specifically focused on China's lithium supply chain, simulating its resilience performance under the dual shocks of growing new energy vehicle demand and supply disruptions, and found that upstream resource dependence constitutes a key bottleneck constraining supply chain security. Regarding the evolution of the supply chain ecosystem, Jagani et al. [10] analyzed the changing roles of suppliers in the electric vehicle supply chain, revealing a trend of transformation from traditional hierarchical structures to networked ecosystems. Alsaleh and Farooq [11], through simulation modeling, explored the trade-off optimization pathways among sustainability, resilience, and efficiency in the global electric vehicle supply chain. At the methodological level, models such as the Analytic

Hierarchy Process (AHP), entropy weight method, and TOPSIS have been widely applied in the comprehensive evaluation of supply chain resilience [4,12]. Chen et al. [13] empirically examined the recovery capability of the electric vehicle supply chain in the face of disruptions.

Although existing studies have laid a solid foundation for understanding the supply chain resilience of new energy vehicles, the following limitations remain. First, most existing research has been conducted at the national or overall industry level, with relatively few assessments addressing the international supply chain resilience of provincial-level industries, and the integration of “regional” and “international” perspectives remains insufficiently explored. Under the “dual circulation” new development paradigm, the supply chain resilience of provincial-level industries must be examined within the global division of labor—that is, their international supply chain resilience must be assessed. This involves not only conventional operational and supply-demand risks but also responses to systemic challenges such as geopolitical conflicts, exchange rate fluctuations, trade barriers, and the amplification of the bullwhip effect in global networks. Second, the majority of studies remain at the level of resilience measurement and fail to further diagnose the key obstacle factors constraining resilience enhancement and their coupling mechanisms, making it difficult to provide a quantitative basis for precise policy formulation. Third, existing evaluation methods mostly adopt single or simple combined weighting approaches, lacking effective integration of subjective and objective weights and the progressive incorporation of multi-dimensional methodological tools.

Hubei Province, as a traditional stronghold of China’s automobile industry, is making a full-fledged transition toward new energy and intelligent connected vehicles. The stability of its supply chain is of great strategic significance to national automobile industry security. Focusing on Hubei’s international supply chain for new energy vehicles, this study aims to construct a multi-dimensional indicator system applicable to evaluating its resilience, analyze the dynamic evolution patterns of its resilience level and, in comparison with leading domestic regions, explore the key obstacle factors that constrain further resilience enhancement. In doing so, it provides a scientific and quantitative decision-making basis for relevant departments and enterprises in Hubei to accurately identify risk vulnerabilities and formulate targeted improvement strategies.

On the basis of constructing an evaluation indicator system, this paper adopts the AHP–entropy weight combined weighting method and the TOPSIS model to measure the resilience of Hubei’s international supply chain for new energy vehicles. Furthermore, the obstacle degree model and the fsQCA method are employed to diagnose key constraining factors and their configurational effects. Finally, targeted optimization strategies are proposed based on the empirical findings.

The remainder of this paper is organized as follows: Section 2 presents the research design, elaborating on the construction of the evaluation index system and the methodological model. Section 3 reports the empirical results and analysis, presenting the results of weight calculation, resilience measurement, obstacle diagnosis, and configuration analysis. Section 4 summarizes the research conclusions, proposes policy recommendations, and discusses the research limitations.

2. Research Design and Methods

2.1. Construction of the Evaluation Indicator System

2.1.1. Principles and Dimensions for Construction

To ensure the rationality and validity of the evaluation indicator system, this study adheres to the following four fundamental principles: (1) Scientific principle: Indicator selection must be grounded in well-established supply chain resilience theories, objectively and faithfully reflecting the essence of resilience while avoiding subjective arbitrariness. (2) Systematicity: The indicator system should encompass multiple core dimensions of supply chain resilience, with clear hierarchical structures and logical coherence among dimensions and indicators, collectively forming a complete evaluation system. (3) Representativeness: Under each dimension, key indicators that best characterize that dimension and have a significant impact on international supply chain resilience should be selected, striving for conciseness and efficiency while avoiding information overlap among indicators. (4) Operability: Indicators must have clear conceptual definitions, and the required data should be obtainable through channels such as public statistics, industry reports, corporate annual reports, and authoritative databases, thereby ensuring the feasibility of empirical analysis.

Compared with traditional supply chain resilience that focuses on domestic or regional contexts, international supply chain resilience involves cross-border flows of materials, information, and capital, resulting in significantly different risk structures and capability requirements [14]. International supply chains not only face conventional operational and supply-demand risks but are also more susceptible to systemic shocks such as geopolitical conflicts, exchange rate fluctuations, trade barriers, and the amplification of the bullwhip effect in global networks [13]. Therefore, evaluating international supply chain resilience requires strengthening the examination of cross-border risk exposure and global collaborative capacity on the basis of classic resilience dimensions. Accordingly, drawing on the resilience framework proposed by Pettit et al. [3] and integrating the characteristics of the new energy vehicle industry—such as its high dependence on upstream mineral resources and its deeply globalized supply chain—this paper decomposes the evaluation system into four dimensions of robustness, redundancy, agility, and innovativeness, starting from the three core capabilities of resisting shocks, coping with disruptions, and recovering and adapting. Specifically, the robustness dimension focuses on assessing the dependency risks associated with critical international resources and core international suppliers; the agility dimension emphasizes the stability and recovery capability of international logistics corridors and the efficiency of cross-border information synergy; and the redundancy and innovativeness dimensions serve to build a more autonomous and adaptive global supply chain network.

2.1.2. Indicator Selection and Description

Under this four-dimensional framework, and taking into account the characteristics of the new energy vehicle industry—such as high technological integration, long industrial chains, and strong dependence on upstream resources—as well as the regional features of Hubei as a key automotive industry base in China, 18 specific evaluation indicators were preliminarily selected through literature review and expert consultation, thereby forming the evaluation indicator system for the international supply chain resilience of Hubei's new energy vehicle industry as presented in Table 1.

The indicator system presented in Table 1 strengthens the assessment perspective of the “international supply chain” within a generic supply chain resilience framework. In the robustness dimension, “external dependence on key raw materials (A12)” and “supply chain concentration (A11)” directly quantify the dependency risks of the

industrial chain on overseas strategic resources and leading international suppliers, which represent the core manifestation of international supply chain vulnerability [15]. The agility dimension purposefully incorporates indicators such as “logistics network stability (A14),” “average recovery time from logistics disruptions (A33),” and “supplier geographical diversification index (A34)” to measure the capacity for coping with cross-border logistics interruptions—such as international transport blockages and port closures—as well as the ability to disperse country-specific risks through global supplier configurations [16]. Indicators in the redundancy and innovativeness dimensions, such as “financial resource support (A24)” and “number of invention patents per 10,000 people (A42),” serve as the cornerstones for building resilient buffers and reducing external dependence through technological advancement, ultimately enhancing the autonomous and controllable level of the international supply chain [17]. Compared with traditional supply chain evaluation systems that primarily focus on cost, quality, and delivery, this indicator system, through the systematic embedding of the aforementioned indicators, achieves a focused evaluation of the specific risks faced and the core capabilities required when a regional industry is deeply integrated into the global division of labor network.

Table 1. Evaluation Indicator System for the International Supply Chain Resilience of New Energy Vehicles in Hubei Province.

Criterion Layer	Indicator Layer	Indicator Description	Unit	Attribute
Robustness (A1)	Supply Chain Concentration (A11)	Proportion of procurement amount for core components (e.g., batteries, motors, electronic controls) sourced from the top three suppliers.	%	Negative
	Foreign Dependence of Key Raw Materials (A12)	Ratio of import value of critical raw materials (e.g., lithium, cobalt, nickel) to total procurement value of such materials.	%	Negative
	Supply Chain Digitalization Level (A13)	Proportion of core enterprises utilizing supply chain management information systems (e.g., ERP, SCM).	%	Positive
	Logistics Network Stability (A14)	Annual normal operation rate of key international logistics channels, such as the Wuhan section of the China-Europe Railway Express and major international shipping routes.	%	Positive
Redundancy (A2)	Inventory Turnover Days for Key Components (A21)	Average inventory days of key components for core enterprises in the chain, reflecting short-term buffering capacity.	Days	Moderate *
	Proportion of Alternative Suppliers (A22)	Ratio of certified backup suppliers for core raw materials and components to the total number of suppliers.	%	Positive
	Excess Capacity Margin (A23)	(Regional theoretical total capacity—actual annual output)/actual annual output.	%	Positive
	Financial Resource Support (A24)	Ratio of financial support (e.g., bank loans, industrial funds) received by the NEV industry to the industry’s total output value.	%	Positive
Agility (A3)	Average Order Fulfillment Cycle (A31)	Average time from receiving a customer order to completing delivery.	Days	Negative
	Supply Chain Information Sharing Level (A32)	Degree to which core enterprises share demand forecasts, inventory, and production plans with first-tier suppliers (based on expert scoring or surveys).	1–5 points	Positive
	Average Recovery Time from Logistics Disruption (A33)	Average time required to restore normal capacity levels after disruption of major international logistics channels due to unexpected events.	Days	Negative
	Supplier Geographical Diversification Index (A34)	Distribution of core suppliers across different countries (regions); measured by the reciprocal of the Herfindahl-Hirschman Index (HHI).	—	Positive
Innovativeness (A4)	R&D Investment Intensity (A41)	Ratio of internal R&D expenditure to primary business revenue in the regional NEV industry.	%	Positive

Invention Patents per 10,000 Employees (A42)	Number of valid invention patents related to the regional Patents/10,000 NEV industry/number of industry employees (per 10,000 persons).	000 persons	Positive
Depth of Industry–University–Research Collaboration (A43)	The number of research and development institutions or major projects jointly established by leading new energy vehicle enterprises, universities, and research institutes in the region.	Number	Positive
Proportion of High-Tech Enterprises (A44)	Ratio of high-tech enterprises within the regional NEV industry chain to the total number of enterprises in the chain.	%	Positive
Proportion of New Product Revenue (A45)	Proportion of revenue from new products in the new energy vehicle industry to primary business revenue, reflecting the market transformation capability of innovation achievements.	%	Positive
Adoption Rate of Green Processes (A46)	Proportion of factories in core manufacturing segments of the industry chain adopting green processes such as cleaner production and recycling.	%	Positive

Note: * Inventory turnover days of key components (A21) is a moderate indicator. Inventory turnover days is typically a negative indicator (fewer days indicate higher efficiency); however, as a “safety stock” buffer against supply chain disruptions, an increase in its value within a certain range signifies enhanced redundancy. Based on the Best Practice Guide for Supply Chain Management in the Automotive Industry issued by the China Association of Automobile Manufacturers and expert consultation, the ideal moderate value is set at 45 days. During data normalization, it is converted into a positive indicator using the formula $y_{ij} = 1 - \frac{|x_{ij}-45|}{\max|x_{ij}-45|}$.

