A SUPPLY CHAIN RISK EVALUATION MODEL BASED ON INTEGRATION OF DATA CHARACTERISTICS AND SUBJECTIVE PREFERENCE

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ABSTRACT

In order to assess supply chain risks quantitatively, a multi-attribute group decision-making evaluation model that integrating the data characteristics of decision matrix and subjective preferences of expert groups is proposed. The objective weights of the indicators are obtained based on the data characteristics of the decision matrix, and then the subjective weights of the indicators are obtained on the basis of the preference information of the expert group about the importance of the indicators. The comprehensive weight of the indicator is determined by the convex combination of the objective and subjective weights. Finally, comprehensive evaluation are performed for the evaluation objects. The model has a small amount of calculation and is easy to operate. A case study has verified the validity and practicability of the model.

***Keywords**: Index weights, Data characteristics, Subjective preference, Relative entropy*

INTRODUCTION

Quantitative assessment of supply chain risks can provide important decision-making basis for supply chain risk management, multi-attribute group decision-making has always been an important content in the field of decision-making problems. When applying and studying the multi-attribute group decision-making evaluation model, how to determine the index weight is a key issue. Different index weights may lead to different evaluation results, the method of determining index weights is also related to the scientificity and rationality of the evaluation process. When determining the index weight, common methods include objective weighting method, subjective weighting method and comprehensive weighting method. The objective weighting method is usually based on the decision matrix obtained by the expert group evaluating the assessment object by the evaluation index, or based on the decision matrix formed by the system analysts collecting data for the assessment objects according to the evaluation indicators. It determine the index weight by means of optimal fuzzy measure (Tan, 2011), advantage weight vector (Kaya & Kahraman,

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2011), level difference maximization (Titkanloo, Keramati, & Fekri, 2018) etc. The objective weighting method is used more often, and its data source is relatively objective. The indicator weight is determined by the data characteristics of the decision matrix, and the evaluation objects can be distinguished and sorted, but the interpretability is poor, because the index weight has nothing to do with the nature or connotation of the index. The subjective weighting method is sometimes directly assigned by system analysts (Scala, Rajgopal, & Vargas, 2016), and sometimes by evaluation experts to judge the importance of the indicators, and then through certain methods such as standard deviation weighting (Torra, 2010), extreme value statistics (Peeters, Basten, & Tinga, 2018) calculate the indicator weights. The data sources of the subjective weighting method are more subjective, and the data sources reflect the subjective preference of evaluation experts or system analysts for different indicators, so the indicator weights obtained by the subjective weighting method usually have better explanatory properties. The comprehensive weighting method integrates the weights obtained by the objective weighting method and the subjective weighting method, and the related research and application of the comprehensive weighting method are few.

When determining the weights of supply chain risk indicators in this paper, it integrates the data characteristics of the decision matrix with the preference information of the evaluation experts for different indicators. The indicator weights not only reflect the data characteristics of the decision matrix, but also reflect the expert group's preference information of the evaluation indicators. So as to avoid the deficiencies of objective and subjective weighting methods.

LITERATURE REVIEW

Supply chain risk evaluation is the basis of supply chain risk management, so it has attracted the attention of many scholars. Among them, some scholars have studied the evaluation of single risk. Mohebalizadehgashti, Zolfagharinia, and Amin (2020) used logistic regression model and Bayesian network method based on relative weight. Zhang, Hu, and Zhang (2015) evaluated the supply chain credit risk based on support vector machine. Some scholars established the supply chain evaluation index system. Mangla, Kumar, and Barua (2014, 2015) evaluated the risk of the supply chain from the perspectives of technology, market and environmental, combined with fuzzy comprehensive evaluation and fuzzy set. Li, Du, Wang, Sun, and Xiong (2016) studied the risk evaluation of manufacturing supply chain and pharmaceutical excipients supply chain based on fuzzy comprehensive evaluation method. Seluk (2008) established a supply chain risk factor system from five risk perspectives (environment, procurement, planning, production, and cooperation), and conducted risk evaluation based on ISM-AHP. Other scholars have considered the node enterprises of the supply chain network from a macro perspective and established a supply chain network evaluation system. Deng and Jiang (2019) considered the enterprise preference from an overall perspective and evaluated the supply chain risk based on the conditional value at risk. Rayas and Serrato (2017) evaluated the multi-level supply chain risk from the perspective of the whole supply chain network, the importance of different enterprises in the supply chain is determined by the node characteristics such as medium and medium number centrality of complex network theory. In addition, Giri and Bardhan (2012) analyzed the operation mode of agricultural product supply chain under IOT environment, divided it into four angles: perception layer, network layer and so on, and quantitatively evaluated the risk factors affecting the supply chain in combination with OWA multi-attribute decision-making method. Wu, Jia, Li, Song, Xu, and Liu (2019) in the context of dangerous goods supply chain, a risk evaluation framework for suppliers, transportation routes, outsourcing schemes and materials was proposed. Some scholars have studied supply chain risk assessment methods, including Failure Mode and Effects Analysis (FMEA) (Zhao, Zuo, & Blackhurst, 2019), Data Envelopment Analysis (DEA) (Nilsson & Darley, 2006), and Analytical Network Process (ANP) (Bharti, Giri, & Jayant, 2015).

