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Selection third-party logistics service providers in supply chain finance by a hesitant fuzzy linguistic combined compromise solution method

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ABSTRACT

In supply chain finance, the multiple criteria decision making (MCDM) problem of selecting a suitable third-party logistics (3PL) service supplier is of great significance to financial institutions. A suitable 3PL service supplier can not only help financial institutions carry out the supply chain finance business, but also can replace financial institutions to supervise the operation of a target financing supply chain, thus reducing the operational risks of financial institutions. As a useful MCDM method, the combined compromise solution (CoCoSo) method mainly combines a compromise decision algorithm with an aggregation strategy to obtain a compromise solution. This study extends the CoCoSo method to hesitant fuzzy linguistic environment to solve the multi-expert MCDM problem of the 3PL service supplier selection. Target criteria whose values are in linguistic forms are considered in the process of normalizing the decision matrix. A new integration approach with respect to subordinate compromise scores is introduced, and the subjective and objective weights of criteria are considered simultaneously in this extended process to avoid one-sidedness of criterion weights. A case study about the 3PL service supplier selection is given, in which the sensitivity analysis and comparative analysis are provided to highlight the advantages of the proposed method.

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1. Introduction

Logistics in supply chain is a physical carrier on which the capital flow can depend, so that the inventory pledge financing is always the core link of supply chain finance. Without the flow of inventory, supply chain financing modes such as accounts payable and prepayment are impossible. It can be said that the logistics in a supply chain

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is the basis for the development of the supply chain financial business. As the main coordinator of supply chain finance, logistics enterprises can not only provide logistics and warehousing services for small and medium-sized enterprises, but also provide goods custody supervision services for financial institutions to build a bridge of cooperation between banks and enterprises. To prevent the occurrence of false transactions, financial institutions usually need to introduce professional third-party logistics (3PL) service providers to supervise the goods transactions of upstream and downstream enterprises in the supply chain, so as to prevent the possible collusion of upstream and downstream enterprises in the supply chain from causing risks to the financial system. For example, in China, many banks have commissioned the China Foreign Trade and Transportation Group to provide logistics supervision services to their customers, so that banks can grasp the real situation of logistics in a supply chain in time to reduce credit risk.[1] Overall, a suitable 3PL service supplier enables financial institutions to carry out the supply chain finance business, and it can replace financial institutions to supervise the operation of a target financing supply chain, thus reducing the operational risks of financial institutions.

Since the evaluation on the service quality of third-party logistics service providers in supply chain finance needs a large number of qualitative and quantitative indicators to support, it can be regarded as a multiple criteria decision making (MCDM) problem. Various MCDM methods have been developed to deal with the problems on selecting 3PL service providers. For example, Gürcan, Yazıcı, Beyca, Arslan, and Eldemir (2016) applied the AHP (Analytic Hierarchy Process) for the 3PL provider selection. Bansal and Kumar (2013) proposed a hybrid model integrating AHP with PROMETHEE (preference ranking organization method for enrichment evaluation) for the 3PL selection. Yayla, Oztekin, Gumus, and Gunasekaran (2015) developed a hybrid fuzzy method which combines fuzzy-AHP and fuzzy- TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) for the 3PL transportation provider evaluation. Singh, Gunasekaran, and Kumar (2018) proposed a hybrid model of fuzzy-AHP and fuzzy-TOPSIS for cold chain management. Sremac, Stević, Pamučar, Arsić, and Matić (2018) used the rough SWARA-WASPAS (Step-Wise Weight Assessment Ratio Analysis-Weighted Aggregated Sum Product Assessment) method for the selection of 3PL suppliers. Ecer (2018) applied the integrated fuzzy-AHP and EDAS (Evaluation based on Distance from Average Solution) model for the 3PL provider selection. However, there are two limitations in the aforementioned literature. On the one hand, most of them only selected a 3PL service provider from the perspective of manufacturing enterprises. On the other hand, the methods used in the literature need to form a comparison matrix, which are time-consuming and complicated, and thus are not suitable for the situation with large number of criteria and alternatives.

In the process of solving the MCDM problem about the 3PL service provider selection in supply chain finance, it is inevitable to cope with the compromise of performance values of enterprises under different or even conflicting evaluation indicators. In many cases, a comprehensive analysis on the basic properties of non-inferior or compromise solutions can aid the decision-making process (Yu, 1973). At present, MCDM methods have been researched in an attempt to find a compromise solution, such as the TOPSIS method which obtains a compromise solution with the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution (Behzadian, Otaghsara, Yazdani, & Ignatius, 2012), the VIKOR (VIsekriterijumska optimizacija i KOmpromisno Resenje) method which determines a compromise solution with a maximum group utility value and a minimum 'individual' regret value (Liao, Xu, & Zeng, 2015), the COPRAS (Complex Proportional Assessment) method (Podvezko, 2011; Stefano, Casarotto, Vergara, & Rocha, 2015) which deduces a compromise solution with the maximum value of the sum of maximum weighted normalization criteria and the minimum value of the sum of minimum weighted normalization criteria, the EDAS method (Keshavarz Ghorabaee, Zavadskas, Olfat, & Turskis, 2015) which derives a compromise solution with higher values of positive distance from average and lower values of negative distance from average, and the CODAS (COmbinative Distance-based ASsessment) method (Ghorabaee, Zavadskas, Turskis & Antucheviciene, 2017) which deduces a compromise solution with the maximum value of the Euclidean and Taxicab distances of alternatives from the negative-ideal solution. However, when these methods are used to solve an MCDM problem, the ranking results produced by these methods may change greatly because of the change of weight distribution of criteria. In other words, the reliability and stability of the results produced by these methods are limited. To improve this limitation, Yazdani, Zarate, Zavadskas, and Turskis (2019) proposed a so-called Combined Compromise Solution (CoCoSo) method, which integrates the combined compromise decision-making algorithm with some aggregation strategies to obtain a multi-faceted compromise solution, and the compromise solution obtained by this method is consistent with that obtained by other MCDM methods, but not easily affected by the change of weight distribution of criteria. This implies that the CoCoSo method has advantages in reliability and stability of decision-making results.

The CoCoSo method integrates three subordinate performance values of alternatives by an aggregation strategy to get the final compromise solution for an MCDM problem. It uses the combination of arithmetic average aggregation operator and geometric average aggregation operator to effectively utilize the advantages of the two methods. Nevertheless, the aggregation strategy used in the CoCoSo method takes each subordinate performance value as equally important, which is not rational. It would be more reasonable to set the corresponding importance of each subordinate performance value. In this respect, the ORESTE (organísation, rangement et Synthèse de données relarionnelles, in French, Roubens, 1982), as a general ranking method, considers the importance of each element and does not need to provide an accurate weight for each element. It is simple and efficient. Hence, this paper uses the aggregation function in the ORESTE method to aggregate three subordinate rankings from three subordinate performance values to get the comprehensive ranking of alternatives.

Generally, due to the increase uncertainties in the assessment environment and the limitation of available information, experts prefer to use linguistic terms to express their cognition in the process of evaluation. The Hesitant Fuzzy Linguistic Term Set (HFLTS) (Rodríguez, Martinez, & Herrera, 2012) can express simple or complex linguistic evaluation information of experts. Compared with fuzzy numbers and interval values, the HFLEs (hesitant fuzzy linguistic elements, which are the elements of an

HFLTS) have obvious advantages (Liao, Xu, Herrera-Viedma, & Herrera, 2018). However, there is still a problem that how to reasonably convert HFLEs into numerical values for calculation. In this regard, Liao et al. (2019) proposed a score function of HFLEs based on the hesitancy degree of an HFLE and linguistic scale functions, making the transformation results reasonable. Based on this score function, this paper combines the CoCoSo method with HFLEs, and then proposes a hesitant fuzzy linguistic CoCoSo (HFL-CoCoSo) method. In addition, since the weight allocation of criteria has a vital impact on final results for an MCDM problem, this paper introduces a method to deduce the comprehensive weights of criteria by integrating subjective criterion weights with objective criterion weights.

In addition, in some MCDM problems, the performance values of alternatives are not necessarily the bigger the better (on benefit criteria) or the smaller the better (on cost criteria), but the closer to a given value the better. However, most MCDM methods only consider benefit and cost criteria, and few methods take into account target criteria, especially the target criteria that need to be evaluated in linguistic values. In this regard, the HFL-CoCoSo method proposed in this paper shall consider three types of criteria, namely the benefit, cost and target criteria, which can further correspond to the real decision-making situation to some extent.

In summary, the contributions of this paper lie in follows:

a. The CoCoSo method is extended to the HFL environment, which enhances the practicability of the method in solving practical problems;
b. On the basis of the original CoCoSo method and ORESTE method, this paper introduces a new integration approach to make the final ranking result reasonable;
c. The comprehensive weights of criteria are determined by combining subjective criterion weights with objective criterion weights. Furthermore, in the process of normalizing the initial decision matrix, target criteria under the HFL environment are considered, which makes the method conform to the actual situation of MCDM problems;
d. The proposed method is implemented to select the optimal 3PL service provider for financial institutions, which can help financial institutions develop supply chain finance business.

The framework of this study is arranged as follows: Section 2 briefly reviews the knowledge of the HFLTS and the CoCoSo method. Section 3 proposes a new integration approach for subordinate compromise scores. Section 4 introduces the procedure of the HFL-CoCoSo method considering the weights of experts and criteria. Section 5 gives a case study for the application of the proposed method. The paper is concluded in Section 6.