“Supply chain information sharing level (A32)” is a qualitative indicator, evaluated through a structured questionnaire where experts rate it on a 1–5 Likert scale (1 = “almost no sharing,” 5 = “fully real-time sharing”), with the arithmetic mean of the expert ratings taken as the annual data.

2.2. Research Methodology and Model Construction

2.2.1. Data Standardization

Because the indicators in the evaluation system differ in dimensions, magnitudes, and attributes, the raw data must be normalized to eliminate the influence of incommensurability on the comprehensive evaluation results. This study adopts the range normalization method based on the following considerations. First, the range method linearly maps data to the [0, 1] interval, preserving the distribution characteristics of the original data while eliminating dimensional effects [18]. Second, compared with Z-score normalization, which requires the data to approximately follow a normal distribution, the range method imposes no special requirements on data distribution and is therefore more suitable for cases involving multiple data types such as ratios, days, and scores in this study. Third, the non-negative matrix obtained after range normalization directly matches the input requirements of the subsequent TOPSIS model, and it is one of the most widely used normalization methods in the field of supply chain resilience evaluation [4,12]. Jahan and Edwards [18], in their review of multiple normalization techniques, noted that the min–max method exhibits favorable applicability and robustness in multi-criteria decision-making problems.

The conventional TOPSIS model generally adopts vector normalization to achieve dimensionless processing of indicators, while min–max normalization is also a commonly used dimensionless technique in multi-criteria decision-making. The two standardization approaches each have their merits and drawbacks: a comparative analysis based on the AHP model by Vafaei et al. (2018) [19] indicated that min–max normalization can amplify the score differences among evaluation objects, yielding higher discrimination; however, this method is sensitive to extreme values, and its ranking stability declines in the

presence of outliers. Vector normalization is less affected by extreme values but tends to compress the original differences among indicators. Given that the data in this study contain no obvious extreme values and that stronger discrimination among samples is desired, this paper adopts min–max normalization for data preprocessing.

Let there be m evaluation objects (e.g., m years or regions) and n evaluation indicators. Let x_{ij} represent the original value of the i -th evaluation object on the j -th indicator.

For positive indicators (where larger values indicate better performance), the range method is employed for standardization:

$$y_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (1)$$

In Equation (1), y_{ij} represents the standardized value of the i -th evaluation object on the j -th indicator; $\max(x_j)$ and $\min(x_j)$ denote the maximum and minimum values of indicator j across all evaluation objects, respectively.

For negative indicators (where smaller values indicate better performance), the standardization formula is

$$y_{ij} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \quad (2)$$

The meanings of the symbols in Equation (2) are the same as those in Equation (1). After processing using Equations (1) and (2), all indicator values y_{ij} are mapped into the $[0, 1]$ interval, with larger values indicating superior performance.

For the moderate indicator A21 (inventory turnover days of key components) in Table 1, let the ideal moderate value be x_0 (based on the industry best practice guide issued by the China Association of Automobile Manufacturers and expert consultation, $x_0 = 45$ days in this study), and its standardization formula is as follows:

$$y_{ij} = 1 - \frac{|x_{ij} - x_0|}{\max |x_{ij} - x_0|} \quad (3)$$

In Equation (3), $|x_{ij} - x_0|$ represents the absolute deviation between the actual value and the ideal value; $\max |x_{ij} - x_0|$ denotes the maximum absolute deviation among all evaluation objects. This formula standardizes the object that deviates farthest from the ideal value to 0, and the object exactly equal to the ideal value to 1, thereby converting the moderate indicator into a positive indicator and maintaining directional consistency with the other indicators.

In summary, the effectiveness of min–max normalization has been widely validated in the field of multi-criteria decision-making. Yoon and Hwang [20] pointed out in their original exposition of the TOPSIS method that any normalization technique can be applied within the TOPSIS framework as long as it preserves the relative order information of the original data. Subsequent studies have further confirmed that min–max normalization offers advantages in preserving data distribution characteristics and enhancing evaluation discrimination. Therefore, adopting this method as the unified standardization strategy in this study is methodologically robust.

2.2.2. Combined Weighting Model Using AHP-Entropy Weight Method

The Analytic Hierarchy Process (AHP), proposed by Saaty [21], is a method that transforms expert experiential judgments into quantitative weights through pairwise comparisons. The AHP method derives weights from expert pairwise comparison judgment matrices, with its input data consisting of relative importance ratings on a 1–9 scale, and it does not involve the normalization of original indicator data. Therefore, the min–max normalization described in Section 2.2.1 is applied exclusively to the entropy weight method and the TOPSIS model. This study employs the 1–9 scale method to conduct pairwise comparisons of the importance of indicators at each level, thereby constructing a judgment matrix. The meaning of the 1–9 scale is shown in Table 2.

Meanwhile, based on the hierarchical structure presented in Table 1, 15 experts in the fields of supply chain management, the new energy vehicle industry, and regional economy were invited (the composition of the experts is detailed in Table 3).

Table 2. The Scales and Their Definitions in the AHP Judgment Matrix.

Scale	Definition
1	Two factors are of equal importance
3	One factor is moderately more important than the other
5	One factor is strongly more important than the other
7	One factor is very strongly more important than the other
9	One factor is extremely more important than the other
2, 4, 6, 8	Intermediate values between the two adjacent judgments

Table 3. Cross-reference table of data sources for the evaluation indicators.

Indicator Code	Indicator Name	Primary Data Source	Specific Acquisition Method
A11	Supply chain concentration	Core enterprise annual reports, prospectuses	Extract procurement amounts of the top three suppliers and calculate their proportion
A12	External dependence on key raw materials	China Customs statistics, industry reports (BNEF)	Import value/total procurement value, with trend extrapolation for some years
A13	Supply chain digitalization level	Enterprise annual reports, survey data from the Hubei Provincial Department of Economy and Information Technology	Calculate the proportion of core enterprises adopting ERP/SCM systems
A14	Logistics network stability	China–Europe Railway Express (Wuhan) operational reports, Wuhan Customs	Annually normally operated train trips/planned train trips
A21	Inventory turnover days of key components	Core enterprise annual reports, Wind database	Inventory turnover days, taking the average of core enterprises along the chain
A22	Proportion of backup suppliers	Enterprise questionnaire surveys, industry interviews	Number of certified backup suppliers/total number of suppliers
A23	Capacity redundancy rate	China Automotive Industry Yearbook, enterprise annual reports	(Theoretical capacity – actual output)/actual output
A24	Financial resource support	Hubei Provincial Financial Office, public data on industrial funds	(Loan amount + fund amount)/total industrial output value
A31	Average order fulfillment cycle	Enterprise annual reports, industry association surveys	Average number of days from order receipt to delivery
A32	Supply chain information sharing level	Expert questionnaire survey	15 experts rated on a 1–5 Likert scale; the mean value is taken
A33	Average recovery time from logistics disruptions	Wuhan Customs, China–Europe Railway Express operational reports	Statistical recovery days from disruption events
A34	Supplier geographical diversification index	Enterprise annual reports, Bloomberg supply chain data	Reciprocal of the Herfindahl–Hirschman Index (HHI)
A41	R&D investment intensity	China Statistics Yearbook on High Technology Industry, enterprise annual reports	Internal R&D expenditure/main business revenue
A42	Number of invention patents per 10,000 people	China National Intellectual Property Administration, Hubei Statistical Yearbook	Number of valid invention patents/number of employees
A43	Depth of industry–university–research collaboration	Public news reports, university–enterprise official website announcements	Number of jointly established R&D institutions and major projects
A44	Proportion of high-tech enterprises	Hubei Provincial Department of Science and Technology, high-tech enterprise certification website	Number of high-tech enterprises/total number of enterprises in the industrial chain

A45	Sales revenue share of new products	China Automotive Industry Yearbook, enterprise annual reports	New product sales revenue/main business revenue
A46	Green process adoption rate	Enterprise ESG reports, MIIT green factory list	Proportion of factories adopting cleaner production and similar processes

For the judgment matrix $A = (a_{kl})$, its maximum eigenvalue $\lambda_{\max}$ and the corresponding eigenvector are calculated. After normalization, the subjective weight vector of the indicators is obtained, denoted as $W^s = (w_1^s, w_2^s, \dots, w_n^s)^T$. To test the logical consistency of the judgments, the consistency ratio CR needs to be calculated.

$$CR = \frac{CI}{RI} \quad (4)$$

In Equation (4), $CI = (\lambda_{\max} - n)/(n - 1)$ denotes the consistency index, and RI denotes the average random consistency index. The value of RI depends on the order of the matrix n (see Table 3). When $CR < 0.10$, the consistency of the judgment matrix is considered acceptable.

For group decision-making involving multiple experts, this study employs the geometric mean method to aggregate the elements of each expert's judgment matrix, thereby obtaining a comprehensive judgment matrix, from which the comprehensive weights are then calculated. All collected expert questionnaires passed the consistency test $CR < 0.10$.

2.2.3. Determining Objective Weights Using the Entropy Weight Method

The entropy weight method originates from information theory, proposed by Shannon [22]. Its core idea is that the greater the dispersion of indicator data, the more information the indicator carries, and therefore the higher its weight should be in the comprehensive evaluation. Range normalization and the calculation of characteristic proportions p_{ij} in this section serve different purposes: range normalization aims to eliminate the dimensional and magnitude differences among indicators, making indicators with different units commensurable; the calculation of characteristic proportions is an inherent step of the entropy weight method, transforming the normalized values into a probability distribution form so as to measure the information content of each indicator using the information entropy formula. These two steps are in a progressive relationship.

Based on the standardized matrix $Y = (y_{ij})_{m \times n}$, the calculation steps are as follows:

First, calculate the characteristic proportion p_{ij} of the i -th evaluation object under the j -th indicator:

$$p_{ij} = y_{ij} / \sum_{i=1}^m y_{ij} \quad (5)$$

Next, calculate the entropy value e_j of the j -th indicator:

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln(p_{ij}) \quad (6)$$

where when $p_{ij} = 0$, it is stipulated that $p_{ij} \ln(p_{ij}) = 0$.

Then, calculate the coefficient of divergence g_j for the j -th indicator:

$$g_j = 1 - e_j \quad (7)$$

Finally, the coefficient of divergence is normalized to obtain the objective weight w_j^o based on the entropy weight method:

$$w_j^o = g_j / \sum_{j=1}^n g_j \quad (8)$$

The objective weight vector is denoted as $W^o = (w_1^o, w_2^o, \dots, w_n^o)^T$.