EVALUATION MODEL

Let the evaluation object set be P, $P=\{p_i, i=1,2,\cdots,t\}$, t is the number of assessment objects, which can be multiple supply chains that are comparable, or the same supply chain in different periods; The evaluation expert set is D, $D=\{d_k, k=1,2,\cdots,s\}$, s is the number of evaluation experts; The evaluation index set is $C, C=\{c_j, j=1,2,\cdots,q\}$, q is the number of indicators.

Experts Evaluate the Assessment Objects and Importance of Indicators

Experts evaluate the assessment objects according to the index set C, the expert d_k's evaluation value of the assessment object p_i based on the index c_j is recorded as e_{ij}^k, the evaluation value of the expert group on the assessment object constitutes the decision matrix $E_i=(e_{ij}^k)_{s\times q}$.

Expert groups rank the importance of indicators qualitatively. If expert d_k ranks index c_j as "first important", $m_{kj}=1$, if expert d_k ranks index c_j as "second most important", $m_{kj}=2$, other analogy, m_{kj} is a natural number, $m_{kj}\in\{1,2,\cdots,q\}$. When experts rank the importance of indicators, multiple indicators are allowed to be judged as equally important, that is, $m_{k1}, m_{k2}, \dots, m_{kq}$ can take the same value. The evaluation value obtained by the expert group sorting all the indicators qualitatively constitutes a matrix $M=(m_{kj})_{s\times q}$.

Indicators' Objective Weight

When the expert group evaluates the assessment object p_i based on the index c_j, if the evaluation results of the expert group are more consistent, the more weight should be given to the index c_j, and vice versa. In this paper, the entropy value is used to measure the evaluation's consistency of the assessment object p_i by the expert group based on the index c_j. In the multi-attribute group decision-making evaluation, the types of indicators that are generally involved are high-quality indicators, low-quality indicators, interval indicators, and fixed indicators. First, the decision matrix is specially standardized.

$$
f_{ij}^{k}=\begin{cases}\left[\dfrac{e_{ij}^{k}}{\max\limits_{1\le k\le s}(e_{ij}^{k})}\right]^{\tau},c_j\in c^{(1)}\\ \left[\dfrac{\min\limits_{1\le k\le s}(e_{ij}^{k})}{e_{ij}^{k}}\right]^{\tau},c_j\in c^{(2)}\\ \left[1-\dfrac{\max(\varsigma-e_{ij}^{k},e_{ij}^{k}-\theta,0)}{\max\limits_{1\le k\le s}(\varsigma-e_{ij}^{k},e_{ij}^{k}-\theta,0)}\right]^{\tau},c_j\in c^{(3)}\\ \left(1-\dfrac{\left|e_{ij}^{k}-\varepsilon\right|}{\max\limits_{1\le k\le s}\left|e_{ij}^{k}-\varepsilon\right|}\right)^{\tau},c_j\in c^{(4)}\end{cases} \tag{1}
$$