2. Preliminaries

This section reviews the concept of HFLTS and introduces a score function of HFLE. Furthermore, the general procedure of the original CoCoSo method is retrospected.

2.1. Hesitant fuzzy linguistic term set (HFLTS)

The HFLTS, an ordered finite subset of the consecutive linguistic terms of a linguistic term set, was first introduced by Rodríguez et al. (2012). After that, Liao, Xu, Zeng, and Merigó (2015) further expressed the concept of HFLTS in mathematical form as below: Let $S = \{s_\alpha | \alpha = 0, 1, \ldots, 2\tau\}$ be a linguistic term set and $x \in X$ be defined. An HFLTS on X, can be expressed as $H_S = \{<x, h_S(x)>|x \in X\}$, where $h_S(x) = \{s_{\varphi_l}(x)|s_{\varphi_l}(x) \in S; \varphi_l \in \{0, 1, \ldots, 2\tau\}; \ l = 1, 2, \ldots, L\}$ with $s_{\varphi_l}(x)$ being the continuous terms in S and L being the number of linguistic terms in $h_S(x)$. $h_S(x)$ is named as an HFLE, which represents a set of possible linguistic terms of the linguistic variable x to S.

Based on the hesitancy degree and linguistic scale functions, a score function of HFLEs was proposed by Liao et al. (2019):

$$G(h_S(x)) = (1 - HD(h_S(x))) \times (\frac{1}{L}\sum\nolimits_{l=1}^{L} g(s_{\varphi_l}(x))) \tag{1}$$

where $HD(h_S(x))$ is the hesitancy degree of $h_S(x)$, which reflects the reliability of the HFLE $h_S(x)$, and $g(s_{\varphi_l}(x))$ is the semantic of s_{φ_l}. $HD(h_S(x))$ and $g(s_{\varphi_l}(x))$ can be respectively calculated by following equations:

$$HD(h_S(x)) = \frac{L(h_S(x)) \ln (L(h_S(x)))}{(2\tau + 1) \ln (2\tau + 1)} \tag{2}$$

$$g(s_{\varphi_l}(x)) = \varphi_l / 2\tau \tag{3}$$

where $g(s_{\varphi_l}(x))$ indicates that the semantics of linguistic terms are uniformly distributed. If the unbalanced distribution is considered, then different thresholds must be involved in the linguistic scale function and it is usually difficult for experts to give appropriate thresholds according to actual situations. For more details, readers can refer to Liao et al. (2019).

2.2. The combined compromise solution (CoCoSo) method

Yazdani et al. (2019) proposed the CoCoSo method to deduce compromise solutions for MCDM problems by combining the compromise decision-making algorithm with aggregation strategies. They proved that the results obtained by the CoCoSo method are reliable and stable for the variation of criteria. They applied this method to solve the problem of logistics provider selection.

The CoCoSo method comes mainly from three ideas:

1. Based on the idea that the desirability degrees of alternatives are related to the distances between alternatives and negative ideal solutions, the CoCoSo method normalizes performance values according to the types of criteria, as shown in Equation (4):

$$r_{ij} = \frac{|x_{ij} - \delta|}{\max_i x_{ij} - \min_i x_{ij}}, \ \text{ for } i = 1, 2, \ldots, m; j = 1, 2, \ldots, n \tag{4}$$

where x_{ij} represents the performance value of the i th alternative over the j th criterion and r_{ij} is the normalized performance value, with $\delta = \min_i x_{ij}$ for benefit criterion and $\delta = \max_i x_{ij}$ for cost criterion.

2. Based on the idea of the WASPAS method (Chakraborty, Zavadskas, & Antucheviciene, 2015), the CoCoSo method respectively calculates the weighted sum and weighted product of comparability sequences for each alternative, as shown by Equations (5) and (6):

$$P_i^1 = \sum\nolimits_{j=1}^{n} (w_j r_{ij}) \tag{5}$$

$$P_i^2 = \sum\nolimits_{j=1}^{n} (r_{ij})^{w_j} \tag{6}$$

where P_i^1 and P_i^2 represent the weighted sum performance value and weighted product performance value of the i th alternative, respectively, with w_j being the weight of the j th criterion.

3. Based on the idea of the MULTIMOORA method (Brauers & Zavadskas, 2010), the CoCoSo method uses three subordinate aggregation operators from different perspectives to generate three subordinate compromise scores for each alternative, as shown in Equations (7)–(9):

$$Q_{ia} = \frac{P_i^1 + P_i^2}{\sum_{i=1}^{m} (P_i^1 + P_i^2)} \tag{7}$$

$$Q_{ib} = \frac{P_i^1}{\min_i P_i^1} + \frac{P_i^2}{\min_i P_i^2} \tag{8}$$

$$Q_{ic} = \frac{\gamma(P_i^1) + (1-\gamma)(P_i^2)}{\gamma \max_i P_i^1 + (1-\gamma) \max_i P_i^2} \tag{9}$$

Finally, the method integrates the three subordinate compromise scores of each alternative by a hybrid integration operator shown as Equation (10) to derive the final ranking of alternatives:

$$Q_i = \frac{1}{3}(Q_{ia} + Q_{ib} + Q_{ic}) + (Q_{ia} Q_{ib} Q_{ic})^{\frac{1}{3}} \tag{10}$$

where Q_{ia}, Q_{ib}, Q_{ic} are three subordinate compromise scores and Q_i is the comprehensive compromise performance value of the i th alternative. The value of the balance parameter γ is determined by experts.

Concerning detailed explanations on the specific operation steps of the CoCoSo method to solve MCDM problems, readers can refer to Yazdani et al. (2019).

3. The combined compromise solution method with a new integration approach

Based on the combination of the arithmetic average integration operator and geometric average integration operator, the hybrid integration operator given as Equation (10) synthesizes the advantages of the two integration operators. However, this integration approach takes the three subordinate compromise scores (which have great differences in scores) as equally important. For the three subordinate aggregation operators given in Section 2.2, it is not difficult to find that $Q_{ia}<1,\ Q_{ib}\geq 2,\ Q_{ic}<1$. If we use Equation (10) for integration, the value of Q_{ib} will have a greater impact on the final result than those of Q_{ia} and Q_{ic}, but in practice, Q_{ib} may be the least important of the three subordinate compromise scores.

To overcome the above limitation, an ordinal aggregation method, ORESTE, is introduced to aggregate the three subordinate compromise scores. This method not only helps experts assign the importance of three subordinate compromise scores according to the actual situation, but also does not need to give a specific and precise weight for each subordinate aggregation operator, which makes the decision-making process simple and efficient (Wu & Liao, 2018).

Let $r(Q_\upsilon)$ $(\upsilon = 1, 2, 3)$ represent the importance of the three subordinate aggregation operators, and the values of them are determined by experts. According to the descending orders of three subordinate compromise scores of alternatives, we can obtain three subordinate ranks of each alternative, expressed as $r_\upsilon(A_i)$ for $\upsilon = 1, 2, 3$, $i = 1, 2, \ldots, m$. Then, the global preference score of alternative A_i corresponding to the subordinate aggregation operator Q_υ, $PS_\upsilon(A_i)$, can be calculated by Equation (11) based on the hybrid Euclidean distance (Liao, Xu, & Zeng, 2014):

$$PS_\upsilon(A_i) = \sqrt{0.5 \times (0.5 \times ((r_\upsilon(A_i))^2 + (r(Q_\upsilon))^2) + \max\{(r_\upsilon(A_i))^2, (r(Q_\upsilon))^2\})} \tag{11}$$

where $r_\upsilon(A_i)$ and $r(Q_\upsilon)$ are obtained based on the rule of Besson's mean ranks (Roubens, 1982). With this rule, if alternative A_i ranks in the ψ th position, then $r_\upsilon(A_i) = \psi$; if alternatives A_i and A_t rank in the ψ th position simultaneously, then, $r_\upsilon(A_i) = r_\upsilon(A_t) = (\psi + \psi + 1)/2$.

Afterwards, the global rank of alternative A_i corresponding to the aggregation operator Q_υ, $R_\upsilon(A_i)$, can be obtained based on the ascending ranking of $PS_\upsilon(A_i)$. If $PS_\upsilon(A_i) = PS_\upsilon(A_t)$, then $R_\upsilon(A_i) = R_\upsilon(A_t)$; if $PS_\upsilon(A_i)>PS_\upsilon(A_t)$, then $R_\upsilon(A_i)<R_\upsilon(A_t)$; and if $PS_\upsilon(A_i)<PS_\upsilon(A_t)$, then $R_\upsilon(A_i)>R_\upsilon(A_t)$.

Finally, the three global ranks are integrated by Equation (12) to derive the comprehensive rank $R(A_i)$ of each alternative.

$$R(A_i) = \sum_{\upsilon=1}^{3} R_\upsilon(A_i) \tag{12}$$

Ranking $R(A_i)$ in ascending order, the alternative A_i that has the lowest $R(A_i)$ is found out as the optimal alternative.

4. The hesitant fuzzy linguistic-combined compromise solution (HFL-CoCoSo) method

To expand the application scope of the CoCoSo method, this section proposes a new multi-expert MCDM method that combines the CoCoSo method with the HFLEs in describing ambiguous and complex MCDM problems. In Section 4.1, the weights of experts are derived based on the hesitancy degree of experts' evaluation information. In Section 4.2, the subjective criterion weights and objective criterion weights are respectively calculated and then combined to obtain the comprehensive criterion weights. In Section 4.3, the HFL-CoCoSo method is described and in Section 4.4, we give the specific procedures of the HFL-CoCoSo method.

