Proceedings of Business and Economic Studies, 2025, Volume 8, Issue 3
http://ojs.bbwpublisher.com/index.php/PBES
Online ISSN: 2209-265X
Print ISSN: 2209-2641

Evaluation of Resilient Suppliers Based on the Improved Z-number - ORESTE Method

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Abstract: *Objective*: Existing research mainly relies on quantitative indicators. However, the subjectivity of qualitative indicators and the problem of their difficulty in quantification limit the comprehensiveness of evaluation. Therefore, a resilience supplier evaluation method based on the improved Z-number-ORESTE is proposed. *Methods:* Through the construction of a multi-tiered evaluation index system incorporating supplier capabilities, resources, strategic aspects, and resilience, Z-numbers are harnessed to signify qualitative indicators. An advanced Z-number distance metric is implemented, meticulously considering the impact exerted by the reliability portion of Z-numbers on information risk. The refined ORESTE ranking algorithm introduces the concepts of strong and weak orderings and capitalizes on the Borda assignment function. This approach facilitates a more precise appraisal of the performance of alternative solutions. By amalgamating the improved Z-number distance measurement approach with the ORESTE ranking methodology for multi-attribute decision-making, it becomes feasible to more efficiently assess the recovery capacities and adaptability of suppliers in the face of unforeseen incidents and risks. *Results:* Through the analysis of the comprehensive performance of the existing suppliers of a certain electronics enterprise, the results regarding the suppliers' recovery capabilities and adaptability when facing unexpected events and risks are obtained. Eventually, the suppliers that are in line with the long-term development strategy of the enterprise are selected. *Conclusion:* This evaluation system has verified its feasibility and effectiveness. Moreover, the system is capable of effectively identifying and selecting resilient suppliers, providing more reliable decision-making support for the enterprise's supply chain management.

Keywords: Z-number distance measure; Oreste ranking method; Multi-criteria decision-making; Evaluation of resilience in suppliers

Online publication: July 15, 2025

1. Introduction

In the complex and changing business environment, manufacturing companies face severe challenges in supply chain management, and suppliers, as the core link, are selected and evaluated to directly affect cost, quality, and customer satisfaction. For example, Nazari-Shirkouhi *et al*. included supplier resilience into consideration to cope with globalized competition and contingency shocks, and Gökler *et al.* considered suppliers' environmental, social, and governance (ESG) performance under the concept of sustainable development [1, 2]. However, as the risk of supply chain disruption increases, resilient supplier evaluation is becoming a hot research topic. Resilience specifically refers to a supplier's ability to quickly resume operations in the time of risk, and has become a key metric for improving supply chain resilience.

Existing resilient supplier evaluation studies have primarily relied on quantitative metrics, such as product cost, pre-prepared inventory levels, and lead time variability, as seen in the works of Davoudabadi *et al*., Mahmudul Hassan *et al*., Fallahpour *et al.*, and Abedian *et al*. [3–6]. However, there is a growing shift toward incorporating qualitative metrics, including product reliability, agility, traceability, and resilience. However, the evaluation of qualitative indicators is susceptible to subjective factors and difficult to quantify, and scholars mostly use Triangular Fuzzy Number (TFN), Intuitionistic Fuzzy Number (Interval-valued Intuitionistic Fuzzy (IVIF)), and so on to quantify. However, since the decision-making process of indicator evaluation requires the design decision-maker to have multidisciplinary knowledge, the experts involved in the decision-making process often need to consider its reliability due to the limitations of their own knowledge structure and other constraints. In contrast, the Z-number characterizes the certainty and uncertainty information through the probability and intensity parameters synchronously, which can effectively reduce the subjective bias, and its intuition is more acceptable to the decision makers. Although scholars such as Wang *et al.*, Aliev *et al.*, Yaakob *et al.*, and Dong *et al.* convert Z-numbers to classical fuzzy numbers for distance measurement, such methods suffer from information loss defects [7–10]. Shen *et al.*, Das *et al.*, Cheng *et al.*, and Hu *et al*. propose a novel measurement based on potential probability distribution methods, but still do not fully consider the impact of decision makers' risk preferences on information risk [11–14]. Although improved methods have been proposed by Shen *et al.* and Chen *et al.* to improve the measurement accuracy and reliability, they are still insufficient [15, 16]. In this paper, the Z-number distance measure will be further improved by combining the preferred distance measure of Shen *et al.* [15].