Among them, $c^{(1)}$ is a high-quality index, $c^{(2)}$ is a low-quality index, $c^{(3)}$ is an interval index, and $c^{(4)}$ is a fixed index. $[\varsigma,\theta]$ is the best value interval of interval index, $\varsigma\le\theta$. ε is the best value of the fixed index $c^{(4)}$; $\tau\ge 1$, τ is a special standardized adjustment coefficient, the value of τ is within a reasonable range, the value is the larger, the standardized value f_{ij}^{k} is the more scattered (Yager, 2003). If $\max\limits_{1\le k\le s}(\varsigma-e_{ij}^{k},e_{ij}^{k}-\theta,0)=0$, then take $\dfrac{\max(\varsigma-e_{ij}^{k},e_{ij}^{k}-\theta,0)}{\max\limits_{1\le k\le s}(\varsigma-e_{ij}^{k},e_{ij}^{k}-\theta,0)}=0$; if $\max\limits_{1\le k\le s}\left|e_{ij}^{k}-\varepsilon\right|=0$, then take $\dfrac{\left|e_{ij}^{k}-\varepsilon\right|}{\max\limits_{1\le k\le s}\left|e_{ij}^{k}-\varepsilon\right|}=0$.

It can be seen from formula (1) that when c_j is a high-quality index $c^{(1)}$, the larger the value of e_{ij}^{k}, the larger the value of f_{ij}^{k}, and the maximum value of f_{ij}^{k} is 1. When c_j is a low-quality index $c^{(2)}$, the larger the value of e_{ij}^{k}, the smaller the value of f_{ij}^{k}, and the maximum value of f_{ij}^{k} is 1. When c_j is an interval index $c^{(3)}$, if e_{ij}^{k} is in the best value range, $e_{ij}^{k}\in[\varsigma,\theta]$, f_{ij}^{k} takes the maximum value of 1, and the farther e_{ij}^{k} is from the best value range $[\varsigma,\theta]$, the smaller the value of f_{ij}^{k}. When c_j is a fixed index $c^{(4)}$, if e_{ij}^{k} is the best value ε, f_{ij}^{k} takes the maximum value 1, and the farther e_{ij}^{k} is from the best value ε, the smaller the value of f_{ij}^{k}.

The evaluation entropy value of the expert group for the index c_j with the assessment object p_i is

$$
h_{ij}=-\frac{1}{\ln s}\sum_{k=1}^{s}\left(f_{ij}^{k}\Big/\sum_{k=1}^{s}f_{ij}^{k}\right)\ln\left(f_{ij}^{k}\Big/\sum_{k=1}^{s}f_{ij}^{k}\right) \tag{2}
$$

Among, if $f_{ij}^k \Big/ \sum_{k=1}^{s} f_{ij}^k = 0$, then take $f_{ij}^k \Big/ \sum_{k=1}^{s} f_{ij}^k \ln f_{ij}^k \Big/ \sum_{k=1}^{s} f_{ij}^k = 0$.

The weight of the index c_j to the assessment object p_i is

$$w_{ij} = h_{ij} \Big/ \sum_{j=1}^{q} h_{ij} \tag{3}$$

w_{ij} is the weight of the index c_j on the assessment object p_i. According to the principle of relative entropy, the index weight vector $W' = (w_1', w_2', \cdots, w_q')^{\mathrm{T}}$ can be obtained, so that all assessment objects use the same index weight. In order to solve a consistent index weight vector, the following optimization model is established.

$$\begin{cases} \min U(W') = \sum_{i=1}^{t} \sum_{j=1}^{q} w_j' \ln \dfrac{w_j'}{w_{ij}} \\ \text{s.t.} \quad w_j' \geq 0, \sum_{j=1}^{q} w_j' = 1 \end{cases}$$

The optimization model has a global optimal solution (Meng & Chen, 2015), and the solution is

$$w_j' = \prod_{i=1}^{t} w_{ij} \Big/ \sum_{j=1}^{q} \prod_{i=1}^{t} w_{ij} \tag{4}$$

Subjective Weights of Indicators

According to the evaluation value m_{kj} obtained by experts sorting the importance of the indicators qualitatively, the evaluation value is converted through the membership function

$$n_{kj} = \frac{\ln(\lambda - m_{kj})}{\ln(\lambda)} \tag{5}$$

From formula (5), we can see that $n_{kj} \in (0,1)$, λ is the conversion parameter, $\lambda = \max_{1 \leq j \leq q}(m_{kj}) + 2$. Membership function matrix can be formed by n_{kj}, $N = (n_{kj})_{s \times q}$.

