sustainability

MDPI

Article

Electric Vehicle Supply Chain Risk Assessment Based on Combined Weights and an Improved Matter-Element Extension Model: The Chinese Case

Huixin Liu and Xiang Hao *

School of Marxism, Qingdao University of Technology, Qingdao 266520, China; liuhx626@126.com
* Correspondence: hx202307@163.com

Abstract: In order to meet energy and environmental challenges, many countries will implement the replacement of fuel vehicles for the future clean energy transition; so, the number of electric vehicles (EVs) operating in cities will grow significantly. It is crucial to assess the risks of the electric vehicle supply chain (EVSC) and prevent them. Based on this, this paper proposes an EVSC risk research framework with combined weights and an improved matter-element extension model: (i) Firstly, the EVSC evaluation index system is constructed from the six stages of supply chain planning, sales, procurement, manufacturing, distribution, after-sales, and external risks. (ii) The subjective and objective weights are calculated by the decision laboratory method and entropy weight method, respectively, and then the minimum deviation method is used for a combined design to overcome the defects of a single method. (iii) An improved matter-element extension model (MEEM) is constructed by introducing asymmetric proximity degree and risk bias. (iv) The model is applied to a case study and its feasibility and superiority are verified through sensitivity analysis and comparative analysis. The final results show that the method and framework proposed in this paper are in line with EVSC risk assessment standards and superior to other models, which can help EVSC managers to identify potential risks, formulate appropriate risk prevention measures, promote the stable development of electric vehicles, and provide a reference for the development of energy and environment.

Keywords: electric vehicle; supply chain; combination weight; improved matter-element extension model; risk assessment; risk prediction

Citation: Liu, H.; Hao, X. Electric Vehicle Supply Chain Risk Assessment Based on Combined Weights and an Improved Matter-Element Extension Model: The Chinese Case. *Sustainability* **2024**, *16*, 4249. https://doi.org/10.3390/su16104249

Academic Editor: Pablo García Triviño

Received: 19 April 2024
Revised: 15 May 2024
Accepted: 16 May 2024
Published: 17 May 2024

1. Introduction

The increasingly serious environmental pollution and energy crisis have become the top issues to be addressed in the world today, and this crisis is prompting countries around the world to make clean energy transition a core issue [1]. According to the International Energy Agency (IEA) CO_2 Emissions Report 2023 released in March 2024, the carbon emissions of the transportation industry increased by 240 million tons in 2023 compared to 2022. Under this circumstance, the development of sustainable transport has become the top priority in the energy transition [2]. Electric vehicles (EVs) have become a research hotspot because of their energy-saving and green characteristics. In 2021, the U.S. House of Representatives enacted the Electric Vehicle Freedom Act to promote the development of the EV industry in the next five years, and the Netherlands, the United Kingdom, and France have also introduced relevant policies to promote the construction of EVs [3]. In the European electric vehicle market, in order to stimulate EV consumption in Germany, the subsidy price is up to EUR 9000 per unit [4]. The explosive growth in the number of EVs in China in recent years has further promoted the development of this industry. Therefore, how to maintain a stable and healthy development of the EV industry and how to predict risks in time to reduce losses have become the focus of the research in this field.

An effective supply chain management can enable enterprises in the supply chain to obtain and maintain stable and lasting competitive advantages, thus improving the stability of industry development. It is therefore critical to assess the overall risk in EVscs and to prevent it. The matter-element extension model (MEEM) includes matter-element analysis and extension theory [5,6]. Matter-element analysis can describe the object to be evaluated in the form of ordered triples with three elements: things, features, and magnitude [7]. Extension theory can promote the transformation of things to be evaluated and solve the incompatibility problem under limited conditions [8]. The two have obvious advantages in studying the evaluation of complex systems [9,10], which can help to solve the complexity of the EV supply chain involving many factors. The central idea of the MEEM is to establish the classical domain and section domain of the indicators to be evaluated and process the measurement data of the indicators, so as to determine the grade of the things to be evaluated [11,12]. The classical domain is determined according to the EVSC characteristics and the interval in which the magnitude is located, while the segment domain represents the magnitude range of the EVSC [13].

However, the traditional MEEM adopts approximate processing to determine the evaluation level through the correlation degree method and ignores some information of the matter element to be evaluated, thus affecting the accuracy of the evaluation results [14]. Therefore, the asymmetric proximity degree $\overline{\mathrm{Kj}(\mathrm{R})}$ is introduced in this paper to replace the maximum membership degree with a large deviation to determine the evaluation level, and to eliminate the deviation caused by the approximation treatment in the traditional model. Secondly, this paper sets a characteristic bias "y", extends the MEEM, and obtains the risk bias based on the evaluation results. This can provide managers with a certain risk prediction, so as to effectively avoid unnecessary losses and improve the stability of EVSC operation.

EVSC influencing factors can be divided into subjective factors and objective factors. When an expert is associated with a link in the EV supply chain, such as having experienced a poor after-sales service, the subjective psychology of the regression factor in the scoring process will lead to the increase in the score value. The influence of the objective factors, such as the product quality, is obviously higher than that of service, and this comparison greatly increases the score difference between them. However, a survey has shown that the number of people who choose good after-sales service is almost equal to the number of people who choose quality [15]; so, subjective factors are needed to reduce the objective score difference between the two. Therefore, in the evaluation process, it is one-sided to adopt a single objective method or subjective method, which should be combined to make the evaluation result more accurate. Considering this, this paper uses the minimum deviation method to calculate the weight of the EVSC in combination with subjective and objective weights to avoid the defects of a single method.

This paper aims to use the improved MEEM model to assess the risk of the EVCS. Its novelty is as follows: (i) A comprehensive impact index system is constructed from the six stages of the supply chain, and the overall risk of the EVSC is systematically considered. (ii) The asymmetry close degree is used to replace the maximum membership degree with a large deviation to determine the evaluation level, and the deviation caused by the approximation treatment of the traditional model is eliminated. (iii) A characteristic bias "y" is set, and the MEEM is extended to obtain the risk bias based on the evaluation results. (iv) A sensitivity analysis and comparative analysis are used to verify the results and models to ensure the reliability of the results.

2. Literature Review

The development of EVs is not only in line with the current energy revolution, but also of momentous significance to the advancement of the world environment. However, EVs involve a complex supply chain system with many risk factors, and once a problem occurs in one of the links, it may result in the collapse of the entire supply chain. Therefore, research in this field is of great significance. This section reviews some of the research in the field of EVs and the application of the MEEM in risk assessment, so as to prepare for the following index system construction and model application.

2.1. Research Status in the Field of EVs

EVs use a lower cost electricity as the energy carrier, and the energy-saving effect is very significant compared to that of gasoline vehicles, even far higher than the climate and health benefits. In recent years, many scholars have been invested in this field, and the research in this area has begun to take shape. Wu, Jia et al. [16] established the EVSC risk assessment index system and introduced the confusing language term set of fuzzy comprehensive evaluation to identify and evaluate the latent risk factors of the EVSC in China under uncertain circumstances. Gu, Ieromonachou et al. [17] studied the four-level automotive supply chain composed of government, EV manufacturers, retailers, and consumers, and adopted Stackelberg's game theory and mathematical model based on incomplete information conditions to maximize the total profit of the entire supply chain. Betancourt-Torcat, Poddar et al. [18] proposed a method for the optimal planning and decision-making process of primary energy, carbon capture and storage, distribution of vehicle charging stations, power generation, and EV charging station networks to meet the electricity demand of the overall economy, including electricity, in areas where vehicles operate and are under green constraints. Yan, Zhang et al. [19] established an evaluation standard system of 16 sub-criteria in three dimensions, combined with the variable weight and cloud model, carried out a risk assessment based on China's EVSC, and provided a reference for risk prevention for the corresponding enterprises. Patel, Vyas et al. [20] put forward a conceptual model that can be applied to maintain a sustainable EVSC to meet environmental concerns and human needs. Zhang, Zhu et al. [21] proposed a reliable and privacy-protecting block chain-based automotive supply chain, which utilizes the impermanence of block chain to maintain the privacy of product sales information and business relationships. Zhao, Wang et al. [22] promoted PV uptake by maximizing customer requirements and reducing costs by quickly and efficiently selecting the optimum distribution route for movable power from multiple roads. Shirvani, Baseri et al. [23] analyzed the identified vulnerabilities, threats, challenges, and attacks of the different security aspects of electric vehicles, as well as their possible surface/subsurface and countermeasures. The development of EVs is in line with the change in world energy and environment, which is of vital significance for the development of the current world; so, research in this area has great practical significance and is worth of further discussion.