4.1. Determine the weights of experts based on the hesitancy degrees of HFLEs

Consider a multi-expert MCDM problem that experts $E_k(k = 1, 2, \ldots, e)$ are invited to give linguistic evaluation information for each alternative A_i on each criterion c_j. Based on the linguistic translation rules (Rodríguez et al., 2012), each expert's linguistic evaluations can be converted to HFLEs, and thus we can establish an HFL decision matrix corresponding to each expert as follows:

$$H_S^{E_k} = \begin{pmatrix} h_S^{E_k}(x_{11}) & \cdots & h_S^{E_k}(x_{1j}) & \cdots & h_S^{E_k}(x_{1n}) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ h_S^{E_k}(x_{i1}) & \cdots & h_S^{E_k}(x_{ij}) & \cdots & h_S^{E_k}(x_{in}) \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ h_S^{E_k}(x_{m1}) & \cdots & h_S^{E_k}(x_{mj}) & \cdots & h_S^{E_k}(x_{mn}) \end{pmatrix} \quad \text{for } k = 1, 2, \ldots, e$$

where $h_S^{E_k}(x_{ij})$ represents the performance value of alternative A_i over criterion c_j evaluated by expert E_k.

Then, we can compute the hesitancy degree of each HFLE by Equation (2). The hesitancy degree HD^{E_k} of expert E_k is obtained by Equation (13):

$$HD^{E_k} = \frac{1}{m \times n} \sum_{i=1}^{m} \sum_{j=1}^{n} HD(h_S^{E_k}(x_{ij})) \tag{13}$$

Thus, the relative weight w^{E_k} of expert E_k can be calculated by Equation (14):

$$w^{E_k} = (0.5 - HD^{E_k}) / \sum_{k=1}^{e} (0.5 - HD^{E_k}) \tag{14}$$

Afterwards, compute the semantic of each linguistic term in all decision matrices based on the linguistic scale function as shown in Equation (3). Then, we can calculate the score $G(h_S^{E_k}(x_{ij}))$ of each HFLE by Equation (1) and generate the numerical decision matrices corresponding to the HFL decision matrices. Next, by Equation (15), a collective decision matrix $G = (G(h_S(x_{ij})))_{m \times n}$ can be obtained by aggregating the numerical decision matrices associated to all experts, where

$$G(h_S(x_{ij})) = \sum_{k=1}^{e} w^{E_k} G(h_S^{E_k}(x_{ij})) \tag{15}$$

4.2. Determine the weights of criteria

1. Calculate the subjective weights of criteria based on experts' evaluation information on criteria

   Each expert requires to provide their evaluation information on the importance of criteria based on a given LTS (Linguistic Term Set). Suppose that $h_S^{E_k}(y_j)$ represents the hesitant fuzzy linguistic evaluation of the importance of criterion c_j given by expert E_k. Then, the importance of criteria with respect to each expert can be represented as the following vector:

   $$I_S^{E_k} = (h_S^{E_k}(y_1), h_S^{E_k}(y_2), \ldots, h_S^{E_k}(y_j), \ldots, h_S^{E_k}(y_n))^T \text{ for } k = 1, 2, \ldots, e$$

   By Equation (1), the score of each HFLE in $I_S^{E_k}$, $G(h_S^{E_k}(y_j))$, can be calculated. Combining the weight of each expert given as Equation (14), the collective subjective weight w_j^* of criterion c_j is obtained by the weighted average operator, shown as follows:

   $$w_j^* = \sum_{k=1}^{e} w^{E_k} G(h_S^{E_k}(y_j)) \text{ for } j = 1, 2, \ldots, n \tag{16}$$

   To guarantee that the sum of the weights of all criteria equals 1, the subjective weight of criterion c_j should be normalized by the following equation:

   $$w_j' = w_j^* / \sum_{j=1}^{n} w_j^* \text{ for } j = 1, 2, \ldots, n \tag{17}$$

2. Calculate the objective weights of criteria based on experts' evaluation information on alternatives

   If an expert is unable to provide their preference information between criteria, an objective method can be used to determine the weights of criteria.

   Based on the hesitant fuzzy linguistic evaluation information of alternatives on criteria provided by the expert, we can measure the distance between alternatives under the same criterion according to the score values of HFLEs. The greater the sum of the distances between the evaluation information of alternatives on a criterion is, the greater the weight should be assigned to the criterion. In this sense, the objective criterion weights can be calculated by the following equation:

   $$w_j'' = \frac{\sum_{i=1}^{m} \sum_{t=1}^{m} |G(h_S(x_{ij})) - G(h_S(x_{tj}))|}{\sum_{j=1}^{n} \sum_{i=1}^{m} \sum_{t=1}^{m} |G(h_S(x_{ij})) - G(h_S(x_{tj}))|} \tag{18}$$

   where $h_S(x_{ij})$ represents the performance value of alternative A_i under criterion c_j and $G(h_S(x_{ij})$ represents the score value of $h_S(x_{ij})$, which can be calculated by Equation (1).

3. Calculate the comprehensive weights of criteria
Finally, a parameter μ ($\mu \in [0,1]$) can be introduced to integrate the subjective weights and objective weights of criteria. The value of parameter μ is determined according to the preference of an expert. The comprehensive weight of criterion c_j is obtained by:

$$w_j = \mu w_j' + (1-\mu) w_j'' \text{ for } j = 1, 2, \ldots, n \tag{19}$$

4.3. The hesitant fuzzy linguistic-combine compromise solution method

Based on the compromise normalization equation (Yazdani et al., 2019), we can normalize the score value of each alternative under each criterion by the following equation:

$$\hat{G}(h_S(x_{ij})) = \frac{|G(h_S(x_{ij})) - \delta'|}{\max_i G(h_S(x_{ij})) - \min_i G(h_S(x_{ij}))} \tag{20}$$

If $h_S(x_{ij})$ is an HFLE on a benefit criterion, then, $\delta' = \min_i G(h_S(x_{ij}))$; if $h_S(x_{ij})$ is an HFLE on a cost criterion, then, $\delta' = \max_i G(h_S(x_{ij}))$; if $h_S(x_{ij})$ is an HFLE on a target criterion and the score value of the target HFLE is δ^*, then, the normalized score value $\hat{G}^*(h_S(x_{ij}))$ can be calculated by:

$$\hat{G}^*(h_S(x_{ij})) = 1 - \frac{|G(h_S(x_{ij})) - \delta^*|}{\max_i G(h_S(x_{ij})) - \min_i G(h_S(x_{ij}))} \tag{21}$$

Based on the comprehensive weights of criteria obtained by Equation (19), we can calculate the weighted sum $P_i^{1\prime}$ and the weighted product $P_i^{2\prime}$ for alternative A_i, which are respectively shown as follows:

$$P_i^{1\prime} = \sum\nolimits_{j=1}^{n} (w_j \hat{G}(h_S(x_{ij}))) \text{ for } i = 1, 2, \ldots, m \tag{22}$$

$$P_i^{2\prime} = \sum_{j=1}^{n} (\hat{G}(h_S(x_{ij})))^{w_j} \text{ for } i = 1, 2, \ldots, m \tag{23}$$

Afterwards, three aggregation operators are applied to derive three subordinate compromise scores of alternatives.

The first aggregation operator is shown in Equation (24), which represents the arithmetic average of the weighted sum and the weighted product for alternative A_i.

$$Q_1(A_i) = \frac{P_i^{1\prime} + P_i^{2\prime}}{\sum_{i=1}^{m} (P_i^{1\prime} + P_i^{2\prime})} \text{ for } i = 1, 2, \ldots, m \tag{24}$$

The second aggregation operator is shown in Equation (25), which represents the sum of relative scores of the weighted sum and the weighted product for alternative

A_i compared with the worst values.

$$Q_2(A_i) = \frac{P_i^{1\prime}}{\min_i P_i^{1\prime}} + \frac{P_i^{2\prime}}{\min_i P_i^{2\prime}} \quad \text{for } i = 1, 2, \ldots, m \tag{25}$$

The third aggregation operator is shown in Equation (26), which releases the balanced compromise of the weighted sum and the weighted product for alternative A_i. Without loss of generality, we always let the balance parameter$\gamma = 0.5$.

$$Q_3(A_i) = \frac{\gamma(P_i^{1\prime}) + (1-\gamma)(P_i^{2\prime})}{\gamma \max_i P_i^{1\prime} + (1-\gamma) \max_i P_i^{2\prime}} \quad \text{for } i = 1, 2, \ldots, m \tag{26}$$

Eventually, using the aggregation method introduced in Section 3 to integrate the three subordinate compromise scores, the final ranking results can be obtained.

4.4. The procedure of the HFL-CoCoSo method

In this subsection, in order to facilitate the application of the proposed method in solving multi-expert MCDM problems, the steps of the HFL-CoCoSo method are described as follows:

Step 1. Construct individual decision matrices corresponding to the experts.

For an MCDM problem, after defining alternatives and criteria, the experts are invited to evaluate the alternatives with respect to the criteria based on a given LTS. Then, the HFL decision matrix corresponding to each expert's evaluation information can be established by converting the linguistic evaluation to corresponding HFLEs.