According to the membership function matrix N, find the average ranking degree of the expert group for each index

$$g_j = \frac{1}{s} \sum_{k=1}^{s} n_{kj} \tag{6}$$

The sorting error degree generated by the expert group sorting the index set *C* qualitatively for the index c_j is obtained

$$x_j = \frac{1}{s}\sum_{k=1}^{s}\left|n_{kj} - g_j\right| \tag{7}$$

To find the overall ranking degree of each index by the expert group

$$y_j = g_j(1 - x_j) \tag{8}$$

Formula (8) combines the average ranking degree g_j and the ranking error degree x_j to find the overall ranking degree y_j. The larger the ranking error degree x_j , the smaller the overall ranking degree y_j . Finally, the overall ranking degree y_j is normalized, and subjective weight of each indicator is

$$w_j'' = y_j \Big/ \sum_{j=1}^{q} y_j \tag{9}$$

Comprehensive Index Weight

The objective weight w_j' of the indicator is determined by the numerical characteristics from the decision matrix, and the subjective weight w_j'' of the indicator is determined by the subjective preference from the expert group on the importance of each indicator. The objective weight coefficient is represented by ρ, and the subjective weight coefficient is represented by η. The comprehensive weight of the index is obtained by the convex combination of objective weight w_j' and subjective weight w_j''

$$w_j = \rho w_j' + \eta w_j'' \tag{10}$$

$0 \le \rho \le 1,\ 0 \le \eta \le 1,\ \rho + \eta = 1$. The larger ρ , the greater the influence of the numerical characteristics from the decision matrix on the comprehensive weight.

Evaluation for Assessment Objects and Sensitivity Analysis

According to the evaluation value e_{ij}^k of the assessment object by the expert group, the evaluation value of the expert d_k on the assessment object set *P* with the index set *C* is formed into a matrix $E^k = (e_{ij}^k)_{t \times q}$.

In order to eliminate the difference and influence of different dimensions, the matrix E^k is standardized generally

$$r_{ij}^{k}=\begin{cases}\dfrac{e_{ij}^{k}-\min\limits_{1\le i\le t}(e_{ij}^{k})}{\max\limits_{1\le i\le t}(e_{ij}^{k})-\min\limits_{1\le i\le t}(e_{ij}^{k})}, c_j\in c^{(1)}\\ \dfrac{\max\limits_{1\le i\le t}(e_{ij}^{k})-e_{ij}^{k}}{\max\limits_{1\le i\le t}(e_{ij}^{k})-\min\limits_{1\le i\le t}(e_{ij}^{k})}, c_j\in c^{(2)}\\ 1-\dfrac{\max(\varsigma-e_{ij}^{k}, e_{ij}^{k}-\theta,0)}{\max\limits_{1\le i\le t}(\varsigma-e_{ij}^{k}, e_{ij}^{k}-\theta,0)}, c_j\in c^{(3)}\\ 1-\dfrac{\left|e_{ij}^{k}-\varepsilon\right|}{\max\limits_{1\le i\le t}\left|e_{ij}^{k}-\varepsilon\right|}, c_j\in c^{(4)}\end{cases} \quad (11)$$

Among them, $c^{(1)}$, $c^{(2)}$, $c^{(3)}$, $c^{(4)}$, ς, θ, ε have the same meaning as formula (1). For high-quality indicators $c^{(1)}$ and low-quality indicators $c^{(2)}$, if $\max\limits_{1\le i\le t}(e_{ij}^{k})=\min\limits_{1\le i\le t}(e_{ij}^{k})$, $\dfrac{e_{ij}^{k}-\min\limits_{1\le i\le t}(e_{ij}^{k})}{\max\limits_{1\le i\le t}(e_{ij}^{k})-\min\limits_{1\le i\le t}(e_{ij}^{k})}=1$, $\dfrac{\max\limits_{1\le i\le t}(e_{ij}^{k})-e_{ij}^{k}}{\max\limits_{1\le i\le t}(e_{ij}^{k})-\min\limits_{1\le i\le t}(e_{ij}^{k})}=1$. For interval indicators $c^{(3)}$,if $\max\limits_{1\le i\le t}(\varsigma-e_{ij}^{k}, e_{ij}^{k}-\theta,0)=0$, $\dfrac{\max(\varsigma-e_{ij}^{k}, e_{ij}^{k}-\theta,0)}{\max\limits_{1\le i\le t}(\varsigma-e_{ij}^{k}, e_{ij}^{k}-\theta,0)}=0$. For fixed indicators $c^{(4)}$,if $\max\limits_{1\le i\le t}\left|e_{ij}^{k}-\varepsilon\right|=0$, $\dfrac{\left|e_{ij}^{k}-\varepsilon\right|}{\max\limits_{1\le i\le t}\left|e_{ij}^{k}-\varepsilon\right|}=0$.