2.2. Application of the Matter-Element Extension Model (MEEM) in the Evaluation Process

The EVSC involves many influencing factors, and in the evaluation process, it is often necessary to draw internal rules among factors to study the transformation of incompatible problems, so as to determine the grade of things to be evaluated. Under this background, the Chinese scholar CAI Wen proposed matter-element analysis in the 1980s. At present, after the development of this method, it has been extensively used in numerous fields including safety assessment and quality and risk assessment. Li and Li [5] used the MEEM in the assessment of energy sustainability on regional economic growth and social stability to objectively evaluate the impact of energy sustainability on regional sustainability in view of the lack of a unified system to finalize the associated influencing factors of energy sustainability evaluation methods. Xu, Wang et al. [6] discussed the performance assessment of PPP projects during operation, expressed the index information through IFC mapping and extension, and established the performance evaluation model (MEEM) based on IFC. Luo, Wang et al. [24] considered the dynamic characteristics of supply chain operations, designed a supply chain flexibility evaluation system from the perspective of operational efficiency, and established a comprehensive evaluation model of supply chain flexibility with the MEEM to patch up the uncertainty and incompatibility of the evaluation factors used to evaluate supply chain flexibility. Tan, Wei et al. [25] comprehensively studied the explicit and implicit benefits of wind farms and proposed an ideal MEEM-GRA model for wind farm siting. The example analysis showed that the proposed model could determine the integrative benefits of wind farm siting and guide the siting optimization. Wang, Yang et al. [7] applied the MEEM to evaluate and analyze the stabilization of five electronic power generation industries in China, establish a credible evaluation model, and put forward policy advice for the power generation field. Yan, Dong et al. [14] established an improved MEEM comprehensive evaluation model to assess the service quality of EV charging stations from the perspectives of the subject and object, and the results have a certain reference value for improving the service performance. Zhao, Di et al. [10] divided different cable health levels based on the MEEM, accurately evaluated the cable health status, and then provided references for the implementation of state maintenance. The MEEM has proven its reliability in many aspects of risk assessment applications. Applying this model to EVSC risk assessment can effectively solve the complexity of many influencing factors, make an objective assessment of the EVSC, and make targeted prevention to reduce unnecessary losses.

3. Establishment of the Index System

The stages involved in the EVSC are similar to those in most supply chains and can be divided into six stages: planning, sales, procurement, manufacturing, distribution, and after-sales and external environment. However, from the analysis of the energy-saving and environmental protection characteristics of EVs, it still has unique risk factors in different stages, such as supply chain information sharing risk, technology risk, and the corresponding policy change risk [16]. Thus, when establishing the indicator system of the EVSC risk assessment model, we should not only consider the constraints of the general supply chain stage, but also select targeted indicators according to the unique characteristics of EVs. Considering that the production of batteries and electric vehicles requires precious metal materials/minerals and chip processors, transnational cooperation is sometimes required in the EV supply chain. In this context, global geopolitical issues seem to need to be explored. In the selection of suppliers, local conflicts should be avoided, such as those involving Russia, Ukraine, and the Palestine–Israel region, to ensure the political stability of the EV supply chain. When inevitably selecting suppliers from conflict areas, such as for EV accessories that are unique, the weight of political factors will be magnified, and global geopolitical issues should be evaluated separately.

This paper invited 10 experts (Table 1) to construct the EVSC risk model index system by using the Delphi method [26,27]. However, the construction of the index system should follow the following principles: (1) Comprehensiveness: the indicator system should consider several key first-level factors, such as environment, society, salt caverns, and the supply and demand side. (2) Quantification: the indicators should be measurable and comparable, and can be quantified and analyzed through appropriate models and methods. (3) Feasibility and practicability: the index system should be based on existing data and information, and have the feasibility of actual operation.

Table 1. Expert information.

Serial Number	Unit	Professional Title
1	Southeast University	Professor
2	Nanjing University	Professor
3	Zhejiang University	Professor
4	Shenzhen Institute of Automotive Research, Beijing Institute of Technology	Professional consultant
5	Electric Vehicle Research Institute, Chinese Academy of Sciences	Professional consultant
6	National Energy Administration—Shenzhen Office	Government agency
7	National Energy Administration-Shandong Office	Government agency
8	Yutong Group	General manager
9	Yutong Group	Engineer
10	The law firm of Taisung	Lawyer

Finally, the index system of the EVSC evaluation model was divided into 6 first-level indicators and 18 second-level indicators, and the construction results and process are shown in Table 2 and Figure 1.

Table 2. EVSC location index system.

First-Level Indicators	Secondary Indicators	Introduction
Planning Stage V1	End-market demand forecasting risk V11	The fluctuation of market demand is beyond the control of the supply chain, and the highly competitive market greatly augments the tentativeness of consumer demand preference, making it harder to predict precisely and easily increasing the operational risk [16,17].
	Supply chain information sharing risk V12	The level of information sharing mirrors the fluidity and sufficiency of information flow in the supply chain of EVs. Only when the upstream and downstream enterprises in the EVSC achieve full information sharing can they make production and sales plans [19,28].
	Risk of policy change V13	The EVSC may involve many countries, where the policies of EVs are different [18].
Purchase stage V2	Supplier selection risk V21	Because of the complexity of suppliers, the partnership between companies and suppliers is lapsed, the efficiency is low, and the possibility of passive impact on the business activities of companies [16,29].
	Delay in delivery V22	Any heel-dragging in delivery will damage the production line, and on-time delivery is a credit withdrawal [28].
	Inventory control risk V23	It is pivotal to keep a reasonable inventory; when the inventory of the EVSC is unreasonable, it is easy to find a supply and demand imbalance, thus affecting the stable operation of the EVSC [19,30].
Production stage V3	Product quality risk V31	The EVSC involves many parts, and if the quality of the parts is not up to standard, it will reduce customer confidence in the EV [28,31].
	Production line setting risk V32	EV assembly is complex, and an improper production line setup affects production efficiency, causes waste of resources, and may cause the supply chain to fail to operate properly [19,29].
	Risk of a too-long market cycle V33	The market cycle is the time required from product research and design to normal production, and a long cycle will cause the supply chain to run smoothly [16,32].
Logistics distribution stage V4	The response of logistics system is low V41	Unlike the transportation between the assembly points of the vehicle, the transportation of the vehicle from the assembly plant to the sales department may include the transportation and distribution of the sales department to the end user, and the low responsiveness will cause the blockage of the supply chain [29,32].
	Logistics network planning and design is not reasonable V42	In the EVSC operation process, parts will be transferred, stored, and exchanged in different areas, and unreasonable logistics planning will lead to the normal production of enterprises [16,33].
	Technical equipment is backward/operators are not standard V43	Loss caused by technical uncertainty or operator error in the course of technical activities [32,34].
Return stage V5	Inventory risk after order-driven return V51	Today's inventory management is a balance mechanism of the supply chain. When the return leads to the deviation between inventory and planning, it is easy to affect management [35].
	Product recall risk V52	Due to product quality and order cancellation and other reasons, the return stage not only leads to a sudden increase in supply chain costs, but also reduces supply chain benefits [29,36].
	Risk of imperfect after-sales service system V53	An imperfect after-sales system will not be able to deal with the emergency of the product in time, resulting in a serious crisis of trust [35].
Other risks V6	Uncontrollable risk V61	Risks that cannot be overcome, foreseen, or avoided through experience, anticipation, or care [16,37].
	Risk of insufficient funds V62	Once the economic situation fluctuates, the main links in the EVSC finance model will face considerable risks, thus aggravating the financial risks of the entire supply chain [34,38].
	Resource depletion risk V63	If the shortage of resources causes the supply of a certain part to fail to keep up with the manufacturing requirements, it will cause the stagnation of the entire supply chain, bringing great risks [32].
	Brain drain risk V64	Enterprises will spend considerable resources to cultivate talents, and the brain drain may take away the core technology and market resources of enterprises, thus dealing a serious blow to enterprises [17,36].