Step 2. Aggregate all individual decision matrices into a collective one.

Compute the hesitancy degree of experts based on their evaluation information by Equation (13) and derive the experts' weights by Equation (14). Then, determine the semantic of each linguistic term in all decision matrices by Equation (3), and calculate the score of each HFLE by Equation (1). According to Equation (15), aggregate the individual decision matrices into a collective decision matrix.

Step 3. Determine the comprehensive weights of criteria.

Obtain the preference information between criteria provided by the experts. Then, calculate the subjective weights of criteria by Equations (16) and (17), and compute the objective weights of criteria by Equation (18). Combine the subjective and objective weights of each criterion to deduce the comprehensive weights of criteria by Equation (19).

Step 4. Calculate three types of subordinate performance values of the alternatives.

Normalize the performance values of alternatives by Equations (20) and (21). Then, according to the comprehensive weights of criteria obtained in Step 3, calculate the weighted sum and weighted product of each alternative by Equations (22) and (23). Utilize three aggregation operators as shown in Equations (24)–(26) to obtain three subordinate compromise performance values with respect to each alternative.

Step 5. Obtain the final ranking of alternatives.

According to the rankings of the three subordinate compromise performance values in descending order, we derive the global preference score of each alternative over each aggregation operator by Equation (11). Based on the global preference score, determine the global ranking and aggregate the global ranking with respect to each alternative over each aggregation operator by Equation (12). Then, the comprehensive ranking of alternatives can be obtained.

5. Case study: the selection of third-party logistics service providers for financial institutions

In this section, a case study of the optimal 3PL service provider selection is given, which shows the applicability of the proposed method. Section 5.1 briefly describes the background of the case, namely, the importance of solving the MCDM problem of evaluating and selecting a suitable 3PL service provider for financial institutions. Section 5.2 applies the proposed method to solve the problem. Sensitive analysis and comparative analysis are provided in the next subsections, respectively.

5.1. Case description

Supply chain finance is a financing mode in which banks connect core enterprises with upstream and downstream enterprises to provide flexible financial products and services. As of 2008, 46 of the world's 50 largest banks provided supply chain financing services to enterprises, and the remaining 4 were actively planning to launch the business. After more than ten years of development, due to the huge potential market of supply chain finance, supply chain financial services have been basically provided by various financial institutions.[2] However, supply chain finance must focus on the overall operation of the supply chain, but financial institutions may not understand the operation of the supply chain, which increases the operational risks. At this time, it is particularly important to select a suitable 3PL service provider for cooperation. Financial institutions can deeply participate in supply chain financing through cooperation with 3PL service providers. In addition to providing basic logistics services such as product storage and transportation, 3PL service providers can also provide financial institutions and small and medium-sized enterprises with additional services such as quality assessment, supervision, disposal and credit guarantee, so as to promote financial institutions to obtain more customers and more profits.

In many cases, there is only one enterprise that needs financing, and this enterprise has no corresponding accounts receivable and credit guarantee of other

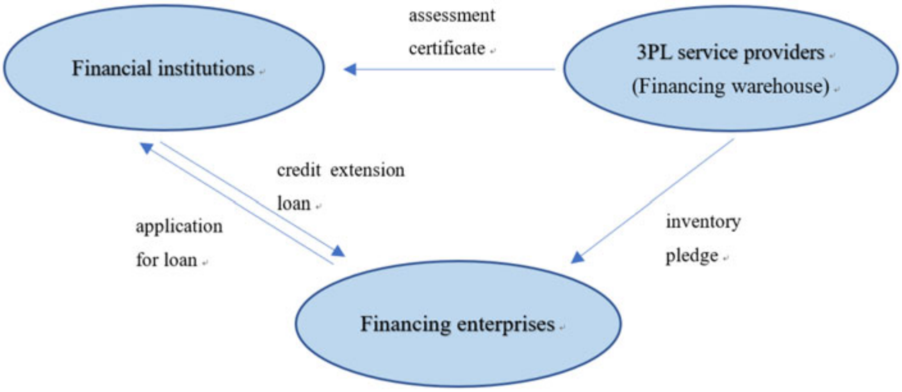

Figure 1. Financing warehouse mode of supply chain finance.

enterprises in the supply chain except goods. At this moment, financial institutions can use the financing warehouse to grant credit to them. Financing warehouse is a kind of financing mode that enterprises use inventory as pledge after evaluation and certification by 3PL service providers, and then financial institutions grant credit to them. A typical financing warehouse of supply chain finance is shown in Figure 1.

In this model, the risk of depreciation of mortgaged goods is the focus of financial institutions. Therefore, when receiving the application of an enterprise's financing warehouse business, financial institutions should examine whether the enterprise has stable inventory, whether there are long-term cooperative trading partners and the overall operation of the supply chain, as a basis for credit decision-making. However, financial institutions may not be good at assessing the market value of pledged goods, and also not good at logistics supervision of pledged goods. So, this financing mode usually need to cooperate with 3PL service providers. Financial institutions can grant certain credit lines to 3PL service providers according to the scale and operational capacity of 3PL service providers, and 3PL service providers are directly responsible for the operation and risk management of financing enterprises' loans. This can not only simplify the process, improve the operation efficiency of production and marketing supply chain of financing enterprises, but also transfer the credit risk of financial institutions themselves and reduce the operating costs of financial institutions. Therefore, selecting a suitable 3PL service provider is of great significance to financial institutions.

As one of the largest banks in China, U enterprise inevitably needs to select a suitable 3PL service provider to help it carry out supply chain finance business. There are six candidates and eight evaluation criteria determined. The six candidates (A_1, A_2, A_3, A_4, A_5, A_6) are well-known comprehensive logistics enterprises in China that can provide 3PL services. The specific information of the eight criteria (c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8) is displayed in Table 1. Among these eight criteria, criteria c_3, c_5 and c_7 are more important than other criteria in the decision-making process of financial institutions in selecting 3PL service providers. Criterion c_3 can help financial institutions monitor the operation of financing enterprises. Criterion c_5 can reduce the risk of financial institutions in supply chain finance. Criterion c_7 affects the operation efficiency of the whole supply chain. The target linguistic evaluation of criterion c_1 is $\{S_3, S_4\}$ and that of criterion c_8 is $\{S_4, S_5\}$.

Table 1. The description of criteria for 3PL service provider selection.

Criterion	Description	Type	Reference
c_1	Diversity of services available	Target	Ecer, 2018; Sharma & Kumar, 2015; Spencer, Rogers, & Daugherty, 1994
c_2	Ability to provide value-added services	Benefit	Chu & Wang, 2012; Tsai, Wen, & Chen, 2007; Yan, Chaudhry, & Chaudhry, 2003
c_3	Information accessibility, including timeliness and reliability of information obtained	Benefit	Aghazadeh, 2003; Ecer, 2018; Bansal & Kumar, 2013; Yayla et al., 2015
c_4	Flexibility, ability to adapt to changing environments and to address special requirements	Benefit	Liu & Wang, 2009; Sharma & Kumar, 2015; Singh et al., 2018
c_5	Financial stability, exposing the continuity and reliability of services	Benefit	Ecer, 2018; Menon, McGinnis, & Ackerman, 1998; Sremac et al., 2018; Tsai et al., 2007
c_6	Response time to service requirements, involving delivery performance	Cost	Bansal & Kumar, 2013; Ecer, 2018; Sharma & Kumar, 2015; Yeung, 2006
c_7	Incompatibility, the degree of difficulty in cooperation and communication	Cost	Bansal & Kumar, 2013; Ecer, 2018; Jharkharia & Shankar, 2007
c_8	Willingness to bear risk, depending on the degree of risk aversion. It should not be too low or too high	Target	Leahy, Murphy, & Poist, 1995; Moberg & Speh, 2004; Sremac et al., 2018

Four experts (E_1, E_2, E_3, E_4) are invited to evaluate with linguistic expressions according to the given LTSs. The LTS for the evaluation of alternatives over criteria is given as $S = \{s_0 : verylow(vl),\ s_1 : low(l),\ s_2 : slightlylow(sl),\ s_3 : medium(m),\ s_4 : slightlyhigh(sh),\ s_5 : high(h),\ s_6 : veryhigh(vh)\}$. The LTS for the evaluation of the importance of criteria is given as $S' = \{s_0 : very\ less\ important\ vli),\ s_1 : less\ important\ (li),\ s_2 : a\ little\ less\ important\ (alli),\ s_3 : medium\ (m),\ s_4 : a\ little\ more\ important\ (almi),\ s_5 : more\ important\ (mi),\ s_6 : very\ more\ important\ (vmi)\}$. The evaluation information given by each expert with respect to the alternatives over the criteria and the evaluation information about the criteria importance are respectively displayed in Tables 2–6.