2.2.4. Determination of the Combined Weights

A purely subjective weighting method is susceptible to the influence of experts' knowledge structures and personal preferences, while a purely objective weighting method may overlook the strategic importance of indicators. To simultaneously account for both decision-makers' experiential judgments and the objective patterns revealed by the data, this study employs the multiplicative synthesis method to calculate the combined weights [23]:

$$w_j^c = \frac{w_j^s \cdot w_j^o}{\sum_{j=1}^n (w_j^s \cdot w_j^o)} \quad (9)$$

where w_j^s denotes the subjective weight derived from the AHP method, w_j^o denotes the objective weight derived from the entropy weight method, and w_j^c denotes the combined weight. This approach enables the two types of weights to correct each other: when either weight is zero, the combined weight is also zero, which aligns with decision-making logic; and when both the subjective and objective weights are high, the combined weight is reinforced. The combined weight vector ultimately used for the TOPSIS evaluation is expressed as $W^c = (w_1^c, w_2^c, \dots, w_n^c)^T$.

The combined AHP–entropy weight–TOPSIS method has already seen preliminary applications in the field of supply chain resilience evaluation. The methodological advancements of this study are as follows: first, in the weighting process, the basis for calculating objective weights is differentiated according to the two scenarios of temporal analysis and horizontal comparison, thereby avoiding a mismatch between the weights and the evaluation context; second, the TOPSIS comprehensive evaluation is progressively integrated with the obstacle degree diagnosis model and fuzzy-set qualitative comparative analysis (fsQCA), thus filling the gap left by the majority of existing studies that remain confined to a single evaluation level.

2.2.5. TOPSIS Evaluation Model

The TOPSIS method, proposed by Hwang and Yoon [20], ranks evaluation objects by calculating their relative closeness to the ideal solution. Its core idea is that the optimal alternative should be closest to the positive ideal solution and farthest from the negative ideal solution.

First, the standardized matrix $Y = (y_{ij})_{m \times n}$ is weighted using the combined weights w_j^c to construct the weighted normalized decision matrix $V = (v_{ij})_{m \times n}$:

$$V_{ij} = w_j^c \cdot y_{ij} \quad (10)$$

Next, determine the positive ideal solution V^+ and the negative ideal solution V^- :

$$V^+ = (v_1^+, v_2^+, \dots, v_n^+) = (\max v_{i1}, \max v_{i2}, \dots, \max v_{in}) \quad (11)$$

$$V^- = (v_1^-, v_2^-, \dots, v_n^-) = (\min v_{i1}, \min v_{i2}, \dots, \min v_{in}) \quad (12)$$

Then, calculate the Euclidean distances D_i^+ and D_i^- from each evaluation object i to the positive and negative ideal solutions, respectively:

$$D_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^+)^2} \quad (13)$$

$$D_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - v_j^-)^2} \quad (14)$$

Finally, calculate the relative closeness C_i of each evaluation object:

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (15)$$

The value of C_i ranges from 0 to 1. A larger C_i value indicates that the resilience level of the evaluation object is closer to the positive ideal solution, i.e., the resilience is better; conversely, a smaller value indicates proximity to the negative ideal solution. Based on the magnitude of C_i , all evaluation objects can be ranked according to their resilience levels.

2.2.6. Obstacle Degree Diagnosis Model

After the overall resilience evaluation is completed using the TOPSIS model, an obstacle degree diagnosis model [24] is introduced to further identify the specific factors constraining resilience improvement. This model quantitatively identifies key bottleneck factors by calculating the degree to which each indicator hinders the resilience target.

The calculation of the obstacle degree is based on three elements: factor contribution (i.e., the combined weight w_j^c of indicator j , indicator deviation (i.e., the gap between the standardized value y_{ij} of indicator j and the optimal value of 1), and the obstacle degree O_{ij} . The formula for calculating the obstacle degree of the j -th indicator for the i -th evaluation object is as follows:

$$O_{ij} = \frac{(1-y_{ij}) \cdot w_j^c}{\sum_{j=1}^n [(1-y_{ij}) \cdot w_j^c]} \times 100\% \quad (16)$$

Here, $(1-y_{ij})$ represents the indicator deviation; the smaller y_{ij} is (i.e., the worse the performance), the larger the deviation and the higher the likelihood that it becomes an obstacle. w_j^c represents the factor contribution; the greater the weight of an indicator, the larger its impact on the overall target. By calculating the obstacle degree O_{ij} for each indicator and ranking them by value, the key obstacle factors affecting Hubei's supply chain resilience level can be precisely identified, providing a direct and quantitative basis for subsequently formulating targeted improvement strategies.

3. Empirical Results and Analysis

3.1. Data Sources and Sample Determination

The evaluation object is the international supply chain of Hubei Province's new energy vehicle industry. To reveal the evolutionary patterns of its resilience and establish its positioning through horizontal comparison, the empirical analysis encompasses two levels: first, a temporal analysis from 2018 to 2025 is conducted with Hubei Province as the sole object to observe the longitudinal development trend of its resilience level; second, using the year 2025 as a cross-section, Hubei Province, Shanghai Municipality, and Guangdong Province are selected for horizontal comparative analysis.

3.1.1. Data Sources

The data for the indicator system constructed in this study were primarily sourced from the following four types of channels:

Macro statistics and industry reports: Macro-level data such as industrial scale, R&D investment, number of enterprises, and number of patents were mainly obtained from the China Automotive Industry Yearbook, the Hubei Statistical Yearbook, the China Statistics Yearbook on High Technology Industry, the annual reports issued by the China Association of Automobile Manufacturers (CAAM), and the statistical communiqués on national economic and social development of Hubei Province, Shanghai Municipality, and Guangdong Province.

Enterprise public information: Targeting specific operational indicators of the supply chain, such as supply chain concentration, inventory turnover days, and order fulfillment cycle, this study primarily sourced data from the annual reports, corporate social

responsibility reports, sustainability reports, and publicly available prospectuses of representative new energy vehicle complete vehicle manufacturers in Hubei Province, Shanghai Municipality, and Guangdong Province (e.g., Dongfeng Motor Group, SAIC Motor, and GAC Group), as well as their disclosed core suppliers (e.g., CATL and Inovance Technology). These data were obtained through text analysis and data extraction.

Professional databases and market research: For data on logistics network stability, external dependence on key raw materials, and international supplier distribution, this study supplemented these data by consulting industry analysis reports and market research data from professional institutions such as the Wind database, CEIC database, IHS Markit, and BloombergNEF (BNEF).

Expert consultation and questionnaire survey: For qualitative indicators that are difficult to obtain directly from publicly available sources, such as the “supply chain information sharing level,” this study designed a structured questionnaire and invited 15 experts in the field of supply chain management from key new energy vehicle enterprises in Hubei Province, relevant industry associations, and university research institutions to provide ratings (using a 1–5 Likert scale). The average score was then taken as the annual data for each indicator. The approach of using Likert scale ratings and averaging them to assign values to qualitative indicators has been well established in the field of supply chain resilience evaluation. For instance, Li et al. [25] similarly adopted a 1–5 expert scoring and averaging method to handle subjective qualitative indicators in their research on agricultural supply chain resilience measurement. Although this method involves a certain degree of information compression regarding the dispersion of expert opinions, it offers the advantages of strong operability and comparable results in multi-indicator comprehensive evaluation.

3.1.2. Composition of Expert Samples

To ensure the authority and representativeness of the subjective weights obtained via the Analytic Hierarchy Process (AHP), this study invited 15 experts with profound theoretical attainments or extensive practical experience in the fields of supply chain management, new energy vehicle industry, and regional economics to participate in the questionnaire survey, in strict accordance with the expert selection principles of the Delphi Method. The composition of the expert panel covers academic, industrial, and policy perspectives, with their specific distribution presented in Table 4. All invited experts have an average professional or research tenure of more than 12 years, which guarantees the professionalism and stability of their expert judgments.

Table 4. Composition of the Expert Panel for the AHP Survey.

No.	Expert Category	Affiliation and Position	Research and Professional Field	Professional/Research Tenure
E1	University Academic	Professor, Economics and Management School, Wuhan University	Supply Chain Risk Management, Global Value Chains	>15 years
E2	University Academic	Professor, School of Management, Huazhong University of Science and Technology	Industrial Innovation, New Energy Vehicle (NEV) Supply Chain	>12 years
E3	University Academic	Associate Professor, School of Business Administration, Zhongnan University of Economics and Law	Logistics and Supply Chain Management	>10 years
E4	Research Institution Expert	Senior Engineer, China Automotive Technology and Research Center (CATARC)	Automotive Industry Policy, Supply Chain Security	>15 years

E5	Research Institution Expert	Research Fellow, Hubei Academy of Social Sciences	Regional Industrial Economy, Hubei Automotive Industry	>20 years
E6	Enterprise Senior Executive	Director of Supply Chain Management Department, DF Automobile Group Co., Ltd.	Vehicle Manufacturing Supply Chain Operation	>20 years
E7	Enterprise Senior Executive	Deputy General Manager, ND Times (Hubei) Co., Ltd.	Power Battery Supply Chain Management	>15 years
E8	Enterprise Senior Executive	General Manager, a New Energy Vehicle Electric Drive System Company	Core Component Manufacturing and Procurement	>12 years
E9	Enterprise Senior Executive	Operations Director, a Listed Auto Parts Company in Hubei Province	Auto Parts Production and Logistics	>18 years
E10	Enterprise Senior Executive	Chairman of the Board, a Smart Logistics Company in Wuhan	International Multimodal Transport, Supply Chain Solutions	>15 years
E11	Industry Association Expert	Secretary-General, Hubei Provincial Automobile Industry Association	Automotive Industry Planning, Enterprise Coordination	>25 years
E12	Industry Association Expert	Research Fellow, China EV100	NEV Industry Policy, Technology Trends	>10 years
E13	Government Think Tank Expert	Director of Development Research Center, Department of Economy and Information Technology of Hubei Province	Manufacturing Industry Planning, Industrial Policy Formulation	>20 years
E14	Government Think Tank Expert	Head of Port Affairs Division, Wuhan Municipal Bureau of Commerce	International Logistics Channels, Port Services	>15 years
E15	Third-Party Institution Expert	Automotive Industry Director, a World-Renowned International Consulting Firm	Automotive Industry Strategy, Supply Chain Consulting	>12 years

3.1.3. Data Processing and Sample Determination

After collecting the raw data, the presence of missing values was examined and addressed. Among the 18 indicators, five indicators had missing values, with the specific circumstances and treatment methods as follows: ① A22 (proportion of backup suppliers): data for some small and medium-sized enterprises in 2018–2019 were missing and were imputed using linear interpolation; ② A31 (average order fulfillment cycle): data for 2018 were missing and were filled using the three-year moving average method based on the 2019–2021 data; ③ A33 (average recovery time from logistics disruptions): for some years, only records of major disruption events were available, with a lack of statistics on small-scale disruptions, so the average recovery time of the recorded events was used to represent the level for that year. To test the impact of the missing data treatment on the conclusions, sensitivity test results after removing indicators containing estimated values are provided in the robustness check section. For horizontal comparison, data caliber consistency was ensured. For the comparison among Hubei, Shanghai, and Guangdong, the data for 2025 were uniformly adopted. Some indicators that may not be directly reflected in provincial-level statistics were counted and standardized by retrieving the number of major industry–university–research collaboration projects publicly reported in each province or municipality in 2025 that were led by leading new energy vehicle enterprises. Ultimately, two core datasets were formed: first, the Hubei Province 2018–2025 panel dataset for temporal analysis (8 years $\times$ 18 indicators); and second, the 2025 cross-sectional dataset for Hubei, Shanghai, and Guangdong for horizontal comparison (3 regions $\times$ 18 indicators). All data were standardized to eliminate dimensional effects and uniformly transformed into positive indicators before being incorporated into the model calculations.