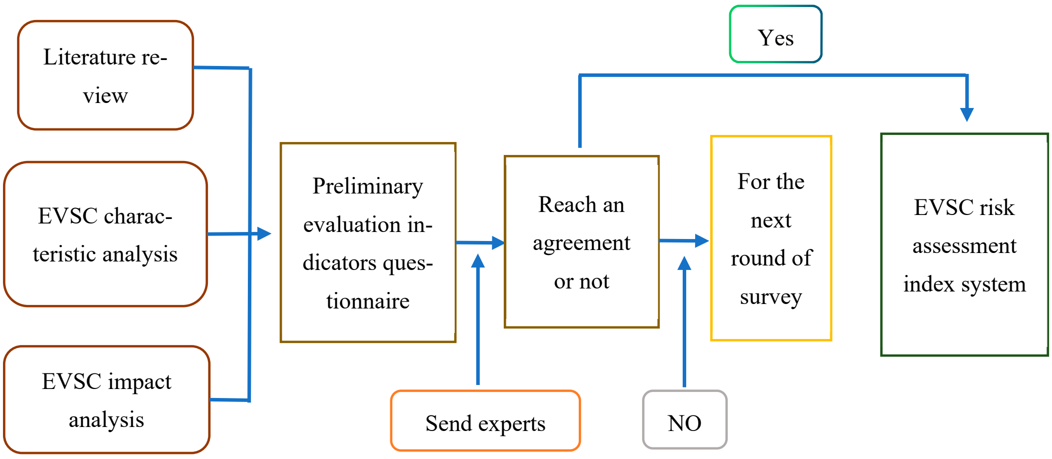

Figure 1. Establishment process of the index system.

4. Theory and Method

4.1. Risk Assessment Framework Based on Combination Weights and the Improved MEEM

In this section, a novel combinational decision framework (DEMATel-EWM-MEEM) is proposed, which is composed of DEMATEL and EWM, minimum deviation method, and an improved MEEM. The research framework is shown in Figure 2.

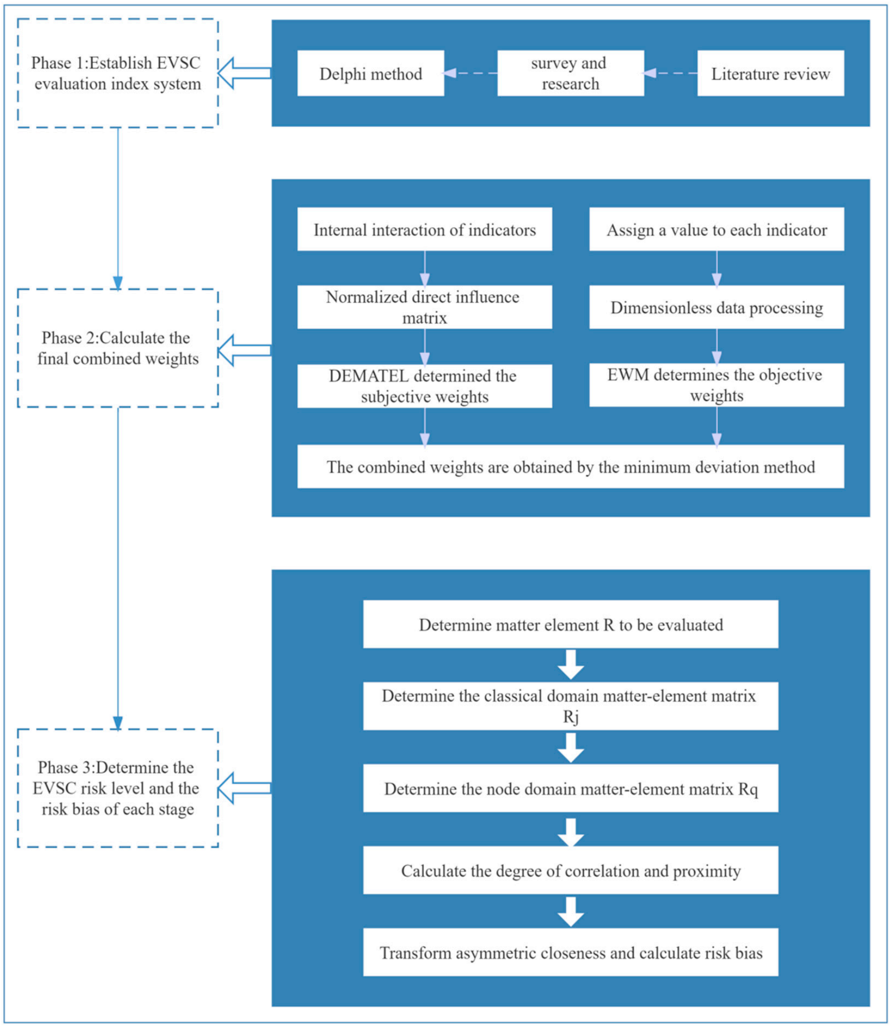

Figure 2. Research framework.

4.2. Weight Design

4.2.1. Subjective Weight (DEMATEL)

The DEMATEL can calculate the influence degree of each factor on other factors and the influence degree by the logical relationship and direct influence matrix among the factors in the system. The reason degree and center degree of each element are calculated as the basis for constructing the model. Thus, the causal relationship between the elements and the position of each element in the system are determined.

Step 1: N experts are invited to score the degree of mutual influence among the indicators, and the initial influence matrix M is constructed.

$$M = \begin{bmatrix} m_{11} & \cdots & m_{1n} \\ \vdots & \ddots & \vdots \\ m_{n1} & \cdots & m_{nn} \end{bmatrix} \tag{1}$$

where m_{ij} shows that the level of the direct effects of the risk index m_i on m_j.

Step 2: The normalized matrix N is obtained by Formula (2).

$$N = (n_{ij})n * n = M(\max_{0 \le i \le n} \sum_{j=1}^{n} m_{ij})^{-1} \tag{2}$$

Step 3: The comprehensive influence matrix T is obtained by Formula (3).

$$T = (t_{ij})n * n = \lim_{h \to \infty} (N^1 + N^2 + \cdots + N^n) \tag{3}$$

When $n \to \infty$, $N^h = 0$ is satisfied.

Step 4: Calculate the center degree, cause degree, impact degree, and impact degree of the indicator system.

$$U_i = C_i + D_i = \sum_{j=1}^{n} t_{ij} + \sum_{i=1}^{n} t_{ij} \; Zi = Ci - Di = \sum_{j=1}^{n} t_{ij} - \sum_{i=1}^{n} t_{ij} \tag{4}$$

Step 5: Calculate the subjective weight.

$$w_1 = \sqrt{(U_i)^2 + (Z_i)^2} / \sum_{i=1}^{n} \sqrt{(U_i)^2 + (Z_i)^2} \tag{5}$$

4.2.2. Objective Weight (EWM)

The EWM calculates the entropy of each indicator according to the impact of the value change of each indicator on the whole, and then determines the weight. The EWM can eliminate the result bias caused by subjective valuation and improve the objectivity and accuracy of the evaluation results when dealing with the problem of multi-index weighting.

Step 1: The decision matrix B = (b_{lk}) m × n is instituted to denote the set of assessment indicators, (l = 1, 2 . . . m; K = 1, 2 . . . n), where m and n indicate the number of experts and the number of indicators, respectively.

Step 2: Formula (6) is used to standardize the indicators, and the standardized matrix P = $(p_{lk})_{m \times n}$ is obtained.

$$p_{lk} = \frac{max\{b_k\} - b_{lk}}{max\{b_k\} - min\{b_k\}} \tag{6}$$

Step 3: The proportion r_{lk} of each index is computed.

$$r_{lk} = \frac{p_{lk}}{\sum_{l=1}^{m} p_{lk}} \tag{7}$$

Step 4: The information entropy H_k of each index is reckoned, where if r_{lk} = 0, $r_{lk} \ln r_{lk}$ = 0, then $0 \le H_k \le 1$.

$$H_k = -\frac{1}{lnm} \sum_{l=1}^{m} r_{lk} ln r_{lk} \tag{8}$$

Step 5: The objective weight of elements is reckoned.

$$\mathrm{w}_2 = \frac{1 - H_k}{\sum_{k=1}^{n}(1 - H_k)} \quad (9)$$

4.2.3. Calculation of the Combined Weights

The weight calculated by the DEMETAL is denoted as w_1, and the weight calculated by the EWM is denoted as w_2; then, the combined weight is expressed as:

$$\mathrm{w} = \alpha^*\mathrm{w}_1 + \beta^*\mathrm{w}_2 \quad (10)$$

$$\begin{cases} maxF(\alpha,\beta) = \sum_{l=1}^{m}\left(\sum_{k=1}^{n}(\alpha\mathrm{w}_1 + \beta\mathrm{w}_2)\right) \\ s.\,t.\ \alpha^2 + \beta^2 = 1 \end{cases} \quad (11)$$

The coefficients α and β are obtained by Lagrange's formula.