5.2. Applying the HFL-CoCoSo method to solve the case

Based on the proposed HFL-CoCoSo method, the specific steps to solve the multi-expert MCDM problem of evaluating and selecting a suitable 3PL service provider are as follows:

Step 1. Based on the transformation rules given by Rodríguez et al. (2012), we can convert the linguistic evaluation information on the performance of alternatives over criteria provided by the experts into HFLEs, and establish the decision matrices with regard to each expert as follows:

$$H_S^{E_1} = \begin{pmatrix} \{s_4,s_5\} & \{s_2,s_3\} & \{s_3,s_4,s_5\} & \{s_4,s_5\} & \{s_1,s_2,s_3\} & \{s_0,s_1\} & \{s_3,s_4\} & \{s_0,s_1\} \\ \{s_2,s_3,s_4\} & \{s_3,s_4,s_5\} & \{s_3,s_4\} & \{s_2,s_3,s_4\} & \{s_3,s_4\} & \{s_1,s_2,s_3\} & \{s_2,s_3,s_4\} & \{s_1,s_2,s_3\} \\ \{s_4,s_5,s_6\} & \{s_5,s_6\} & \{s_2,s_3,s_4,s_5\} & \{s_4,s_5\} & \{s_3,s_4,s_5\} & \{s_0,s_1,s_2\} & \{s_0,s_1,s_2\} & \{s_1,s_2\} \\ \{s_3,s_4,s_5\} & \{s_4,s_5\} & \{s_1,s_2,s_3\} & \{s_3,s_4,s_5\} & \{s_5,s_6\} & \{s_2,s_3,s_4\} & \{s_5,s_6\} & \{s_4,s_5\} \\ \{s_1,s_2\} & \{s_1,s_2,s_3\} & \{s_4,s_5\} & \{s_0,s_1,s_2,s_3\} & \{s_2,s_3\} & \{s_3,s_4\} & \{s_4,s_5\} & \{s_2,s_3,s_4\} \\ \{s_5\} & \{s_4,s_5,s_6\} & \{s_0,s_1,s_2\} & \{s_1,s_2\} & \{s_2,s_3,s_4\} & \{s_1,s_2,s_3,s_4\} & \{s_3,s_4,s_5\} & \{s_0,s_1,s_2,s_3\} \end{pmatrix}$$

Table 2. The evaluation information of alternatives over criteria provided by E_1.

	A_1	A_2	A_3	A_4	A_5	A_6
c_1	Between *sh* and *h*	Between *sl* and *sh*	At least *sh*	Between *m* and *h*	Between *l* and *sl*	*h*
c_2	Between *sl* and *m*	Between *m* and *h*	At least *h*	Between *sh* and *h*	Between *l* and *m*	At least *sh*
c_3	Between *m* and *h*	Between *m* and *sh*	Between *sl* and *h*	Between *l* and *m*	Between *sh* and *h*	At most *sl*
c_4	Between *sh* and *h*	Between *sl* and *sh*	Between *sh* and *h*	Between *m* and *h*	At most *m*	Between *l* and *sl*
c_5	Between *l* and *m*	Between *m* and *sh*	Between *m* and *h*	At least *h*	Between *sl* and *m*	Between *sl* and *sh*
c_6	At most *l*	Between *l* and *m*	At most *sl*	Between *sl* and *sh*	Between *m* and *sh*	Between *l* and *sh*
c_7	Between *m* and *sh*	Between *sl* and *sh*	At most *sl*	At least *h*	Between *sh* and *h*	Between *m* and *h*
c_8	At most *l*	Between *l* and *m*	Between *l* and *sl*	Between *sh* and *h*	Between *sl* and *sh*	At most *m*

Table 3. The evaluation information of alternatives over criteria provided by E_2.

	A_1	A_2	A_3	A_4	A_5	A_6
c_1	*h*	Between *m* and *sh*	At least *h*	Between *m* and *h*	Between *l* and *sl*	Between *sh* and *h*
c_2	Between *l* and *m*	Between *m* and *h*	At least *h*	Between *sl* and *sh*	At most *m*	*h*
c_3	Between *m* and *h*	Between *m* and *sh*	Between *sl* and *m*	At most *sl*	*sh*	Between *l* and *sl*
c_4	Between *m* and *sh*	Between *sl* and *sh*	At least *h*	Between *m* and *h*	At most *sl*	Between *l* and *m*
c_5	Between *l* and *m*	At least *m*	Between *sh* and *h*	*sh*	Between *l* and *m*	Between *sl* and *sh*
c_6	At most *l*	Between *sl* and *m*	At most *sl*	Between *sl* and *sh*	Between *sh* and *h*	Between *sl* and *sh*
c_7	Between *sl* and *sh*	Between *m* and *sh*	At most *m*	At least *h*	*m*	Between *m* and *h*
c_8	*l*	Between *l* and *m*	Between *sl* and *m*	Between *sh* and *h*	Between *sl* and *sh*	At most *sl*

Table 4. The evaluation information of alternatives over criteria provided by E_3.

	A_1	A_2	A_3	A_4	A_5	A_6
c_1	*sh*	Between *m* and *sh*	At least *sh*	*sh*	Between *l* and *sl*	*h*
c_2	Between *sl* and *m*	*m*	At least *h*	*sh*	At most *l*	*h*
c_3	Between *m* and *sh*	*sh*	*sl*	At most *sl*	*m*	Between *l* and *sl*
c_4	*sh*	Between *sl* and *m*	*vh*	Between *sh* and *h*	Between *l* and *m*	*sl*
c_5	*sl*	*m*	Between *sh* and *h*	*h*	Between *sl* and *sh*	Between *sl* and *m*
c_6	*l*	Between *l* and *m*	At most *l*	*sl*	Between *m* and *sh*	*l*
c_7	Between *sl* and *m*	*m*	At most *l*	Between *sh* and *h*	At least *h*	*sh*
c_8	At most *sl*	Between *l* and *sl*	*m*	*h*	Between *sl* and *m*	*l*

Table 5. The evaluation information of alternatives over criteria provided by E_4.

	A_1	A_2	A_3	A_4	A_5	A_6
c_1	Between *sh* and *h*	Between *sl* and *sh*	At least *h*	*sh*	Between *l* and *sl*	Between *sh* and *h*
c_2	Between *m* and *h*	Between *m* and *sh*	At least *sh*	*sl*	Between *l* and *sl*	At least *h*
c_3	Between *sh* and *h*	*sh*	Between *sl* and *sh*	At most *sl*	Between *m* and *sh*	Between *l* and *m*
c_4	*sh*	Between *sl* and *sh*	Between *sh* and *h*	Between *sl* and *h*	At most *sl*	Between *l* and *sl*
c_5	At most *sl*	Between *m* and *h*	*m*	At least *h*	Between *sl* and *sh*	Between *sl* and *m*
c_6	At most *l*	Between *l* and *m*	At most *sl*	Between *sl* and *m*	Between *m* and *sh*	Between *l* and *sh*
c_7	Between *m* and *sh*	Between *sl* and *sh*	Between *l* and *sl*	At least *sh*	*h*	Between *sh* and *h*
c_8	At most *sl*	Between *l* and *sl*	Between *sl* and *sh*	*h*	Between *sh* and *h*	Between *l* and *m*

Table 6. The importance of criteria given by the experts.

Criteria	E_1	E_2	E_3	E_4
c_1	Between *m* and *almi*	Between *alli* and *almi*	*m*	Between *m* and *almi*
c_2	Between *li* and *alli*	At most *li*	Between *li* and *alli*	*alli*
c_3	At least *mi*	At least *almi*	*vmi*	At least *mi*
c_4	Between m and *mi*	Between *m* and *almi*	*almi*	Between *m* and *almi*
c_5	Between *almi* and *mi*	*mi*	Between *almi* and *mi*	Between *m* and *mi*
c_6	Between *alli* and *almi*	Between *li* and *alli*	Between *alli* and *m*	At least *alli*
c_7	At least *mi*	At least *almi*	*almi*	Between *almi* and *vmi*
c_8	Between *alli* and *mi*	Between *li* and *alli*	At most *alli*	*li*

$$H_S^{E_2} = \begin{pmatrix} \{s_5\} & \{s_1,s_2,s_3\} & \{s_3,s_4,s_5\} & \{s_3,s_4\} & \{s_1,s_2,s_3\} & \{s_0,s_1\} & \{s_2,s_3,s_4\} & \{s_1\} \\ \{s_3,s_4\} & \{s_3,s_4,s_5\} & \{s_3,s_4\} & \{s_2,s_3,s_4\} & \{s_3,s_4,s_5\} & \{s_2,s_3\} & \{s_3,s_4\} & \{s_1,s_2,s_3\} \\ \{s_5,s_6\} & \{s_5,s_6\} & \{s_2,s_3\} & \{s_5,s_6\} & \{s_4,s_5\} & \{s_0,s_1,s_2\} & \{s_0,s_1,s_2,s_3\} & \{s_2,s_3\} \\ \{s_3,s_4,s_5\} & \{s_2,s_3,s_4\} & \{s_0,s_1,s_2\} & \{s_3,s_4,s_5\} & \{s_4\} & \{s_2,s_3,s_4\} & \{s_5,s_6\} & \{s_4,s_5\} \\ \{s_1,s_2\} & \{s_0,s_1,s_2,s_3\} & \{s_4\} & \{s_0,s_1,s_2\} & \{s_2,s_3\} & \{s_4,s_5\} & \{s_3\} & \{s_2,s_3,s_4\} \\ \{s_4,s_5\} & \{s_5\} & \{s_1,s_2\} & \{s_1,s_2,s_3\} & \{s_2,s_3,s_4\} & \{s_2,s_3,s_4\} & \{s_3,s_4,s_5\} & \{s_0,s_1,s_2\} \end{pmatrix}$$

