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Enhancing Supply Chain Agility with Industry 4.0 Enablers to Mitigate Ripple Effects Based on Integrated QFD-MCDM: An Empirical Study of New Energy Materials Manufacturers

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Abstract: Given the increasing complexity of the global supply chain, it is an important issue to enhance the agilities of enterprises that manufacture new energy materials to reduce the ripple effects of supply chains. Quality function deployment (QFD) has been applied in many areas to solve multi-criteria decision making (MCDM) problems successfully. However, there is still lack of sufficient research on the use of MCDM to develop two house-of-quality systems in the supply chain of new energy materials manufacturing enterprises to determine ripple effect factors (REFs), supply chain agility indicators (SCAIs), and industry 4.0 enablers (I4Es). This study aimed to develop a valuable decision framework by integrating MCDM and QFD; using key I4Es to enhance the agility of supply chain and reduce or mitigate its ripple effects ultimately, this study provides an effective method for new energy materials manufacturers to develop supply chains that can rapidly respond to change and uncertainty. The case study considered China's largest new energy materials manufacturing enterprise as the object and obtained important management insights, as well as practical significance, from implementing the proposed research framework. The study found the following to be the most urgent I4Es required to strengthen the agility of supply chain and reduce the key REFs: ensuring data privacy and security, guarding against legal risks, adopting digital transformation investment to improve economic efficiency, ramming IT infrastructure for big data management, and investing and using the new equipment of Industry 4.0. When these measures are improved, the agility of the supply chain can be improved, such as long-term cooperation with partners to strengthen trust relationships, supply chain information transparency and visualization to quickly respond to customer needs, and improving customer service levels and satisfaction. Finally, REFs, such as the bullwhip effect caused by inaccurate prediction, facility failure, and poor strain capacity caused by supply chain disruption, can be alleviated or eliminated. The proposed framework provides an effective strategy for formulating I4Es to strengthen supply chain agility (SCA) and mitigate ripple effects, as well as provides a reference for supply chain management of other manufacturing enterprises in the field of cleaner production.

Keywords: quality function deployment; multi-criteria decision making; industry 4.0 enablers; supply chain agility indicators; ripple effect factors; new energy materials manufacturers

MSC: 90B06; 90Bxx; 90

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1. Introduction

Modern enterprises operate in rapidly changing complex environments [1] and increasingly rely on complex networks of supply chain partners to deliver the right quantities of goods and services at the right time, and are placed under constant pressure with respect to cost and quality [2]. Similarly, organizations are increasingly using complex operational strategies, such as lean manufacturing and global sourcing, to gain competitive advantages [3,4]; the rapidly changing complex environments and operational strategies of enterprises together result in higher levels of vulnerability and supply chain risk [5]. Organizations are increasingly prone to unpredictable disruptions that affect the supply chain [5]. For example, in the new energy lithium battery materials manufacturing enterprises, because of large external dependencies, raw materials, inventory shortage statuses, as well as disrupted supply of materials such as lithium carbonate and lithium hydroxide, the development of the new energy materials' industry will also be interrupted [6]. The unpredictability of outages and severity of the consequences of their propagation across multiple network echelons have driven new research trends, namely ripple effects in supply chains [7,8]. Ripple effects constitute a specific field of supply chain disruption that involve study and analyses of how one or more disruptive events propagate through the supply chain and affect its resilience and performance [9]. In recent years, mitigating the chain reactions in supply chains have become the focus of enterprises [7,10–13].

Mitigating ripple effects require reducing the risk of supply chain disruption [9,14,15], and improving supply chain agility (SCA) is a potential strategy to reduce such risks [16–18]. SCA is considered to be one of the characteristics of a successful supply chain in the volatile and increasingly competitive environment today [19–22]; because companies with agile supply chains are able to react more competitively to unforeseen changes in their business environments, they are better able to synchronize supply and demand than their competitors [23,24]. Global business organizations have realized that agile supply chains are necessary for survival in a dynamic, competitive, and unpredictable market [23] and are also the competitive advantage of any company [25]. In new energy manufacturing enterprises, the key to collaborative intelligent manufacturing lies in the agility of the participants' manufacturing behaviors, improving agility, and making the manufacturing process highly flexible in response to the personalized requirements of various projects [23]. Therefore, improving SCA is an important issue in academic and industrial research [26–30].

In the context of Industry 4.0, studying the impact of agile forces has important implications for the entire supply chain [31–34], because the introduction of Industry 4.0 in enterprises allows for transparent collaborations among suppliers, manufacturers, and customers in the process from issuing orders to the end of product life [35]. This disruptive innovation has influenced the development of new paradigms, principles, and models for supply chain management [36–38] and can be seen as a set of technologies, equipment, and processes that operate in an integrated manner at several stages of the production process and at several levels of the supply chain, thus enabling self-sufficient, integrated, and decentralized production with minimal human intervention [39]. Industry 4.0 is emerging as one of the modern supply chain and manufacturing practices but is unfortunately prone to many organizational, legal, strategic, and technological challenges that can be addressed by improving SCA, as both provide sufficient sustainability for the entire organization [33]. In recent years, there have been more studies in academia and business circles to improve the agility of supply chain through Industry 4.0 [40–43].

To summarize, this study aimed to understand the interactions between supply chain ripple effect factors (REFs), supply chain agility indicators (SCAIs), and Industry 4.0 enablers (I4Es) in the development processes of new energy material manufacturing enterprises. The following are the main innovations of this study:

In the past, most studies considered supply chain REFs, agility indicators, and I4Es separately, and there are very few articles that study the ripple effects of supply chain or REFs and SCAIs in the context of Industry 4.0 or combine all three. For the first time, this study combines all three concerns to identify key I4Es to improve SCA and reduce or mitigate the ripple effects in supply chain ultimately.

Based on the above analysis, owing to the development of global economic integration approaches in recent years, enterprises have experienced more complex test environments, especially in view of the economic damage caused by the COVID-19 pandemic; this has led to industries facing unprecedented risk, with different levels of supply-chain interruptions. Thus, alleviating the ripple effects in the supply chain has become a common pursuit among increasing numbers of global enterprises. In particular, with the promotion and development of energy conservation and emission reduction policies, new energy has become a global trend. Therefore, it is necessary for new-energy-material manufacturing enterprises to formulate scientific and effective strategies to alleviate the ripple effects of supply chain.

In view of this background, the present study explored a scientific and effective mathematical model to reduce or eliminate the supply-chain ripple effects in new energy material manufacturing enterprises by integrating MCDM methods with QFD, to explore available decision-making frameworks, as well as research frameworks, through Industry 4.0 enablers (I4Es) to enhance supply chain agility indicators (SCAIs), thereby reducing or mitigating the ripple effect factors (REFs). This study provides a useful mathematical model for integrated QFD-MCDM in supply-chain management. In addition, it is expected that this model can be of reference to other manufacturing enterprises for cleaner production and alleviating the ripple effects of supply chains, so as to promote mathematical applications in industrial engineering.

In recent years, quality function deployment (QFD) has been successfully applied in many fields to solve multi-criteria decision making (MCDM) problems, such as knowledge system selection [44], green building evaluation [45], bike-sharing project evaluation [46], and technical attribute prioritization [47]. However, the development of two house-of-quality (HoQ) measures to connect supply chain REFs, SCAIs, and I4Es by integrating MCDM and QFD has not been possible. To address this gap, this study discusses the following research questions:

(a) What are the key REFs, SCAIs, and I4Es in the supply chains of new energy materials manufacturing enterprises?
(b) How must QFD and MCMD be integrated to link the relationships among the three groups of variables and provide decision support for the supply chains of new energy materials manufacturing enterprises?
(c) How can new energy materials manufacturers effectively enhance SCA through I4Es via the proposed framework to mitigate ripple effect?

Therefore, the purpose of this study was to develop an integrated MCDM–QFD framework for the supply chains of new energy materials manufacturing enterprises to explore valuable management decisions. Using this framework, SCA can be enhanced by identifying key I4Es to mitigate the ripple effects. The relationships among the three variables (REFs, SCAIs, and I4Es) were clarified, and priorities were determined to facilitate the new energy materials manufacturing enterprises to invest limited resources in the most critical applications. For the new energy material manufacturer in this study, China's largest manufacturing enterprise was considered as the research object; to test the feasibility of the QFD–MCDM framework, we proposed the analysis of the industrial development model for I4Es to enhance SCA, enhance agile responses to market changes, and reduce the ripple effects of the supply chain to enhance competitiveness of new energy materials manufacturing enterprises, so as to provide strategic references for supply chain decision makers.

The rest of this article is organized as follows. Section 2 reviews the literature on REFs in supply chains, agility indicators, and I4Es. Section 3 describes the integrated framework of this study. Section 4 describes the empirical research with respect to the case study and discusses the results. Section 5 presents the conclusions and some suggestions.

2. Research Overview

In the face of fierce and uncertain competitive environments, organizations and their supply chains aim to respond rapidly to the unforeseen changes in their businesses; hence, improving SCA is the key to alleviate its ripple effects. As emerging topics, ripple effects, agility, and Industry 4.0 have recently attracted more attention from researchers. Dolgui et al. (2021) summarized journal articles from 2012 to 2020 on the ripple effects in supply chains and found that the number of articles on ripple effects increased from less than 10% in 2012 to nearly 50% by 2020 [9]. However, existing literature note that REFs, SCAIs, and I4Es have very weak links. This study combines the three to determine the key I4Es to improve SCA and to reduce or alleviate the ripple effects of supply chain ultimately.

2.1. Ripple Effect Factors (REFs)

At present, research on ripple effects in supply chains is still in its infancy. Therefore, there is still a large research gap on the ripple effects in supply chains, which is an important research direction in the future [9]. The definition of the ripple effect can be stated as follows. Ivanov et al. (2014) believes that ripple effects describe the impact of interruption on supply chain performance and the range of interruption-based changes in supply chain structures and parameters [8]. According to Levner et al. (2018), the ripple effect is an observed adverse event occurring in an entity that may have a negative impact along the supply chain and spread to other parts of the chain [48]. Dolgui et al. (2018) believes that the ripple effect is the transmission of multiple cascade interruptions in the supply chain and the downstream transmission of decline in supply chain demand satisfaction caused by serious interruptions [15]. Hosseini et al. (2019) argues that ripple reactions may occur when disruptions to the supplier base cannot be localized, with consequences that spread down the supply chain and adversely affect performance [49]. Dolgui et al. (2020) believes that the ripple effect refers to structural dynamics and describes the downstream propagation of a decline in the scale of supply chain demand satisfaction due to severe disruptions [50].

As can be seen from the above, different scholars have different definitions of the ripple effects in supply chains, and different types of enterprises have different expressions for the causes of the ripple effects. Research on the causes of the ripple effect may be summarized as follows. Dmitry et al. (2014) believes that causes of the ripple effects include terrorist attacks, terrorism, piracy, and destruction of information systems (information technology), procurement (exchange rate risk), receivables (number of customers), inventory (cost of inventory holding, demand, and supply uncertainties), and forecasting (inaccurate forecasts and bullwhip effect) [51]. Ivanovi et al. (2019) identified production facility failures and delays in supply chain processes as also contributing to the ripple effects [52]. Hosseini et al. (2020) summarized labor strikes, labor shortages, and economic collapse/crisis, and Hosseini et al. [53]. Seyedmohsen et al. (2020) also believes that environmental damage (discharge, waste, resource exhaustion, sewage) is a cause of the ripple effect [54].

Based on the above discussion and comprehensive review of literature, a total of 50 factors causing ripple effects were identified. The causes of these ripple effects are assessed in Section 4.

2.2. Supply Chain Agility Indicators (SCAIs)

The concept of agility was proposed by researchers at the Iacocca Institute of Lehigh University in 1991 [55]. It was first introduced in the manufacturing field in the context of flexible manufacturing systems [56–58]. Agility is the ability of an enterprise to respond quickly to customers' changing demands and unstable market changes [59]. Therefore, it is one of the most important elements to help organizations survive in turbulent and changeable environments [19,57,60–72].

Supply chain agility (SCA) is the ability of an organization to respond to unexpected market changes and turn these changes into business opportunities [23]. Studies on agility have always been of concern to academia. Yang (2014) developed and empirically tested a conceptual framework to investigate the antecedents of manufacturers' supply chain agilities and the links between their agilities and performances in emerging economies [62]. Eckstein et al. (2015) found that SCA and supply chain adaptability had positive impacts on both cost and operational performances [63]. Abdallah et al. (2020) identified the information technology drivers of SCA and examined their impact on the level of agile supply chain implementation [64]. Asad (2021) provided results related to SCA and supply chain innovation, as well as their impact on supply chain performance in Pakistan's manufacturing industry [65], while Pratondo et al. (2021) evaluated and examined the role of SCA on supply chain resilience and performance sustainability [66].

As can be seen from the above literature, different scholars not only differ in their definitions of SCA but also differ in the division of agility indicators. Rehman (2020) classified agility indicators into five dimensions: cooperative competition, information technology, market supply, customer relationship, and organization and team management [59]. Mohammadi et al. (2018) believed that the index of agility should be based on six dimensions, namely cooperative competition, information technology, market supply, customer relationship, product design, and organization and team management [67].

Based on the above discussion and a comprehensive review of literature, this study summarized the relevant literature on SCA, as well as screened and integrated the classification methods and agility indicators proposed by scholars. A total of 38 agility indicators are listed, and these are also evaluated in Section 4.

2.3. Industry 4.0 Enablers(I4Es)

Industry 4.0 or intelligent manufacturing is the term used for digital transformation, use of the Internet of Things, artificial intelligence, cloud computing, machine learning, and technology analyses such as big data. These concepts build on the interconnectedness between machines and systems using the technologies described above, which self-correct and self-adapt according to the environmental requirements of time [68]. The key concept of Industry 4.0 is to realize interconnection of all things, which enables it to have independent supervision, analytical and judgment capabilities, accurate location and solutions to problems, and to make the production process more flexible so as to adapt to changes in market demands [69].

Garay et al. (2019) proposed a conceptual model that defines the basic components for shaping a new digital supply chain through implementation and acceleration of Industry 4.0 [70]. Ivanov et al. (2019) studied the impacts of digitalization and Industry 4.0 on ripple effects and disruption risk control analysis in supply chains [52]. Research by Chauhan et al. (2019) assessed how emerging themes in Industry 4.0 could be considered in the context of supply chain management and identified important areas for future research [71]. Li et al. (2020) proposed and created the concept of the education supply chain and positioned research in the context of Industry 4.0, sharing global intellectual resources and top talent through transnational mobility and educational joint ventures [72]. Hahn et al. (2020) used the theoretical perspectives of supply chain innovation to study the impact of Industry 4.0 on supply chain management [73]. The research of Amal et al. (2021) focused on Industry 4.0 and its garment supply chain in India's textile industry to develop research questions to reveal the issues facing supply chains for adoption of Industry 4.0 [74].