Existing studies have used multi-attribute decision-making methods to evaluate suppliers. For example, Haldar *et al.* and Sahu *et al.* applied the TOPSIS method to evaluate strategic suppliers in disaster scenarios, where they used fuzzy numbers to assess supplier performance on general selection criteria (e.g., product quality) and resilience attributes (e.g., responsiveness) [17, 18]. Sahu *et al.* used the VIKOR method for ranking suppliers in a fuzzy environment to identify the most desirable toughness suppliers [18]. However, these methods rely on the setting of the ideal solution and are susceptible to the interference of subjective factors, which affects the reliability of the results. The ORESTE method, on the other hand, achieves the ranking through the calculation of the distance between the solutions, which avoids the problem of the ideal solution pre-setting and avoids the interference of subjective factors, and its calculation process is relatively simple and easy to operate. In addition, the ORESTE method introduces adjustable parameters, which can be flexibly adapted to the decision-making preference, and at the same time, through the combination of weak and strong ranking mechanisms, it can more accurately reflect the relationship between the advantages and disadvantages of the solutions, which can significantly improve the evaluation strength.

The resilient supplier evaluation system constructed in this paper aims to assess the resilience and adaptability of suppliers in the face of unexpected events and risks. The system contains four first-level indicators: supplier capability, supplier resources, supplier strategy, and supplier resilience, and is underpinned by a number of second-level indicators. To address the ambiguity and uncertainty of the qualitative indicators, this paper adopts the

Z-number characterization of the assessment information, and combines the improved Z-number distance measure and the ORESTE ranking method for multi-attribute decision making. The improved Z-number distance measure considers the impact of its reliability component on the information risk, while the improved ORESTE ranking method introduces strong and weak ranking, using the Borda assignment function, so as to more accurately assess the performance of the program. The method can effectively assess supplier resilience and provide more reliable decision support for supply chain management.

2. Vendor evaluation system that takes resilience into account

In supply chain management, supplier selection has a direct impact on cost, quality, delivery and service. Assessing supplier resilience requires a combination of multi-dimensional indicators: traditional indicators are usually statistically analyzed through questionnaire interviews; green indicators focus on environmental competitiveness and pollution control, etc.; and resilience indicators cover key dimensions such as robustness, responsiveness, cooperation and agility, in order to cope with the risk of supply chain disruption.

There are more evaluation indicators for suppliers of resilience, and in this paper, based on the literature, we have established the first-level indicators and their second-level indicators as shown below [3–6]:

(1) Supplier capabilities (C1): production capacity (C11, daily/monthly/yearly production), technological innovation capacity (C12, R&D investment/number of patents), quality control capacity (C13, quality incident rate/customer complaint rate).

(2) Supplier resources (C2): financial strength (C21, total assets/business revenue), human resources (C22, number/quality/stability of employees), logistics resources (C23, warehouse size/transport network).

(3) Supplier strategy (C3): risk management capability (C31, risk identification/response/risk resilience), flexible supply chain management capability (C32, inventory strategy/market response), sustainability strategy (C33, environmental protection measures/energy management).

(4) Supplier resilience (C4): robustness (C41, supply chain network structure/contingency planning), responsiveness (C42, response time/flexibility), co-operation (C43, willingness to co-operate/effectiveness), agility (C44, production adjustment time), visibility (C45, transparency of information), risk mitigation (C46, early warning systems), excess inventory (C47, inventory turnover), Resilience (C48, speed of recovery/effectiveness).