$$H_S^{E_3} = \begin{pmatrix} \{s_4\} & \{s_2,s_3\} & \{s_3,s_4\} & \{s_4\} & \{s_2\} & \{s_1\} & \{s_2,s_3\} & \{s_0,s_1,s_2\} \\ \{s_3,s_4\} & \{s_3\} & \{s_4\} & \{s_2,s_3\} & \{s_3\} & \{s_1,s_2,s_3\} & \{s_3\} & \{s_1,s_2\} \\ \{s_4,s_5,s_6\} & \{s_5,s_6\} & \{s_2\} & \{s_6\} & \{s_4,s_5\} & \{s_0,s_1\} & \{s_0,s_1\} & \{s_3\} \\ \{s_4\} & \{s_4\} & \{s_0,s_1,s_2\} & \{s_4,s_5\} & \{s_5\} & \{s_2\} & \{s_4,s_5\} & \{s_5\} \\ \{s_1,s_2\} & \{s_0,s_1\} & \{s_3\} & \{s_1,s_2,s_3\} & \{s_2,s_3,s_4\} & \{s_3,s_4\} & \{s_5,s_6\} & \{s_2,s_3\} \\ \{s_5\} & \{s_5\} & \{s_1,s_2\} & \{s_2\} & \{s_2,s_3\} & \{s_1\} & \{s_4\} & \{s_1\} \end{pmatrix}$$

$$H_S^{E_4} = \begin{pmatrix} \{s_4,s_5\} & \{s_3,s_4,s_5\} & \{s_4,s_5\} & \{s_4\} & \{s_0,s_1,s_2\} & \{s_0,s_1\} & \{s_3,s_4\} & \{s_0,s_1,s_2\} \\ \{s_2,s_3,s_4\} & \{s_3,s_4\} & \{s_4\} & \{s_2,s_3,s_4\} & \{s_3,s_4,s_5\} & \{s_1,s_2,s_3\} & \{s_2,s_3,s_4\} & \{s_1,s_2\} \\ \{s_5,s_6\} & \{s_4,s_5,s_6\} & \{s_2,s_3,s_4\} & \{s_4,s_5\} & \{s_3\} & \{s_0,s_1,s_2\} & \{s_1,s_2\} & \{s_2,s_3,s_4\} \\ \{s_4\} & \{s_2\} & \{s_0,s_1,s_2\} & \{s_2,s_3,s_4,s_5\} & \{s_5,s_6\} & \{s_2,s_3\} & \{s_4,s_5,s_6\} & \{s_5\} \\ \{s_1,s_2\} & \{s_1,s_2\} & \{s_3,s_4\} & \{s_0,s_1,s_2\} & \{s_2,s_3,s_4\} & \{s_3,s_4\} & \{s_5\} & \{s_4,s_5\} \\ \{s_4,s_5\} & \{s_5,s_6\} & \{s_1,s_2,s_3\} & \{s_1,s_2\} & \{s_2,s_3\} & \{s_1,s_2,s_3,s_4\} & \{s_4,s_5\} & \{s_1,s_2,s_3\} \end{pmatrix}$$

Step 2. By Equations (13) and (14), we compute the hesitancy degree of each expert as $HD^{E_1} = 0.189$, $HD^{E_2} = 0.167$, $HD^{E_3} = 0.071$, $HD^{E_4} = 0.152$, and derive the weights of experts as $w^{E_1} = 0.219, w^{E_2} = 0.234$, $w^{E_3} = 0.302$, $w^{E_4} = 0.245$. Then, calculating the score of each HFLE in all matrices by Equation (1), the results are shown as follows:

$$G(H_S^{E_1}) = \begin{pmatrix} 0.674 & 0.374 & 0.506 & 0.674 & 0.252 & 0.075 & 0.524 & 0.075 \\ 0.379 & 0.506 & 0.524 & 0.379 & 0.524 & 0.252 & 0.379 & 0.252 \\ 0.631 & 0.823 & 0.346 & 0.674 & 0.506 & 0.127 & 0.127 & 0.225 \\ 0.506 & 0.674 & 0.252 & 0.506 & 0.823 & 0.379 & 0.823 & 0.674 \\ 0.225 & 0.252 & 0.674 & 0.148 & 0.374 & 0.524 & 0.674 & 0.379 \\ 0.833 & 0.631 & 0.127 & 0.225 & 0.379 & 0.247 & 0.506 & 0.148 \end{pmatrix}$$

$$G(H_S^{E_2}) = \begin{pmatrix} 0.833 & 0.252 & 0.506 & 0.524 & 0.252 & 0.075 & 0.379 & 0.167 \\ 0.524 & 0.506 & 0.524 & 0.379 & 0.445 & 0.374 & 0.524 & 0.252 \\ 0.823 & 0.823 & 0.374 & 0.823 & 0.674 & 0.127 & 0.148 & 0.374 \\ 0.506 & 0.379 & 0.127 & 0.506 & 0.667 & 0.379 & 0.823 & 0.674 \\ 0.225 & 0.148 & 0.667 & 0.127 & 0.374 & 0.674 & 0.5 & 0.379 \\ 0.674 & 0.833 & 0.225 & 0.252 & 0.379 & 0.379 & 0.506 & 0.127 \end{pmatrix}$$

$$G(H_S^{E_3}) = \begin{pmatrix} 0.667 & 0.374 & 0.524 & 0.667 & 0.333 & 0.167 & 0.374 & 0.127 \\ 0.524 & 0.5 & 0.667 & 0.374 & 0.5 & 0.252 & 0.5 & 0.225 \\ 0.631 & 0.823 & 0.333 & 1 & 0.674 & 0.075 & 0.075 & 0.5 \\ 0.667 & 0.667 & 0.127 & 0.674 & 0.833 & 0.333 & 0.674 & 0.833 \\ 0.225 & 0.075 & 0.5 & 0.252 & 0.379 & 0.524 & 0.823 & 0.374 \\ 0.833 & 0.833 & 0.225 & 0.333 & 0.374 & 0.167 & 0.667 & 0.167 \end{pmatrix}$$

$$G(H_S^{E_4}) = \begin{pmatrix} 0.674 & 0.506 & 0.674 & 0.667 & 0.127 & 0.075 & 0.524 & 0.127 \\ 0.379 & 0.524 & 0.667 & 0.379 & 0.506 & 0.252 & 0.379 & 0.225 \\ 0.823 & 0.631 & 0.379 & 0.674 & 0.5 & 0.127 & 0.225 & 0.379 \\ 0.667 & 0.333 & 0.127 & 0.346 & 0.823 & 0.374 & 0.631 & 0.833 \\ 0.225 & 0.225 & 0.524 & 0.127 & 0.379 & 0.524 & 0.833 & 0.674 \\ 0.674 & 0.823 & 0.252 & 0.225 & 0.374 & 0.247 & 0.674 & 0.252 \end{pmatrix}$$

By Equation (13), we aggregate all the above individual decision matrices to a collective decision matrix:

$$G(H_S) = \begin{pmatrix} 0.709 & 0.378 & 0.553 & 0.635 & 0.246 & 0.103 & 0.445 & 0.125 \\ 0.457 & 0.509 & 0.602 & 0.377 & 0.494 & 0.281 & 0.449 & 0.237 \\ 0.723 & 0.776 & 0.357 & 0.807 & 0.595 & 0.111 & 0.14 & 0.381 \\ 0.594 & 0.519 & 0.154 & 0.518 & 0.79 & 0.364 & 0.731 & 0.761 \\ 0.225 & 0.168 & 0.583 & 0.169 & 0.377 & 0.559 & 0.717 & 0.45 \\ 0.757 & 0.786 & 0.21 & 0.264 & 0.376 & 0.254 & 0.596 & 0.174 \end{pmatrix}$$

Step 3. Convert the linguistic evaluation information of the importance of criteria into HFLEs, and the transformed results are displayed in Table 7. Then, by Equations (16) and (17), the subjective weights of criteria can be obtained as $w_1' = 0.12$, $w_2' = 0.054$, $w_3' = 0.207$, $w_4' = 0.14$, $w_5' = 0.167$, $w_6' = 0.069$, $w_7' = 0.19$, $w_8' = 0.053$. Based on the score matrix $G(H_S)$, we can obtain the objective weights of criteria by Equation (18) as $w_1'' = 0.117$, $w_2'' = 0.141$, $w_3'' = 0.117$, $w_4'' = 0.146$,

Table 7. Transformed evaluation information on the importance of criteria.

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8
E_1	$\{s_3, s_4\}$	$\{s_1, s_2\}$	$\{s_5, s_6\}$	$\{s_3, s_4, s_5\}$	$\{s_4, s_5\}$	$\{s_2, s_3, s_4\}$	$\{s_5, s_6\}$	$\{s_2, s_3\}$
E_2	$\{s_2, s_3, s_4\}$	$\{s_0, s_1\}$	$\{s_4, s_5, s_6\}$	$\{s_3, s_4\}$	$\{s_5\}$	$\{s_1, s_2\}$	$\{s_4, s_5, s_6\}$	$\{s_1, s_2\}$
E_3	$\{s_3\}$	$\{s_1, s_2\}$	$\{s_6\}$	$\{s_4\}$	$\{s_4, s_5\}$	$\{s_2, s_3\}$	$\{s_5\}$	$\{s_0, s_1, s_2\}$
E_4	$\{s_3, s_4\}$	$\{s_2\}$	$\{s_5, s_6\}$	$\{s_3, s_4\}$	$\{s_3, s_4, s_5\}$	$\{s_0, s_1, s_2\}$	$\{s_4, s_5\}$	$\{s_1\}$

$w_5'' = 0.114$, $w_6'' = 0.101$, $w_7'' = 0.128$, $w_8'' = 0.136$. Suppose that the parameter $\mu = 0.5$. Then, the comprehensive weights of criteria can be derived by Equation (19) as $w_1 = 0.119$, $w_2 = 0.098$, $w_3 = 0.162$, $w_4 = 0.143$, $w_5 = 0.141$, $w_6 = 0.085$, $w_7 = 0.159$, $w_8 = 0.095$.