The temporal analysis provides a weight reference benchmark for the horizontal comparison; the horizontal comparison establishes a reference frame for the obstacle degree diagnosis; and the obstacle degree diagnosis offers a basis for condition selection in the fsQCA. These three steps progressively deepen and mutually corroborate one another.

3.2. Combined Weight Calculation and Result Analysis

3.2.1. Subjective Weight (AHP) Calculation and Analysis

Fifteen experts from universities, research institutes, industry associations, and key enterprises in the fields of supply chain management and new energy vehicles were invited to conduct pairwise comparisons of indicators at each level based on the 1–9 scale method shown in Table 2. All returned questionnaires passed the consistency test ($CR < 0.10$). The judgment matrices from each expert were aggregated using the geometric mean method to obtain the comprehensive judgment matrix, from which the subjective weights of the indicators were subsequently calculated. For the aggregated judgment matrices and the consistency test results at each hierarchical level, the CR values are as follows: Criterion level, 0.004; Robustness, 0.000; Redundancy, 0.000; Agility, 0.000; and Innovation, 0.006. All values are below the acceptance threshold of 0.10, indicating good consistency of expert judgments. The CR values of the individual judgment matrices provided by the 15 experts ranged from 0.002 to 0.022, all of which passed the consistency test. The specific relevant tables can be found in Supplementary Materials Tables S1–S6.

The subjective weights calculated for the criterion layer are as follows: robustness (A1) 0.285, redundancy (A2) 0.250, agility (A3) 0.240, and innovativeness (A4) 0.225. This indicates that, based on the experiential judgment of the expert group, robustness is regarded as the most important cornerstone supporting supply chain resilience, with its weight significantly higher than those of the other dimensions. The experts widely believe that for Hubei's new energy vehicle industry, which is deeply integrated into the global division of labor, maintaining the stability and reliability of the basic supply chain structure and preventing risks of sourcing disruptions are the foremost tasks at the current stage. Redundancy and agility have similar weights, representing two complementary strategies for enhancing resilience—through *ex ante* reserves and *ex post* rapid response, respectively—and receive comparable emphasis. The weight of innovativeness is relatively lower, but this does not imply it is unimportant; rather, it reflects the experts' assessment that innovation is more of a long-term, fundamental driving force, with a longer period for unleashing its effectiveness, and its direct role in coping with short-term shocks is relatively weaker than that of the first three dimensions. It should be noted that a considerable proportion of the 15 experts came from local institutions in Hubei, which may lead the subjective weights to reflect, to some extent, the phased concerns of Hubei's industrial development. For instance, the higher weights assigned to “external dependence on key raw materials” and “supply chain concentration” may be related to the prominent reality of Hubei's current upstream resource weaknesses. To mitigate this potential bias, this study employs the entropy weight method to extract information from objective data for correction; synthesizing the AHP weights with the entropy weight method weights can partially offset the cognitive bias of a single expert group.

At the indicator layer, the top five indicators in terms of subjective weights are: external dependence on key raw materials (A12, 0.095), supply chain concentration (A11, 0.080), research and development investment intensity (A41, 0.075), average recovery time from logistics disruptions (A33, 0.070), and proportion of backup suppliers (A22, 0.065). This ranking reflects the experts' concerns about critical risks: “bottleneck” risks (A12, A11) and “slow recovery” risks (A33) are perceived as the most prominent threats, while increasing research and development investment (A41) and building supply backups (A22) are regarded as the core coping strategies.

3.2.2. Calculation and Analysis of Objective Weights (Entropy Weight Method)

The entropy weight method determines objective weights based on the amount of information carried by the data of each indicator. To ensure that the source of the weights matches the analytical context, this study calculates objective weights separately for different evaluation tasks: the objective weights for the temporal analysis (Hubei Province, 2018–2025) are calculated based on the standardized panel data of 8 years $\times$ 18 indicators for Hubei; the objective weights for the horizontal comparison (Hubei, Shanghai, and Guangdong in 2025) are calculated based on the standardized cross-sectional data of 3 regions $\times$ 18 indicators; and the objective weights for the fsQCA analysis are calculated based on the standardized cross-sectional data of 12 provinces $\times$ 18 indicators.

The objective weight results for the temporal analysis scenario are reported first below, while the objective weights for the horizontal comparison and fsQCA scenarios are respectively presented in the corresponding sections.

Based on the standardized panel data of Hubei Province from 2018 to 2025, the entropy value e_j , difference coefficient g_j , and objective weights W_o of each indicator were calculated according to Equations (5)–(8). The objective weights at the criterion level are as follows: Innovation (A4) has the highest weight of 0.320, followed by Agility (A3, 0.270); Robustness (A1) and Redundancy (A2) have relatively lower weights of 0.210 and 0.200, respectively. The data reveal that, during the period 2018–2025, the indicators within the Innovation dimension (e.g., R&D investment, patent output, industry–university–research collaboration) and the Agility dimension (e.g., information sharing, logistics recovery) exhibited the greatest volatility and the most pronounced differentiation in Hubei Province. This indicates that efforts and investments in these aspects have fluctuated considerably in recent years, with significant year-to-year variations, thereby acquiring larger weights in the objective weighting process. In contrast, the indicators in the Robustness and Redundancy dimensions showed relatively stable changes and lower discriminatory power, resulting in smaller objective weights.

The top five indicators in terms of objective weight at the indicator level are: invention patents owned per 10,000 people (A42, 0.085), depth of industry–university–research collaboration (A43, 0.080), adoption rate of green processes (A46, 0.075), level of supply chain information sharing (A32, 0.070), and average recovery time from logistics disruptions (A33, 0.065). This highlights that, from the perspective of historical data variation, innovation output efficiency (A42), collaborative innovation activities (A43), and the green transition process (A46) are the primary factors driving the year-to-year evaluation differences in Hubei’s supply chain resilience.

3.2.3. Determination and Comprehensive Analysis of Combined Weights

To integrate expert experiential judgment with the regularities of historical data, the combined weights W_c ultimately used in the TOPSIS evaluation were calculated via a multiplicative synthesis method based on Equation (9). The combined weights effectively fuse subjective and objective information: they incorporate experts’ judgments on strategic priorities and critical risk points while also reflecting the informational value embedded in the actual evolution of indicator data. Table 5 presents the combined weight results obtained for the time-series analysis (i.e., the synthesis of the AHP weights and the entropy weights derived from Hubei’s time-series data).

Table 5. Computed weights of evaluation indicators for the resilience of Hubei's international supply chain for new energy vehicles (time-series analysis scenario).

Criterion Layer	Index Layer	Subjective Weight	Objective Weight	Combined Weight	Ranking
		Ws	Wo	Wc	
Robustness (A1) 0.198	Supply Chain Concentration (A11)	0.080	0.042	0.055	7
	External Dependence of Major Raw Materials (A12)	0.095	0.048	0.074	2
	Digitalization Level of Supply Chain (A13)	0.055	0.035	0.031	14
	Logistics Network Stability (A14)	0.055	0.043	0.038	12
Redundancy (A2) 0.202	Inventory Turnover Days of Key Components (A21)	0.060	0.032	0.031	14
	Proportion of Backup Suppliers (A22)	0.065	0.052	0.055	7
	Capacity Redundancy (A23)	0.060	0.058	0.057	6
	Financial Resource Support (A24)	0.065	0.055	0.059	5
Agility (A3) 0.236	Average Order Fulfillment Cycle (A31)	0.060	0.055	0.054	9
	Supply Chain Information Sharing Level (A32)	0.060	0.072	0.070	4
	Average Recovery Time from Logistics Disruption (A33)	0.070	0.068	0.077	1
	Supplier Geographic Diversification Index (A34)	0.050	0.043	0.035	13
Innovativeness (A4) 0.233	R&D Investment Intensity (A41)	0.075	0.062	0.076	3
	Number of Invention Patents per 10,000 People (A42)	0.055	0.078	0.070	4
	Depth of Industry-University-Research Cooperation (A43)	0.040	0.068	0.044	10
	Proportion of High-Tech Enterprises (A44)	0.030	0.048	0.024	17
	Proportion of New Product Sales Revenue (A45)	0.015	0.035	0.008	18
	Adoption Rate of Green Processes (A46)	0.010	0.065	0.011	16

Note: The criterion-level values represent the sum of the combined weights of the indicators within each dimension. The sum across the four dimensions is 0.869, not equal to 1, because the combined indicator weights Wc shown in the table were obtained by first synthesizing the subjective and objective weights using the multiplicative method per Equation (9) and then normalizing across all 18 indicators as a whole. The criterion-level values, in contrast, are simply the direct sum of the combined indicator weights within each dimension, without further secondary normalization across the four dimensions. This treatment does not affect the validity of the TOPSIS evaluation.

As shown in Table 5, in the time-series analysis scenario, the importance ranking of the four dimensions based on the combined weights is: Agility (0.236) > Innovation (0.233) > Redundancy (0.202) > Robustness (0.198). This indicates that to enhance the resilience of Hubei's international supply chain for new energy vehicles, it is necessary not only to solidify the foundation of robustness but also to attach great importance to the development of agile response capabilities. The fact that agility emerges as the most important dimension reflects the increasingly prominent strategic value of the dynamic capability for rapid recovery and adaptation in an uncertain international environment.