The normalized matrix $R^{k}=(r_{ij}^{k})_{t\times q}$ can be formed by the normalized value r_{ij}^{k}.

Let the weight of expert d_k is φ_k, $\sum\limits_{k=1}^{s}\varphi_k=1$, the comprehensive evaluation value of the assessment object p_i is

$$z_i=\sum_{k=1}^{s}\sum_{j=1}^{q}w_j\varphi_k r_{ij}^{k} \quad (12)$$

According to the size of z_i, the risk level of the assessment object can be judged, and it can also provide decision-making basis for supply chain risk management. If the assessment object is multiple comparable supply chains, the advantages and disadvantages of each supply chain can be found through the evaluation. If the assessment object is the same supply chain in different periods, the risk level of the supply chain can be monitored dynamically through the evaluation.

When the objective weight coefficient takes different values, we calculating and analysing about the change in the comprehensive evaluation value z_i of the assessment object can provide more effective information for decision-making.

EVALUATION INDEX SYSTEM AND DECISION-MAKING STEPS

Evaluation Index System

On the basis of referring to the relevant literature about supply chain risk evaluation (Shaik & Abdul-kader, 2014; Hahn, Hong & Min, 2014), combined with the research needs of this paper, an evaluation index system as shown in Figure 1 is established. The evaluation index set $C=\{c_j, j=1,2,\cdots,6\}$, the indicators adopted temporarily by this indicator system are all high-quality indicators, that is, the higher the score of the assessment object under the indicator, the lower the risk level of the supply chain. When other colleagues apply the model of this paper, the indicator system can be adjusted according to their own needs. Formula (1), formula (11) can deal with various types of evaluation indicators to meet the needs of special standardization and general standardization.

Figure 1: Evaluation Indicators

$$\text{Supply chain risk}(C)\begin{cases}\text{Market response ability}(c_1)\\ \text{Logistics management ability}(c_2)\\ \text{Partnerships}(c_3)\\ \text{Information management ability}(c_4)\\ \text{Accounting management ability}(c_5)\\ \text{Robustness of production system}(c_6)\end{cases}$$

Decision-making Steps

Step 1, According to formulas (1)~(4), the objective weight of the index w_j' is obtained based on the numerical characteristics of the decision matrix.

Step 2, According to formulas (5)~(9), the subjective weight of the index w_j'' is calculated based on the subjective preference of the expert group on the importance of the index.

Step 3, Determining the initial value of the objective weight coefficient ρ and the subjective weight coefficient η , calculating the index weight w_j according to formula (10), and getting the index comprehensive weight vector $W=(w_1, w_2, \cdots, w_q)^{\mathrm{T}}$.

Step 4, According to formula (11), the decision matrix is standardized generally; the weight of expert φ_k is determined, and the comprehensive evaluation value z_i of the assessment object is calculated according to formula (12).

Step 5, If it is necessary, sensitivity analysis of objective weight coefficients ρ is performed.

CASE STUDY

In the part about case study, the risk levels of 4 representative supply chains in China's mobile phone manufacturing industry are evaluated.

Assessment Object, Evaluation Expert

The evaluation object is the supply chain with 4 mobile phone manufacturing head enterprises as the core enterprises, which is represented by p_1, p_2, p_3, p_4, and the evaluation object set $P=\{p_i, i=1,2,3,4\}$。

We selected and invited 8 experts to evaluate the assessment objects and the importance of indicators, the evaluation experts set $D=\{d_k, k=1,2,\cdots,8\}$. All experts come from fields related to China's mobile phone manufacturing industry closely, including 3 experts from research institutions, 3 experts from industry consulting institutions, and 2 senior reporters from industry media.