As can be seen from the above, different scholars not only differ in the application of Industry 4.0 in the supply chain but also differ in the division of I4Es. In terms of these measures, Shinohara et al. (2017) notes that they include senior management support and leadership, change of leadership style, infrastructure (Internet, cloud computing, and other technologies), organizational culture, digital culture, employees' willingness to embrace emerging technologies, and comfort of using such technologies [75]. Lin et al. (2019) proposed that other I4Es include user participation and integration of customer design with manufacturing process [76]; Vrchota et al. (2019) proposed other I4Es, including focusing on customer needs, innovative solutions and products, strengthening services, and employee empowerment [77]. Hoyer et al. (2020) proposes that other I4Es include: occupational health and safety, company size, cost and expense management, as well as cooperation between companies and institutions [78]. Jesus et al. (2020) proposed that the I4Es also include existing technical skill levels within the organization, IT information technology structure, process modularization or dynamic business design, as well as government and policy support [79].

Based on a search and investigation of relevant literature, this study identified 52 I4Es. These I4Es indicators are also evaluated in Section 4.

2.4. Ripple Effects and Supply Chain Agility

In the supply chain, if interruptions cannot be localized and affect the performances of the downstream supply chains, ripple effects are caused [15,51]. As mentioned above, ripple effects are specific areas of supply chain disruption [9]. There are many studies on SCA to alleviate supply chain disruptions, such as follows. Braunscheidel et al. (2009) believe that a company's SCA is defined as its ability to quickly adapt to or respond to market changes and potential and actual disruptions, both internally and with its main suppliers and customers, which contributes to the expansion of SCA [22]. Zegordi et al. (2012) divided the strategies for mitigating supply chain interruptions into preventive and restorative strategies, among which the preventive strategies include SCA [80]. Blome et al. (2013) proposed a model to evaluate the impact of SCA on operational performance so as to better establish SCA and use it to respond to supply chain disruptions [81]. Braunscheidel et al. (2018) argue that enterprises need agility in their supply chains to manage disruption risks and to ensure uninterrupted service to customers. He also notes that the cultivation of agility can be viewed as a risk management program that enables companies to anticipate and respond quickly to market changes and supply chain disruptions [82]. Shekarian et al. (2020) assessed the impact of agility on mitigating various types of supply chain disruptions [83]. Nickel et al. (2021) argued that the COVID-19 pandemic not only affected the global healthcare system but also caused disruptions that challenged the automotive manufacturing industry and its supply chain, and that the use of agility measures could compensate for these impacts [84].

To summarize, the abovementioned use of agile forces to solve the problem of supply chain disruption essentially alleviates ripple effects in the supply chain. According to the literature review, it is found that most studies in the past discussed the use of SCA to solve for market changes, interruption risk, and delivery capacity in the supply chain, but there are still few works on the direct effects of SCA for mitigating ripple effects. Therefore, this study provides a more comprehensive discussion on weakening the ripple effects by combing these works to obtain the overall index of SCA.

2.5. Supply Chain Agility and Industry 4.0

In recent years, the analysis of industry 4.0 in supply chains has been studied extensively [52,68–79], but there are very few studies on the agilities of supply chain. The relevant studies on SCA and Industry 4.0 are as follows: in-depth understanding of organizational needs and the need to build a production environment with Industry 4.0 in mind. Pfeife et al. (2015) analyze and identify processes and workflows that can be automated as well as possibilities for integrating more agile and flexible work structures [40]. The functional and non-functional IT requirements for implementing agile architectures are discussed. Saengchai et al. (2019) identified the impact of SCA on the organizational, legal, strategic, and technological challenges for implementing Industry 4.0 and studied the mediating role of supply chain in the relationship between agility and challenges [33]. Rane et al. (2019) studied redesigning businesses in the context of Industry 4.0 to help organizations improve operational agility to implement blockchain-based IoT integrated architectures [41]. Lavinsaa et al. (2020) studied the impact of Malaysian Industry 4.0 technology restructuring on strategic agility and enterprise competitiveness [42]. Eslami et al. (2021) assessed the relationship between supply chain integration, SCA, and financial performance from the perspective of dynamic capabilities [43]. This study examined whether Industry 4.0 digital technologies can modulate supply chain integration and SCA.

In conclusion, according to the literature, most of the published articles focused on 4.0 implementation through the industry's influence on SCA. However, very few articles have found the key I4Es to improve agility of the supply chain; hence, this study focused on the key I4Es to improve SCA by evaluating the literature.

The above comprehensive research shows that most previous studies consider REFs of supply chain, SCAIs, and I4Es separately; there are few articles to study the ripple effects of supply chain or REFs and SCAIs in the context of Industry 4.0, not to mention studies that combine all three. To fill this gap, this study built a two-stage HoQ framework by integrating MCDM-QFD on the basis of existing research and linking the REFs, SCAIs, and I4Es. Reducing or mitigating the ripple effects in supply chain by identifying key I4Es increases SCA and also provides references for supply chain decision-making in new energy material manufacturing enterprises.

3. Research Method

3.1. Research Framework

In this chapter, the research methods and steps adopted in the analytical model proposed in this study are explained, including the KJ method, failure mode effects analysis (FMEA), Decision-making Trial and Evaluation Laboratory (DEMATEL), fuzzy Delphi method (FDM), QFD, and VlseKriterijumska Optimizacija I Kompromisna Resenje (VIKOR) ranking. Among these methods, the KJ method, which is one of the seven new tools of total quality management, is often used in HoQ models. For example, Zhou et al. (2021) sorted and screened users' original requirements through the KJ method and divided the demand levels [85]. In supply chain management, FMEA, DEMATEL, and FDM are often used to identify key risk factors, and each method has different roles and functions. For example, Zhu et al. (2020) used FMEA to identify and manage potential risks in product deletion decisions in the supply chain, which has become an effective tool for risk assessments of failure modes [86]. He et al. (2021) used DEMATEL to determine the interrelationships between risk factors, whose results are incorporated in QFD [87]. Mabrouk et al. (2021) used FDM to filter and grade the factors for green supplier selection. The VIKOR method is an eclectic sorting algorithm that has been widely used in supply chain management [88]. Yang et al. (2021) used VIKOR to obtain the priority of factors when studying the challenges related to the Internet of Things for sustainable supply chain management in manufacturing [89]. To apply the theoretical formula to the practical calculations of the empirical research in Section 4, this chapter presents detailed background information. This study has identified and summarized the REFs, agility indicators, and I4Es. Therefore, the two-stage HoQ will be adopted as the deployment mode in this study, that is, the two-stage HoQ will be established via research analysis and discussion of the QFD. The constructed HoQ is shown in Figure 1. This analytical model is simplified, and its specific steps are shown in Figure 2.

3.2. First HoQ: Linking REFs to SCAIs

First, the KJ method was used to identify some supply chain REFs in new energy material manufacturing enterprises; then, according to the record of the KJ method, each REF was categorized for influence and possibility of failure in the designed FMEA questionnaire. Thus, the risk priority number (RPN) of each REF was obtained by analysis and calculation, which was used as the risk weight of the HoQ in the first stage. We determined the key REFs and the correlation matrix between the key REFs and SCAIs. Based on the interaction relationships between these two factors, the ranking of key SCAIs was obtained using the VIKOR ranking method.

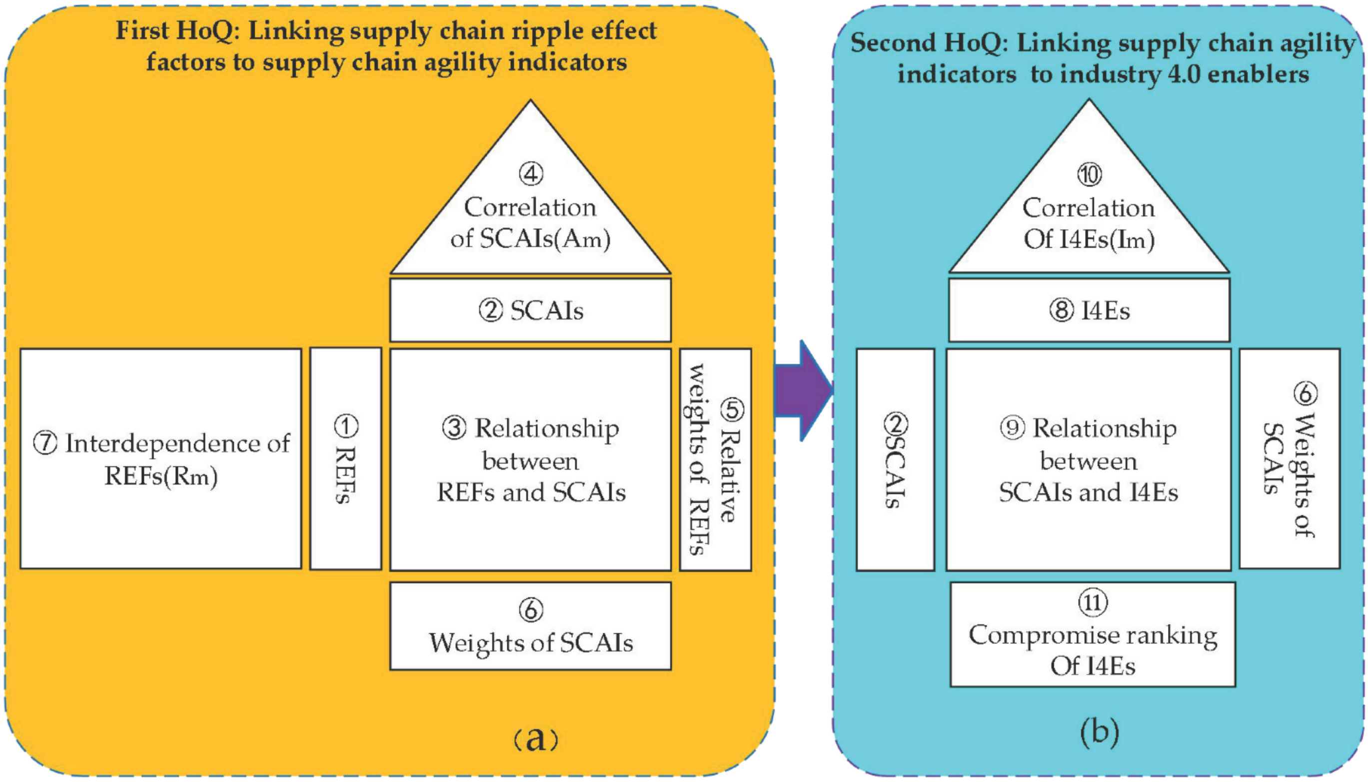


Figure 1. Structure of the two-phase houses of quality (HoQs). (**a**) First HoQ; (**b**) Second HoQ.

3.3. Second HoQ: Linking SCAIs to I4Es

We used FDM to select the key I4Es based on thresholds set by experts. Then, we calculated the correlation matrix of I4Es and the relationship matrix of SCAIs with I4Es. The VIKOR method is used to normalize the comprehensive evaluation matrix such that positive and negative ideal solutions are found. We used $(1 - Q_j)$ as the weights and calculated the group utility, individual regret, and benefit ratio. Then, the VIKOR method was used to adjust the rankings on the condition judgment of I4Es. Finally, the optimal solution to mitigate or reduce ripple effects was obtained by improving SCA with I4Es. The proposed framework is shown in Figure 2.

3.4. KJ Method

The affinity diagram method, also known as KJ method, is one of the seven new tools of total quality management created by Japanese professor Kawa Yoshida Jiro. It uses the internal affinity to summarize and categorize language and characters in the chaotic state and to find new ways of solving problems. The specific steps in the method are as follows:

1. Identify the object (or use): KJ is suitable for problems that need to be solved, but allow sufficient time for the solutions.
2. Collect written materials: When collecting materials, it is important to respect facts and seek out original ideas.
3. Put all the collected information, including the "original ideas," on cards.
4. Organize the cards.

For cards with uneven content, it may enhance internal affinity to combine similar ones (according to self-perception) rather than separating them based on known and existing theories and classification methods to gradually delineate new ideas.

5. Gather similar kinds of cards and write down classification cards for each category.
6. Based on the purpose, select the above data fragments to filter ideas and write articles.

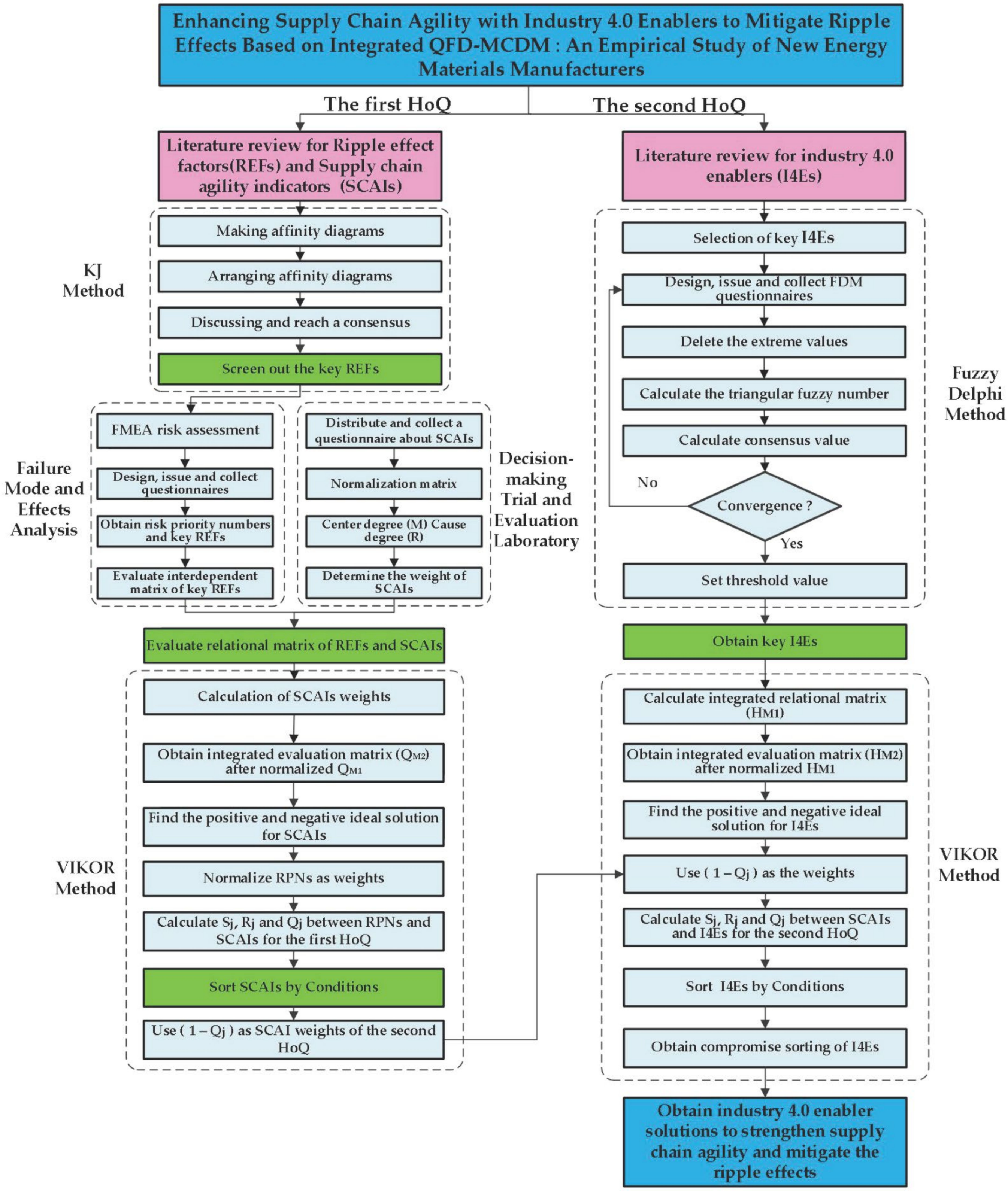


Figure 2. Research flow chart.