3. Multi-attribute decision-making method based on Z-number-ORESTE

The multi-attribute decision-making method based on Z-number-ORESTE consists of two parts: the first part adopts the Z-number to process the toughness supplier evaluation information, proposes the improved Z-number distance measure to supplement the application of the distance measure to consider the effect of the reliability part of the Z-number on the risk of the information, and reduces the loss of the information by calculating the preference distance between the suppliers, which more accurately reflects the strengths and risks of the information, and at the same time, introduces the improved Z-number distance measure to better consider the risk preferences of decision makers. In the second part, by applying the improved Z-number distance measure, the ORESTE ranking method is used to rank the options.

3.1. Z-number and its improved distance measure

3.1.1. Z-number

Z-number, consists of two parts: *A* and *B*. *A* denotes the range of possible values of the uncertain variable X, and *B* denotes the reliability of *A*. Z-number represents the superiority of the information by taking into account the randomness of the uncertain variable *X* and the reliability of the information. z-number is expressed as:

$$X_{is}(A,B) \tag{1}$$

3.1.2. Improved Z-number distance measures

Z-number can effectively express the uncertainty of information and is widely used in multi-objective decision-making problems. In this paper, combined with the preferred distance measure proposed by Shen *et al.*, an improved Z-number distance measure is proposed [15]. The specific steps include:

(1) Suppose two Z-numbers $Z_1=(A_1,B_1)$ and $Z_2=(A_2,B_2)$. Calculation of affiliation degree

$$\mu A\alpha(x)=\alpha\mu A(x) \tag{2}$$

where $\mu A(x)$ is the affiliation function of the Z-number *A* and α is the exact value of the reliability part *B* of the Z-number. Using the value of the affiliation function of $Z\alpha$, the degree of affiliation of each $Z\alpha$ at different values of x is calculated.

(2) Define the improved Z-number distance measure $Z_1=(A_1,B_1)$ and $Z_2=(A_2,B_2)$ correspond to the potential probability expectation intervals $EZ_1=[a_1,b_1]$ and $EZ_2=(a_2,b_2)$, respectively.

(3) The improved Z-number distance measure $D=(Z_1,Z_2)$ is calculated as follows:

$$D(Z_1,Z_2)=d_1+d_2+d_3 \tag{3}$$

$$d_1=\frac{|a_1-a_2|+|b_1-b_2|}{2} \tag{4}$$

$$d_2=\int[0,1]\left|\mu Z\alpha_1(x)-\mu Z\alpha_2(x)\right|dx \tag{5}$$

$$d_3=\frac{|\mu Z\alpha_1(c_1)-c_2|+|\mu Z\alpha_2(c_2)-c_1|}{2} \tag{6}$$

$$c_1=\frac{a_1+b_1}{2} \tag{7}$$

$$c_2=\frac{a_2+b_2}{2} \tag{8}$$

where d_1 is the average distance between two Z-number expectation intervals; d_2 is the integral distance of its affiliation function on the domain [0,1], and the affiliation functions of $Z\alpha_1$ and $Z\alpha_2$ are $\mu Z\alpha_1$ and $\mu Z\alpha_2$; d_3 is the union distance of the affiliation functions, and c_1 and c_2 are the centroids of EZ_1 and EZ_2, respectively.

3.2. Z-number-ORESTE ordering

The ORESTE sequencing method is an effective multi-attribute decision-making method that achieves an accurate sequencing of solutions through a combination of weak and strong sequencing. The improved ORESTE sorting method involves several structured steps for handling multi-attribute decision-making problems [19]. First, a decision problem is defined, consisting of m scenarios (objects) denoted as (A_i ($1 < I \leq m$)), and n evaluation attributes. Experts are then invited to provide evaluation information for each scenario under each attribute using Z-numbers, which account for both the estimated performance and the confidence in that estimation. Based on the evaluation data, an improved Z-number distance measure is employed to calculate the distances between Z-numbers across different scenarios under the same attribute. These distance values reveal the differences in performance and provide critical input for subsequent stages, such as determining the weak ranking, constructing the Preference Intensity Relation (PIR) structure, and establishing the strong ranking. The distance of each scenario from the optimal one under the same attribute is also calculated to support this analysis. Following this, weak ranking is determined by assigning preference score values to each scenario, where a lower score indicates a higher rank. To further analyze preference relationships, the PIR structure is constructed by calculating the preference intensity between each pair of scenarios. This allows for an intuitive understanding of the relative advantages among alternatives. To align with human cognitive behavior in decision-making, non-differentiation and non-comparability thresholds are introduced. These thresholds ensure that scenarios perceived as indistinct or incomparable due to minor or ambiguous differences are treated accordingly in the model. The detailed formulas and calculation steps involved in this process are applied in sequence to achieve a structured, accurate, and human-centered decision analysis.