Evaluation about Assessment Objects and the Importance of Indicators

The expert group evaluates the assessment objects according to the index set C (values 0-100), and the results are shown in Table 1.

Table 1: Evaluation Value of Assessment Object

p_i	d_k	c_1	c_2	c_3	c_4	c_5	c_6	p_i	d_k	c_1	c_2	c_3	c_4	c_5	c_6
p_1	d_1	72	90	86	82	77	91	p_2	d_1	74	88	73	82	83	91
	d_2	77	87	92	76	82	85		d_2	70	91	78	86	86	85
	d_3	70	89	82	89	75	81		d_3	79	93	76	90	80	89
	d_4	79	91	88	75	78	89		d_4	85	90	83	80	82	93
	d_5	68	86	80	88	76	78		d_5	72	92	71	87	79	89
	d_6	75	88	93	80	75	80		d_6	83	84	86	89	78	80
	d_7	81	91	90	78	80	90		d_7	81	89	69	91	84	90
	d_8	82	85	84	84	79	86		d_8	76	91	67	85	85	83
p_3	d_1	63	84	83	82	80	83	p_4	d_1	62	82	83	74	87	79
	d_2	70	86	75	76	84	81		d_2	65	84	87	78	89	81
	d_3	66	85	80	88	77	78		d_3	61	83	80	84	86	76
	d_4	74	87	83	86	81	85		d_4	69	86	75	79	88	83
	d_5	76	88	87	78	82	89		d_5	67	85	78	72	85	74
	d_6	80	83	91	84	81	77		d_6	72	80	71	73	84	70
	d_7	68	84	86	80	78	75		d_7	76	88	85	81	86	87
	d_8	78	86	72	75	79	73		d_8	79	85	73	77	87	72

The expert group ranks the importance of each indicator qualitatively, and their ranking values form the following matrix

$$M=\begin{bmatrix}5&4&2&6&3&1\\6&3&4&5&1&2\\5&3&2&4&1&1\\4&5&3&6&1&2\\4&2&3&5&3&1\\5&2&3&4&2&1\\3&2&2&4&1&1\\6&4&3&5&1&2\end{bmatrix}.$$

The Objective Weight of the Indicators

According to formula (1), the data in Table 1 is standardized specially, and the value of τ is 8, and the standardized matrix corresponding to each assessment object is

$$F_1=\begin{bmatrix}0.353&0.915&0.535&0.519&0.605&1.000\\0.605&0.698&0.917&0.283&1.000&0.579\\0.282&0.837&0.365&1.000&0.490&0.394\\0.742&1.000&0.643&0.254&0.670&0.837\\0.224&0.636&0.300&0.914&0.545&0.291\\0.490&0.765&1.000&0.426&0.490&0.357\\0.907&1.000&0.769&0.348&0.821&0.915\\1.000&0.579&0.443&0.630&0.742&0.636\end{bmatrix},F_2=\begin{bmatrix}0.330&0.643&0.270&0.435&0.753&0.840\\0.212&0.840&0.458&0.636&1.000&0.487\\0.557&1.000&0.372&0.915&0.561&0.703\\1.000&0.769&0.753&0.357&0.683&1.000\\0.265&0.917&0.216&0.698&0.507&0.703\\0.827&0.443&1.000&0.837&0.458&0.300\\0.680&0.703&0.172&1.000&0.828&0.769\\0.408&0.840&0.136&0.579&0.911&0.402\end{bmatrix},$$

$$F_3=\begin{bmatrix}0.148&0.689&0.479&0.568&0.677&0.572\\0.344&0.832&0.213&0.309&1.000&0.471\\0.215&0.758&0.357&1.000&0.499&0.348\\0.536&0.913&0.479&0.832&0.748&0.692\\0.663&1.000&0.698&0.381&0.825&1.000\\1.000&0.626&1.000&0.689&0.748&0.314\\0.272&0.689&0.636&0.467&0.553&0.254\\0.817&0.832&0.154&0.278&0.612&0.205\end{bmatrix},F_4=\begin{bmatrix}0.144&0.568&0.686&0.363&0.834&0.462\\0.210&0.689&1.000&0.553&1.000&0.565\\0.126&0.626&0.511&1.000&0.760&0.339\\0.339&0.832&0.305&0.612&0.914&0.686\\0.268&0.758&0.417&0.291&0.692&0.274\\0.476&0.467&0.197&0.325&0.630&0.176\\0.734&1.000&0.830&0.748&0.760&1.000\\1.000&0.758&0.246&0.499&0.834&0.220\end{bmatrix}.$$