3.5. Failure Mode and Effect Analysis (FMEA)

The FMEA concept was proposed by NASA in 1963, and the method has been extended and applied in various industries to assisting organizations with identifying and quantifying potential deficiencies at the design stage [90]. The empirical evidence shows that the negative effects of supply chain disturbances can be categorized into several supply chain failure modes [91]. Therefore, we focused on the REFs identified using FMEA to determine potential causes and effects. Given that different manufacturing systems are exposed to different risks, their degrees of occurrence and influence vary. Accordingly, three criteria, namely, severity (S), occurrence (O), and detection (D) are discussed, depending on the situation. This study referred to the corresponding semantic levels of international standards to design the FMEA questionnaire and calculated the *RPNs* using Formula (1).

$$RPN = S \times O \times D \tag{1}$$

3.6. Decision-Making Trial and Evaluation Laboratory (DEMATEL)

The decision laboratory analysis process involves analysis of the logical relationships and influence relationship matrix of the elements to calculate the influence of each element on the other factors and the extent of such influence; thus, the reason and center degrees are obtained, and the core factors and improvement strategies of the system are further sought. DEMATEL has been successfully applied to solve multiple practical problems in different areas, and several advanced methods have been introduced to deepen and strengthen it [92]. The steps used in this approach are as follows:

1. The DEMATEL questionnaire was designed for 38 agility indicators collected via literature review and summary, and the degree of influence among the factors was identified according to five scales. The questionnaire results were converted to corresponding values, and the weight value of the influence degree of each factor was obtained after solving the fuzzy average value.
2. Based on the influence degree obtained from the questionnaire results, the original relationship matrix Z of the n factors is established, and the diagonal factor Z_{ii} of the original relationship matrix is 0.
3. The original relation matrix Z is normalized, each row and each column is summed, the maximum value among the row and column summations are determined, and the normalized direct relation matrix X_{ij} is obtained as the matrix normalization.

$$\lambda = \frac{1}{\underset{1 \le i \le n}{max}\left(\sum_{j=1}^{n} Z_{ij}\right)} \tag{2}$$

4. The normalized direct relation matrix X_{ij} is used to calculate the total relation influence matrix T.

$$T = X \times (I - X)^{-1} \tag{3}$$

5. By adding the elements in each row and each column in the total influence relation matrix (T), the sum of each column (D value) and sum of each row (R value) is obtained.

$$D_i = \sum_{j=1}^{n} T_{ij},\ (i = 1, 2, 3 \ldots, n) \tag{4}$$

$$R_j = \sum_{i=1}^{n} T_{ij},\ (j = 1, 2, 3 \ldots, n) \tag{5}$$

6. Determination of weight W_i: The weight can be determined as the geometric mean of the centrality and causality, which are obtained by substitutions in Formulas (6) and (7). In this study, the importance order of SCAI was determined according to the calculated weights.

$$w_i = \sqrt{(D_i)^2 + (R_j)^2} \tag{6}$$

$$W_i = w_i / \sum_{i=1}^{m} w_i \tag{7}$$

7. In the total influence relation matrix T, the sum of all rows and columns is calculated. Further, $D + R$ and $D - R$ are calculated.

3.7. Fuzzy Delphi Method (FDM)

Murray et al. (1985) developed an optimized FDM that combines the traditional Delphi method with fuzzy theory, where expert judgments in FDM are represented by fuzzy numbers [93]. This study uses FDM to screen the key I4Es with the thresholds provided by experts to (1) reduce the survey numbers, (2) express the opinions of experts entirely, (3) improve rationality in keeping with the needs, and (4) conserve time and cost [94]. The steps used in this method are as follows:

Step A: Identify all I4Es, design the FDM questionnaire for all projects to be evaluated, find and form a suitable expert group, and ask each expert to define a possible range of values for each improvement measure.

Step B: After assessing the questionnaires, calculate the "most conservative cognitive value" and "most optimistic cognitive value" given by the experts, and calculate the minimum, geometric mean, and maximum values of the remaining most conservative cognitive values. Further, the minimum, geometric mean, and maximum of the most optimistic cognitive values are calculated.

Step C: Based on the results of each evaluation item in the second step, each triangle fuzzy number $C^i = \left(C^i_L, C^i_M, C^i_U\right)$ with the most conservative cognitive value and triangle fuzzy number $O^i = \left(O^i_L, O^i_M, O^i_U\right)$ with the most optimistic cognitive value are drawn in their respective double-triangle fuzzy number maps.

Step D: The consensus level G^i is then calculated. G^i refers to the "value importance level for reaching a consensus" as far as the opinions of the experts are concerned. The higher the value of G^i, the greater is the consensus on a particular assessment criterion among the experts. The consensus level is calculated by the following rules:

(1) If the double-triangle fuzzy numbers do not overlap, it indicates that there is consensus on the opinion interval values among the experts. Therefore, the consensus importance value G^i of the evaluation project is equal to the arithmetic average of C^i_M and O^i_M:

(2) If two triangular fuzzy numbers overlap, then ($C^i_U > O^i_M$) and $Z^i < M^i$, where ($Z^i = C^i_U - O^i_L$), and ($M^i = O^i_M - C^i_M$). In this case, the "value importance that has reached a consensus" assessment item is calculated using Formula (8).

$$G^i = \frac{\left(C^i_U \times O^i_M\right) - \left(O^i_L \times C^i_M\right)}{\left(C^i_U - C^i_M\right) + \left(O^i_M - O^i_L\right)} \tag{8}$$

(3) If two triangular fuzzy numbers overlap, ($C^i_U > O^i_M$) and $Z^i < M^i$, which implies conflicts among the experts' opinions. Thus, steps A to D need to be iterated until convergence is obtained.

Step E: After setting the threshold value of G^i, remove all criteria that did not reach the threshold value.

3.8. VIKOR

The VIKOR method, proposed by Oplikovich, is an eclectic sorting method. While there are many available ways to address management-related issues, the results can be skewed when there are conflicts or substitutions between the indicators. The VIKOR method overcomes this problem and can be used for ranking, sorting, and selecting a set of conflicting alternatives. The advantage of VIKOR is that it can reflect the subjective preferences of the decision makers and determine more valid results than other methods for issues with conflicting criteria as it is characterized by maximizing "group utility" and minimizing "individual regrets" of the "opponent" [95].

Step 1: Standardize the raw matrix data

$$r_{ij} = \frac{u_{ij}}{\sum_{i=1}^{m} u_{ij}}, 1 \le i \le m, 1 \le j \le n, u_{ij} \in B \tag{9}$$

The original matrix data u_{ij} is denoted as r_{ij} after standardization, where B is the decision set. Find positive and negative ideal solutions.

$$f_i^* = \left[\left(max_j f_{ij} | i \in I_1 \right), \left(min_j f_{ij} | i \in I_2 \right) \right], \forall_i \tag{10}$$

$$f_i^- = \left[\left(min_j f_{ij} | i \in I_1 \right), \left(max_j f_{ij} | i \in I_2 \right) \right], \forall_i \tag{11}$$

In the above formula, j is the alternative, i is the evaluation decision, f_{ij} is the performance evaluation value of the alternative that is obtained from the questionnaire, I_1 is the set of benefit evaluation decisions, I_2 is the set of cost evaluation decisions, f_i^* is the positive ideal solution, and f_i^- is the negative ideal solution.

Step 2: Calculate group utility S_j and individual regret R_j

$$S_j = \sum_{i=1}^{n} w_i \frac{\left(f_i^* - f_{ij}\right)}{\left(f_i^* - f_i^-\right)} \tag{12}$$

$$R_j = max_i \left[w_i \frac{\left(f_i^* - f_{ij}\right)}{\left(f_i^* - f_i^-\right)} \right] \tag{13}$$

In Formula (13), w_i is the relative weight among the evaluation decisions. It should be noted that the standardized RPN values calculated from FMEA in the first stage are used as the weights of the first stage of the HoQ, while the calculated results from the first stage of the HoQ are used as the weights of the second stage of the HoQ.

Step 3: Calculate the sorting values Q_j

$$Q_j = v \frac{\left(S_j - S^*\right)}{\left(S^- - S^*\right)} + (1 - v) \frac{\left(R_j - R^*\right)}{\left(R^- - R^*\right)} \tag{14}$$

$$S^* = min\{S_j\} \ , \quad S^- \ = max\{S_j\} \tag{15}$$

$$R^* = min\{R_j\} \ , \quad R^- \ = max\{R_j\} \tag{16}$$

Step 4: The ranking of alternatives was conducted

When the following two conditions were satisfied, this study sorted the alternatives according to the value of Q_j.

(1) Condition 1:

$$Q'' - Q' \geq \frac{1}{J - 1} \tag{17}$$

In Formula (17), Q' represents the value of the scheme ranked first in order of Q values, Q'' represents the value ranked second in order of Q values, and J represents the total number of schemes accepted for evaluation. This formula indicates that when the difference of the benefit ratio Q_j between two adjacent schemes is greater than or equal to the threshold value of $1/(J - 1)$, the scheme with the first rank is determined to be significantly better than that with the second rank. When multiple schemes exist at the same time, the first and second, second and third, as well as third and fourth schemes are sequentially compared for conformance with Formula (17), namely the first condition.

(2) Condition 2:

Acceptable decision reliability: After sorting by Q, the first ranked solution must have a better S value or R value than the second ranked solution. When multiple schemes exist at the same time, the first and second schemes are compared with the third and fourth schemes to check compliance with the second condition.

Step 5: Rule of judgment

If the relationship between the first and second ranked options satisfy both conditions 1 and 2, then the first option is deemed to be the best. If only condition 2 is met, then both options are considered to be best.

4. Empirical Research

The new energy manufacturing company examined in this case study is a leading global organization in the tungsten industry. The company also actively develops new materials for next generation energy requirements, such as lithium-rich manganese bases and 5 V high-voltage materials; the company serves popular global manufacturers such as Panasonic, Samsung, ATL, BYD, and other well-known battery makers. Its market share ranks among the top in the industry. However, according to the data released by Shanghai Stock Exchange on 5 January 2021, the company's performance from 2017 to 2019 fluctuated sharply, and its profitability was dependent largely on government subsidies, which easily caused ripple effects such as the bullwhip effect and poor strain capacity owing to inaccurate forecasts. In the present study, two HoQs (REFs and SCAIs; SCAIs and I4Es) were applied to this new energy manufacturing enterprise. Six supply chain experts from different departments were asked to contribute their expertise towards producing an overall judgment, and the obtained data were translated into the QFD framework.

4.1. First HoQ: Linking Supply Chain REFs to SCAIs

4.1.1. First Stage: Confirming Important REFs Using the KJ Method

1. The main purpose of the KJ method was to identify the REFs of the supply chain of the company in the case study.
2. The host of the KJ activity was determined, and six enterprise members were considered for discussion.
3. We converted the collected REFs into cards before sorting, classifying, and arranging the cards.
4. Through research and discussion, the previously reported 50 REFs of the supply chain were combined and screened for internal affinity, and the 30 possible REFs that are aligned with the actual situation of the company were obtained, as shown in Table 1.

Table 1. REFs screened by KJ method.

No.	REF	No.	REF
1	Natural disasters (extreme weather/earthquake/flood/tsunami/hurricane)	16	Product quality problem
2	Epidemic conditions (health problems/diseases)	17	Procurement risk (uncoordinated procurement, exchange rate risk, procurement policy)
3	Labor strikes and labor shortages	18	Inappropriate incentives within the organization
4	Fire (factory explosion)	19	Supply chain disruption, production disruption
5	Environmental damage (discharge, waste, resource depletion, sewage)	20	Production systems lack flexibility
6	Production planning policy	21	Low visibility data, lack of real-time monitoring
7	Inventory levels (inventory carrying costs, demand, and supply uncertainties)	22	The transport infrastructure is faulty
8	bullwhip effect caused by inaccurate predictions	23	Excessive just-in-time production results
9	facility failures	24	reliance
10	Economic collapse/crisis	25	Production capacity is insufficient
11	Political factors (political decisions/political conflicts/wars/laws)	26	Breach of information Systems (Information Technology)
12	Terrorist attacks, terrorism, piracy	27	Customized design concept (Design Risk)
13	Lack of information coordination in supply chain	28	Cooperation risk, breach of commitment, unethical behavior
14	Supply chain operation capability (survival/management capability)	29	poor strain capacities
15	Supply Chain globalization (Competition among enterprises)	30	Delayed delivery (delivery error, delivery damage)

4.1.2. Second Stage: Obtaining Key REFs and RPNs Using FMEA

According to the records of the KJ method, each REF and possible failure cause from the designed FMEA questionnaire were sorted based on the responses of all experts according to the standard to score the quantitative convenience of numerical analysis; thus, each REF was obtained by analyzing and calculating the RPN as the risk weight in the first stage of the HoQ.

The failure effects and possible causes of each REF were summarized by the expert panel of the KJ method in the previous stage. After studying and discussing the processes of the KJ method, the influences of and reasons for the results were discussed.

Combined with the FMEA, each expert was invited to evaluate one to five points. Finally, the values of the six valid questionnaires were analyzed and calculated. First, Formula (1) was used to calculate the ripple effect RPN value from the evaluation results of each expert. Then, the RPN values of each expert were then summed, averaged, and sorted from high to low. Finally, based on the rankings of the obtained RPNs, the top 15 REFs are listed, which are the key REFs of the company's supply chain, as shown in Table 2.

Table 2. Key REFs and weights were ranked using FMEA method.