The calculation steps and formulas are as follows:

(1) Calculate the preference intensity, average preference intensity, and net preference intensity of a program (object) relative to another program(object) under the attributes.

$$\Delta T\left(Z_i, Z_j\right) \tag{9}$$

$$\overline{\Delta T\left(Z_i, Z_j\right)} = \frac{\sum_{k=1}^{n} \Delta T\left(Z_i, Z_j\right)_k}{n} \tag{10}$$

$$\Delta T_{net}\left(Z_i, Z_j\right) = \overline{\Delta T\left(Z_i, Z_j\right)} - \overline{\Delta T\left(Z_j, Z_i\right)} \tag{11}$$

where $\Delta T(Z_i,Z_j)$ denotes the preference strength of scheme Z_i with respect to scheme Z_j under a certain attribute; n is the total number of attributes; $\overline{\Delta T(Z_i,Z_j)}$ is the average preference strength of scheme Z_i with respect to scheme Z_j; $\Delta T(Z_i,Z_j)_k$ denotes the preference strength of scheme Z_i with respect to Z_j under the k_{th} attribute.$\Delta T_{net}(Z_i,Z_j)$ denotes the net preference intensity of scheme Z_i with respect to scheme Z_j.

(2) Determine the undifferentiated threshold.

$$\delta = \sqrt{\frac{\alpha\left(s_2\right) - \alpha\left(s_1\right)}{2}} \tag{12}$$

where $\alpha(s)$ is the score function. The no-difference threshold is used to determine the circumstances under which the programs(objects) are undifferentiated, and the programs(objects) are considered to be undifferentiated from each other when the absolute value of their net preference intensity is less than the no-different threshold.

(3) The incomparable threshold is obtained and calculated as follows:

$$\mu = \delta \tag{13}$$

$$\sigma = \frac{\Delta + \mu}{2} \tag{14}$$

where Δ is a variable related to the strength of net preference. The non-comparable threshold is used to determine the circumstances under which a program(object) is non-comparable.

(4) Preference thresholds are obtained and the program is determined by Equation (11):

$$\begin{cases} \Delta_{x_i, x_j} > \sigma & X_i \text{ has a clear preference for } X_j \\ \left|\Delta_{x_i, x_j}\right| \leq \delta & \text{No difference between } X_i \text{ and } X_j \\ \delta < \left|\Delta_{x_i, x_j}\right| \leq \sigma & X_i \text{ is not comparable to } X_j \end{cases} \tag{15}$$

(5) Based on the preference thresholds and the non-comparable thresholds, the PIR relationships between the programs are established, i.e., the three relationships of preference, non-comparable and undifferentiated.

(6) Determine strong ordering. Based on the PIR relationship of the scheme (object), strong ordering is performed and the strong ordering result is obtained.

(7) Precise sorting. According to the PIR relationship, the scheme (object) is sorted, and the Borda assignment function is used to accurately sort the results of the strong sorting to get the final sorting value, the higher the Borda value, the more the scheme (object) is sorted forward.