$$\begin{cases} \alpha = \frac{\sum_{l=1}^{m}\sum_{k=1}^{n}\mathrm{w}_1\mathrm{b}_{lk}}{\sqrt{\left(\sum_{l=1}^{m}\sum_{k=1}^{n}\mathrm{w}_1\mathrm{b}_{lk}\right)^2 + \left(\sum_{l=1}^{m}\sum_{k=1}^{n}\mathrm{w}_2\mathrm{b}_{lk}\right)^2}} \\ \beta = \frac{\sum_{l=1}^{m}\sum_{k=1}^{n}\mathrm{w}_2\mathrm{b}_{lk}}{\sqrt{\left(\sum_{l=1}^{m}\sum_{k=1}^{n}\mathrm{w}_1\mathrm{b}_{lk}\right)^2 + \left(\sum_{l=1}^{m}\sum_{k=1}^{n}\mathrm{w}_2\mathrm{b}_{lk}\right)^2}} \end{cases} \quad (12)$$

Finally, α and β are normalized to obtain α* and β*, respectively.

$$\begin{cases} \alpha* = \alpha/(\alpha+\beta) \\ \beta* = \beta/(\alpha+\beta) \end{cases} \quad (13)$$

4.3. Construction of the Evaluation Model

The EVSC involves a complex supply chain from the manufacturer to the demand side, in which the influencing factors are interrelated; so, the risk assessment of the EVSC needs an evaluation model to transform the incompatible factors. The MEEM is a model that converts practical problems into formal problems and describes the process of problem-solving. It can usefully solve conflicts and transform incompatible problems into compatible problems. The improvements are described in Section 1, and the detailed steps are shown in Formulas (17)–(20).

(1) Establish the matter element to be assessed

The thing to be assessed is denoted as "Q_0", its feature is denoted as "v", and the feature value is denoted as "c". Assume that Q has multiple features: "v_1", "v_2", ... "$\mathrm{v_n}$". The corresponding values of these n features are "c_1", "c_2" ... "c_n". Then, (Q,V,C) is the matter element R.

$$\mathrm{R} = (\mathrm{Q}_0, \mathrm{V}_\mathrm{i}, \mathrm{C}_\mathrm{i}) = \begin{vmatrix} Q_0 & v_1 & c_1 \\ & v_2 & c_2 \\ & \vdots & \vdots \\ & v_n & c_n \end{vmatrix} \quad (14)$$

(2) Establish the classical domain

The classical domain is established depending on the traits of the matter element to be assessed and the area of its value. It is assumed that the assessment grade is divided into "m" grades. $\mathrm{Q_j}$ (j = 1, 2 ... m) is used to represent the "j" level, $\mathrm{v_i}$ (i = 1, 2 ... n) is adopted to denote the ith evaluation index, and $\mathrm{c_{ji}}$ (i = 1, 2 ... n) is used to denote the value domain of the ith assessment index under the grade "j", which is represented by the area ($\mathrm{a_{ji}}$, $\mathrm{b_{ji}}$).

Then, "Q", "v", and "c" are combined through the orderly form, which is the classical domain matter-element matrix "R_j".

$$R_j = (Q_j, V_i, C_{ij}) = \begin{vmatrix} Q_0 & v_1 & c_{1j} \\ & v_2 & c_{2j} \\ & \vdots & \vdots \\ & v_n & c_{nj} \end{vmatrix} = \begin{vmatrix} Q_0 & v_1 & (a_{1j}, b_{1j}) \\ & v_2 & (a_{2j}, b_{2j}) \\ & \vdots & \vdots \\ & v_n & (a_{nj}, b_{nj}) \end{vmatrix} \tag{15}$$

(3) Establish the section domain

The section domain is denoted by "RQ", and "c_{pi}" is the value domain of the nodal domain matter element with respect to the characteristic "v_i": cpi = (a_{ip}, b_{ip}) (i = 1, 2 . . . n), where (a_{ip}, b_{ip}) denotes the union of all ranges of the i-th index of (a_{ji}, b_{ji}) (j = 1,2 . . . m).

$$RQ = (Q_j, V_i, Cp_i) = \begin{vmatrix} Q_0 & v_1 & c_{1p} \\ & v_2 & c_{2p} \\ & \vdots & \vdots \\ & v_n & c_{np} \end{vmatrix} = \begin{vmatrix} Q_0 & v_1 & (a_{1p}, b_{1p}) \\ & v_2 & (a_{2p}, b_{2p}) \\ & \vdots & \vdots \\ & v_n & (a_{np}, b_{np}) \end{vmatrix} \tag{16}$$

(4) Determine the degree of closeness and correlation

$$D_j(v_i) = \left| v_i - \frac{a_{ij} + b_{ij}}{2} \right| - \frac{1}{2}(a_{ij} - b_{ij}) \tag{17}$$

$$K_j(R_0) = 1 - \frac{1}{n(n+1)} \sum_{i=1}^{n} D_j(v_i)\omega_i \tag{18}$$

$D_j(v_i)$ indicates the distance between the classical field and the object element to be assessed, and ω_i indicates the weight of the index.

(5) Determine the evaluation grade

Through Equation (10), the asymmetric closeness $\overline{Kj(R)}$ of things to be evaluated with respect to grade j can be calculated. Then, the evaluation grade "j" under the maximum closeness degree can be determined by max K(R0) = max{Kj(R0)} (j = 1, 2 . . . n).

$$\overline{Kj(R)} = \frac{Kj(R0) - \min Kj(R0)}{max Kj(R0) - \min Kj(R0)} \tag{19}$$

The trait value "y" of the rating variable of the thing to be rated, that is, the degree of closeness of the thing to be rated to the adjacent rating level, is:

$$y = \frac{\sum_j^n j\overline{Kj(R)}}{\sum_j^n \overline{Kj(R)}} \tag{20}$$

5. Case Study

Under the background of increasingly serious environmental pollution and energy revolution, new energy has undoubtedly become a hotspot in this century. In this case, the Chinese government has vigorously advocated and introduced a series of policies to encourage and promote the development of electric vehicles. Yutong electric vehicles have risen with this trend. At the 26th United Nations Climate Change Conference (COP26), Yutong was invited to attend as a representative of "Made in China" in the field of public travel and launched a zero-carbon initiative with the International Federation of Public Transport (UITP) and internationally renowned operators. At the 2022 World Cup in Qatar, 888 Yutong pure electric buses participated in the transportation guarantee, showing the charm of green travel to tourists around the world. Therefore, this paper chose a Yutong electric vehicle as the case for analysis, and the procedure was as follows.

5.1. Weight Design

5.1.1. Subjective Weights

The subjective weights were calculated by the DEMATEL operation steps outlined in Section 4.2.1, and the key data were obtained as follows (impact degree D, affected degree C, centrality E, and causality F, as shown in Table 3).

Table 3. Values of the related attributes.

Index	V11	V12	V13	V21	V22	V23	V31	V32	V33
D	1.320	1.334	1.721	1.027	1.529	1.371	1.266	1.521	1.671
C	2.199	0.378	0.000	1.624	2.861	4.047	0.709	3.040	3.747
E	3.519	2.405	1.721	2.651	4.390	5.418	1.975	4.561	5.418
F	−0.879	1.574	1.721	−0.597	−1.332	−2.676	0.557	−1.519	−2.076
V41	V42	V43	V51	V52	V53	V61	V62	V63	V64
1.976	1.256	2.372	1.345	0.751	1.220	0.976	2.330	1.399	1.211
0.429	1.116	0.558	2.830	1.697	0.225	0.000	0.999	0.768	0.370
2.405	2.372	2.930	4.175	2.448	1.445	0.976	3.329	2.167	1.581
1.547	0.140	1.814	−1.485	−0.946	0.995	0.976	1.331	0.631	0.841

The subjective weights are shown in Table 4.

Table 4. Subjective weights.

Index	V11	V12	V13	V21	V22	V23	V31	V32	V33
w1	0.06	0.033	0.04	0.045	0.076	0.099	0.034	0.079	0.096
V41	V42	V43	V51	V52	V53	V61	V62	V63	V64
0.047	0.039	0.057	0.073	0.043	0.029	0.023	0.059	0.037	0.029

5.1.2. Objective Weights

The objective weights were calculated by the EWM calculation steps outlined in Section 4.2.2. The key data are shown in Tables 5 and 6.

Table 5. Information entropy Hk of each index.

Index	V11	V12	V13	V21	V22	V23	V31	V32	V33
Hk	0.67	0.67	0.76	0.58	0.67	0.68	0.82	0.75	0.67
V41	V42	V43	V51	V52	V53	V61	V62	V63	V64
0.56	0.60	0.60	0.47	0.6	0.81	0.88	0.87	0.86	0.86

Table 6. Objective weights.