No.	REFs	RPN	Sort
R1	Natural disasters (extreme weather/earthquake/flood/Tsunami/hurricane)	20.22	4
R2	Fire (plant explosion)	13.00	13
R3	Inventory level (inventory holding cost, demand, and supply uncertainty)	13.78	11
R4	bullwhip effect caused by inaccurate predictions	34.56	1
R5	facility failures	21.56	2
R6	Economic collapse/crisis	16.56	8
R7	Political factors (political decisions/political conflicts/wars/laws)	13.44	12
R8	Lack of information coordination in supply chain	16.78	7
R9	Supply chain operation capability (survival/ management capability)	15.11	10
R10	Supply chain disruption, production disruption	12.67	15
R11	Low visibility data, lack of real-time monitoring	12.89	14
R12	The transport infrastructure is faulty	17.67	6
R13	Cooperation risk, breach of commitment, unethical behavior	15.56	9
R14	poor strain capacities	21.11	3
R15	Delayed delivery (delivery error and delivery process damage)	18.89	5

From the results, the top five REFs of RPNs are as follows: R4, R5, R14, R1, and R15. The above factors are roughly consistent with those assessed for the actual situation of the anonymous new energy manufacturing enterprise. Therefore, the company should formulate a response plan to mitigate the ripple effects of its supply chain as soon as possible, improve the agility of the enterprise supply chain, and cope with occurrence and adverse consequences of ripple effects.

4.1.3. Third Stage: Using DEMATEL to Screen Key SCAIs

The Decision-making Trial and Evaluation Laboratory (DEMATEL) method was used to screen 38 SCAIs previously, as shown in Table 3.

Table 3. SCAIs.

No.	SCAIs	No.	SCAIs
A1	Integration of supply chain partners	A17	Improving customer service levels and satisfaction.
A2	Work with suppliers to plan purchasing, manufacturing, and logistics activities	A18	Order driven rather than forecast driven
A3	Long-term cooperation with partners to strengthen trust	A19	Provide customized products
A4	Establish partnerships and jointly develop core competencies	A20	Quick customer response
A5	Choose partners with good performance and basic capabilities	A21	Provide customers with high value-added products
A6	Actively build a shared information platform with partners	A22	Improve delivery reliability
A7	Jointly promote modular production, can quickly respond to market demand	A23	Improve delivery reliability
A8	Suppliers manage inventory, have common inventory control objectives, and share inventory information	A24	Improve delivery reliability
A9	Establish a team operation mode of cross—department cooperation	A25	Reduce facility resetting and switching time and increase the number of products produced
A10	Information data integration, improve data accuracy	A26	Reduce facility resetting and switching time and increase the number of products produced
A11	Using information technology	A27	Introduce appropriate information technology and incorporate new hardware, software, and new products
A12	Information transparency and visualization of supply chain to quickly respond to customer needs	A28	Reduce production time for new products
A13	Improve market sensitivity/respond to changing external environment and market needs/respond to market needs	A29	Reduce production time for new products
A14	Timely detection of threats in the environment/enhance the competitiveness of the enterprise to the market and environment	A30	Quality improvement (Improve the quality of all supply chain processes while reducing costs, increasing resource utilization, and increasing processing efficiency)
A15	Collect customer and competitor market information to develop strategies	A31	Shorten the lead time of rapid response/implementation of synchronous engineering, shorten the development cycle time
A16	Shorten the lead time and increase the frequency of new product introduction to market	A32	Employees' trust and support for senior managers

A DEMATEL questionnaire was designed for the 38 SCAIs and sent to six experts, who were asked to judge the interactions between the indicators according to specific operation statuses and personal experiences of the anonymous new energy manufacturing enterprise on an influence scale of zero to five points.

The questionnaires filled by the experts were assessed according to Formula (1) and were then integrated with the original matrix. After summing each row and column, the maximum value among the summed rows and columns was selected for normalization of the matrix; this maximum value was obtained as 115.53. By substituting the original matrix into Formula (2), the value of λ was obtained as λ = 0.008656; the direct relation matrix X can then be obtained by multiplying the value of λ with the original matrix. The difference between the identity and direct relation matrices was obtained, and the inverse of this difference matrix, $(I - X)^{-1}$, was calculated; then, X and $(I - X)^{-1}$ were multiplied, as shown in Formula (3), to calculate the total influence matrix T, sum of each column and row of the total influence matrix T, $D + R$, and $D - R$, according to Formulas (4) and (5); the corresponding weights were then calculated according to Formulas (6) and (7). From the results, the weights were sorted, and the top 15 agility indicators were selected. These results are shown in Table 4.

Table 4. Key agility indicators and weight values.

No.	SCAIs	Weight
A1	Long-term cooperation with partners to strengthen trust	0.032
A2	Establish partnerships and jointly develop core competencies	0.031
A3	Actively build a shared information platform with partners	0.028
A4	Using information technology	0.029
A5	Information transparency and visualization of supply chain to quickly respond to customer needs	0.030
A6	Improving customer service levels and satisfaction.	0.028
A7	Shorten the lead time and increase the frequency of new product introduction to market	0.029
A8	Improve delivery reliability	0.030
A9	Reduce the complexity of product design processes	0.029
A10	Create a virtual enterprise	0.031
A11	Reduce facility resetting and switching time and increase the number of products produced	0.032
A12	Enhance technological awareness and information technology	0.029
A13	Introduce appropriate information technology and incorporate new hardware, software, and new products	0.030
A14	Reduce production time for new products	0.035
A15	Improve logistics capability/purchasing capability/establish agile logistics	0.034

4.1.4. Fourth Stage: Evaluating the Interdependence Matrix between REFs (Rm)

As the REFs themselves are mutually influential, a correlation analysis was conducted before VIKOR ranking. For the above 15 REFs screened by the KJ method and FMEA, a questionnaire was designed and issued with a score range of zero to three points based on the correlation evaluation scale. Six valid questionnaires were distributed and retrieved before importing the results into the HoQ of the first stage, calculated as arithmetic mean values. These results are shown in Table 5.

4.1.5. Fifth Stage: Evaluating the Interdependence Matrix among SCAIs (Am)

The FDM was used to screen 15 key agility indicators that are consistent with the real-world condition of the anonymous new energy manufacturing enterprise. Similar to the previous step, a correlation analysis was carried out for the 15 key agility indicators, and scores were allocated on a scale of zero to three points based on the evaluations. The questionnaire was designed and reused, and the arithmetic mean values were calculated and imported into the HoQ. These results are shown in Table 6.

Table 5. REFs correlation matrix Rm.

R × R	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15
R1	0.00	0.50	1.25	1.00	1.50	1.25	0.75	0.75	0.25	2.50	1.00	2.00	2.00	1.50	2.75
R2	0.50	0.00	1.00	1.25	1.50	1.00	0.75	1.00	1.25	2.00	1.25	1.25	2.25	0.50	2.50
R3	0.00	0.25	0.00	0.75	0.50	0.50	0.25	1.00	1.50	1.25	1.50	0.75	0.75	2.25	1.50
R4	0.50	0.75	1.50	0.00	1.00	1.00	0.75	1.50	1.25	1.50	1.25	0.25	1.00	2.00	0.75
R5	0.25	0.75	1.25	1.00	0.00	1.00	0.00	1.75	1.75	2.50	1.25	2.00	1.75	1.75	2.25
R6	0.50	0.25	2.25	1.75	0.75	0.00	1.50	1.00	1.75	2.25	0.25	0.00	2.00	2.25	2.00
R7	0.00	0.75	0.75	1.75	1.00	1.25	0.00	0.75	1.00	2.50	0.50	2.00	2.25	2.00	1.75
R8	0.25	0.50	1.00	2.25	1.00	0.75	0.00	0.00	1.50	1.25	1.00	0.50	2.00	2.00	1.25
R9	0.75	0.00	1.00	1.50	1.00	0.75	0.00	1.50	0.00	1.75	1.50	0.75	1.75	2.50	2.00
R10	0.00	0.25	0.75	0.50	0.50	1.00	0.50	1.00	1.75	0.00	0.50	1.00	1.75	1.25	2.50
R11	0.50	0.25	1.50	2.00	0.00	1.00	0.75	2.25	1.50	2.25	0.00	0.75	1.50	2.75	1.25
R12	0.75	0.75	0.75	1.25	1.25	0.75	0.00	1.25	0.50	2.75	0.00	0.00	1.00	1.50	2.00
R13	0.75	0.75	0.50	1.25	0.00	0.75	0.50	1.00	2.25	2.50	1.75	0.50	0.00	1.25	1.25
R14	1.00	0.25	1.75	2.00	0.75	0.75	1.00	1.25	2.00	2.50	1.25	0.50	1.25	0.00	1.50
R15	0.75	0.50	1.00	2.00	0.50	0.75	0.50	0.75	1.00	2.00	0.50	0.25	2.50	1.25	0.00

Table 6. SCAIs correlation matrix Am.

A × A	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
A1	0.00	3.00	2.00	0.75	1.75	1.50	0.50	1.75	0.25	0.00	1.00	1.50	1.75	1.25	2.00
A2	2.75	0.00	2.50	1.75	2.50	2.00	1.25	2.00	1.25	0.75	1.25	1.00	2.25	1.50	1.25
A3	2.25	2.75	0.00	2.00	2.50	2.25	1.00	1.75	2.00	0.50	1.00	2.00	1.75	0.50	1.75
A4	2.00	1.25	2.25	0.00	2.75	2.50	1.00	2.25	1.00	1.50	1.00	2.25	1.75	1.50	1.00
A5	2.00	2.25	2.25	2.25	0.00	1.50	1.50	1.50	1.50	0.75	2.00	2.00	2.00	1.25	1.25
A6	1.25	2.00	1.50	1.25	0.75	0.00	1.75	2.00	2.00	1.25	2.00	1.50	1.75	2.50	1.75
A7	1.25	2.00	1.25	1.25	1.00	2.00	0.00	3.00	2.50	1.75	2.00	1.50	2.50	2.50	2.75
A8	1.75	1.75	1.25	1.50	2.25	1.50	0.50	0.00	2.00	1.00	2.00	1.25	1.50	1.50	2.00
A9	1.25	1.50	1.75	1.00	0.75	1.50	2.50	2.00	0.00	0.75	1.75	0.25	1.50	0.75	1.00
A10	0.75	0.25	1.00	2.00	1.75	1.50	0.25	1.25	0.50	0.00	1.00	2.00	0.75	0.25	0.25
A11	0.00	0.50	0.00	1.50	0.75	1.00	1.25	1.50	0.50	0.75	0.00	1.50	1.50	1.00	2.00
A12	2.00	1.50	2.25	2.75	1.75	1.25	1.00	1.25	0.00	2.50	0.75	0.00	2.75	1.75	1.50
A13	1.50	2.00	2.50	3.00	1.25	1.75	1.00	2.25	0.25	0.25	1.50	1.50	0.00	2.25	1.25
A14	1.00	1.25	0.00	1.00	1.75	1.75	1.75	0.75	0.75	0.75	1.25	0.75	0.50	0.00	1.50
A15	2.00	0.75	1.50	1.50	1.00	2.25	1.00	3.00	0.50	0.75	0.50	1.00	1.50	0.75	0.00

4.1.6. Sixth Stage: Evaluating the Relationship Matrix between REFs and SCAIs

In the HoQ analysis, the correlations among the factor indexes must be taken into account, so the product of the correlation matrix was used as the result of the initial matrix in this study. According to the literature summary in Section 2, it is noted that each REF affects another factor that has its own correlation characteristics. Therefore, the ripple effect association matrix must be included in the comprehensive consideration of the initial matrix. For correlation analysis between the ripple effect risk factors of the supply chain and SCAIs, the same evaluation scale was used to evaluate the corresponding scores; then, the arithmetic mean was calculated, and the correlation matrix R × A of the REFs and SCAIs was obtained, as shown in Table 7.

Once the analysis and relevance of the REFs and SCAIs as well as their correlation were complete, the REFs' relation matrix R was multiplied by R × A and SCAIs' correlation matrix A to obtain the initial matrix Q_{M1}, whose results are shown in Table 8.

Table 7. The correlation matrix R × A of REFs and SCAIs.

R × A	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
R1	0.25	1.50	0.75	1.25	0.75	0.75	1.75	1.50	1.00	1.00	1.00	0.75	1.25	0.25	1.50
R2	1.25	1.50	0.50	1.50	1.00	0.75	2.50	1.50	1.25	1.50	1.00	1.50	0.75	0.75	1.00
R3	1.75	1.50	0.50	2.00	1.75	1.75	2.75	2.50	0.75	1.50	1.50	1.25	1.00	1.00	2.00
R4	1.50	2.00	2.25	2.00	2.00	2.50	1.75	2.00	0.50	2.25	0.50	1.50	1.50	2.00	2.00
R5	1.00	0.75	1.75	1.25	1.00	1.00	2.25	2.25	1.00	1.75	1.50	0.50	1.50	1.50	1.25
R6	1.50	1.50	1.25	2.25	2.50	2.00	2.00	1.75	0.75	1.75	1.75	2.00	0.75	2.25	2.00
R7	2.25	2.00	2.00	1.00	1.75	1.75	2.00	2.25	0.75	1.75	1.25	1.75	1.25	1.50	2.00
R8	2.50	2.50	2.75	2.50	2.00	1.50	2.00	2.25	1.25	0.50	1.00	1.50	1.25	1.25	1.25
R9	1.50	2.00	1.50	1.25	1.50	2.25	3.00	2.25	1.25	1.25	1.75	2.50	1.25	0.75	1.75
R10	2.25	2.75	2.00	1.75	2.50	2.00	2.50	3.00	1.25	1.25	0.50	1.00	1.50	2.00	2.25
R11	2.00	1.75	2.50	1.25	2.75	2.25	2.25	1.25	2.00	2.00	1.25	1.00	0.75	1.25	0.75
R12	1.75	0.50	0.25	1.25	2.00	1.00	2.25	2.50	2.00	1.25	1.25	1.00	0.75	1.25	2.00
R13	3.00	2.50	1.75	1.25	2.75	2.75	2.25	1.75	1.25	1.50	0.50	1.00	1.00	1.00	0.50
R14	1.50	2.50	2.25	0.75	2.00	1.75	2.00	1.75	1.50	2.00	1.50	2.00	1.75	1.25	2.50
R15	1.50	1.00	0.50	0.50	1.25	1.50	1.75	2.25	0.75	0.25	2.00	1.00	0.75	1.50	1.25

Table 8. Integrated relational matrix by considering three matrices (Q_{M1}).