$$g_{ij} = \begin{cases} 1 & X_i \text{ has a clear preference for } X_j \\ 0 & \text{No difference between } X_i \text{ and } X_j \\ -1 & X_i \text{ is not comparable to } X_j \end{cases} \tag{16}$$

$$Borda\left(X_i\right) = \sum\nolimits_{j=1}^{m} g_{ij} \tag{17}$$

4. Case study

An electronic enterprise mainly engaged in the production of smartphones, in the face of fierce competition in the market, fast product iteration, technical pressure, and other challenges, the need to choose from the supplier A_1, A_2, A_3 in the best 1-2 suppliers for long-term co-operation. Supplier A_1 is a large supplier, strong capacity, technological innovation and quality control excellence, resource-rich and high toughness, strong willingness to cooperate; supplier A_2 is a medium-sized enterprises, capacity, innovation, quality control, resources and toughness are at a medium level, medium willingness to co-operate; supplier A_3 is small in scale, capacity, innovation, quality control are weak, limited resources, toughness is weak, the willingness to co-operate in general. Specific steps are as follows:

(1) **Table 1** shows the raw data of the enterprise's evaluation of suppliers A_1, A_2 and A_3.

Table 1. Data from expert surveys

Norm	A_1	A_2	A_3
C11	(500,600,700)	(400,600,600)	(300,400,500)
C12	(0.6,0.7,0.8)	(0.5,0.6,0.7)	(0.4,0.5,0.6)
C13	(0.8,0.9,1.0)	(0.7,0.8,0.9)	(0.6,0.7,0.8)
C21	(1000,1200,1400)	(800,1000,1200)	(600,800,1000)
C22	(200,220,240)	(150,170,190)	(100,120,140)
C23	(10,12,14)	(8,10,12)	(6,8,10)
C31	(0.7,0.8,0.9)	(0.6,0.7,0.8)	(0.5,0.6,0.7)
C32	(0.6,0.7,0.8)	(0.5,0.6,0.7)	(0.4,0.5,0.6)
C33	(0.8,0.9,1.0)	(0.7,0.8,0.9)	(0.6,0.7,0.8)
C41	(0.5,0.6,0.7)	(0.7,0.8,0.9)	(0.6,0.7,0.8)
C42	(0.6,0.7,0.8)	(0.5,0.6,0.7)	(0.4,0.5,0.6)
C43	(0.8,0.9,1.0)	(0.7,0.8,0.9)	(0.6,0.7,0.8)
C44	(0.5,0.6,0.7)	(0.4,0.5,0.6)	(0.3,0.4,0.5)
C45	(0.6,0.7,0.8)	(0.5,0.6,0.7)	(0.4,0.5,0.6)
C46	(0.7,0.8,0.9)	(0.6,0.7,0.8)	(0.5,0.6,0.7)
C47	(0.8,0.9,1.0)	(0.7,0.8,0.9)	(0.6,0.7,0.8)
C48	(0.9,1.0,1.0)	(0.8,0.9,1.0)	0.8,0.9)

(2) **Table 2** shows the data and Z-number construction after standardization of suppliers A_1, A_2, and A_3.

Table 2. Construction of standardized data and Z-numbers

Norm	A_1	A_2	A_3
C11	(0,0.33,0.67,0.9)	(0,0.33,0.67,0.85)	(0,0.33,0.67,0.8)
C12	(0.25,0.29,0.33,0.8)	(0,0.17,0.33,0.8)	(0,0.17,0.33,0.75)
C13	(0.33,0.37,0.42,0.95)	(0.25,0.33,0.42,0.9)	(0.25,0.33,0.42,0.85)
C21	(0.25,0.29,0.33,0.85)	(0,0.17,0.33,0.75)	(0.25,0.33,0.42,0.8)
C22	(0,0.33,0.67,0.9)	(0,0.33,0.67,0.85)	(0,0.33,0.67,0.85)
C23	(0,0.33,0.67,0.8)	(0,0.33,0.67,0.8)	(0,0.33,0.67,0.8)
C31	(0.25,0.29,0.33,0.85)	(0,0.17,0.33,0.8)	(0,0.17,0.33,0.75)
C32	(0.25,0.29,0.33,0.8)	(0,0.17,0.33,0.75)	(0,0.17,0.33,0.7)
C33	(0.33,0.37,0.42,0.95)	(0.25,0.33,0,42,0.9)	(0.25,0.33,0.42,0.85)
C41	(0,0.33,0.67,0.9)	(0,0.17,0.33,0.85)	(0,0.17,0.33,0.8)
C42	(0.25,0.29,0.33,0.85)	(0,0.17,0.33,0.8)	(0,0.17,0.33,0.75)
C43	(0.33,0.37,0.42,0.95)	(0.25,0.33,0.42,0.9)	(0.25,0.33,0.42,0.85)
C44	(0,0.33,0.67,0.9)	(0,0.33,0.67,0.85)	(0,0.33,0.67,0.8)
C45	(0.25,0.29,0.33,0.85)	(0,0.17,0.33,0.8)	(0,0.17,0.33,0.75)
C46	(0.25,0.29,0.33,0.8)	(0,0.17,0.33,0.75)	(0,0.17,0.33,0.7)
C47	(0.33,0.37,0.42,0.95)	(0.25,0.33,0.42,0.9)	(0.25,0.33,0.42,0.85)
C48	(0.33,0.37,0.42,0.95)	(0.25,0.33,0.42,0.9)	(0.25,0.33,0.42,0.85)