At the indicator level, the top five indicators ranked by combined weights are: average recovery time from logistics disruptions (A33, 0.077), research and development investment intensity (A41, 0.076), external dependence on key raw materials (A12, 0.074), supply chain information sharing level (A32, 0.070), and number of invention patents per 10,000 people (A42, 0.070). This clearly reveals that the rapid recovery capability from logistics disruptions and sustained innovation investment are the most critical resilience constituents at the current stage, while upstream resource security constitutes another core strategic pivot determining the resilience level.

3.3. Resilience Level Measurement and Evaluation

3.3.1. Time-Series Evolution Analysis

The standardized data of the 18 indicators for the eight evaluation objects (years) of Hubei Province from 2018 to 2025, together with the combined indicator weights shown in Table 5, were incorporated into the constructed TOPSIS model. Following Formulas (10) through (15), the weighted normalized decision matrix, the positive and negative ideal solutions, and the Euclidean distances D_i^+ and D_i^- from each year to the positive and negative ideal solutions were calculated in sequence, finally yielding the closeness coefficient C_i that reflects the relative level of supply chain resilience for each year. The calculation results are presented in Table 6. The change trend of the closeness coefficient of the international supply chain resilience for new energy vehicles is shown in Figure 1.

Table 6. Closeness Coefficient (C_i) and Ranking of International Supply Chain Resilience for New Energy Vehicles in Hubei Province.

Evaluation Object (Year)	Distance to Positive Ideal Solution D_i^+	Distance to Negative Ideal Solution D_i^-	Closeness Coefficient C_i	Annual Ranking
2018	0.0485	0.0208	0.3002	8
2019	0.0452	0.0245	0.3515	7
2020	0.0401	0.0312	0.4377	6
2021	0.0338	0.0398	0.5408	5
2022	0.0275	0.0485	0.6382	4
2023	0.0221	0.0552	0.7143	3
2024	0.0185	0.0608	0.7667	2
2025	0.0148	0.0665	0.8181	1

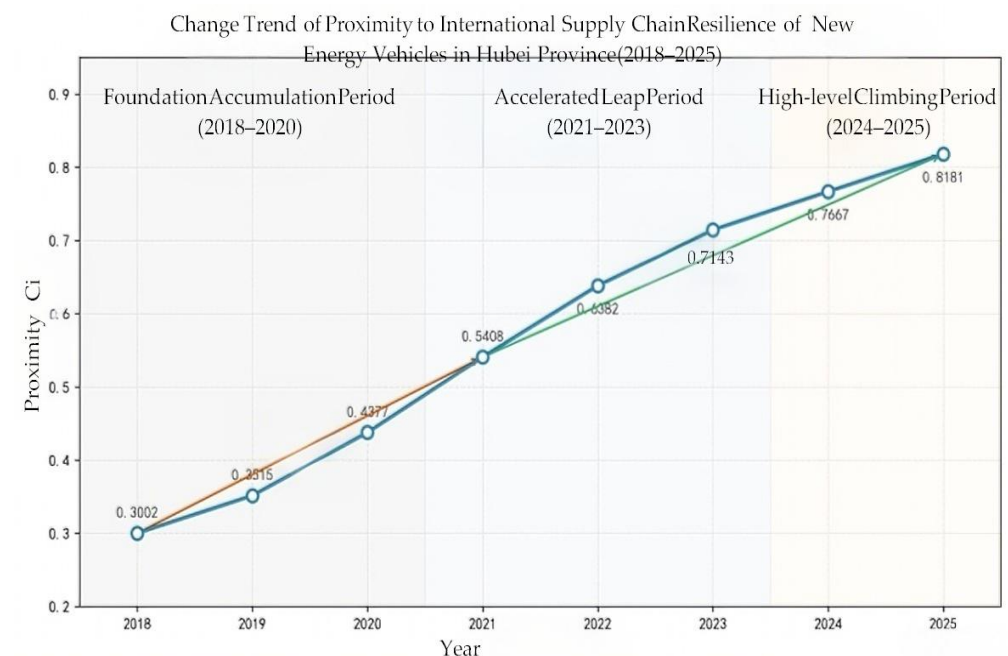


Figure 1. Trend of the closeness coefficient of the international supply chain resilience of Hubei's new energy vehicle industry (2018–2025).

(1) Overall Trend

As shown in Table 6, from 2018 to 2025, the closeness coefficient C_i of the international supply chain resilience of Hubei's new energy vehicle industry increased continuously from 0.3002 to 0.8181, exhibiting an overall steady upward trend. The

growth of the C_i value was not linear, with a significantly greater magnitude of improvement after 2021 than in the earlier period. Specifically, from 2018 to 2021, the average annual growth rate of C_i was approximately 21.7%; whereas from 2021 to 2025, the average annual growth rate remained at a high-level plateau of around 10.9%, indicating strong and sustained growth momentum. This reflects that, after global supply chains were hit by shocks such as the pandemic, the industry and government in Hubei increased investment in supply chain security and resilience building, and the relevant measures have continuously released their effectiveness over the medium to long term.

The Min–Max normalization method depends on the extreme values within the evaluation objects. When the indicators show an overall improving trend over the years, the standardized values for earlier years will be compressed into a lower range, which may, to some extent, amplify the magnitude of progress in later periods. However, all indicators in this study were selected through theoretical deliberation, and their improvement itself reflects the genuine effectiveness of resilience-building efforts. Taking 2020 and 2022 as examples: in 2020, affected by the COVID-19 pandemic, logistics network stability (A14) and average order fulfillment cycle (A31) deteriorated temporarily, and the growth rate of the closeness coefficient slowed correspondingly that year C_i only increased from 0.3515 to 0.4377), which is consistent with the direction of external shocks. In 2022, impacted by the surge in lithium prices, the indicator of external dependence on key raw materials (A12) came under pressure, but improvements in the innovativeness dimension partially offset this impact, allowing C_i to continue rising, albeit with a moderated increase (from 0.5408 to 0.6382). This “shock-response” pattern indicates that the upward trend of the closeness coefficient is not merely a methodological artifact but rather a comprehensive reflection of the interplay between resilience-building inputs and external shocks. To minimize the influence of the standardization method as much as possible, a cross-validation of the conclusions was subsequently conducted by substituting the evaluation model (Grey Relational Analysis).

(2) Stage Characteristics

Based on the changes in the C_i value, the period from 2018 to 2025 can be broadly divided into three developmental stages:

Stage 1: Foundation accumulation period (2018–2020). During this stage, the C_i value increased from 0.3002 to 0.4377, exhibiting steady growth. The improvement in supply chain resilience primarily stemmed from the scale effects brought about by industrial expansion, initial explorations into localizing the supply of key components, and the gradual popularization of digital management.

Stage 2: Accelerated leap period (2021–2023). During this stage, the C_i value rose rapidly from 0.4377 to 0.7143. In the aftermath of 2020, the risk of global supply chain disruptions intensified, and “supply chain self-reliance and controllability” was elevated to a strategic priority. Hubei responded proactively, making simultaneous efforts across multiple dimensions, including innovation-driven development, agility enhancement, and redundancy backup.

Stage 3: High-level climbing period (2024–2025). The C_i value increased from 0.7143 to 0.8181, entering the high-resilience zone above 0.8. This indicates that the international supply chain resilience of Hubei’s new energy vehicle industry has entered a “high-resilience” phase, with the systematic investments made in the earlier period beginning to generate cumulative effects and network synergies. Although the growth rate has somewhat decelerated, the absolute increase in the resilience level remains significant, and the overall supply chain has now acquired strong capabilities in disturbance resistance and recovery.

In terms of dimensional contributions, during the foundation accumulation period, the robustness and redundancy dimensions provided the main growth momentum;

during the accelerated leap period, the contribution rates of the innovativeness and agility dimensions increased significantly; and in the high-level climbing period, all dimensions exerted force in a balanced manner. In particular, the improvement in the depth of industry–university–research collaboration and the sales revenue share of new products indicates that innovation transformation capability is becoming a new engine for the continuous enhancement of resilience.

3.3.2. Horizontal Comparative Analysis

To position the international supply chain resilience of Hubei’s new energy vehicle industry within the domestic industrial landscape and reveal its relative strengths and weaknesses, Shanghai Municipality (representing the core area of the Yangtze River Delta) and Guangdong Province (representing the core area of the Pearl River Delta) were selected as comparison objects. These two regions serve as dual highlands of technology, capital, and market for China’s new energy vehicle industry, possess leading supply chain development levels, and thus constitute ideal benchmarks. Using the same indicator system, weights, and TOPSIS model, the overall resilience closeness coefficient C_i and the sub-dimensional (criterion layer) closeness coefficients of the three regions in 2025 were calculated. The results are shown in Tables 7 and 8.

Table 7. Comparison of Closeness Coefficients for International Supply Chain Resilience of New Energy Vehicles in Hubei, Shanghai and Guangdong (2025).

Evaluation Object (Region)	Distance to Positive Ideal Solution D_i^+	Distance to Negative Ideal Solution D_i^-	Closeness Coefficient C_i	Ranking
Shanghai Municipality	0.0128	0.0688	0.8432	1
Guangdong Province	0.0152	0.0652	0.8181	2
Hubei Province	0.0148	0.0665	0.8180	3

(1) Overall Level

Based on the calculation results presented in Table 7, the closeness coefficients of the international supply chain resilience for new energy vehicles in the three regions in 2025 rank as follows: Shanghai (0.8432) > Guangdong (0.8181) > Hubei (0.8180). Hubei trails Guangdong by a marginal gap of merely 0.0001, placing both within the same top tier. Moreover, the gap with the top-ranked Shanghai has narrowed significantly. This indicates that Hubei’s full-industry-chain deployment in the new energy and intelligent connected vehicle sectors over recent years, along with its strategic investments in supply chain security, is being translated into quantifiable resilience advantages, signaling a transition from the “catching-up” stage to the “keeping pace” stage.

(2) Structural Differences

The disparity in the overall closeness coefficient arises from the unbalanced development of capabilities across various dimensions. To thoroughly analyze the resilience structure, this study further calculated the sub-dimensional closeness coefficients of the three regions across the four criterion-layer dimensions, as presented in Table 8. These data reveal the performance differences among the two provinces and one municipality on different capability dimensions. The radar comparison chart of the four dimensions of supply chain resilience is shown in Figure 2.