Q_{M1}	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
R1	659.81	706.75	665.13	689.28	669.30	725.52	462.39	782.63	506.22	402.78	601.30	613.59	739.70	599.95	665.55
R2	626.55	673.14	630.95	653.02	636.70	685.45	437.38	742.27	483.78	383.09	570.78	583.47	703.73	572.73	634.30
R3	466.02	491.27	463.58	489.27	467.42	504.83	325.22	549.34	350.44	282.44	415.30	424.22	519.66	418.06	462.06
R4	542.86	569.34	543.69	564.83	548.95	592.05	372.92	642.16	409.19	330.66	482.69	497.23	606.52	489.81	538.41
R5	689.73	731.28	697.36	714.17	694.09	750.80	479.59	815.14	523.11	423.23	621.55	631.05	774.81	627.08	689.20
R6	674.55	706.44	675.94	702.59	682.22	729.78	459.09	792.78	511.25	408.03	600.69	615.77	748.63	611.63	667.39
R7	655.13	692.80	659.44	680.95	660.36	714.03	454.81	772.42	496.77	397.84	591.22	602.20	729.02	591.39	650.02
R8	551.23	578.75	551.88	577.75	554.91	596.42	380.61	650.91	418.38	334.22	494.64	507.59	612.17	498.27	544.33
R9	599.97	633.84	598.50	623.34	605.48	652.72	417.05	705.72	454.09	358.03	537.13	552.89	663.48	536.50	592.59
R10	452.83	486.98	459.86	479.13	459.03	494.56	319.13	541.42	347.22	284.86	411.00	419.11	517.94	420.59	464.45
R11	687.25	712.45	685.73	707.77	691.91	741.27	467.34	801.30	511.83	413.56	603.86	620.63	756.89	613.08	668.23
R12	517.56	538.95	513.81	532.83	525.00	563.25	353.00	604.39	391.09	311.13	459.45	471.56	568.19	463.38	509.47
R13	551.48	573.00	548.25	570.66	553.41	596.30	378.36	647.11	413.88	336.13	488.00	498.59	611.91	494.19	541.28
R14	639.16	673.14	640.19	658.28	648.27	694.25	436.72	751.45	488.38	389.80	572.69	587.94	711.05	579.66	634.80
R15	534.84	558.42	536.73	549.72	539.16	575.77	362.89	624.81	403.56	318.06	476.38	489.50	588.28	478.47	520.02

4.1.7. Seventh Stage: Prioritizing Key SCAIs

The correlation degree and rankings of the REFs and SCAIs were obtained by the VIKOR method. The calculation process of the grey VIKOR method is as follows:

A. Normalize the original data: The initial matrix Q_{M1} is standardized such that the data are within the interval [0, 1] after standardization. The standardized initial matrix Q_{M2} is shown in Table 9.

B. Find the positive and negative ideal solutions: The data of the standardized initial matrix Q_{M2} were substituted in Formulas (10) and (11), and the positive ideal solutions f_i^* and negative ideal solutions f_i^- of each SCAI were calculated, as shown in Table 10.

C. Calculate group utility S_j and individual regret R_j: The RPNs of the REFs obtained by FMEA were standardized, as shown in Table 11.

Table 9. Integrated evaluation matrix (Q_{M2}) after normalization (Q_{M1}).

Q_{M2}	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
R1	0.0052	0.0056	0.0053	0.0055	0.0053	0.0058	0.0037	0.0062	0.0040	0.0032	0.0048	0.0049	0.0059	0.0048	0.0053
R2	0.0050	0.0053	0.0050	0.0052	0.0051	0.0054	0.0035	0.0059	0.0038	0.0030	0.0045	0.0046	0.0056	0.0045	0.0050
R3	0.0037	0.0039	0.0037	0.0039	0.0037	0.0040	0.0026	0.0044	0.0028	0.0022	0.0033	0.0034	0.0041	0.0033	0.0037
R4	0.0043	0.0045	0.0043	0.0045	0.0044	0.0047	0.0030	0.0051	0.0032	0.0026	0.0038	0.0039	0.0048	0.0039	0.0043
R5	0.0055	0.0058	0.0055	0.0057	0.0055	0.0060	0.0038	0.0065	0.0041	0.0034	0.0049	0.0050	0.0061	0.0050	0.0055
R6	0.0054	0.0056	0.0054	0.0056	0.0054	0.0058	0.0036	0.0063	0.0041	0.0032	0.0048	0.0049	0.0059	0.0049	0.0053
R7	0.0052	0.0055	0.0052	0.0054	0.0052	0.0057	0.0036	0.0061	0.0039	0.0032	0.0047	0.0048	0.0058	0.0047	0.0052
R8	0.0044	0.0046	0.0044	0.0046	0.0044	0.0047	0.0030	0.0052	0.0033	0.0027	0.0039	0.0040	0.0049	0.0040	0.0043
R9	0.0048	0.0050	0.0047	0.0049	0.0048	0.0052	0.0033	0.0056	0.0036	0.0028	0.0043	0.0044	0.0053	0.0043	0.0047
R10	0.0036	0.0039	0.0036	0.0038	0.0036	0.0039	0.0025	0.0043	0.0028	0.0023	0.0033	0.0033	0.0041	0.0033	0.0037
R11	0.0055	0.0057	0.0054	0.0056	0.0055	0.0059	0.0037	0.0064	0.0041	0.0033	0.0048	0.0049	0.0060	0.0049	0.0053
R12	0.0041	0.0043	0.0041	0.0042	0.0042	0.0045	0.0028	0.0048	0.0031	0.0025	0.0036	0.0037	0.0045	0.0037	0.0040
R13	0.0044	0.0045	0.0043	0.0045	0.0044	0.0047	0.0030	0.0051	0.0033	0.0027	0.0039	0.0040	0.0049	0.0039	0.0043
R14	0.0051	0.0053	0.0051	0.0052	0.0051	0.0055	0.0035	0.0060	0.0039	0.0031	0.0045	0.0047	0.0056	0.0046	0.0050
R15	0.0042	0.0044	0.0043	0.0044	0.0043	0.0046	0.0029	0.0050	0.0032	0.0025	0.0038	0.0039	0.0047	0.0038	0.0041

Table 10. Positive ideal solution and negative ideal solution of SCAIs.

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
f_i^*	0.0055	0.0058	0.0055	0.0057	0.0055	0.0060	0.0038	0.0065	0.0041	0.0034	0.0049	0.0050	0.0061	0.0050	0.0055
f_i^-	0.0036	0.0039	0.0036	0.0038	0.0036	0.0039	0.0025	0.0043	0.0028	0.0022	0.0033	0.0033	0.0041	0.0033	0.0037

Table 11. Relative weights of RPNs after normalization.

	R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15
RPN	20.22	13.00	13.78	34.56	21.56	16.56	13.44	16.78	15.11	12.67	12.89	17.67	15.56	21.11	18.89
Wi	0.0767	0.0493	0.0522	0.1310	0.0817	0.0628	0.0510	0.0636	0.0573	0.0480	0.0489	0.0670	0.0590	0.0800	0.0716

These results belong to the HoQ framework. In Formulas (12) and (13), w_i is the relative weight of each evaluation criterion, namely the standardized RPN, and the group utility S_j and individual regret R_j wee calculated by substituting the weight values shown in Table 11 in Formulas (12) and (13), as shown in Table 12.

Table 12. Results of group utility S_j and individual regret R_j.

REFs	Weight	SCAIs														
		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
R1	0.0767	0.0097	0.0077	0.0104	0.0081	0.0081	0.0076	0.0082	0.0091	0.0074	0.0111	0.0074	0.0063	0.0105	0.0099	0.0080
R2	0.0493	0.0131	0.0117	0.0138	0.0128	0.0120	0.0126	0.0130	0.0131	0.0110	0.0141	0.0119	0.0111	0.0136	0.0128	0.0119
R3	0.0522	0.0493	0.0513	0.0514	0.0500	0.0504	0.0501	0.0502	0.0507	0.0513	0.0522	0.0512	0.0510	0.0519	0.0522	0.0522
R4	0.1310	0.0812	0.0868	0.0848	0.0832	0.0809	0.0812	0.0871	0.0828	0.0848	0.0861	0.0864	0.0827	0.0858	0.0860	0.0870
R5	0.0817	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
R6	0.0628	0.0040	0.0064	0.0057	0.0031	0.0032	0.0051	0.0080	0.0051	0.0042	0.0068	0.0062	0.0045	0.0064	0.0046	0.0060
R7	0.0510	0.0074	0.0080	0.0081	0.0072	0.0073	0.0073	0.0079	0.0080	0.0076	0.0092	0.0073	0.0069	0.0091	0.0087	0.0088
R8	0.0636	0.0372	0.0397	0.0390	0.0369	0.0377	0.0383	0.0392	0.0382	0.0379	0.0402	0.0383	0.0371	0.0403	0.0392	0.0406
R9	0.0573	0.0217	0.0228	0.0238	0.0221	0.0216	0.0219	0.0223	0.0229	0.0225	0.0265	0.0230	0.0211	0.0248	0.0248	0.0244
R10	0.0480	0.0480	0.0480	0.0480	0.0480	0.0480	0.0480	0.0480	0.0480	0.0480	0.0472	0.0480	0.0480	0.0480	0.0474	0.0475
R11	0.0489	0.0005	0.0038	0.0024	0.0013	0.0005	0.0018	0.0037	0.0025	0.0031	0.0034	0.0041	0.0024	0.0034	0.0033	0.0045
R12	0.0670	0.0487	0.0527	0.0518	0.0517	0.0482	0.0490	0.0528	0.0516	0.0503	0.0533	0.0516	0.0504	0.0539	0.0525	0.0530
R13	0.0590	0.0344	0.0382	0.0370	0.0360	0.0353	0.0356	0.0372	0.0362	0.0366	0.0365	0.0374	0.0369	0.0374	0.0375	0.0384
R14	0.0800	0.0171	0.0190	0.0193	0.0190	0.0156	0.0177	0.0214	0.0186	0.0158	0.0190	0.0186	0.0163	0.0199	0.0182	0.0192
R15	0.0716	0.0468	0.0507	0.0484	0.0501	0.0472	0.0489	0.0521	0.0498	0.0487	0.0535	0.0494	0.0478	0.0520	0.0509	0.0533
S_j	—	0.4193	0.4470	0.4439	0.4297	0.4159	0.4251	0.4512	0.4366	0.4292	0.4591	0.4407	0.4225	0.4570	0.4481	0.4548
R_j	—	0.0812	0.0868	0.0848	0.0832	0.0809	0.0812	0.0871	0.0828	0.0848	0.0861	0.0864	0.0827	0.0858	0.0860	0.0870

D. Calculate the benefit ratio Q_j: The last step involves calculating the interest ratio Q_j. In Formula (14), where v is the decision-making mechanism coefficient. When $v > 0.5$, it is implied that the final decision is made based on the majority of all the decisions;

when $v = 0.5$, it means that the final decision is made on the basis of approval; when $v < 0.5$, it means that the final decision is made on the basis of rejection. After careful consideration and discussion, it was decided that v would be set to 0.5 in this study to maximize group utility and minimize individual regret simultaneously. The results calculated according to Formulas (14)–(16) are shown in Table 13. In Formulas (15) and (16), $max\{S_j\}$ is the maximum group utility, $min\{R_j\}$ is the minimum individual regret, and the significance of Q_j is the profit ratio produced by j schemes. The schemes were sorted according to the results in Table 13. Further, based on the two conditions listed in the methods in Section 3, Q_j was substituted into Formula (17). If both conditions are true, the schemes can be sorted by comparing the sizes of Q_j (minimum value).

Table 13. Calculation results of benefit ratio Q_j.

	SCAIs														
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12**	**A13**	**A14**	**A15**
Q_j	0.0657	0.8398	0.6363	0.3490	0.0000	0.1292	0.9086	0.3927	0.4742	0.9237	0.7320	0.2236	0.8739	0.7880	0.9408
	$S^* = 0.4159, S^- = 0.4591, R^* = 0.0809, R^- = 0.0871, v = 0.5$														

E. Sort SCAIs: Q_j belongs to the minimum value index, and the smaller the value is, the better is the index. Therefore, $1 - Q_j$ was taken as the weight of the SCAIs in this study and imported into the second stage of the HoQ. The ranking results of the SCAIs are shown in Table 14 and belong to the HoQ framework in Figure 1 (3). Thus far, the analysis of the first stage of HoQ is complete. Now, the constructed model of the first stage of the HoQ is shown in Figure 3, which is a result of the quality function expansion of the first stage.

Table 14. Sorting results of SCAIs.

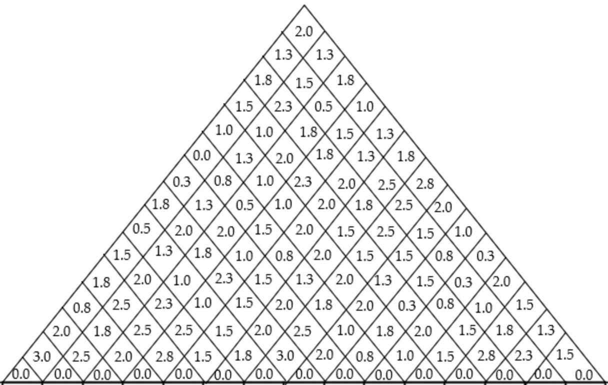
	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**	**A10**	**A11**	**A12**	**A13**	**A14**	**A15**
S_j	0.4193	0.4470	0.4439	0.4297	0.4159	0.4251	0.4512	0.4366	0.4292	0.4591	0.4407	0.4225	0.4570	0.4481	0.4548
R_j	0.0812	0.0868	0.0848	0.0832	0.0809	0.0812	0.0871	0.0828	0.0848	0.0861	0.0864	0.0827	0.0858	0.0860	0.0870
Q_j	0.0657	0.8398	0.6363	0.3490	0.0000	0.1292	0.9086	0.3927	0.4742	0.9237	0.7320	0.2236	0.8739	0.7880	0.9408
S_j Ranking	2	10	9	6	1	4	12	7	5	15	8	3	14	11	13
R_j Ranking	3	13	7	6	1	2	15	5	8	11	12	4	9	10	14
Q_j Ranking	2	11	8	5	1	3	13	6	7	14	9	4	12	10	15
$1 - Q_j$	0.9343	0.1602	0.3637	0.6510	1.0000	0.8708	0.0914	0.6073	0.5258	0.0763	0.2680	0.7764	0.1261	0.2120	0.0592

4.2. Second HoQ: Linking SCAIs to I4Es

First Stage: Using FDM to Screen the Index of I4Es

A total of 52 I4Es summarized from previously published works were screened using the FDM. First, a fuzzy Delphi questionnaire was designed for the 52 promotional measures and sent to six experts; they were each asked to assign minimum and maximum values over a score range of 0–10 for each measure in accordance with actual conditions in an anonymous new energy manufacturing enterprise. After collecting the results of the questionnaire, high outliers beyond two standard deviations were removed. It was observed that there were no extreme values and that all the questionnaire data were within the range of two standard deviations. Thus, the data of the above I4Es are all within two standard deviations. The triangular fuzzy number was then calculated according to the FDM.