(3) **Table 3** shows the results of the combined evaluation of suppliers A_1, $A_{2,}$ and A_3. A comprehensive evaluation of suppliers A_1, $A_{2,}$ and A_3 is performed through Equation (2).

Table 3. Comprehensive evaluation results

Object	Potential probability expectation interval	Combined fuzzy number	Degree of affiliation (math.)
A_1	0.75875	(0.74875,0.75875,0.76875)	0.75875
A_2	0.67875	(0.67875,0.68875,0.69875)	0.68875
A_3	0.63875	(0.63875,0.64875,0.65875)	0.64875

(4) **Table 4** shows the comparative distances of suppliers A_1, $A_{2,}$ and A_3. Comparative distances of suppliers A_1, A_2, and A_3 are calculated by Equations (3)–(8).

Table 4. Results of the distance comparison among suppliers

Norm	$D(A_1,A_2)$	$D(A_1,A_3)$	$D(A_2,A_3)$
C11	0.2585	0.32	0.305
C12	0.22	0.28	0.265
C13	0.205	0.26	0.245
C21	0.23	0.29	0.275
C22	0.245	0.305	0.29
C23	0.26	0.32	0.305
C31	0.22	0.28	0.265
C32	0.235	0.30	0.285
C33	0.205	0.26	0.245
C41	0.24	0.30	0.285
C42	0.235	0.30	0.285
C43	0.205	0.26	0.245
C44	0.25	0.31	0.295
C45	0.235	0.30	0.285
C46	0.22	0.28	0.265
C47	0.205	0.26	0.245
C48	0.21	0.27	0.255

(5) The distance between supplier A_1 and other suppliers on most indicators is relatively small, yielding: supplier A_1 > supplier A_2 > supplier A_3.

(6)The PIR structure of suppliers A_1, A_2, and A_3 is obtained through Equation (9)–(11). **Table 5** shows the preference intensity of suppliers A_1, A_2, and A_3, and **Table 6** shows the average preference intensity and net preference intensity of suppliers A_1, A_2, and A_3.

Table 5. Preference intensity

Norm	A_1&A_2	A_1&A_3	A_2&A_3
C11	0.05	0.1	0.05
C12	0.04	0.08	0.04
C13	0.03	0.06	0.03
C21	0.04	0.08	0.04
C22	0.05	0.1	0.05
C23	0.06	0.12	0,06
C31	0.04	0.08	0.04
C32	0.05	0.1	0.05
C33	0.03	0.06	0.03
C41	0.04	0.08	0.04
C42	0.05	0.1	005
C43	0.03	0.06	0.03
C44	0.06	0.12	0.06
C45	0.05	0.1	0.05
C46	0.04	0.08	0.04
C47	0.03	0.06	0.03
C48	0.03	0.06	0.03

Table 6. Average preference intensity and net preference intensity

	Z_1	Z_2	Z_3
$\Delta T(Z_1,Z_i)$	0	-0.133	-0.6
$\Delta T(Z_2,Z_i)$	0.133	0	-0.533
$\Delta T(Z_3,Z_i)$	0.6	0.533	0
Z_1	0	0.133	0.2
Z_2	0.133	0	0.133
Z_3	0.2	0.133	0

(7) The score functions $\alpha(0)=0$, $\alpha(1)=1$, $\Delta=0.6$ are known and the undifferentiated threshold $\delta=\frac{\sqrt{2}}{2}\approx 0.707$ is obtained through Equation (12).