Step 4. Normalize the score values of alternatives over the criteria by Equations (20) and (21), and the results are shown as follows:

$$\hat{G}(H_S) = \begin{pmatrix} 0.348 & 0.34 & 0.891 & 0.73 & 0 & 1 & 0.484 & 0.863 \\ 0.126 & 0.552 & 1 & 0.326 & 0.456 & 0.61 & 0.477 & 0.687 \\ 0.374 & 0.984 & 0.453 & 1 & 0.642 & 0.982 & 1 & 0.461 \\ 0.132 & 0.568 & 0 & 0.547 & 1 & 0.428 & 0 & 0.137 \\ 0.562 & 0 & 0.958 & 0 & 0.241 & 0 & 0.024 & 0.352 \\ 0.438 & 1 & 0.125 & 0.149 & 0.239 & 0.669 & 0.228 & 0.786 \end{pmatrix}$$

Calculate the weighted sum and weighted product for each alternative by Equations (22) and (23), and obtain three subordinate compromise scores with respect to each alternative by Equations (24)–(26), respectively. Without loss of generality, we let the balance parameter $\gamma = 0.5$. The calculation results are shown in Table 8.

Step 5. Suppose that the order of the importance of three subordinate aggregation operators is $r(Q_3) \succ r(Q_1) = r(Q_2)$. According to the ranking in descending order of the three subordinate compromise performance values, we derive three global preference scores with respect to each alternative over each aggregation operator by Equation (11). Then, we obtain three global rankings based on three global preference scores, and aggregate three global rankings by Equation (12). Finally, the comprehensive ranking of the alternatives can be obtained. The results are shown in Table 9, from which we can determine that the optimal 3PL service provider is A_3.

5.3. Sensitivity analysis

In the proposed HFL-CoCoSo method, we determine the criterion weights by the combination of subjective criterion weights and objective criterion weights. This section focuses on sensitivity analysis of the balance parameter μ used in the combinatorial operators to examine the effects of parameter values on the ranking of the alternatives.

The criterion weights generated when the balance parameter μ is equal to 0 to 1 are shown in Table 10, from which we can see that the change of the parameter μ has a greater impact on the criterion weights w_2, w_3 and w_8, and a smaller impact on the criteria weights w_1 and w_4. It illustrates that the criterion weights w_2, w_3 and w_8 are

Table 8. The results computed by three subordinate aggregation operators.

	P_i^{1*}	P_i^{2*}	$Q_1(A_i)$	Ranks	$Q_2(A_i)$	Ranks	$Q_3(A_i)$	Ranks
A_1	0.567	6.596	0.175	4	3.505	3	0.856	4
A_2	0.535	7.285	0.191	2	3.559	2	0.934	2
A_3	0.734	7.635	0.205	1	4.322	1	1	1
A_4	0.34	5.408	0.14	5	2.447	5	0.687	5
A_5	0.293	4.203	0.11	6	2	6	0.537	6
A_6	0.393	6.934	0.179	3	2.991	4	0.875	3

Table 9. The comprehensive ranking results of the alternatives.

	$PS_1(A_i)$	$R_1(A_i)$	$PS_2(A_i)$	$R_2(A_i)$	$PS_3(A_i)$	$R_3(A_i)$	$R(A_i)$	Ranks
A_1	3.683	4	2.883	3	3.5	4	11	4
A_2	2.385	2	2.385	2	1.803	2	6	2
A_3	2.222	1	2.222	1	1	1	3	1
A_4	4.507	5	4.507	5	4.359	5	15	5
A_5	5.344	6	5.344	6	5.22	6	18	6
A_6	2.883	3	3.683	4	2.646	3	10	3

Table 10. The criterion weights caused by variation of the balance parameter μ.

	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8
$\mu = 0$	0.117	0.141	0.117	0.146	0.114	0.101	0.128	0.136
$\mu = 0.1$	0.12	0.063	0.198	0.141	0.162	0.072	0.184	0.061
$\mu = 0.2$	0.119	0.071	0.189	0.141	0.156	0.075	0.178	0.07
$\mu = 0.3$	0.119	0.08	0.18	0.142	0.151	0.079	0.171	0.078
$\mu = 0.4$	0.119	0.089	0.171	0.142	0.146	0.082	0.165	0.086
$\mu = 0.5$	0.119	0.098	0.162	0.143	0.141	0.085	0.159	0.095
$\mu = 0.6$	0.118	0.106	0.153	0.144	0.135	0.088	0.153	0.103
$\mu = 0.7$	0.118	0.115	0.144	0.144	0.13	0.091	0.147	0.111
$\mu = 0.8$	0.118	0.124	0.135	0.145	0.125	0.095	0.14	0.119
$\mu = 0.9$	0.117	0.132	0.126	0.145	0.119	0.098	0.134	0.128
$\mu = 1$	0.12	0.054	0.207	0.14	0.167	0.069	0.19	0.053
Maximum difference	0.003	0.087	0.09	0.006	0.053	0.032	0.062	0.083

sensitive to the importance distribution of subjective and objective criterion weights. The impact of the value of the balance parameter μ on the ranking results of the alternatives is illustrated in Figure 2, from which we can find that the ranking of alternatives A_1 and A_6 are affected by the parameter values. When the parameter μ equals to 0.1 to 0.7, alternative A_1 ranks the 4th and alternative A_6 ranks the 3th; when the parameter μ equals to 0.1, 0.2, 0.8 and 0.9, alternative A_1 and alternative A_6 rank the same, that is to say, they both rank the 3.5th; when the parameter μ equals to 1, alternative A_1 ranks the 3th and alternative A_6 ranks the 4th. It illustrates that the ranking of alternatives A_1 and A_6 are sensitive to the importance distribution of subjective and objective criterion weights.

5.4. Comparative analysis

To testify the advantages of the proposed HFL-CoCoSo method, this section compares the integration approach of the proposed method with that of the original method for the ranking results of the alternatives, and also compares the proposed method with the HFL-MULTIMOORA method.

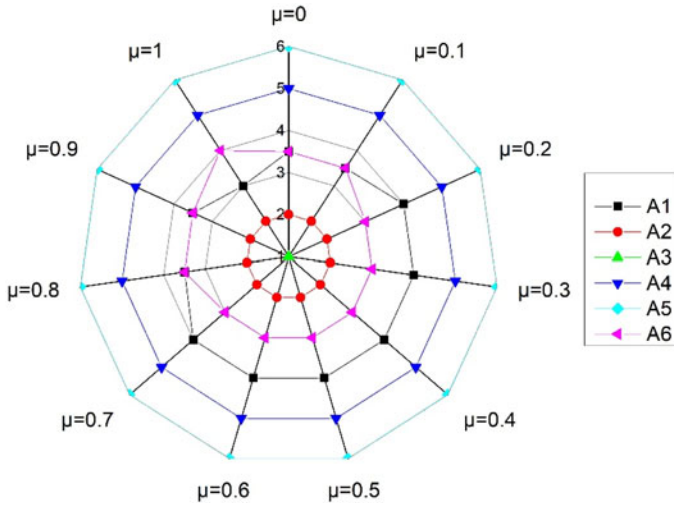

Figure 2. The ranking results of the alternatives based on the value of the balance parameter μ.

1. Comparisons the proposed method with the original CoCoSo method
   Based on the information in Section 5.2, through the hybrid integration operator in the original CoCoSo method shown as Equation (27) to aggregate three subordinate compromise scores, we can obtain the comprehensive compromise performance values of the alternatives as $Q_1 = 2.319$, $Q_2 = 2.421$, $Q_3 = 2.803$, $Q_4 = 1.709, Q_5 = 1.373$, $Q_6 = 2.125$. Then, we can derive that the ranking result is $A_3 \succ A_2 \succ A_6 \succ A_1 \succ A_4 \succ A_5$.

$$Q_i = \frac{1}{3}(Q_1(A_i) + Q_2(A_i) + Q_3(A_i)) + (Q_1(A_i)Q_2(A_i)Q_3(A_i))^{\frac{1}{3}} \tag{27}$$

   According to the comprehensive ranking results of the alternatives in Table 9, we can obtain $A_3 \succ A_2 \succ A_1 \succ A_6 \succ A_4 \succ A_5$. Compared with the ranking result derived by the integration approach in the original CoCoSo method, the ranking of alternatives A_1 and A_6 were changed. From Table 8, we can see that the subordinate compromise performance values $Q_1(A_1)$ and $Q_3(A_1)$ rank the 4th, but $Q_2(A_1)$ ranks the 3th. The subordinate compromise performance values $Q_1(A_6)$ and $Q_3(A_6)$ rank the 3th, but $Q_2(A_6)$ ranks the 4th. According to the general integration approach, the result should be: alternative A_1 ranks the 4th and alternative A_6 ranks the 3th. However, because the value of $Q_2(A_i)$ is much higher than those of $Q_1(A_i)$ and $Q_3(A_i)$, it has a great impact on the results, and the integration approach in the original CoCoSo method does not assign weights to $Q_1(A_i)$, $Q_2(A_i)$ and $Q_3(A_i)$, which leads to the unreasonable ranking results. The aforementioned analysis indicates that the reasonableness and effectiveness of the integration approach in the proposed HFL-CoCoSo method.
2. Comparison the HFL-CoCoSo method with the HFL-MULTIMOORA method
   The HFL-MULTIMOORA method (Liao et al., 2019) is similar to the HFL-CoCoSo method. In each method, three sub-rankings are obtained by three subordinate aggregation operators, and then the final ranking of alternatives is

deduced based on the ORESTE method. This section compares these two methods based on the data in Section 5.2.