In the most conservative sense, C_L^i is the minimum among the minimum values, C_M^i is the geometric average of the minimum values, and C_U^i is the maximum among the minimum values. In the most optimistic sense, O_L^i is the minimum among the maximum values, O_M^i is the geometric average of the maximum values, and O_U^i is the maximum among the maximum values. Thus far, the data analysis of the questionnaire is complete. Based on the results, the final consensus importance value G^i is determined by judgment conditions, and the ranking structure of the measures is improved, as shown in Table 15.



															SCAIs / REFs	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15	Wi
0.00	0.50	1.25	1.00	0.50	1.25	0.75	0.75	0.25	2.50	1.00	2.00	2.00	1.50	2.75	R1	0.75	1.50	0.75	1.25	0.75	0.75	1.75	1.50	1.00	1.00	1.00	0.75	1.25	0.25	1.50	0.0767
0.50	0.00	1.00	1.25	0.00	1.00	0.75	1.00	1.25	2.00	1.25	1.25	2.25	0.50	2.50	R2	1.25	1.50	0.50	1.50	1.00	0.75	2.50	1.50	1.25	1.50	1.00	1.50	0.75	0.75	1.00	0.0493
0.00	0.25	0.00	0.75	0.25	0.50	0.25	1.00	1.50	1.25	1.50	0.75	0.75	2.25	1.50	R3	1.75	1.50	0.50	2.00	1.75	1.75	2.75	2.50	0.75	1.50	1.50	1.25	1.00	1.00	2.00	0.0522
0.50	0.75	1.50	0.00	0.75	1.00	0.75	1.50	1.25	1.50	1.25	0.25	1.00	2.00	0.75	R4	1.50	2.00	2.25	2.00	2.00	2.50	1.75	2.00	0.50	2.25	0.50	1.50	1.50	2.00	1.25	0.1310
0.25	0.75	1.25	1.00	0.00	1.00	0.00	1.75	1.75	2.50	1.25	2.00	1.75	1.75	2.25	R5	1.00	0.75	1.75	1.25	1.00	1.00	2.25	2.25	1.00	1.75	1.50	0.50	1.50	1.50	2.00	0.0817
0.50	0.25	2.25	1.75	0.25	0.00	1.50	1.00	1.75	2.25	0.25	0.00	2.00	2.25	2.00	R6	1.50	1.50	1.25	2.25	2.50	2.00	2.00	1.75	0.75	1.75	1.75	2.00	0.75	2.25	2.00	0.0628
0.00	0.75	0.75	1.75	0.75	1.25	0.00	0.75	1.00	2.50	0.50	2.00	2.25	2.00	1.75	R7	2.25	2.00	2.00	1.00	1.75	1.75	2.00	2.25	0.75	1.75	1.25	1.75	1.25	1.50	1.25	0.0510
0.25	0.50	1.00	2.25	0.50	0.75	0.00	0.00	1.50	1.25	1.00	0.50	2.00	2.00	1.25	R8	2.50	2.50	2.75	2.50	2.00	1.50	2.00	2.25	1.25	0.50	1.00	1.25	1.25	1.25	1.75	0.0636
0.75	0.00	1.00	1.50	0.00	0.75	0.00	1.50	0.00	1.75	1.50	0.75	1.75	2.50	2.00	R9	1.50	2.00	1.50	1.25	1.50	2.25	3.00	2.25	1.25	1.25	1.75	2.00	1.25	0.75	2.25	0.0573
0.00	0.25	0.75	0.50	0.25	1.00	0.50	1.00	1.75	0.00	0.50	1.00	1.75	1.25	2.50	R10	2.25	2.75	2.00	1.75	2.50	2.00	2.50	3.00	1.25	1.25	0.50	1.75	1.50	2.00	0.75	0.0480
0.50	0.25	1.50	2.00	0.25	1.00	0.75	2.25	1.50	2.25	0.00	0.75	1.50	2.75	1.25	R11	2.00	1.75	2.50	1.25	2.75	2.25	2.25	1.25	2.00	2.00	1.25	1.50	0.75	1.25	2.00	0.0489
0.75	0.75	0.75	1.25	0.75	0.75	0.00	1.25	0.50	2.75	0.00	0.00	1.00	1.50	2.00	R12	1.75	0.50	0.25	1.25	2.00	1.00	2.25	2.50	2.00	1.25	1.25	2.50	0.75	1.25	0.50	0.0670
0.75	0.75	0.50	1.25	0.75	0.75	0.50	1.00	2.25	2.50	1.75	0.50	0.00	1.25	1.25	R13	3.00	2.50	1.75	1.25	2.75	2.75	2.25	1.75	1.25	1.50	0.50	1.00	1.00	1.00	0.50	0.0590
1.00	0.25	1.75	2.00	0.25	0.75	1.00	1.25	2.00	2.50	1.25	0.50	1.25	0.00	1.50	R14	1.50	2.50	2.25	0.75	2.00	1.75	2.00	1.75	1.50	2.00	1.50	1.00	1.75	1.25	2.50	0.0800
0.75	0.50	1.00	2.00	0.50	0.75	0.50	0.75	1.00	2.00	0.50	0.25	2.50	1.25	0.00	R15	1.50	1.00	0.50	0.50	1.25	1.5	1.75	2.25	0.75	0.25	2.00	1.00	0.75	1.50	1.25	0.0716
															(1−Qj) Weight	0.9343	0.1602	0.3637	0.6510	1.0000	0.8708	0.0914	0.6073	0.5258	0.0763	0.2680	0.7764	0.1261	0.2120	0.0591	

Figure 3. First HoQ between REFs and SCAIs.

Table 15. Fuzzy Delphi method (FDM) results of key I4Es.

No.	I4Es	G^i	Rank	Selected I4Es
1	Top management support and leadership, change leadership style	6.5000	15	I1
2	Infrastructure (Internet, CPS, cloud computing, etc.)	8.2857	1	I2
3	Customer participation, customer design and manufacturing process integration, maintenance of customer relationship	5.8000	37	
4	Ensuring data privacy and security	7.2609	6	I3
5	Financial resources	6.7436	8	I4
6	Manage employee response to change, technology upgrade and operational improvement (Change management)	6.0000	31	
7	Enterprise strategic management, strategic coordination between the adoption of new technology and expectations	6.0000	28	
8	Organizational culture, digital culture	7.0000	7	
9	Focus on customer demand innovation solutions and products, strengthen service	5.4211	45	
10	Use digital technology for new product innovation, intelligent	6.6364	11	I5
11	Employees' willingness to use new technologies and their comfort in using them	6.0000	35	
12	New technology for security, dealing with insecurity, security holes	6.5238	13	I6
13	Compatibility with existing technology, technology platform integration	6.7143	9	I7

Table 15. *Cont.*

No.	I4Es	G^i	Rank	Selected I4Es
14	Horizontal and vertical integration of value chain	5.5600	40	
15	Existing technical skill level within the organization, IT information technology structure	6.7143	9	I8
16	Competition and pressure from business partners, market competition pressure	6.2778	23	
17	Good supply chain management and collaboration keep the organization's goals clear and focused	6.0400	27	
18	Availability of collaboration tools	5.6667	38	
19	Organizational structure changes, organization digitization	6.3500	20	
20	The organization maintains the sustainability of existing operations	6.3333	21	
21	Global engagement, connections on a global scale	5.5714	39	
22	Process modularization or dynamic design of business processes	5.4348	44	
23	Hardware and software connectivity, Internet, and machine production convergence	6.0000	28	
24	Improving IT infrastructure for big data management	7.4000	3	I9
25	Team work and expertise, lean production experience	6.0000	30	
26	Investing in and using new Industry 4.0 equipment.	7.5926	2	I10
27	Support from academic researchers	5.8462	36	
28	Government and policy support	7.3043	4	I11
29	Direct information sharing and communication among supply chain members	6.5238	13	I12
30	Supply chain digitization	6.1200	25	
31	Provide appropriate training and skills education to employees	5.4444	43	
32	Empowering employees, allowing them autonomy and innovation	6.0000	31	
33	Employee compliance, commitment, and participation	5.3125	47	
34	Development of data and simulation tools	7.2727	5	I13
35	Improve IT standards and implement I4.0 regulations	6.4762	17	
36	Global standards and data sharing protocols	6.3333	22	
37	product lifecycle management	6.2105	24	
38	Virtual testing and simulation	5.0000	49	
39	Fully integrate enterprise resource planning	6.0000	31	
40	Real-time inventory tracking, real-time data collection and analysis	6.4500	18	
41	Raw material and production traceability	5.4783	41	
42	Adopting digital transformation investments to improve economic efficiency	6.5000	15	I14
43	Guarding against legal risks	6.5938	12	I15
44	State economic security	6.1111	26	
45	Cost and expense management	6.3636	19	
46	Companies and institutions work together	6.0000	31	
47	Clean development mechanism, low waste	5.0000	49	
48	Housing and service infrastructure maintenance	4.5238	51	
49	Occupational health and safety	5.3636	46	
50	Scale of company	5.4444	42	
51	Project management	5.2581	48	
52	Centralized management of products, processes, and resources	4.4000	52	

After careful consideration, the threshold value in this study was set to $G^i > 6.5$, and the measures that did not meet the threshold were removed. Thus, the original 52 criteria were reduced to 15 key I4Es, which belong to the HoQ framework in Figure 1 (10). Then, the VIKOR ranking method was used to analyze the agility index and I4Es, which were the same as those in the first stage of HoQ and omitted here (the specific implementation process can be seen in Appendix A). Finally, the ranking results of the I4Es were obtained. Thus far, the analysis of the second stage of the HoQ is complete, and its constructed model is shown in Figure 4, which is a result of the expansion of the quality function of the second stage, as shown in Table 16.

Table 16. Ranking results of I4Es.

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15
S_j	0.3770	0.3677	0.3596	0.3736	0.3606	0.3589	0.3750	0.3751	0.3674	0.3602	0.3759	0.3664	0.3671	0.3671	0.3582
R_j	0.0795	0.0770	0.0766	0.0795	0.0785	0.0792	0.0777	0.0780	0.0764	0.0777	0.0789	0.0773	0.0775	0.0758	0.0773
Q_j	1.0000	0.4148	0.1483	0.9005	0.4192	0.4742	0.6932	0.7407	0.3214	0.3053	0.8850	0.4176	0.4639	0.2359	0.2030
S_j Ranking	15	10	3	11	5	2	12	13	9	4	14	6	8	7	1
R_j Ranking	15	4	3	14	11	13	8	10	2	9	12	5	7	1	6
Q_j Ranking	15	6	1	14	8	10	11	12	5	4	13	7	9	3	2

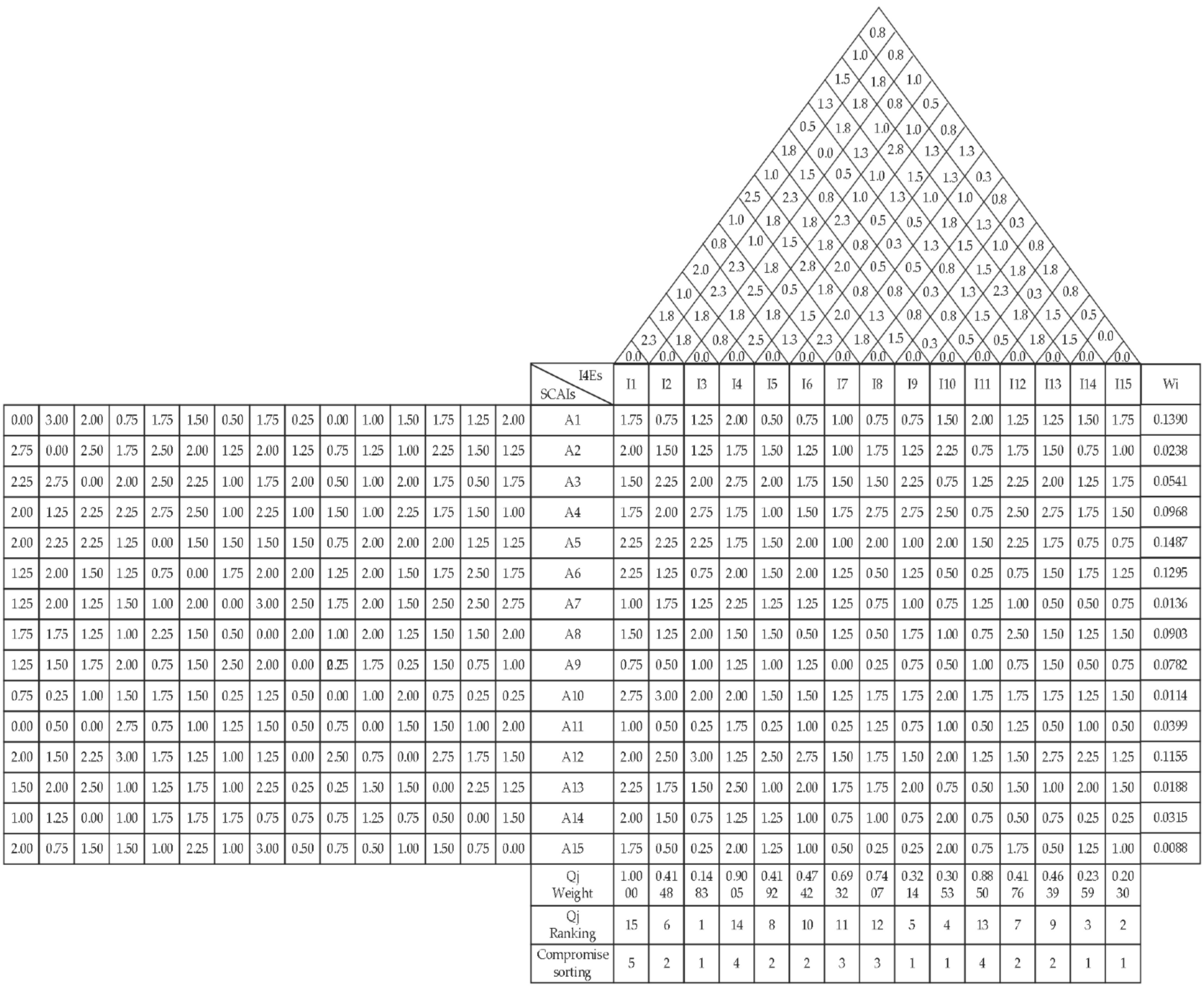


Figure 4. Second HoQ between SCAIs and I4Es.

4.3. Results and Discussion

This study applied the integrated MCDM–QFD decision framework to provide a strategy for a new energy materials manufacturing enterprise to resist the risk of supply chain disruption. New energy material manufacturing enterprises can enhance I4Es in advance by applying the framework proposed in this study to strengthen SCA and reduce or alleviate the ripple effects in the supply chain. The following sections provide a discussion of the research results for the three variables linked by the two HoQ stages.