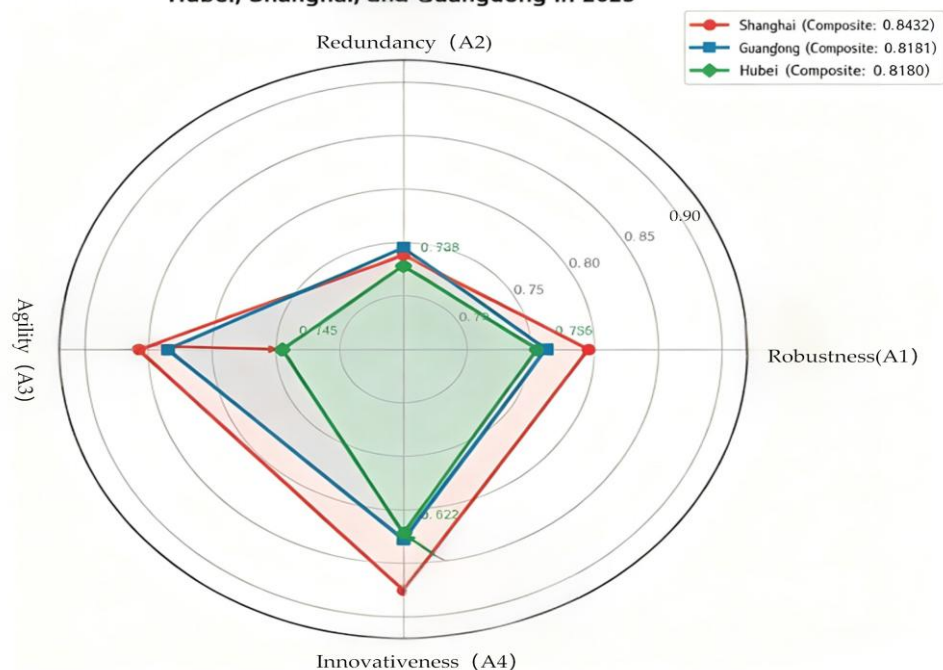
Table 8. Comparison of Closeness Coefficients in Each Dimension of Supply Chain Resilience Among Hubei, Shanghai and Guangdong (2025).

Region	Robustness (A1)	Redundancy (A2)	Agility (A3)	Innovativeness (A4)
Shanghai Municipality	0.795	0.738	0.858	0.875
Guangdong Province	0.762	0.745	0.835	0.828
Hubei Province	0.755	0.728	0.745	0.822

In terms of robustness, Hubei (0.755) is at a level similar to Guangdong (0.762) and slightly lower than Shanghai (0.795). Hubei performs well in “supply chain digitalization level” and “logistics network stability,” benefiting from its status as a national transportation hub. However, “external dependence on key raw materials” and “supply chain concentration” remain relative weak points, with its reliance on overseas critical minerals still significantly higher than that of Shanghai and Guangdong.

In terms of redundancy, Hubei (0.728) exhibits the smallest gap with Shanghai (0.738) and Guangdong (0.745). This is attributable to Hubei’s substantial investment in financial resource support and capacity deployment. Nevertheless, Hubei’s management of the “proportion of backup suppliers” remains relatively rudimentary, and the number of locally based enterprises with international competitiveness within the alternative supplier system is insufficient.

In terms of agility, Hubei (0.745) remains its greatest weakness, significantly lower than Shanghai (0.858) and Guangdong (0.835). Although Hubei’s own performance has improved considerably, the two indicators—“supply chain information sharing level” and “average recovery time from logistics disruptions”—remain bottlenecks constraining its agility improvement. Shanghai, leveraging its highly digitized port clearance system, and Guangdong, relying on its flexible market-driven logistics and coordination mechanisms, possess distinct advantages in rapid recovery.

Four-Dimensional Comparison of Supply Chain Resilience among Hubei, Shanghai, and Guangdong in 2025**Figure 2.** Radar chart of the four dimensions of supply chain resilience for Hubei, Shanghai, and Guangdong in 2025.

In terms of innovativeness, Hubei (0.822) performs prominently, already approaching Shanghai (0.875) and surpassing Guangdong (0.828). Hubei possesses abundant resources from universities and research institutes, maintaining a lead in “research and development investment intensity” and “number of invention patents per 10,000 people.” Moreover, “depth of industry–university–research collaboration” and “sales revenue share of new products” have improved markedly in recent years, indicating that the channel for transforming innovation outcomes into market applications is becoming increasingly unimpeded.

3.4. Diagnosis of Key Obstacle Factors

Based on the TOPSIS comprehensive evaluation, the obstacle degree model is introduced for in-depth diagnosis. According to Formula (16), the obstacle degrees of the 18 evaluation indicators for Hubei Province in 2025 are calculated. A larger value indicates a stronger hindering effect of that indicator on the supply chain resilience reaching the ideal state. The calculation results are ranked by obstacle degree, and the top ten key obstacle factors are identified, as shown in Table 9.

Table 9. Key Obstacle Factors for International Supply Chain Resilience of New Energy Vehicles in Hubei Province (2025).

Ranking	Obstacle Factor (Index Layer)	Obstacle Degree Oj (%)	Cumulative Obstacle Degree (%)
1	External Dependence of Major Raw Materials (A12)	11.82	11.82
2	Average Recovery Time from Logistics Disruption (A33)	10.55	22.37
3	Supply Chain Information Sharing Level (A32)	9.18	31.55
4	Number of Invention Patents per 10,000 People (A42)	8.32	39.87
5	Depth of Industry-University-Research Cooperation (A43)	7.45	47.32
6	Supply Chain Concentration (A11)	6.88	54.20
7	Adoption Rate of Green Processes (A46)	6.12	60.32
8	R&D Investment Intensity (A41)	5.87	66.19
9	Proportion of Backup Suppliers (A22)	5.23	71.42
10	Supplier Geographic Diversification Index (A34)	4.85	76.27

From the perspective of the dimensional distribution of obstacle factors, the top ten obstacle factors are widely spread across the four dimensions, yet they exhibit significant concentration. The agility dimension contains three key obstacle factors, with a total obstacle degree as high as 24.41%, making it the primary weak area hindering the improvement of Hubei’s supply chain resilience. According to the ranking in Table 8, “external dependence on key raw materials” is the most prominent single obstacle, reflecting the “resource security” risk at the upstream of Hubei’s new energy vehicle industrial chain. The high external dependence on critical strategic minerals such as lithium, cobalt, and nickel exposes the entire industry to the risks of geopolitical fluctuations and drastic price swings in international markets, representing the most vulnerable link in supply chain resilience. Following this are “average recovery time from logistics disruptions” and “supply chain information sharing level.” Both obstacles belong to the agility dimension and collectively point to deficiencies in “response speed” and “collaborative capacity” within Hubei’s supply chain. Slow logistics recovery reveals weaknesses in the emergency logistics system and the efficiency of multimodal transport connectivity; whereas a low level of information sharing reflects the existence of data barriers between upstream and downstream enterprises along the industrial chain and between government and industry, making it difficult to achieve rapid decision-making and coordinated action during a crisis. “Number of invention patents per 10,000 people”

and “green process adoption rate” are obstacles belonging to different segments of the innovativeness dimension, revealing Hubei’s dual shortcomings in innovation output and green transformation. The relatively insufficient efficiency of invention patent output indicates that the industrial orientation and practical effectiveness of R&D activities need to be strengthened; the low green process adoption rate suggests insufficient penetration of low-carbon technologies such as cleaner production and circular utilization in core manufacturing processes, thereby constraining the ability to enhance the sustainable competitiveness of the supply chain through green and high-end development.

The obstacle degree ranking presented above reveals the hindering extent of individual indicators; however, supply chain resilience is a quintessential complex system, where multiple obstacle factors may generate nonlinear interactive effects through linkage, coupling, and compensation mechanisms. To delve deeper into which conditional combinations of obstacle factors synergistically lead to a “low resilience” state, this study introduces the fuzzy-set qualitative comparative analysis (fsQCA) method for configuration analysis. The fsQCA method, proposed by Ragin [26], is a case-oriented analytical method based on set theory and Boolean algebra, which is particularly suited to uncovering multiple conjunctural causation. Unlike traditional regression analysis, which focuses on the net effect of individual variables, fsQCA can identify multiple condition configurations that lead to the same outcome (i.e., equifinality), making it especially appropriate for analyzing complex system problems such as supply chain resilience, where multiple obstacle factors interact in a coupled manner [27]. This study follows the standardized fsQCA analytical procedure proposed by Schneider and Wagemann [28], conducting data calibration, necessary condition analysis, and condition configuration analysis in sequence. In fsQCA, “fuzzy sets” refer to the calibration of cases’ membership degrees in each condition into continuous values within the interval [0, 1] based on fuzzy set theory. All antecedent conditions and outcome variables in this study are derived from the measured values of the 18 evaluation indicators or the exact closeness coefficients calculated via the TOPSIS model; the calibration step transforms these precise data into membership scores suitable for set-theoretic analysis, which is a standard operating procedure of the fsQCA method [26].

(1) Variable selection and data calibration

To meet the analytical requirements of fsQCA for medium-sized samples, this study expanded the sample from the three regions of Hubei, Shanghai, and Guangdong to 12 major provinces with a substantial scale in the new energy vehicle industry, including Zhejiang, Anhui, Jilin, Chongqing, and Guangxi, using 2025 cross-sectional data for analysis. The outcome variable is “low supply chain resilience,” measured by the TOPSIS closeness coefficient C_i , with provinces below the median calibrated as having low resilience. Based on the obstacle degree ranking and theoretical significance, six key obstacle factors were selected as causal conditions after respective positive transformations: low resource autonomy (negative transformation of A12), slow logistics recovery speed (A33), low information sharing level (A32), weak industry–university–research collaboration (A43), high supplier concentration (A11), and low geographical diversification (A34). All variables were calibrated into fuzzy-set membership scores ranging from 0 to 1 using the upper quartile, median, and lower quartile as the three anchor points. As shown in Table 10.

Table 10. Calibration anchor points for fsQCA conditional variables and outcome variables.

Variable Type	Variable Name	Full Membership (0.95)	Crossover Point (0.50)	Full Non-Membership (0.05)
Outcome variable	Low supply chain resilience	0.782	0.685	0.532
Condition 1	Low resource autonomy	0.785	0.652	0.438
Condition 2	Slow logistics recovery speed	0.742	0.618	0.415
Condition 3	Low information sharing level	0.725	0.595	0.402
Condition 4	Weak industry–university–research collaboration	0.698	0.572	0.385
Condition 5	High supplier concentration	0.712	0.588	0.395
Condition 6	Low geographical diversification	0.668	0.545	0.372

Note: The calibration employed the indirect calibration method. The upper quartile (75th percentile) of each variable was set as the anchor for full membership (calibration value 0.95), the median as the crossover point (calibration value 0.50), and the lower quartile (25th percentile) as the anchor for full non-membership (calibration value 0.05). The outcome variable “low supply chain resilience” was calibrated by reversely processing the TOPSIS closeness coefficient C_i .