According to formula (2), finding the index entropy value of the expert group for each assessment object, and the entropy value matrix is

$$H=\begin{bmatrix}0.946&0.991&0.964&0.946&0.986&0.960\\0.942&0.989&0.898&0.976&0.984&0.971\\0.920&0.995&0.935&0.957&0.989&0.940\\0.890&0.989&0.936&0.962&0.995&0.929\end{bmatrix}.$$

Finding the initial weight of the index for each assessment object by formula (3), and get the initial weight matrix

$$W^c = \begin{bmatrix} 0.164 & 0.171 & 0.166 & 0.163 & 0.170 & 0.166 \\ 0.163 & 0.172 & 0.156 & 0.169 & 0.171 & 0.169 \\ 0.160 & 0.174 & 0.163 & 0.167 & 0.172 & 0.164 \\ 0.156 & 0.173 & 0.164 & 0.169 & 0.175 & 0.163 \end{bmatrix}.$$

According to formula (4), the objective weight of each indicator is obtained, and the objective weight vector of the indicator is $W' = (0.144, 0.190, 0.149, 0.168, 0.188, 0.161)^T$.

Index's Subjective Weight

The ranking value matrix M is transformed numerically by formula (5), the membership function value matrix is

$$N = \begin{bmatrix} 0.528 & 0.667 & 0.862 & 0.333 & 0.774 & 0.936 \\ 0.333 & 0.774 & 0.667 & 0.528 & 0.936 & 0.862 \\ 0.356 & 0.712 & 0.827 & 0.565 & 0.921 & 0.921 \\ 0.667 & 0.528 & 0.774 & 0.333 & 0.936 & 0.862 \\ 0.565 & 0.827 & 0.712 & 0.356 & 0.712 & 0.921 \\ 0.356 & 0.827 & 0.712 & 0.565 & 0.827 & 0.921 \\ 0.613 & 0.774 & 0.774 & 0.387 & 0.898 & 0.898 \\ 0.333 & 0.667 & 0.774 & 0.528 & 0.936 & 0.862 \end{bmatrix}.$$

According to formula (6), finding the average ranking degree g_j of each index, the average ranking degree vector of the index $G = (0.469, 0.722, 0.763, 0.449, 0.867, 0.898)^T$.

According to formula (7), finding the ranking error x_j of each index, and getting the index ranking error vector $X = (0.124, 0.078, 0.049, 0.097, 0.072, 0.027)^T$.

According to formula (8), finding the overall ranking degree y_j of each index, the overall ranking degree vector $Y = (0.411, 0.665, 0.725, 0.406, 0.805, 0.873)^T$.

According to formula (9), the subjective weight of each indicator is obtained, and the subjective weight vector of the indicator is $W'' = (0.106, 0.171, 0.187, 0.104, 0.207, 0.225)^T$.

Comprehensive Evaluation of Assessment Objects

The initial value of the objective weight coefficient ρ is 0.5. According to formula (10), the comprehensive weight of the index is obtained, and the comprehensive weight vector of the index is $W = (0.124, 0.181, 0.168, 0.136, 0.198, 0.193)^T$.

According to formula (11), the data in Table 1 is standardized generally, and the standardized matrix corresponding to each expert is obtained as

$$R^1 = \begin{bmatrix} 0.833 & 1.000 & 1.000 & 1.000 & 0.000 & 1.000 \\ 1.000 & 0.750 & 0.000 & 1.000 & 0.600 & 1.000 \\ 0.083 & 0.250 & 0.769 & 1.000 & 0.300 & 0.333 \\ 0.000 & 0.000 & 0.769 & 0.000 & 1.000 & 0.000 \end{bmatrix}, R^2 = \begin{bmatrix} 1.000 & 0.429 & 1.000 & 0.000 & 0.000 & 1.000 \\ 0.417 & 1.000 & 0.176 & 1.000 & 0.571 & 1.000 \\ 0.417 & 0.286 & 0.000 & 0.000 & 0.286 & 0.000 \\ 0.000 & 0.000 & 0.706 & 0.200 & 1.000 & 0.000 \end{bmatrix},$$