4.3.1. First HoQ: REFs and SCAIs

The analysis results in Table 2 show that the first three key REFs are the bullwhip effect caused by inaccurate predictions, facility failures, and poor strain capacities. As shown at the bottom of Table 14, the first three key SCAIs are information transparency and supply chain visualization to quickly respond to customer needs, long-term cooperation with partners to strengthen trust, and improving customer service levels and satisfaction. These key factors and indicators are important issues that must be considered by the decision makers of new energy materials manufacturing enterprises. Priority strengthening of these important SCAIs will greatly reduce or alleviate the key REFs. The three REFs are discussed in greater detail below.

Bullwhip effect caused by inaccurate predictions: In general, China's new energy material manufacturing industry is still in the growth stage. However, owing to the severe impacts of the global financial storm over the past decade, China's export of new energy products has been seriously blocked, resulting in market demands that are lower than the supply; this has also caused serious decline in product prices, inaccurate forecasts by the decision makers of new energy materials manufacturing enterprises, and overcapacity. In this context, the new energy materials manufacturers should scientifically predict market demands, rationally arrange for production cycles, and control corporate cash flow management so as to improve the financial performance of the industry [96]. Therefore, accurate forecasting ability is particularly important for new energy material manufacturing enterprises to alleviate supply chain disruptions.

Facility failures: To adequately develop the new energy materials manufacturing enterprises, the problems of the corresponding support facility failures must be solved. However, events caused by facility failures are increasing in recent years: In September 2020, the new energy composite structural parts expansion project of a Chinese company was cancelled owing to the failure of its facilities. Moreover, the imperfect product inspection systems attributable to facility failures seriously hinder the development of the new energy materials industry [97]. Therefore, accurate facility failure handling capacity is particularly important for new energy materials manufacturing enterprises to alleviate the ripple effects of supply chain disruptions.

Poor strain capacities: Poor strain capacity refers to inflexibilities of the supply sources, poor capabilities and reliabilities of suppliers, fluctuations in production capacities, and material shortages of the new energy enterprises. The sudden outbreak of the COVID-19 pandemic in 2020 has severely impacted China's manufacturing of new energy materials. In terms of project construction, owing to the negative effects of the pandemic, new energy enterprises have been plagued by insufficient raw material outputs and lagging supply of key equipment when resuming production. For example, from January to February 2020, the cumulative output of new energy projects of the State Grid of China decreased by 38% when compared with the same period in the previous year. With the continuous development of enterprises, the flexibility demands of new energy materials manufacturing enterprises are also increasing, and rapid adaptability is the key to the development of these enterprises [98].

The three most critical REFs noted above are affected by all the identified SCAIs, but the top three indicators have the greatest impact. The REFs determined in this study are consistent with the actual situations of the firm in the case study. First, the company is located on the southeast coast of China, and the development of the new energy industry has very good natural conditions and industrial foundation. At present, an industrial chain has been preliminarily formed in this region but there is still the problem of overcapacity in some parts of this industrial chain, which is prone to inaccurate predictions. Second, new energy is not a fully mature field in engineering design, system integration, detection, or certification, as well as operation or maintenance, which makes it difficult to eliminate hidden faults and easily leads to facility failures. Finally, at present, new energy materials manufacturing does not have good division of labor within the industrial chain and unsmooth supply sources are often a problem, which results in poor strain capacity.

4.3.2. Second HoQ: SCAIs and I4Es

Since SCA acts as an intermediary between the ripple effects and I4Es, it is a link between the two variables; however, SCA is an abstract concept that may be difficult to understand for the enterprise decision makers. Therefore, this study organized the three key indicators of SCA in a form that is easier to understand: new energy materials manufacturing enterprises should cooperate with partners for a long time to strengthen their trust relationships; further, they must make the information transparent and visible to the upper, middle, and lower reaches of the supply chain to quickly respond to customer needs and improve customer service levels and satisfaction. The first five I4Es are discussed below.

Based on the analytical results of Figure 4, the factors that are used to strengthen SCA of the key I4Es are as follows: ensuring data privacy and security; guarding against legal risks; adopting digital transformation investments to improve economic efficiency; improving IT infrastructure for big data management; investing in and using new Industry 4.0 equipment.

Ensuring data privacy and security: The most important I4Es to enhance SCA is ensuring data privacy and security for supply chain members so as to strengthen trust with the partners over the long term, in addition to making information transparent and visible to the upper, middle, and downstream of the supply chain. New energy materials' manufacturing enterprises use new technologies, so data protection is necessary by general consensus in the industry. To build security protection systems for all scenarios, China promulgated the Cyber Security Law in November 2016, thus indicating that data security has been legally implemented in China. However, data security leakage events may cause serious legal consequences and loss of reputation to companies, which are generally more serious than those caused by traditional leakage accidents [99]. Therefore, by ensuring data privacy and security, the new energy materials manufacturing enterprises can strengthen SCAIs and reduce or mitigate the REFs such as the bullwhip effect caused by inaccurate predictions and poor strain capacities.

Guarding against legal risks: Studies have shown that exogenous risks represented by legal risks are derived from the environmental complexities and uncertainties in which the new energy industry is located and are characterized by a wide range, sudden onset, and difficulty in controlling [100]. In this context, at the eighth International Clean Energy Forum in 2019, the Chinese experts discussed the current problems of China's new energy industry as well as domestic and foreign approval issues in the process of developing the new energy industry, in addition to the legal risks in the development process. The significance of new energy manufacturing enterprises in preventing legal risks was expounded. Thus, by preventing legal risks, the SCAIs of new energy materials manufacturing enterprises can be strengthened, which is of positive significance to solve the REFs such as the bullwhip effect.

Adopting digital transformation investments to improve economic efficiency: Digital transformation has fully permeated to new energy material manufacturing enterprises. For example, Lingyu et al.'s research in 2021 analyzed the forming factors for new energy industry aggregation under the context of digitalization [101]. Under the context of carbon neutrality, as mentioned in China's 14th five-year plan, the new energy industry has begun accelerating the process of digital transformation through digital and intelligent technologies to ensure safety and to improve the utilization efficiency of new energy materials. Therefore, more and more new energy manufacturing enterprises have started investing in digital transformation. For example, to achieve digitalization, the Shanghai Electric Group launched “SEunicloud” as an Internet platform for the new energy manufacturing industry in September 2019. Therefore, by ensuring investment in digital transformation to improve economic benefits, new energy materials manufacturing enterprises can strengthen SCAIs and guarantee the alleviation or reduction of REFs.

Improving IT infrastructure for big data management: To solve the problems of improper management and low efficiency, new energy manufacturing enterprises began building big data centers to improve the management of and ability to control the new energy industry [102]. In the context of China’s supply-side reform, the application of big data to new energy manufacturing enterprises is an inevitable choice for China to move towards being a manufacturing power. Therefore, more and more new energy manufacturing enterprises are consolidating IT infrastructure for big data management: In April 2021, the State Grid of China officially announced the launch of the “STATE GRID NEW ENERGY CLOUD” as a new energy manufacturing Internet platform based on cloud computing, big data, and other advanced technologies. Therefore, consolidating IT infrastructure for big data management has positive effects on strengthening SCAIs and alleviating the REFs.

Investing in and using new Industry 4.0 equipment: In recent years, new energy enterprises have developed rapidly, and their investment scales have expanded [103]. In the Internet era, we can build a new energy ecosystem and create a complete business chain only by integrating the entire industrial chain of new energy and integrating it deeply with digital equipment. Therefore, investment in and implementation of new Industry 4.0 equipment are of great significance to new energy manufacturing enterprises. The Chinese government has also constantly issued new policies to encourage new energy manufacturing enterprises to increase their investments in new equipment. For example, Ningde City of Fujian Province issued regulations in October 2021 that new energy manufacturing enterprises with production equipment investments of more than 5 million yuan in new projects will be provided a subsidy of 5% of the purchase amount of the equipment after project completion and launch. Therefore, when new energy manufacturing enterprises invest in and implement new Industry 4.0 equipment, they can strengthen SCAIs and alleviate the REFs such as facility failures and poor strain capacities.

Starting from the key I4Es proposed, this research identified the important SCAIs to reduce the main REFs in the supply chain; from the above analysis, to strengthen the agility of the supply chain and thereby reduce the ripple effects of the key factors, the focus should be on strengthening the promotion measures of Industry 4.0, such as through the following: ensuring data privacy and security, guarding against legal risks, adopting digital transformation investment to improve economic efficiency, ramming IT infrastructure for big data management, and investing and using the new equipment of Industry 4.0. When these measures are improved, the agility of the supply chain can be improved, such as in long-term cooperation with partners to strengthen trust relationships, supply chain information transparency and visualization to quickly respond to customer needs, and improving customer service levels and satisfaction. Finally, REFs, such as the bullwhip effect caused by inaccurate prediction, facility failure, and poor strain capacity caused by supply chain disruption, can be alleviated or eliminated.

The Plato principle emphasizes priority management. Owing to limited resources, enterprises can invest their most important resources in the most critical promotion strategies first. From the above analysis, it is seen that new energy material manufacturing enterprises can first improve the most important I4Es to strengthen the critical SCAIs and alleviate the critical REFs. Therefore, it is important to develop an appropriate approach to mitigate the REFs and maximize SCA in the new energy materials manufacturing industry. The framework proposed in this study provides an effective strategy to formulate I4Es to enhance SCAIs and alleviate REFs. Accordingly, managers can plan I4Es in advance to cope with the ever-changing REFs in the supply chain and improve the SCAIs. Thus, enterprises must continue to invest money and time in I4Es to transform the ripple effects of supply chain management and other risks into new opportunities, to ultimately achieve the goal of improving global competitiveness. The proposed framework provides an effective strategy for formulating I4Es to strengthen SCAIs and mitigate REFs as well as a reference for supply chain management of other manufacturing enterprises in the field of cleaner production.

5. Conclusions

In a globally competitive market with increasing uncertainties, new energy materials manufacturers have realized the necessity of creating supply chains for manufacturing systems that can rapidly cope with uncertainties. From the perspective of the supply chain, this study mainly considered REFs, SCAIs, and I4Es to broaden the perspectives of supply chain management of new energy material manufacturing enterprises. The key findings of this study are as follows:

(1) The top three REFs are the bullwhip effect caused by inaccurate predictions, facility failures, and poor strain capacities.
(2) The top three indicators of SCAIs are information transparency and visualization of supply chains to quickly respond to customer needs, long-term cooperation with partners to strengthen trust, and improving customer service levels and satisfaction.
(3) The top five I4Es are ensuring data privacy and security, guarding against legal risks, adopting digital transformation investments to improve economic efficiency, improving IT infrastructure for big data management, and investing in, and using, new Industry 4.0 equipment.

The main contributions of this study are as follows:

First, a QFD method based on the integrated KJ–FMEA–DEMATEL–FDM-VIKOR framework was proposed. By identifying the key REFs, agility indicators, and I4Es in the supply chains of new energy materials manufacturing enterprises, the MCDM–QFD framework constructed herein provides decision support for improving supply chain management capabilities.

Second, the REFs, SCAIs, and I4Es were integrated with the QFD framework, and the relationships among the different variables were investigated and explored in depth to provide feasible solutions for the new energy materials manufacturing enterprises; these involved applying the I4Es to strengthen SCAIs and alleviate the ripple effects. Since the interactions among the REFs were rarely considered in previous studies, the present study also analyzed the interactions of REFs in the first house of mass.

Finally, using the proposed framework, new energy materials manufacturers can effectively use their limited resources and adjust their manufacturing system strategies, operations, and management while clearly understanding the aspects in which they can improve their I4Es to enhance SCAIs, thereby reducing or mitigating the ripple effects.

At present, most academic studies on integrated MCDM-QFD mathematical methods focus on individual modes. For example, Zaim et al. (2014) proposed a hybrid analysis network process (ANP)-weighted fuzzy method to rank and analyze the technical characteristics of products (or services) in the establishment of QFD [104]. Kumar et al. (2020) adopted a method that integrates FMEA with AHP to identify the relevant risk factors [105]. Chauhan et al. (2021) identified the associated risks in the HoQ model using the fuzzy TOPSIS method [106]. From the literature analysis, it is seen that there is very little research on the comprehensive MCDM-QFD integrated mathematical model in current academic circles and even fewer instances of the QFD integrated method for supply chain management of new energy material manufacturing enterprises.

This study presents a unique MCDM-QFD integrated mathematical method based on KJ-FMEA-DEMATEL-FDM-VIKOR, which is a more scientific model to alleviate the ripple effects of supply chain in new energy material manufacturing enterprises. The house-of-quality (HoQ) approach was used to integrate these mathematical methods, so that the advantages of each method could be applied in research and analyses. For example, as one of the most effective risk analysis methods, FMEA risk assessments and priority of the failure modes are important considerations, which have been widely used in several fields to improve system security and reliability [107]. DEMATEL is considered an effective method for identifying causal chain components of complex systems; it can effectively handle interdependences among the evaluation factors and determine the key factors through a visual structure model [108]. FDM combines the Delphi method with fuzzy theory analysis and solves the fuzziness of expert judgment using fuzzy set theory to improve the efficiency and quality of the traditional Delphi method [109]. VIKOR is a useful multiscale decision-making method that focuses on sorting and selecting from a set of alternatives and identifying compromise solutions to problems with conflicting criteria to help the decision maker arrive at the final decision [110]. The unique MCDM–QFD integrated mathematical approach helps explore the relationships between pairs of variables (REFs and SCAIs, SCAIs and I4Es). By realizing two HoQs, the REFs in the supply chain were transformed to SCAIs and then converted to I4Es. Using the integrated QFD approach to the system process, new energy materials manufacturers can gain detailed knowledge on how the I4Es affect the REFs of the supply chain and which SCAI solutions should be prioritized.

However, the present study also has some limitations that may be explored in future studies. First, the proposed method often involves subjective judgment, so introducing fuzzy theory to the model is a possible solution to address ambiguity and uncertainty. Second, manufacturing systems in different industries can use the proposed framework to reduce or mitigate their ripple effects; however, the different characteristics associated with a specific industry must be considered to determine the degree of demand for SCAIs. Moreover, in the present study, these factors are independent results and were not subject to statistical inspection; in a future study, methods such as the structural equation model (SEM) can be used to test the driving factors of interdependence. In addition, more research is needed on I4Es to reduce the role of the REFs in the supply chain. Finally, a user-friendly decision support system can be developed for the framework to improve automation of related activities that can help monitor, plan, and optimize supply chains in real time.

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Abbreviations

REFs	Ripple effect factors
SCAIs	Supply chain agility indicators
SCA	Supply chain agility
I4Es	Industry 4.0 enablers
MCDM	Multi-criteria decision making
QFD	Quality function deployment
HoQ	Houses of quality
FMEA	Failure mode and effect analysis
DEMATEL	Decision-making Trial and Evaluation Laboratory
FDM	Fuzzy Delphi method
VIKOR	VlseKriterijumska Optimizacija I Kompromisna Resenje

Appendix A

Table A1. I4Es correlation matrix Im.