Index	V11	V12	V13	V21	V22	V23	V31	V32	V33
w2	0.080	0.046	0.044	0.073	0.060	0.076	0.033	0.060	0.073
V41	V42	V43	V51	V52	V53	V61	V62	V63	V64
0.060	0.058	0.073	0.096	0.060	0.024	0.026	0.035	0.026	0.022

5.1.3. Combined Weights

Step 3-1: According to the minimum deviation combination weighting Formulas (11)–(13), the weight distribution coefficient $\alpha^* = 0.46$ $\beta^* = 0.54$ was calculated.

Step 3-2: The combined weight w was obtained through Formula (10), as illustrated in Table 7 and Figure 3.

Table 7. Combined weights.

Index	V11	V12	V13	V21	V22	V23	V31	V32	V33
w1	0.06	0.033	0.040	0.045	0.076	0.099	0.034	0.079	0.096
w2	0.080	0.046	0.044	0.073	0.060	0.076	0.033	0.060	0.073
w	0.071	0.040	0.042	0.060	0.067	0.087	0.033	0.069	0.084
V41	V42	V43	V51	V52	V53	V61	V62	V63	V64
0.047	0.039	0.057	0.073	0.043	0.029	0.023	0.059	0.037	0.029
0.060	0.058	0.073	0.096	0.060	0.024	0.026	0.035	0.026	0.022
0.054	0.049	0.065	0.085	0.052	0.026	0.025	0.046	0.031	0.025

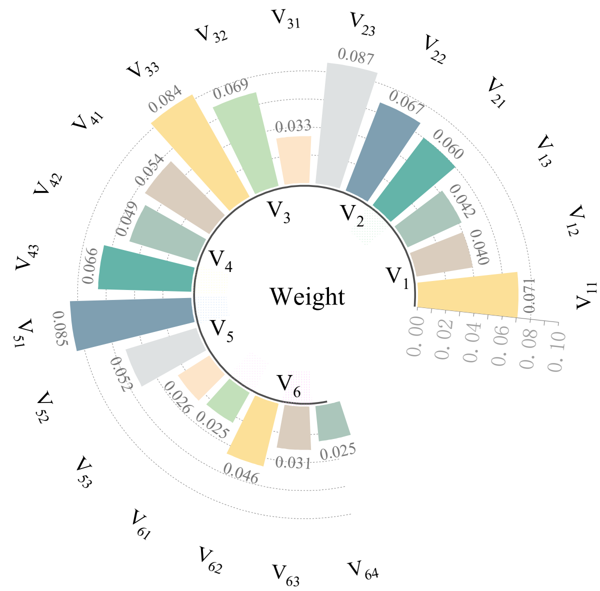

Figure 3. Combined weights.

5.2. *Risk Assessment of EVSC Cases with the Improved MEEM*

With reference to the "New Energy Vehicle Development Plan (2021–2035)" of The General Office of the State Council of China and the full discussion of experts, the EVSC level was determined to be divided into five levels. "I" denotes the risk is "very low", "II" indicates that the risk is "low", "III" denotes that the risk is "medium", "IV" means that the risk is "high", and "V" indicates that the risk is "high" (Table 8).

Table 8. Risk classification criteria.

Level standard	I (0,2]	II (2,4]	III (4.6]	IV (6,8]	V (8,10]	Joint domain [1,10]

According to the above table criteria, R_j, R_p, and R_0 were determined according to Formulas (14)–(16), respectively.

$$R_j = (Q_j, V_i, C_{ij}) = \begin{bmatrix} Q_j & V_i & j = \text{I} & j = \text{II} & j = \text{III} & j = \text{IV} & j = \text{V} \\ & v_1 & (0,2) & (2,4) & (4,6) & (6,8) & (8,10) \\ & v_2 & (0,2) & (2,4) & (4,6) & (6,8) & (8,10) \\ & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ & v_{19} & (0,2) & (2,4) & (4,6) & (6,8) & (8,10) \end{bmatrix}$$

$$R_p = (Q_j, V_i, C_{ip}) = \begin{bmatrix} Q_j & v_1 & (1,10) \\ & v_2 & (1,10) \\ & \vdots & \vdots \\ & v_{19} & (1,10) \end{bmatrix}$$

$$R_0 = (Q_0, V_i, C_i) = \begin{bmatrix} Q_0 & v_1 & c_1 \\ & v_2 & c_2 \\ & \vdots & \vdots \\ & v_{19} & c_{19} \end{bmatrix} = \begin{bmatrix} Q_0 & v_1 & 2 \\ & v_2 & 2 \\ & \vdots & \vdots \\ & v_{19} & 1.7 \end{bmatrix}$$

'c_i' in R_0 is the average score of experts under different indicators. The distance of the 19 risk indicators to the grades I, II, III, IV, and V was calculated by Formula (17). The results are presented in Table 9.

Table 9. Distance of every indicator to each risk level.

Index	I	II	III	IV	V
V11	0.2	−0.2	1.8	3.8	5.8
V12	0.2	−0.2	1.8	3.8	5.8
V13	0.7	−0.7	1.3	3.3	5.3
V21	−0.3	0.3	2.3	4.3	6.3
V22	0.5	−0.5	1.5	3.5	5.5
V23	0.2	−0.2	1.8	3.8	5.8
V31	0.2	−0.2	1.8	3.8	5.8
V32	0.3	−0.3	1.7	3.7	5.7
V33	0.7	−0.7	1.3	3.3	5.3
V41	1.2	−0.8	0.8	2.8	4.8
V42	0.2	−0.2	1.8	3.8	5.8
V43	1.8	−0.2	0.2	2.2	4.2
V51	0.2	−0.2	1.8	3.8	5.8
V52	−0.8	0.8	2.8	4.8	6.8
V53	0.2	−0.2	1.8	3.8	5.8
V61	−0.5	0.5	2.5	4.5	6.5
V62	1.7	−0.3	0.3	2.3	4.3
V63	0.2	−0.2	1.8	3.8	5.8
V64	−0.3	0.3	2.3	4.3	6.3

From Formulas (17)~(20) and the data in Table 8, the asymmetric proximity degree and characteristic quantity values of risk indicators at the different levels of each stage can be calculated, so as to determine the risk grade and deviation degree of each stage, as Table 10 illustrates.

Table 10. Proximity degree and risk level of each stage of the supply chain risk.

Risk Stages	I	II	III	IV	V	Risk Level	y	Level of Bias
Planning stage	0.9961	1.0038	0.9817	0.9595	0.9373	II	2.16	I
Purchase phase	0.9963	1.0036	0.9670	0.9303	0.8937	II	2.13	I
Production stage	0.9918	1.0081	0.9733	0.9384	0.9036	II	2.18	I
Delivery stage	0.9861	1.0047	0.9901	0.9662	0.9424	II	2.29	I
Return stage	1.0012	0.9989	0.9746	0.9505	0.9263	I	1.78	II
Other risks	0.9956	1.0002	0.9896	0.9748	0.9599	II	2.20	I
Comprehensive risk	0.9989	1.0006	0.9959	0.9906	0.9854	II	/	/

From the above results, it can be seen that the comprehensive risk of the EVSC is at level II and the risk is low. The risk level of the regression stage is at level I, but the deviation level is at level II. This indicates that EVs have potential risks in the after-sales service stage, which may lead to increased risks. Managers should take note of this and formulate corresponding measures to prevent them in advance, for example, to increase customer feedback channels to understand the specific reasons for product return or to train after-sales service personnel. The risk bias results of other stages are at level I, which indicates that the risk has a downward trend and the development of the EV supply chain tends to be stable in the short term. This is due to the support of countries around the world for clean energy, and the support of EV policies is gradually increasing.

6. Further Analysis and Discussion

6.1. Sensitivity Analysis

The weight distribution coefficient $\alpha^* = 0.46$ $\beta^* = 0.54$ calculated by the minimum deviation method above (Section 5.1.3) is the most ideal distribution in theory, but the fact is often slightly deviated from the theory. The optimal weight combination (0.46, 0.54) derived from the minimum deviation method represents the allocation of subjective and objective weights, which can exclude the occurrence of outliers in the weights. When a certain index is restricted by subjective or objective factors and deviates from the normal level, the combination method of double weights can reduce the abnormal influence that may be produced by a single method. However, in practice, due to the constraints of various factors, the subjective and objective distributions will not be completely rational. The increase in objective factors caused by the introduction of a major support policy by the government, or the decrease in the subjective expectation of many customers for EVs due to the fire of electric vehicles, for example, will change the subjective weight and objective weight. Therefore, this section gradually changes the allocation of subjective weights and objective weights to represent possible deviations in practice and analyzes the impact of different weight allocations on the final risk of each scheme.