$$R^3 = \begin{bmatrix} 0.500 & 0.600 & 1.000 & 0.833 & 0.000 & 0.385 \\ 1.000 & 1.000 & 0.000 & 1.000 & 0.455 & 1.000 \\ 0.278 & 0.200 & 0.667 & 0.667 & 0.182 & 0.154 \\ 0.000 & 0.000 & 0.667 & 0.000 & 1.000 & 0.000 \end{bmatrix}, R^4 = \begin{bmatrix} 0.625 & 1.000 & 1.000 & 0.000 & 0.000 & 0.600 \\ 1.000 & 0.800 & 0.615 & 0.455 & 0.400 & 1.000 \\ 0.313 & 0.200 & 0.615 & 1.000 & 0.300 & 0.200 \\ 0.000 & 0.000 & 0.000 & 0.364 & 1.000 & 0.000 \end{bmatrix},$$

$$R^5 = \begin{bmatrix} 0.111 & 0.143 & 0.563 & 1.000 & 0.000 & 0.267 \\ 0.556 & 1.000 & 0.000 & 0.938 & 0.333 & 1.000 \\ 1.000 & 0.429 & 1.000 & 0.375 & 0.667 & 1.000 \\ 0.000 & 0.000 & 0.438 & 0.000 & 1.000 & 0.000 \end{bmatrix}, R^6 = \begin{bmatrix} 0.273 & 1.000 & 1.000 & 0.438 & 0.000 & 1.000 \\ 1.000 & 0.500 & 0.682 & 1.000 & 0.333 & 1.000 \\ 0.727 & 0.375 & 0.909 & 0.688 & 0.667 & 0.700 \\ 0.000 & 0.000 & 0.000 & 0.000 & 1.000 & 0.000 \end{bmatrix},$$

$$R^7 = \begin{bmatrix} 1.000 & 1.000 & 1.000 & 0.000 & 0.250 & 1.000 \\ 1.000 & 0.714 & 0.000 & 1.000 & 0.750 & 1.000 \\ 0.000 & 0.000 & 0.810 & 0.154 & 0.000 & 0.000 \\ 0.615 & 0.571 & 0.762 & 0.231 & 1.000 & 0.800 \end{bmatrix}, R^8 = \begin{bmatrix} 1.000 & 0.000 & 1.000 & 0.900 & 0.000 & 1.000 \\ 0.000 & 1.000 & 0.000 & 1.000 & 0.750 & 0.786 \\ 0.333 & 0.167 & 0.294 & 0.000 & 0.000 & 0.071 \\ 0.500 & 0.000 & 0.353 & 0.200 & 1.000 & 0.000 \end{bmatrix}.$$

Taking the expert weight vector as $\Phi = (0.125, 0.125, 0.125, 0.125, 0.125, 0.125, 0.125, 0.125)^T$. According to formula (12), the comprehensive evaluation value of the assessmentn object is $z_1 = 0.587, z_2 = 0.694, z_3 = 0.384, z_4 = 0.342$.

From the results, it can be seen that in terms of the risk situation about the assessment object, p_2 f p_1 f p_3 f p_4, that is, p_2 is the best, p_1 is second, p_1 is better than p_3, and p_3 is slightly better than p_4.

When the objective weight coefficient ρ is 0.0~1.0, the comprehensive evaluation value of the assessment object changes very little and can be ignored, so this paper will not make sensitivity analysis specifically.

CONCLUSION

Based on the numerical characteristics of the decision matrix, the objective weight of the index is determined by the numerical characteristics of the decision matrix. Based on the expert group's subjective preference to the importance of the index, the subjective weight of the index is determined by the expert group's subjective preference to the importance of the index.

The comprehensive weight of the index is obtained through the convex combination of the objective weight x and the subjective weight, so that the comprehensive weight of the index can reflect simultaneously the numerical characteristics of the decision matrix and the preference information of the expert group for the importance of the index, thereby overcoming the shortcomings of the objective weighting method and the subjective weighting method. This model can provide method support for multi-attribute group decision making of supply chain risk.

This model can standardize multiple types of evaluation indicators, so that other researchers can adjust the evaluation indicator system flexibly according to their own needs when using the model established in this paper.

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