I × I	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15
1	0.00	2.25	1.75	1.00	2.00	0.75	1.00	2.50	1.00	1.75	0.50	1.25	1.50	1.00	0.75
I2	0.75	0.00	1.75	1.75	2.25	2.25	1.00	1.75	2.25	1.50	0.00	1.75	1.75	1.75	0.75
I3	0.75	1.25	0.00	0.75	1.75	2.50	1.75	1.50	1.75	0.75	0.50	1.25	1.00	0.75	1.00
I4	1.50	2.75	2.00	0.00	2.50	1.75	0.50	2.75	1.75	2.25	1.00	1.00	2.75	1.00	0.50
I5	1.25	1.75	0.25	0.75	0.00	1.25	1.50	1.75	2.00	0.75	0.50	1.25	1.50	1.25	0.75
I6	0.25	0.50	2.50	0.50	1.25	0.00	2.25	2.00	0.75	0.50	0.25	0.50	1.00	1.25	1.25
I7	0.50	1.00	0.50	0.75	1.50	1.50	0.00	1.75	1.25	0.75	0.50	1.25	1.75	1.00	0.25
I8	0.50	2.50	2.75	0.75	1.50	1.00	1.25	0.00	1.50	0.75	0.25	0.75	1.50	1.25	0.75
I9	1.00	3.00	2.00	0.25	1.00	1.00	0.25	2.25	0.00	0.25	0.75	1.25	1.50	1.00	0.25
I10	2.00	1.25	0.50	2.00	1.75	1.50	1.75	1.25	2.25	0.00	0.50	1.50	2.25	1.75	0.75
I11	1.25	1.00	1.50	1.00	1.75	2.00	0.50	0.75	0.75	1.25	0.00	0.50	1.75	0.25	1.75
I12	1.50	1.50	2.25	0.25	1.00	0.25	0.00	0.75	1.50	0.50	0.50	0.00	1.75	1.50	0.75
I13	1.00	1.50	1.75	1.75	1.75	1.75	1.50	1.00	1.25	1.25	0.50	1.50	0.00	1.50	0.50
I14	2.75	1.25	1.25	1.50	1.00	1.50	1.50	1.50	1.00	0.25	0.75	1.25	1.75	0.00	0.00
I15	2.25	1.00	1.75	1.50	1.25	1.25	1.00	0.75	0.75	0.50	1.75	0.50	1.00	1.25	0.00

Table A2. The correlation matrix A × I of SCAIs and I4Es.

A × I	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15
A1	1.75	0.75	1.25	2.00	0.50	0.75	1.00	0.75	0.75	1.50	2.00	1.25	1.25	1.50	1.75
A2	2.00	1.50	1.25	1.75	1.50	1.25	1.00	1.75	1.25	2.25	0.75	1.75	1.50	0.75	1.00
A3	1.50	2.25	2.00	2.75	2.00	1.75	1.50	1.50	2.25	0.75	1.25	2.25	2.00	1.25	1.75
A4	1.75	2.00	2.75	1.75	1.00	1.50	1.75	2.75	2.75	2.50	0.75	2.50	2.75	1.75	1.50
A5	2.25	2.25	2.25	1.75	1.50	2.00	1.00	2.00	1.00	2.00	1.50	2.25	1.75	0.75	0.75
A6	1.25	1.25	0.75	2.00	1.50	2.00	1.25	0.50	1.25	0.50	0.25	0.75	1.50	1.75	1.50
A7	1.00	1.75	1.25	2.25	1.25	1.25	1.25	0.75	1.00	0.75	1.25	1.00	0.50	0.50	0.75
A8	1.50	1.25	2.00	1.50	1.50	0.50	1.25	0.50	1.75	1.00	0.75	2.50	1.50	1.25	1.25
A9	0.75	0.50	1.00	1.25	1.00	1.25	0.00	0.25	0.75	0.50	1.00	0.75	1.50	0.50	0.75
A10	2.75	3.00	2.00	2.00	1.50	1.50	1.25	1.75	1.75	2.00	1.75	1.75	1.75	1.25	1.50
A11	1.00	0.50	0.25	1.75	0.25	1.00	0.25	1.25	0.75	1.00	0.50	1.25	0.50	1.00	0.50
A12	2.00	2.50	3.00	1.25	2.50	2.75	1.50	1.75	1.50	2.00	1.25	1.50	2.75	2.25	1.25
A13	2.25	1.75	1.50	2.50	1.00	2.00	1.75	1.75	2.00	0.75	0.50	1.50	1.00	2.00	1.50
A14	2.00	1.50	0.75	1.25	1.25	1.00	0.75	1.00	0.75	2.00	0.75	0.50	0.75	0.25	0.25
A15	1.75	0.50	0.25	2.00	1.25	1.00	0.50	0.25	0.25	2.00	0.75	1.75	0.50	1.25	1.00

Table A3. Integrated relational matrix by considering three matrice (H_{M1}).

H_{M1}	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15
A1	451.20	621.52	614.31	377.83	610.00	533.39	427.72	625.72	549.16	367.02	221.88	421.69	620.83	459.23	267.03
A2	568.03	774.67	770.66	471.22	769.42	676.45	527.78	780.64	676.38	463.89	280.23	524.11	774.03	564.45	334.39
A3	563.08	763.38	757.69	474.28	758.61	665.92	533.67	766.53	674.48	452.17	274.89	520.70	762.00	562.36	332.67
A4	570.13	775.94	774.42	481.27	776.31	685.39	542.09	792.73	690.00	470.86	279.72	533.98	780.61	573.86	342.20
A5	566.36	772.77	764.64	470.36	760.97	669.98	527.75	773.53	672.36	455.64	279.09	523.05	767.56	562.70	329.02
A6	517.81	712.91	702.95	434.89	706.44	618.63	486.92	715.66	628.14	425.13	252.77	483.23	714.89	522.94	310.50
A7	612.63	835.39	824.63	510.78	822.55	718.94	572.64	841.70	730.89	495.00	301.08	565.61	833.70	610.73	357.83
A8	493.52	675.33	674.92	416.45	672.94	584.34	470.05	677.80	595.59	403.55	240.66	457.81	676.97	496.94	295.91
A9	417.41	573.00	566.72	340.70	564.45	493.94	380.08	576.52	497.83	342.09	206.91	383.58	575.38	415.41	242.83
A10	344.75	469.42	467.88	292.36	465.06	413.53	331.34	470.00	414.78	275.00	168.39	323.36	463.13	347.48	203.80
A11	330.59	449.53	443.27	279.25	446.06	393.39	313.92	457.33	400.25	266.06	161.56	310.31	451.98	333.05	194.66
A12	571.22	790.13	783.80	480.59	784.30	684.64	530.92	788.36	689.16	468.92	282.06	534.42	789.61	577.55	337.25
A13	535.52	732.91	720.45	450.25	721.91	637.98	501.59	728.78	645.58	429.36	261.59	498.92	727.53	540.53	314.66
A14	333.63	451.67	451.03	278.27	451.36	393.72	313.30	456.81	401.13	271.36	162.48	306.88	456.64	333.22	198.17
A15	440.08	598.11	590.44	364.64	590.17	524.84	405.64	602.41	520.19	354.61	218.38	407.03	593.00	435.50	253.94

Table A4. Integrated evaluation matrix (H_{M2}) after normalization (H_{M1}).

H_{M2}	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15
A1	0.0039	0.0054	0.0053	0.0033	0.0053	0.0046	0.0037	0.0054	0.0048	0.0032	0.0019	0.0036	0.0054	0.0040	0.0023
A2	0.0049	0.0067	0.0067	0.0041	0.0067	0.0059	0.0046	0.0068	0.0059	0.0040	0.0024	0.0045	0.0067	0.0049	0.0029
A3	0.0049	0.0066	0.0066	0.0041	0.0066	0.0058	0.0046	0.0066	0.0058	0.0039	0.0024	0.0045	0.0066	0.0049	0.0029
A4	0.0049	0.0067	0.0067	0.0042	0.0067	0.0059	0.0047	0.0069	0.0060	0.0041	0.0024	0.0046	0.0068	0.0050	0.0030
A5	0.0049	0.0067	0.0066	0.0041	0.0066	0.0058	0.0046	0.0067	0.0058	0.0039	0.0024	0.0045	0.0066	0.0049	0.0028
A6	0.0045	0.0062	0.0061	0.0038	0.0061	0.0054	0.0042	0.0062	0.0054	0.0037	0.0022	0.0042	0.0062	0.0045	0.0027
A7	0.0053	0.0072	0.0071	0.0044	0.0071	0.0062	0.0050	0.0073	0.0063	0.0043	0.0026	0.0049	0.0072	0.0053	0.0031
A8	0.0043	0.0058	0.0058	0.0036	0.0058	0.0051	0.0041	0.0059	0.0052	0.0035	0.0021	0.0040	0.0059	0.0043	0.0026
A9	0.0036	0.0050	0.0049	0.0029	0.0049	0.0043	0.0033	0.0050	0.0043	0.0030	0.0018	0.0033	0.0050	0.0036	0.0021
A10	0.0030	0.0041	0.0040	0.0025	0.0040	0.0036	0.0029	0.0041	0.0036	0.0024	0.0015	0.0028	0.0040	0.0030	0.0018
A11	0.0029	0.0039	0.0038	0.0024	0.0039	0.0034	0.0027	0.0040	0.0035	0.0023	0.0014	0.0027	0.0039	0.0029	0.0017
A12	0.0049	0.0068	0.0068	0.0042	0.0068	0.0059	0.0046	0.0068	0.0060	0.0041	0.0024	0.0046	0.0068	0.0050	0.0029
A13	0.0046	0.0063	0.0062	0.0039	0.0062	0.0055	0.0043	0.0063	0.0056	0.0037	0.0023	0.0043	0.0063	0.0047	0.0027
A14	0.0029	0.0039	0.0039	0.0024	0.0039	0.0034	0.0027	0.0040	0.0035	0.0023	0.0014	0.0027	0.0039	0.0029	0.0017
A15	0.0038	0.0052	0.0051	0.0032	0.0051	0.0045	0.0035	0.0052	0.0045	0.0031	0.0019	0.0035	0.0051	0.0038	0.0022

Table A5. Positive ideal solution and negative ideal solution of I4Es.

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15
f_i^*	0.0053	0.0072	0.0071	0.0044	0.0071	0.0062	0.0050	0.0073	0.0063	0.0043	0.0026	0.0049	0.0072	0.0053	0.0031
f_i^-	0.0029	0.0039	0.0038	0.0024	0.0039	0.0034	0.0027	0.0040	0.0035	0.0023	0.0014	0.0027	0.0039	0.0029	0.0017

Table A6. Standardized SCAIs weight value.

SCAIs	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
Ranking	2	11	8	5	1	3	13	6	7	14	9	4	12	10	15
Weight	0.1390	0.0238	0.0541	0.0968	0.1487	0.1295	0.0136	0.0903	0.0782	0.0114	0.0399	0.1155	0.0188	0.0315	0.0088

Table A7. Results of group utility S_j and individual regret R_j.

SCAIs		I4Es														
		I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15
A1	0.1390	0.0795	0.0770	0.0766	0.0795	0.0785	0.0792	0.0777	0.0780	0.0764	0.0777	0.0789	0.0773	0.0775	0.0758	0.0773
A2	0.0238	0.0038	0.0037	0.0034	0.0041	0.0034	0.0031	0.0041	0.0038	0.0039	0.0032	0.0036	0.0038	0.0037	0.0040	0.0034
A3	0.0541	0.0095	0.0101	0.0095	0.0085	0.0092	0.0088	0.0081	0.0106	0.0092	0.0101	0.0102	0.0094	0.0102	0.0094	0.0083
A4	0.0968	0.0146	0.0149	0.0127	0.0123	0.0119	0.0100	0.0114	0.0123	0.0120	0.0102	0.0148	0.0118	0.0135	0.0129	0.0093
A5	0.1487	0.0244	0.0241	0.0234	0.0259	0.0243	0.0224	0.0257	0.0263	0.0263	0.0256	0.0234	0.0245	0.0258	0.0257	0.0263
A6	0.1295	0.0435	0.0411	0.0413	0.0423	0.0399	0.0399	0.0428	0.0424	0.0403	0.0395	0.0449	0.0412	0.0403	0.0410	0.0376
A7	0.0136	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
A8	0.0903	0.0382	0.0375	0.0355	0.0366	0.0359	0.0373	0.0357	0.0385	0.0370	0.0361	0.0391	0.0376	0.0371	0.0370	0.0343
A9	0.0782	0.0541	0.0532	0.0529	0.0572	0.0536	0.0541	0.0581	0.0539	0.0551	0.0522	0.0528	0.0550	0.0529	0.0550	0.0551
A10	0.0114	0.0108	0.0108	0.0106	0.0107	0.0108	0.0107	0.0106	0.0110	0.0109	0.0109	0.0108	0.0106	0.0110	0.0108	0.0107
A11	0.0399	0.0399	0.0399	0.0399	0.0397	0.0399	0.0399	0.0398	0.0398	0.0399	0.0399	0.0399	0.0393	0.0399	0.0399	0.0399
A12	0.1155	0.0170	0.0135	0.0124	0.0150	0.0117	0.0122	0.0186	0.0160	0.0146	0.0132	0.0157	0.0139	0.0133	0.0138	0.0146
A13	0.0188	0.0051	0.0050	0.0051	0.0049	0.0050	0.0047	0.0051	0.0055	0.0048	0.0054	0.0053	0.0048	0.0052	0.0047	0.0050
A14	0.0315	0.0312	0.0314	0.0309	0.0315	0.0311	0.0315	0.0315	0.0315	0.0315	0.0308	0.0313	0.0315	0.0312	0.0315	0.0309
A15	0.0088	0.0054	0.0054	0.0054	0.0055	0.0054	0.0053	0.0057	0.0055	0.0056	0.0054	0.0052	0.0054	0.0056	0.0056	0.0056
S_j	—	0.3770	0.3677	0.3596	0.3736	0.3606	0.3589	0.3750	0.3751	0.3674	0.3602	0.3759	0.3664	0.3671	0.3671	0.3582
R_j	—	0.0795	0.0770	0.0766	0.0795	0.0785	0.0792	0.0777	0.0780	0.0764	0.0777	0.0789	0.0773	0.0775	0.0758	0.0773

Table A8. Calculation results of benefit ratio Q_j.

	I4Es														
	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10	I11	I12	I13	I14	I15
Q_j	1.0000	0.4148	0.1483	0.9005	0.4192	0.4742	0.6932	0.7407	0.3214	0.3053	0.8850	0.4176	0.4639	0.2359	0.2030
	$S^* = 0.3582, S^- = 0.3770, R^* = 0.0758, R^- = 0.0795, v = 0.5$														

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