Take (α^*, β^*) = (0.2, 0.8) (0.4, 0.6) (0.5, 0.5) (0.6, 0.4) (0.8, 0.2). Among them, (0.8, 0.2) represents the proportion of the subjective weight of 0.8, and the proportion of the objective weight of 0.2, which means that the main reference in decision making is a subjective weight. There is no reliable factor as a reference, but it is based on subjective investigation, such as the market in a short period of time considering the influx of a large number of suppliers. (0.6, 0.4) indicates that the subjective weight accounts for 0.6 and the objective weight accounts for 0.4, which means that there are certain actual situations as the basis, but the subjective factors occupy more. (0.5, 0.5) means that subjective factors and objective factors are considered equally. The results are shown in Table 11 and Figure 4.

Table 11. Risk levels under different distribution coefficients.

(α^*, β^*)	I	II	III	IV	V	Risk Level
(0.2, 0.8)	0.9969	0.9954	0.9899	0.9921	0.9864	I
(0.4, 0.6)	0.9976	0.9991	0.9936	0.9914	0.9860	II
(0.46, 0.54)	0.9989	1.0006	0.9959	0.9906	0.9854	II
(0.5, 0.5)	0.9991	1.0016	0.9972	0.9901	0.9882	II
(0.6, 0.4)	0.9998	1.0024	1.0012	0.9876	0.9864	II
(0.8, 0.2)	1.0009	1.0030	1.0045	0.9864	0.9854	III

As it can be seen from Table 11 and Figure 4 of the analysis results, when the distribution of the subjective weights gradually increases, the asymmetric proximity degree in grades I, II, and III gradually increases, while the asymmetric proximity degree in grades IV and V gradually decreases. However, the overall risk level of the EVSC does not fluctuate greatly, and most of the risk levels were level II, which verified the stability of the model in this paper. When the allocation of the objective weight reaches 0.8, the overall risk level is level I, and the risk shows a downward trend. When the allocation of subjective weight reaches 0.8, the overall risk level is III, and the risk shows an upward trend. The analysis of the reasons shows that, when objective factors are considered too extensively or experts are influenced by the environment and other aspects, they tend to ascribe scores that are exceedingly high in the psychological evaluation process, which affects the final risk level.

In order to make up for the defects of this single method and make the subjective and objective constraints in line with each other, this paper put forward the minimum deviation method to calculate the best allocation ratio, so that the weight of each factor in the EVSC can reach the value most relevant to the actual situation, and then applies the model to obtain the most realistic risk level.

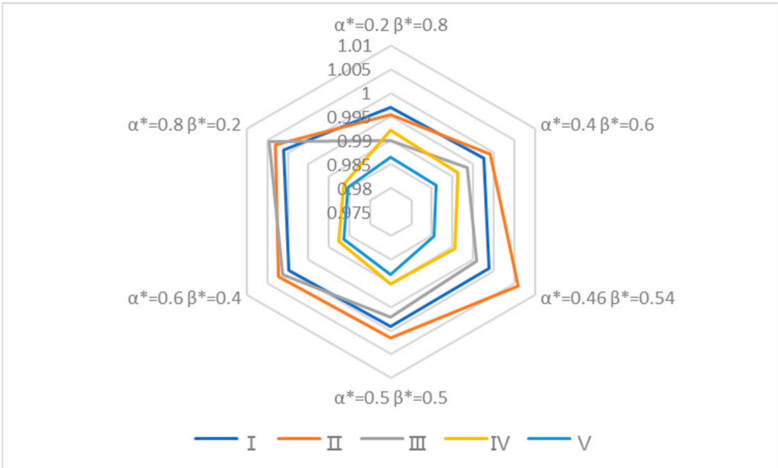

Figure 4. Risk levels under different distribution coefficients.

6.2. Comparative Analysis

In order to further verify the reliability of the method presented in this paper, the proposed method was compared to the following five methods: (i) The hierarchical analysis and similarity preference order method (AHP-TOPSIS) proposed by Liu and Wei [39]. (ii) The data envelopment analysis and fuzzy weighted aggregation method (DEA-FWASPAS) adopted by Dahooie, Hajiagha et al. [40]. (iii) Fuzzy hierarchical analysis and preference order structure evaluation (Fuzzy-AHP-promethee) applied by Bai and Zhang [41]. (iv) The TODIM-VIKOR method adopted by Zhang, Yan et al. [34]. (v) The SFS-TOPSIS method proposed by Gundogdu and Kahraman [42].

The main steps of each method are as follows.

(i) AHP-TOPSIS: $\pi = \frac{aR_i^+ + bD_i^-}{(aR_i^+ + bD_i^-) + (aR_i^- + bD_i^+)}$

$$\mathrm{D_i}^- = \left(\sqrt{\sum_{j=1}^{z} \left(z_{ij} - z_j^-\right)^2}\right)/\max \mathrm{d}^- \quad \mathrm{D_i}^+ = \left(\sqrt{\sum_{j=1}^{z} \left(z_{ij} - z_j^+\right)^2}\right)/\max \mathrm{d}^+$$

$$\mathrm{R_i}^+ = \frac{\sum_{j=1}^{n} w_j \zeta_{ij}^+}{max\gamma_i^+} \quad \mathrm{R_i}^- = \frac{\sum_{j=1}^{n} w_j \zeta_{ij}^-}{max\gamma_i^-}$$

where π is the relative proximity degree, that is, the value taken by the final ordering; D is the Euclidean distance; and R is the correlation degree with the ideal solution. Other steps and explanations are not described in this paper.

(ii) DEA-FWASPAS: $\mathrm{K_i} = \lambda \sum_{j=1}^{n} Q_i + (1-\lambda) \sum_{j=1}^{n} P_i$

$$\lambda = \frac{\sum_{j=1}^{n} P_i}{\sum_{j=1}^{n} P_i + \sum_{j=1}^{n} Q_i}$$

$\mathrm{Q_i}$ and $\mathrm{P_i}$ are fuzzy performance measures of WSM and WPM, respectively; and λ are coefficient values or tradeoff parameters of FWASPAS. Other steps and explanations are not described in this paper.

(iii) Fuzzy-AHP-PROMETHEE:

$$\eta(\text{Aa}) = \frac{1}{m-1}\sum_{b=1}^{m}\prod{}^{+}(\text{Aa},\text{Ab}) - \frac{1}{m-1}\sum_{b=1}^{m}\prod{}^{-}(\text{Aa},\text{Ab})$$

$$\prod{}^{+}(\text{Aa},\text{Ab}) = \sum_{j=1,Aa\neq Ab}^{n} w_i V_j^{+};\ \prod{}^{-}(\text{Aa},\text{Ab}) = \sum_{j=1,Aa\neq Ab}^{n} w_i V_j^{-}$$

η(Aa) is the value taken in the final sorting, V_j is the gain matrix, and (Aa,Ab) indicates that the alternative Aa has a higher priority than Ab, and vice versa. Other steps and explanations are superfluous for this paper.

(iv) TODIM-VIKOR:

$$\varphi_i(A_j, A_s) = \begin{cases} \sqrt{\frac{(x_{ij}-x_{is})w_i}{\sum_{i=1}^{n} w_{ir}}}\ x_{ij} \geq x_{is} \\ -\frac{1}{\theta}\sqrt{\frac{(x_{ij}-x_{is})\sum_{i=1}^{n} w_{ir}}{w_i}}\ x_{ij} < x_{is} \end{cases}$$

$$\Psi(A_j) = \frac{\sum_{s=1}^{m}\psi(A_j,A_s) - \min\limits_{1\leq j<m}\left\{\sum_{s=1}^{m}\psi(A_j,A_s)\right\}}{\max\limits_{1\leq j<m}\left\{\sum_{s=1}^{m}\psi(A_j,A_s)\right\} - \min\limits_{1\leq j<m}\left\{\sum_{s=1}^{m}\psi(A_j,A_s)\right\}}\ j,s = 1,2,,,m$$

where A_j is the evaluation scheme advantage, A_s is the standard value, and Ψ (A_j) is the comprehensive value.