(2) Analysis of necessary conditions for individual conditions

First, we test whether the six causal conditions and their negations (~) constitute necessary conditions for the “low resilience” outcome. As shown in Table 11, the consistency values of all conditions are below the threshold standard of 0.9, indicating that no single necessary condition leads to low resilience. This confirms that low supply chain resilience is not determined by any single shortcoming but rather results from the synergistic interaction of multiple obstacle factors, making configuration analysis necessary.

Table 11. Necessity test of individual conditions for “low supply chain resilience”.

Antecedent Conditions	Consistency	Coverage
Low level of independent resource allocation	0.782	0.815
Slow logistics recovery speed	0.745	0.798
Low level of information sharing	0.728	0.762
Weak industry–university–research collaboration	0.695	0.732
High supplier concentration degree	0.712	0.745
Low geographical diversification	0.665	0.718

(3) Analysis of conditional configurations

The fsQCA 4.0 software was employed to analyze the truth table, with the consistency threshold set at 0.80, the frequency threshold at 1, and the PRI consistency threshold at 0.70. Through standard analysis, the complex, parsimonious, and intermediate solutions were obtained. Following established research practice, the intermediate solution was primarily reported, complemented by the parsimonious solution to distinguish core conditions from peripheral conditions. As shown in Table 12, a total of three conditional configurations leading to “low supply chain resilience” were identified.

Table 12. Conditional configurations leading to low supply chain resilience.

Conditional Configuration	Path H1	Path H2	Path H3
Low level of independent resource allocation	●	●	○
Slow logistics recovery speed	●	○	●
Low level of information sharing	●	○	○
Weak industry–university–research collaboration	○	●	●
High supplier concentration	○	○	●

Low geographical diversification	●	●	●
Raw coverage	0.452	0.398	0.335
Unique coverage	0.128	0.085	0.062
Consistency	0.918	0.895	0.882
Overall coverage		0.568	
Overall consistency		0.875	

Note: ● indicates the presence of a core condition, ● indicates the presence of a peripheral condition, and a blank space indicates that the condition may be either present or absent.

As shown in Table 12, the three pathways have an overall coverage of 0.568 and an overall consistency of 0.875, indicating that these three configurations can explain approximately 57% of the cases of low supply chain resilience, with a relatively high explanatory power.

Pathway H1 (“Resource–Logistics–Information” triple lock-in type): With low resource autonomy, slow logistics recovery speed, and low information sharing level as the core conditions, this indicates that the coupling of these three obstacle factors constitutes the most prominent pathway leading to low resilience (raw coverage of 0.452). Typical representative cases of this pathway are central and western provinces such as Jilin and Guangxi, whose common characteristics include high dependence on imports for critical upstream resources, a single foreign trade corridor coupled with weak logistics emergency capabilities, and insufficient information coordination between upstream and downstream segments of the industrial chain. This combination makes it exceedingly easy for a single shock to be amplified into a systemic crisis under the superimposition of the three weaknesses.

Pathway H2 (“Resource–Innovation” Dual Weakness Type): With low resource autonomy and weak industry–university–research collaboration as the core conditions, supplemented by slow logistics recovery speed. This pathway illustrates that even if the information sharing level is acceptable, the supply chain will still fall into a low-resilience state if upstream resources are controlled by others and there is a simultaneous lack of capability for material substitution and technological breakthroughs through industry–university–research collaboration. This pathway is manifested in regions such as Anhui, where emerging industries are expanding rapidly but basic research and resource deployment have yet to catch up.

Pathway H3 (“Logistics–Supplier” Dual Concentration Risk Type): With slow logistics recovery speed and high supplier concentration as the core conditions, supplemented by low resource autonomy. This pathway reveals the risk compounding effect resulting from the dual concentration of logistics corridors and supplier structures. Once the primary logistics corridor is disrupted and the sources of supply cannot be quickly switched because the suppliers are too concentrated, the system will be paralyzed due to the lack of alternative pathways.

(4) Configuration positioning and obstacle resolution pathways for Hubei Province

By plugging Hubei Province’s 2025 data into the above configurations for comparison, it is found that Hubei’s current obstacle factor structure most closely approximates the characteristics of Pathway H2—namely, the “resource-innovation” dual weakness type has been alleviated but still harbors hidden concerns. Although industry–university–research collaboration (A43) in Hubei has improved, the depth of collaborative research in upstream supply chain areas such as materials science and battery recycling remains insufficient; while the resource autonomy level (A12) has risen, its external dependence is still considerably high. At the same time, Hubei’s logistics recovery speed, though better than that of most central and western provinces, still lags behind that of

Shanghai and Guangdong, and thus it also partially exhibits the peripheral characteristics of Pathway H1.

This configuration analysis provides key insights for subsequent policy design: enhancing Hubei's supply chain resilience should not rely on isolated, single-point strategies that merely address symptoms, but should instead adopt combined and targeted measures based on the configuration characteristics. First, in response to the characteristics of Pathway H2, the "Innovation-Integrated Chain" program should be vigorously implemented to overcome resource dependence through deep industry–university–research collaboration. Second, addressing the characteristics of Pathway H1, the "Digital-Connected Chain" initiative should be accelerated to shorten the shock transmission chain through information sharing and logistics resilience building. Third, in light of the potential risks of Pathway H3, the "Foundation-Strengthening and Chain-Securing" project should be deepened to promote supplier diversification and the construction of backup international corridors. The coordinated advancement of these three pathways constitutes a systematic solution for Hubei to progress toward a higher level of resilience.

3.5. Robustness Tests

To test the reliability of the aforementioned TOPSIS model evaluation results and to avoid the fundamental reversal of conclusions due to differences in the choice of weighting method, specification of the evaluation model, or sample structure, this study conducts the following four robustness checks. The results of these checks are summarized in Table 13.

(1) Robustness check by replacing the weighting method

Using only the AHP subjective weights and only the entropy weight method objective weights separately, the TOPSIS model was rerun to calculate the resilience closeness coefficient series for Hubei Province from 2018 to 2025. Spearman's rank correlation analysis was conducted between the ranking results under the two single-weight schemes and those under the combined weighting scheme. The rank correlation coefficient between the combined-weight ranking and the AHP-weight ranking was 0.952 ($p < 0.01$), and that between the combined-weight ranking and the entropy-weight ranking was 0.905 ($p < 0.01$), both being highly positively correlated and statistically significant. This indicates that although different weighting methods may cause some fluctuation in the absolute closeness coefficient values, the judgment on the relative superiority or inferiority of Hubei's supply chain resilience across the years remains highly consistent, and the core conclusions are not significantly affected by changes in the weighting method.

(2) Robustness check by replacing the comprehensive evaluation model

The TOPSIS model calculates closeness based on Euclidean distance, which may be sensitive to outliers and relies on the assumption of complete compensation between distances to the positive and negative ideal points. To verify the robustness of the evaluation conclusions against model selection, this study employs Grey Relational Analysis (GRA) as an alternative model to re-evaluate the data for Hubei Province from 2018 to 2025. GRA assesses superiority or inferiority by calculating the grey relational degree between the evaluation objects and the optimal reference sequence, imposes lower requirements on data distribution and sample size, and can effectively compensate for the potential limitations of TOPSIS. After calculating the grey relational degree rankings for each year, they were compared with the TOPSIS rankings. The Spearman rank correlation coefficient was 0.929 ($p < 0.01$), indicating a highly consistent evaluation ranking between the two models, with ranking differences not exceeding one position. This demonstrates

that the resilience evaluation conclusions of this study are not affected by the choice of a specific comprehensive evaluation model and exhibit good model robustness.

(3) Robustness check by replacing the research sample

Building upon the horizontal comparison, the scope of comparison was expanded from Shanghai and Guangdong to include four additional provinces representative of the new energy vehicle industry: Zhejiang, Anhui, Jilin, and Chongqing. Using the 2025 cross-sectional data, the resilience closeness coefficients of the seven provinces (municipalities) were calculated and ranked. The ranking results after sample expansion are as follows: Shanghai (1), Guangdong and Hubei tied (2), Zhejiang (4), Anhui (5), Chongqing (6), and Jilin (7). Compared with the original three-region comparison results, Hubei's relative leading position remains unchanged, and the conclusion regarding its gap with the benchmark region also remains consistent, thereby confirming the robustness of the horizontal comparison findings.

(4) Robustness check for dimensional heterogeneity

To test whether the resilience evaluation conclusions are biased by the dimensional weight structure, this study separately calculated the sub-dimensional resilience scores for each of the four criterion layers and ranked them. The results show that Shanghai maintains a leading position in all four dimensions, Guangdong leads Hubei in the redundancy and agility dimensions, while Hubei equals Guangdong in the innovativeness dimension and is gradually catching up in the robustness dimension. It is noteworthy that Hubei's ranking in the innovativeness dimension (2nd) is significantly better than its ranking in the agility dimension (4th). This structural difference corroborates the findings in Table 8 and also indicates that the overall ranking conclusion possesses a certain degree of tolerance to changes in the dimensional structure, rather than being driven by anomalies in any single dimension.

(5) Robustness check for weight perturbation

To test the sensitivity of the evaluation results to minor changes in the weights, a random perturbation of $\pm 10\%$ (uniform distribution) was applied to the combined weights of the 18 indicators. The TOPSIS model was re-run 1000 times, and the ranking distribution of Hubei Province in the three-region comparison was recorded. The results show that the probability of Hubei ranking third is 72.3%, the probability of Hubei tying for second with Guangdong is 25.8%, and the probability of ranking second alone is merely 1.9%. Hubei never fell out of the top three, with its ranking fluctuating between "second (tied)" and "third," indicating that the evaluation conclusions exhibit a high degree of robustness to weight perturbations.

(6) Robustness check by replacing the calculation basis of the entropy weights

To verify the applicability of the entropy weights calculated based on Hubei's time-series data in the horizontal comparison, the entropy weights were recalculated using the 2025 cross-sectional data of Hubei, Shanghai, and Guangdong. These recalculated weights were then combined with the original AHP weights to rerun the TOPSIS analysis. The ranking of the closeness coefficients for the three regions remained consistent under both entropy weight calculation bases (Shanghai > Guangdong > Hubei), and the difference in closeness coefficients between Hubei and Guangdong changed from 0.0001 to 0.0015, with the relative positions remaining unaltered. Spearman's rank correlation coefficient was 1.000 ($p < 0.01$), indicating that the choice of the entropy weight calculation basis does not affect the core conclusions of the horizontal comparison.