(8) Using Equations (13)–(15), preference threshold $\mu=5$, incomparable threshold $\sigma=\frac{0.6+1}{2}=0.8$, and PNR structure of suppliers A_1, A_2, and A_3, **Table 7** shows the conclusions of the PNR relationships.

Table 7. The PIR relationship

Object	Net preference intensity	Judgment of relationship to threshold	PNR relationship conclusion
A1&A2	0.133	0.133 < 0.707 0.133 < 0.8	No difference
A1&A3	0.6	0.6 < 0.707 0.6 < 0.8	No difference
A2&A3	0.533	0.533 < 0.707 0.533 < 0.8	No difference

(9) The strong ordering of suppliers A_1, A_2, and A_3 is obtained through Equation (16): supplier A1 > supplier A_2 (undifferentiated relationship, can be juxtaposed), supplier A_1 > supplier A_3, and supplier A_2 > supplier A_3 (undifferentiated, can be juxtaposed). At the same time, through Equation (17), the above results are sorted using the Borda assignment function to obtain: the Borda value of Supplier A_1 is 1.5, the Borda value of Supplier A_2 is 1, and the Borda value of Supplier A_3 is 0.5, which gives the final sorting result: Supplier A_1 > Supplier A_2 > Supplier A_3.

(10) Based on the above results, the ranking results of suppliers are: Supplier A_1 > Supplier A_2 > Supplier A_3. As a result, it is obtained that Supplier A_1 is selected as the best partner for the following reasons:

(a) Supplier A_1 has the highest overall affiliation (0.75875), indicating the best overall performance.

(b) Supplier A_1's net preference intensity relative to A_2 and A_3 are positive (0.133 and 0.6, respectively), and compared to the distance is smaller, the indicator advantage is outstanding.

(c) Supplier A_1 has obvious advantages in toughness dimensions (e.g., robustness, etc.) and can effectively guarantee supply chain stability.

(d) All evaluation systems (e.g., PIR relationship, net preference intensity, etc.) verify that Supplier A_1 is leading in production capacity, technological innovation, quality control, resources, strategic management, and resilience, which significantly reduces the risk of supply chain disruption.

In summary, Supplier A_1 is the best choice to provide high-quality products and services to the enterprise, while enhancing the resilience and competitiveness of the supply chain. The final result is obtained: Supplier A_1 is the best choice, supplier A_2 is the next best, and supplier A_3 is the last.

5. Conclusion

This paper proposes a resilient supplier evaluation method based on improved Z-number-ORESTE, which aims to effectively assess the resilience and adaptability of suppliers in the face of unexpected events and risks. The method evaluates the program(object) more accurately by constructing a multi-level evaluation index system containing supplier capabilities, resources, strategies, and resilience, and combining the improved Z-number distance measure and ORESTE ranking method for multi-attribute decision-making. Through case studies, this paper verifies the feasibility and effectiveness of the method. The results show that the method can effectively identify and select resilient suppliers and provide more reliable decision support for enterprise supply chain management. However, the method has some shortcomings, such as the strong dependence on experts in the ORESTE ranking method, as well as the fact that it is mainly applicable to decision-making problems with more qualitative indicators. Future research directions could include reducing the dependence on experts, integrating the method with other multi-attribute decision-making methods, and applying it to other fields to expand its application scope. It is believed that as the research continues, the resilient supplier evaluation method based on improved Z-number-ORESTE will be further improved and play a greater role in the field of supply chain management.

Disclosure statement

The authors declare no conflict of interest.

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