(v) SFS-TOPSIS = $\frac{\sum_{j=1}^{n}\left|Q_{ij}-(d_{ij}^{-})^{\beta}\cdot\pi_{ij}^{+}\right|}{\sum_{j=1}^{n}\left|Q_{ij}-(d_{ij}^{-})^{\beta}\cdot\pi_{ij}^{+}\right|+\sum_{j=1}^{n}\left|Q_{ij}-(-\lambda\left(d_{ij}^{+}\right)^{\gamma}\cdot\pi_{ij}^{-})\right|)}$

$$\pi_{ij}^{+} = \begin{cases} w_j^{\hbar}/w_j^{\hbar} + (1-w_j^{\hbar})^{\frac{1}{\hbar}},\ Sc(z_{ij}) = Sc(A_j^{+}) \\ w_j^{\mathfrak{t}}/w_j^{\mathfrak{t}} + (1-w_j^{\mathfrak{t}})^{\frac{1}{\mathfrak{t}}},\ Sc(z_{ij}) < Sc(A_j^{+}) \end{cases}$$

$$\pi_{ij}^{-} = w_j^{\mathfrak{t}}/w_j^{\mathfrak{t}} + (1-w_j^{\mathfrak{t}})^{\frac{1}{\mathfrak{t}}}$$

where d is the Euclidean distance, π is the relative proximity, and A is the ideal solution based on SFS.

Other detailed steps are not described in this paper.

The final calculation results are shown in Table 12.

Table 12. Final comparison of the methods.

Methods	Core Decision Value	Risk Level
DEMATEL-EWM-MEEM (this paper)	$\overline{\text{Kj(R)}}$ = (0.9989, 1.0006, 0.9959, 0.9906, 0.9854)	II
AHP-TOPSIS	Di^{+} = (0.965, 0.725, 0.825, 0.603, 0.813) Di^{-} = (0.689, 0.918, 0.832, 1.00, 0.731) π =(0.528, 0.518, 0.521, 0.56, 0.54)	II
DEA-FWASPAS	Ki = (0.450, 0.427, 0.388, 0.409, 0.396)	III
Fuzzy-AHP-PROMETHEE	η = (−0.192, 0.121, −0.432, −0.618, −0.324)	II
TODIM-VIKOR	Q = (0.4159, 0.5033, 0.0437, 0.3908, 0.3824)	II
SFS-TOPSIS	π = (0.5036, 0.5708, 0.5322, 0.6059, 0.6336)	II

The comparison results show that, among the six methods, except for DEA-FWASPAS, the final risk level is III, and all the other methods are level II, which confirms the accuracy and reliability of the proposed method.

TOPSIS and VIKOR are based on the approximation of the ideal solution to obtain the final ranking. The MEEM is based on the optimization of a wide variety of known general decisions in light of the needs of the incompatible problems generated at each stage, and then the corresponding evaluation is made. The final calculation results of the (i), (iv), and (v) methods are level II, but the calculation results of TOPSIS and VIKOR at each level are uneven, and only the corresponding optimal level can be selected. Regarding the reasons, the precise differentiation between TOPSIS and VIKOR results in a reverse sequence of schemes that fails to identify relative risks beyond the optimal outcomes. In this paper, the risk bias "y" was introduced and combined with $\overline{\mathrm{Kj}(\mathrm{R})}$ and applied to the MEEM to distinguish the correlation accuracy, so that the risk bias can be determined after the grades of each stage are ascribed.

The final risk level of method (ii) has a deviation of one level from the calculated result of this method. According to the analysis of the reasons, the DEA can only make a corresponding evaluation in limited cases. Although FWASPAS makes corresponding changes, when some data points deviating from the group center are affected, the fuzzy clustering results still have a large deviation, which leads to confusion in the differentiation of level II and level III.

Method (iii) introduces a fuzzy language set, and the result is consistent with the method in this paper. However, PROMETHEE only discusses the case where the attribute value is a hesitant fuzzy number when solving the application of evaluation, and uses a hesitant fuzzy set to describe semantics. In the actual evaluation, due to the diversification of target attributes and the uncertainty of the decision makers, real numbers appear in the evaluation process, resulting in information distortion.

To sum up, the decision model of this method is superior to the other analyzed methods.

7. Conclusions

Aiming at addressing the classical methods and inherent research gaps, this paper proposes an improved MEEM research framework that overcomes the defects of a single subjective or objective weight, provides the best weight under the assignment of the minimum deviation method, and introduces asymmetric similarity degree and risk bias. By applying this method to obtain the final evaluation results and provide the risk bias of each stage, decision managers can apply the best countermeasures according to the corresponding risk and bias degree, reduce losses to the greatest extent, and avoid the waste of resources. The development of electric vehicles not only conforms to the theme of clean development in today's world, but also plays a significant role in energy reform, and research in this area is of great significance.

In the evaluation results of the EV supply chain, the risk of the regression stage tends to increase to level II. Managers should pay more attention to after-sales service; reasonably formulate after-sales processes according to the needs of enterprises, products, and customers; and conduct management with the goal of improving customer satisfaction. Since the supply chain involves many links and is vulnerable to the influence of public policies, managers should not only consider the policy attitude of the local government towards EVs, but also the policy of the supplier on the sale of accessories. Especially when it comes to transnational cooperation, global geopolitical issues cannot be ignored. Managers should have a detailed understanding of the public policies of suppliers or the demand side and adhere to the political and economic concept of win–win cooperation.

The limitations and future prospects of this study can be summarized as follows: (i) In the process of EVSC risk assessment, the factors considered in the indicator system are too complex, which is not limited to the selection in this paper. How to select the impact indicators as perfectly as possible is an unresolved problem that needs further consideration. (ii) To better ensure the stable operation of the supply chain, how to make decisions to maximize the utilization of resources so as to avoid redundant waste still needs to be further verified. (iii) In the development of clean energy has become the focus of the future, electricity is one of the key areas, especially in the transportation industry. Regarding the transition from fuel vehicles to EVs, with the "new energy" and "dual carbon" and other proposals, the International Energy Agency (IEA) has high hopes for it. This development has become the current research hotspot. It is very important to ensure the stable operation of the EVSC. (iv) It is of great interest to apply the proposed method to other practical problems or to extend the presented method to other areas. In the meantime, considering the superiority of the MEEM, this research method can be extended to other evaluation problems.

Author Contributions: H.L.: Conceptualization, Methodology, Formal analysis, Data curation, and Writing—original draft. X.H.: Conceptualization, Methodology, Data curation, Validation, and Writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The authors do not have permission to share data.