Table 13. Summary of robustness test results.

Test Type	Test Method	Correlation with Original Ranking	Consistency of Conclusions
Substitution of weighting method	AHP weights vs. combined weights	0.952 ***	Consistent
	Entropy method weights vs. combined weights	0.905 ***	Consistent
Substitution of evaluation model	Grey Relational Analysis vs. TOPSIS	0.929 ***	Consistent
Substitution of research sample	Expanded to 7-province comparison	—	Ranking position stable
Dimensional heterogeneity	Criterion-layer sub-dimensional test	—	Structural differences interpretable
Weight perturbation test	1000 random perturbations of $\pm 10\%$	—	Ranking probability stable
Substitution of entropy weight basis	Cross-sectional entropy weights (three regions) vs. Hubei time-series entropy weights	1.000 ***	Consistent

Note: *** indicates significance at the 1% level.

4. Conclusions and Policy Recommendations

4.1. Main Research Conclusions

This study constructed an indicator system encompassing four dimensions—robustness, redundancy, agility, and innovativeness—and employed the AHP-entropy weight method, the TOPSIS model, the obstacle degree model, and fuzzy-set qualitative comparative analysis (fsQCA) to measure, evaluate, and diagnose the international supply chain resilience of the new energy vehicle industry in Hubei Province. The conclusions are as follows:

First, the resilience level of Hubei’s international supply chain for new energy vehicles achieved significant and sustained growth from 2018 to 2025. The closeness coefficient rose steadily from 0.3002 in 2018 to 0.8181 in 2025, with an average annual increase of approximately 15.4%. This process can be divided into three stages: the foundation accumulation period (2018–2020), the accelerated leap period (2021–2023), and the high-level ascent period (2024–2025). Within this framework, a closeness coefficient of 0.8181 indicates that the comprehensive resilience level of Hubei’s supply chain has reached 81.81% of the optimal ideal state. This suggests that, driven by the restructuring of global supply chains and strong domestic policy impetus, Hubei’s resilience building has shifted from early-stage passive adaptation and foundation-laying to systematic proactive construction and has achieved phased results.

Second, Hubei has transitioned from the “catch-up” phase to the “keeping pace” phase, though a structural gap with the benchmark city remains. A comparison among the three regions in 2025 shows that Hubei’s resilience closeness coefficient (0.8180) is nearly on par with that of Guangdong (0.8181), both situated in the first tier, while the gap with Shanghai (0.8432) has narrowed to 0.025. In terms of individual dimensions, Hubei exhibits outstanding performance in innovativeness (0.822), approaching Shanghai’s level (0.875). The agility dimension remains the primary weakness (0.745), with a notable gap compared with Shanghai (0.858) and Guangdong (0.835), largely constrained by slow post-disruption logistics recovery and insufficient supply chain information sharing. The robustness dimension (0.755) ranks at an intermediate level, and the high external dependence on upstream critical mineral resources constitutes a structural challenge that limits its further improvement.

Third, the obstacle factors are concentrated and exhibit multiple coupling effects, and the key to enhancing resilience has shifted from isolated breakthroughs to systemic synergy. The obstacle degree model identified the top ten obstacle factors, with a cumulative obstacle degree of 76.27%, among which “external dependence on major raw

materials" (obstacle degree: 11.82%), "average recovery time from logistics disruptions" (10.55%), and "supply chain information sharing level" (9.18%) ranked as the top three, confirming that the agility dimension and the upstream segment of the robustness dimension are currently the two weakest links. The fsQCA configuration analysis further revealed that obstacle factors do not act in isolation but rather form three typical pathways leading to low resilience through coupling mechanisms: the "resource-logistics-information" triple lock-in type (H1), the "resource-innovation" dual weakness type (H2), and the "logistics-supplier" dual concentration risk type (H3). Hubei's current obstacle factor structure exhibits marginal characteristics of both H1 and H2, with "insufficient resource autonomy" and "slow logistics recovery speed" emerging as recurrent core conditions. This reveals a deep-seated contradiction in the current development: high external dependence on upstream critical minerals is a fundamental risk, while the insufficient responsiveness in logistics and information collaboration amplifies the shock transmission effect. The superposition of these two factors constitutes the primary obstacle to resilience improvement. The key to enhancing resilience has thus shifted from merely increasing buffer resources to breaking structural lock-in through the systemic coupling of innovation breakthroughs and digital collaboration.

4.2. Managerial Implications and Policy Recommendations

Based on the above conclusions, the following three policy recommendations are proposed to enhance the international supply chain resilience of Hubei's new energy vehicle industry.

First, focusing on upstream resource security and supplier structure, implement the "Strengthening Foundation and Securing Chains" project to solidify the foundation of robustness. The government should take the lead in establishing a provincial-level critical materials assurance alliance, supporting leading enterprises in globally deploying mineral resources such as lithium, cobalt, and nickel through strategic investments and long-term agreement cooperation. Simultaneously, a comprehensive battery recycling and reutilization system covering the entire industrial chain should be vigorously constructed to fundamentally reduce external dependence. In parallel, a local supplier cultivation program should be implemented, utilizing the "chain leader system" to promote technical collaboration and preferential procurement between vehicle manufacturers and local component enterprises. Particularly in highly sensitive areas such as chips and power devices, the cultivation of a group of specialized, refined, distinctive, and innovative enterprises should be accelerated to form a diversified and redundant supply system, thereby systematically reducing supply chain concentration risks.

Second, to address the problems of slow response and poor coordination, a "Digital Chain Connectivity" initiative is proposed to comprehensively enhance agility. The key lies in integrating information flows and optimizing logistics. This requires government guidance, along with the joint participation of leading enterprises and platform companies, to accelerate the construction of a provincial-level supply chain collaboration cloud platform covering the entire chain of R&D, production, logistics, and sales. Mandating standardized access and sharing of key data will break down information silos, enabling real-time risk perception and collaborative decision-making. Meanwhile, the international multimodal transport network centered on Wuhan should be optimized, and the efficient connection between the China–Europe Railway Express, river–sea intermodal transport, and air cargo should be strengthened. Detailed supply chain disruption contingency plans should also be formulated, and regular drills conducted, so that digitalization and contingency planning can substantially compress disruption detection and recovery times.

Third, addressing the bottleneck of insufficient innovation outcome transformation, deepen the “Innovation-Integrated Chain” program to activate endogenous driving forces. The fundamental solution lies in transforming the advantages of scientific and educational resources into industrial competitive strengths. The existing industry–university–research collaboration model should be reformed, and an industry-demand-oriented “Auto Valley Supply Chain Innovation Special Project” should be established. A mechanism of “enterprises setting the questions, academia providing the answers, and the market verifying the results” should be implemented, targeting weak links in the supply chain—such as materials, processes, and software—for joint R&D. The policy loop for innovation incentives should be strengthened by increasing transformation subsidies and certification premiums for green processes and low-carbon technologies. Furthermore, a risk compensation fund should be established for the application of first-article and first-set products to incentivize vehicle manufacturers within the province to prioritize the procurement of locally developed high-end innovative products, thereby driving the upgrade of the supply chain toward an innovation chain characterized by high added value and high controllability.

4.3. Research Limitations and Future Prospects

This study is subject to the following limitations. Regarding data, some indicators rely on subjective expert scoring, and for indicator A12 (external dependence on major raw materials), trend extrapolation was applied to estimate values for certain years. Future research could incorporate objective data sources, such as disaggregated customs trade data and data exported from enterprise ERP systems, and extend the time window to cover the middle of the 15th Five-Year Plan period. For the qualitative indicator A32, the mean of expert scores was adopted as the indicator value, which fails to adequately reflect the dispersion of expert opinions; future studies could introduce two-tuple linguistic models or fuzzy evaluation methods to process such qualitative information. In terms of the sample, the fsQCA analysis included only 12 provinces, constituting a medium-to-small-N configuration design, with certain configurations supported by only a single case. Moreover, the cross-sectional comparison did not encompass all representative cities within major new energy vehicle industry clusters, such as the Chengdu–Chongqing region. Subsequent research could expand the analysis to panel data from more provinces or adopt multi-period fsQCA (temporal QCA, TQCA) to enhance the spatiotemporal robustness of causal inferences. At the methodological level, the subjective weights derived from the AHP remain influenced by expert cognitive biases, and the fully compensatory assumption of the TOPSIS model may obscure early warning signals when certain indicators undergo extreme deterioration. Future work could introduce the Analytic Network Process (ANP) to handle feedback relationships among indicators or adopt non-fully compensatory multi-criteria decision-making methods such as VIKOR for cross-validation.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/wevj17070365/s1>. Table S1: Judgment matrix and weights of the criterion layer; Table S2: Judgment matrix and weights of the Robustness (A1) indicator layer; Table S3: Judgment matrix and weights of the Redundancy (A2) indicator layer; Table S4: Judgment matrix and weights of the Agility (A3) indicator layer; Table S5: Judgment matrix and weights of the Innovativeness (A4) indicator layer; Table S6. Distribution of CR values for each expert’s judgment matrix.

Author Contributions: Conceptualization, Y.W.; Methodology, Y.W. and C.Y.; Software, Y.W.; Validation, C.Y.; Formal analysis, C.Y.; Investigation, C.Y.; Resources, Y.W.; Data curation, Y.W.; Writing—original draft, C.Y. and Y.W.; Writing—review and editing, C.Y.; Visualization, C.Y. and

Y.W.; Supervision, C.Y. and Y.W.; Project administration, Y.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Soft Science Research Program of Hubei Provincial Science and Technology Plan (Grant No. 2025EDA103; Project Title: Research on Optimization Strategies of Industrial Green Innovation Ecosystem in Hubei Province: A Case Study of the Automotive Industry; This work was supported by the Funding Project of “Key Project of Scientific Research Program of Hubei Education Department, China” (No. Q20231810).and Doctoral Scientific Research Foundation of Hubei University of Automotive Technology (No. BK202447).

Institutional Review Board Statement: This study was conducted using publicly available data and expert consultations with informed consent, and it did not involve human subjects, human biological samples, or personal data collection. According to the "Ethical Review Measures for Biomedical Research Involving Humans" of the People's Republic of China, the Ethics Committee of Hubei University of Automotive Technology has waived its ethical review and approval of this study.

Informed Consent Statement: Informed consent for participation was obtained from all subjects involved in the study.

Data Availability Statement: The datasets presented in this article are not readily available because the included data for this study were collected from multiple websites and are subject to relevant user agreements. Requests to access the datasets should be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

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