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

References

1. Dutta, A.; Bouri, E.; Saeed, T.; Vo, X.V. Impact of energy sector volatility on clean energy assets. *Energy* **2020**, *212*, 118657. [CrossRef]
2. Sun, Y.M.; Liu, S.; Li, L. Grey Correlation Analysis of Transportation Carbon Emissions under the Background of Carbon Peak and Carbon Neutrality. *Energies* **2022**, *15*, 3064. [CrossRef]
3. Sheldon, T.L.; Dua, R.; Alharbib, O.A. How Cost-effective are Electric Vehicle Subsidies in Reducing Tailpipe-CO2 Emissions? An Analysis of Major Electric Vehicle Markets. *Energy J.* **2023**, *44*, 223–250. [CrossRef]
4. Peiseler, L.; Serrenho, A.C. How can current German and EU policies be improved to enhance the reduction of CO_2 emissions of road transport? Revising policies on electric vehicles informed by stakeholder and technical assessments. *Energy Policy* **2022**, *168*, 113124. [CrossRef]
5. Li, S.; Li, R.R. Energy Sustainability Evaluation Model Based on the Matter-Element Extension Method: A Case Study of Shandong Province, China. *Sustainability* **2017**, *9*, 2128. [CrossRef]
6. Xu, Z.; Wang, X.; Xiao, Y.; Yuan, J. Modeling and performance evaluation of PPP projects utilizing IFC extension and enhanced matter-element method. *Eng. Constr. Arch. Manag.* **2020**, *27*, 1763–1794. [CrossRef]
7. Wang, Y.L.; Yang, J.; Zhou, M.; Zhang, D.; Song, F.; Dong, F.; Zhu, J.; Liu, L. Evaluating the sustainability of China's power generation industry based on a matter-element extension model. *Util. Policy* **2021**, *69*, 101166. [CrossRef]
8. Liang, G.; Niu, D.; Liang, Y. Core Competitiveness Evaluation of Clean Energy Incubators Based on Matter-Element Extension Combined with TOPSIS and KPCA-NSGA-II-LSSVM. *Sustainability* **2020**, *12*, 9570. [CrossRef]
9. Bi, A.R.; Luo, Z.; Kong, Y.; Zhao, L. Comprehensive weighted matter-element extension method for the safety evaluation of underground gas storage. *R. Soc. Open Sci.* **2020**, *7*, 191302. [CrossRef]
10. Zhao, G.; Di, H.; Bai, H.; Lin, Y. A cable health assessment method based on multi-agent and matter-element extension model. *Sustain. Energy Technol. Assess.* **2023**, *56*, 103108. [CrossRef]
11. Dong, J.; Wang, D.; Liu, D.; Ainiwaer, P.; Nie, L. Operation Health Assessment of Power Market Based on Improved Matter-Element Extension Cloud Model. *Sustainability* **2019**, *11*, 5470. [CrossRef]
12. Ma, L.H.; Chen, H.; Yan, H.; Li, W.; Zhang, J.; Zhang, W. Post evaluation of distributed energy generation combining the attribute hierarchical model and matter-element extension theory. *J. Clean. Prod.* **2018**, *184*, 503–510. [CrossRef]
13. Xiao, Q.; Wan, S.; Lu, F.; Li, S. Risk Assessment for Engagement in Sharing Economy of Manufacturing Enterprises: A Matter-Element Extension Based Approach. *Sustainability* **2019**, *11*, 4774. [CrossRef]
14. Yan, Q.; Dong, H.; Zhang, M. Service Evaluation of Electric Vehicle Charging Station: An Application of Improved Matter-Element Extension Method. *Sustainability* **2021**, *13*, 7910. [CrossRef]
15. Xiao, Y.-X.; Zhang, R.-Q. Supply chain network equilibrium considering coordination between after-sale service and product quality. *Comput. Ind. Eng.* **2023**, *175*, 108848. [CrossRef]
16. Wu, Y.; Jia, W.; Li, L.; Song, Z.; Xu, C.; Liu, F. Risk assessment of electric vehicle supply chain based on fuzzy synthetic evaluation. *Energy* **2019**, *182*, 397–411. [CrossRef]
17. Gu, X.; Ieromonachou, P.; Zhou, L. Subsidising an electric vehicle supply chain with imperfect information. *Int. J. Prod. Econ.* **2019**, *211*, 82–97. [CrossRef]
18. Betancourt-Torcat, A.; Poddar, T.; Almansoori, A. A realistic framework to a greener supply chain for electric vehicles. *Int. J. Energy Res.* **2019**, *43*, 2369–2390. [CrossRef]
19. Yan, Q.; Zhang, M.; Li, W.; Qin, G. Risk Assessment of New Energy Vehicle Supply Chain Based on Variable Weight Theory and Cloud Model: A Case Study in China. *Sustainability* **2020**, *12*, 3150. [CrossRef]
20. Patel, A.R.; Vyas, D.R.; Markana, A.; Jayaraman, R. A Conceptual Model for Integrating Sustainable Supply Chain, Electric Vehicles, and Renewable Energy Sources. *Sustainability* **2022**, *14*, 14484. [CrossRef]

21. Zhang, C.; Zhu, L.; Xu, C.; Sharif, K.; Lu, R.; Chen, Y. APPB: Anti-Counterfeiting and Privacy-Preserving Blockchain-Based Vehicle Supply Chains. *IEEE Trans. Veh. Technol.* **2022**, *71*, 13152–13164. [CrossRef]
22. Zhao, S.; Wang, Y.; Jiang, Z.; Hu, T.; Chu, F. Research on emergency distribution optimization of mobile power for electric vehicle in photovoltaic-energy storage-charging supply chain under the energy blockchain. *Energy Rep.* **2022**, *8*, 6815–6825. [CrossRef]
23. Shirvani, S.; Baseri, Y.; Ghorbani, A. Evaluation Framework for Electric Vehicle Security Risk Assessment. *IEEE Trans. Intell. Transp. Syst.* **2023**, *25*, 33–56. [CrossRef]
24. Luo, X.; Wang, Z.; Lu, L.; Guan, Y. Supply Chain Flexibility Evaluation Based on Matter-Element Extension. *Complexity* **2020**, *2020*, 8057924. [CrossRef]
25. Tan, Q.; Wei, T.; Peng, W.; Yu, Z.; Wu, C. Comprehensive evaluation model of wind farm site selection based on ideal matter element and grey clustering. *J. Clean. Prod.* **2020**, *272*, 122658. [CrossRef]
26. Li, Q.; Wang, F.; Yu, Y.; Huang, Z.C.; Li, M.T.; Guan, Y.T. Comprehensive performance evaluation of LID practices for the sponge city construction: A case study in Guangxi, China. *J. Environ. Manag.* **2019**, *231*, 10–20. [CrossRef]
27. Zečević, S.; Tadić, S.; Krstić, M. Intermodal Transport Terminal Location Selection Using a Novel Hybrid MCDM Model. *Int. J. Uncertain. Fuzziness Knowl.-Based Syst.* **2017**, *25*, 853–876. [CrossRef]
28. Shi, L.; Lv, S.; Liu, C.; Zhou, Y.; Cipcigan, L.; Acker, T.L. A framework for electric vehicle power supply chain development. *Util. Policy* **2020**, *64*, 101042. [CrossRef]
29. Soares, L.O.; Reis, A.d.C.; Vieira, P.S.; Hernández-Callejo, L.; Boloy, R.A.M. Electric Vehicle Supply Chain Management: A Bibliometric and Systematic Review. *Energies* **2023**, *16*, 1563. [CrossRef]
30. Ma, P.; Meng, Y.; Gong, Y.; Li, M. Optimal models for sustainable supply chain finance: Evidence from electric vehicle industry. *Int. J. Prod. Res.* **2023**, *61*, 5075–5093. [CrossRef]
31. Luo, C.; Leng, M.; Huang, J.; Liang, L. Supply chain analysis under a price-discount incentive scheme for electric vehicles. *Eur. J. Oper. Res.* **2014**, *235*, 329–333. [CrossRef]
32. Cheng, J.; Wang, J.; Gong, B. Game-Theoretic Analysis of Price and Quantity Decisions for Electric Vehicle Supply Chain Under Subsidy Reduction. *Comput. Econ.* **2020**, *55*, 1185–1208. [CrossRef]
33. Zhao, X.; Peng, B.; Zheng, C.; Wan, A. Closed-loop supply chain pricing strategy for electric vehicle batteries recycling in China. *Environ. Dev. Sustain.* **2022**, *24*, 7725–7752. [CrossRef]
34. Zhang, M.; Yan, Q.; Li, W.; Tang, G.; Lin, H. Sustainability performance assessment of photovoltaic coupling storage charging stations with novel multi-criteria decision-making technique. *Int. J. Electr. Power Energy Syst.* **2022**, *142*, 108301. [CrossRef]
35. Kuppusamy, S.; Magazine, M.J.; Rao, U. Buyer selection and service pricing in an electric fleet supply chain. *Eur. J. Oper. Res.* **2021**, *295*, 534–546. [CrossRef]
36. Zhang, Y.; Rysiecki, L.; Gong, Y.; Shi, Q. A SWOT Analysis of the UK EV Battery Supply Chain. *Sustainability* **2020**, *12*, 9807. [CrossRef]
37. Gebhardt, M.; Beck, J.; Kopyto, M.; Spieske, A. Determining requirements and challenges for a sustainable and circular electric vehicle battery supply chain: A mixed-methods approach. *Sustain. Prod. Consum.* **2022**, *33*, 203–217. [CrossRef]
38. Naor, M.; Coman, A.; Wiznizer, A. Vertically Integrated Supply Chain of Batteries, Electric Vehicles, and Charging Infrastructure: A Review of Three Milestone Projects from Theory of Constraints Perspective. *Sustainability* **2021**, *13*, 3632. [CrossRef]
39. Liu, J.C.; Wei, Q.S. Risk evaluation of electric vehicle charging infrastructure public-private partnership projects in China using fuzzy TOPSIS. *J. Clean. Prod.* **2018**, *189*, 211–222. [CrossRef]
40. Dahooie, J.H.; Hajiagha, S.H.R.; Farazmehr, S.; Zavadskas, E.K.; Antucheviciene, J. A novel dynamic credit risk evaluation method using data envelopment analysis with common weights and combination of multi-attribute decision-making methods. *Comput. Oper. Res.* **2021**, *129*, 105223. [CrossRef]
41. Bai, W.; Zhang, L. How to finance for establishing hydrogen refueling stations in China? An analysis based on Fuzzy AHP and PROMETHEE. *Int. J. Hydrogen Energy* **2020**, *45*, 34354–34370. [CrossRef]
42. Gündoğdu, F.K.; Kahraman, C. Spherical fuzzy sets and spherical fuzzy TOPSIS method. *J. Intell. Fuzzy Syst.* **2019**, *36*, 337–352. [CrossRef]