The steps for selecting a suitable 3PL service provider using the HFL-MULTIMOORA method are as follows:

Steps 1–3. They are the same as those in the HFL-CoCoSo method.

Step 4. Determine three subordinate ranks of the alternatives. We utilize Equation (28) to normalize the collective decision matrix:

$$G^N(h_S(x_{ij})) = \frac{G(h_S(x_{ij}))}{\sqrt{\sum_{i=1}^{m} (G(h_S(x_{ij})))^2}} \tag{28}$$

where $G^N(h_S(x_{ij}))$ is a normalized value of the score value of $h_S(x_{ij})$ computed by Equation (1). The normalized collective decision matrix is shown as:

$$G^N(H_S) = \begin{pmatrix} 0.477 & 0.273 & 0.504 & 0.508 & 0.197 & 0.132 & 0.33 & 0.123 \\ 0.307 & 0.367 & 0.549 & 0.302 & 0.395 & 0.359 & 0.333 & 0.234 \\ 0.486 & 0.56 & 0.325 & 0.645 & 0.475 & 0.142 & 0.104 & 0.376 \\ 0.399 & 0.375 & 0.14 & 0.414 & 0.631 & 0.466 & 0.541 & 0.75 \\ 0.151 & 0.121 & 0.531 & 0.135 & 0.301 & 0.715 & 0.531 & 0.444 \\ 0.509 & 0.567 & 0.191 & 0.211 & 0.3 & 0.325 & 0.441 & 0.172 \end{pmatrix}$$

Then, we apply three subordinate aggregation operators shown as Equations (29)–(31) to calculate three subordinate utility values for each alternative. According to the descending orders of $M_1(A_i)$ and $M_3(A_i)$ and the ascending order of$M_2(A_i)$, three subordinate ranks of the alternatives, $R_1'(A_i)$, $R_1'(A_i)$ and $R_1'(A_i)$, can be determined. The calculation results are displayed in Table 11.

$$M_1(A_i) = \sum_{j=1}^{g} w_j G^N(h_S(x_{ij})) - \sum_{j=g+1}^{n} w_j G^N(h_S(x_{ij})) \tag{29}$$

$$M_2(A_i) = \max_j w_j |\theta - G^N(h_S(x_{ij}))| \tag{30}$$

$$M_3(A_i) = \prod_{j=1}^{g} (G^N(h_S(x_{ij})))^{w_j} / \prod_{j=g+1}^{n} (G^N(h_S(x_{ij})))^{w_j} \tag{31}$$

where $c_j (j = 1, 2, \ldots, g)$ are the benefit criteria and $c_j (j = g+1, g+2, \ldots, n)$ are the cost criteria. $\theta = \max_i G^N(h_S(x_{ij}))$ for the benefit criterion and $\theta = \min_i G^N(h_S(x_{ij}))$ for the cost criterion. w_j is the criterion weights derived by Step 3 in Section 5.2.

Step 5. Suppose that the order of the importance of three subordinate aggregation models is $r(M_3) \succ r(M_1) = r(M_2)$. We can calculate three global preference scores, $PS_\upsilon'(A_i), \upsilon = 1, 2, 3,$ with respect to each alternative under each aggregation model by Equation (32). Then, we derive three global rankings, $R_\upsilon'(A_i), \upsilon = 1, 2, 3,$ based

Table 11. Three subordinate ranks of the alternatives derived by the HFL-MULTIMOORA method.

	$M_1(A_i)$	Ranks	$M_2(A_i)$	Ranks	$M_3(A_i)$	Ranks
A_1	0.145	2	0.061	3	0.806	2
A_2	0.14	3	0.049	2	0.79	3
A_3	0.238	1	0.036	1	1.127	1
A_4	0.082	4	0.069	5	0.642	4
A_5	0.014	6	0.073	6	0.529	6
A_6	0.061	5	0.062	4	0.612	5

Table 12. The comprehensive ranking results of the alternatives determined by the HFL-MULTIMOORA method.

	$PS_1'(A_i)$	$R_1'(A_i)$	$PS_2'(A_i)$	$R_2'(A_i)$	$PS_3'(A_i)$	$R_3'(A_i)$	$R'(A_i)$	Ranks
A_1	2.264	2	2.761	3	1.581	2	7	2
A_2	2.761	3	2.264	2	2.236	3	8	3
A_3	1.904	1	1.904	1	1	1	3	1
A_4	3.335	4	3.953	5	2.915	4	13	4
A_5	4.596	6	4.596	6	4.301	6	18	6
A_6	3.953	5	3.335	4	3.606	5	14	5

on the ascending order of three global preference scores, and aggregate three global rankings by Equation (33). Afterwards, the comprehensive ranking of the alternatives can be obtained and the results are shown in Table 12, from which we can determine that the ranking result is $A_3 \succ A_2 \succ A_6 \succ A_1 \succ A_4 \succ A_5$.

$$PS_\upsilon'(A_i) = \sqrt{0.5 \times \left((r_\upsilon'(A_i))^2 + (r(M_\upsilon))^2 \right)} \tag{32}$$

$$R'(A_i) = \sum\nolimits_{\upsilon=1}^{3} R_\upsilon'(A_i) \tag{33}$$

From Figure 3, we can find that the two ranking results of the alternatives determined by the HFL-CoCoSo and HFL-MULTIMOORA methods are different except for the best alternative A_3 and the worst alternative A_5. This may be due to the fact that the relevant calculations of the target criteria c_1 and c_8 are not taken into account in the HFL-MULTIMOORA method. In addition, the HFL-MULTIMOORA method first normalized the score values, and then separately calculated for the type of each criterion, resulting in the criteria types to be distinguished in each calculation, adding operation steps which are relatively time-consuming; while in the HFL-CoCoSo method, after normalizing the score values of the alternatives under each criterion, the type of each criterion is distinguished, and then we just need to perform unified calculation based on these normalized values, which is simple and easy to operate. As can be seen from the above, compared with the HFL-MULTIMOORA method, the HFL-CoCoSo method takes into account the target criteria and has a wider range of applications with simplicity and efficiency.

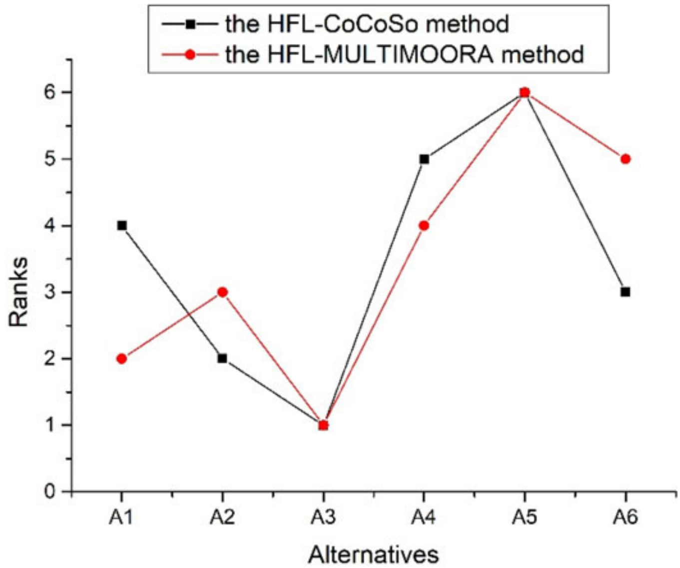

Figure 3. Comparison of the ranking results derived by the HFL-CoCoSo method and HFL-MULTIMOORA method.

6. Conclusions

In supply chain finance, the MCDM problem of selecting a suitable 3PL service supplier is of great significance to financial institutions. To solve this problem, this paper proposed an HFL-CoCoSo method, which integrates the original CoCoSo method with HFLTSs based on the score function of HFLEs considering both the hesitancy degrees of HFLEs and the linguistic scale functions of linguistic terms. Furthermore, to make the method reasonable, this paper used a new integration approach to fuse subordinate compromise scores based on the ORESTE method. On the determination of criterion weights, we combined the subjective criterion weights with the objective criterion weights, making the final result reliable. In the normalization of criteria, we considered the target criteria in order to increase the scope of application of this method. Finally, a case study was given to prove the applicability of the proposed method, in which sensitivity analysis and comparative analysis were provided to highlight the advantages of the proposed method. It is not difficult to see from the case study that the proposed method can not only provide a multi-faceted compromise solution, but also be simple and easy-understood. Thus, it can be readily applied to solve MCDM problems in different fields.

For this paper, the proposed HFL-CoCoSo method is only compared with the similar HFL-MULTIMOORA method. It lacks the analysis of the advantages and disadvantages of the proposed method compared with other methods. In the future, we will further compare this method with other MCDM methods, for example the FCM-ARAS method (Sremac, Zavadskas, Matić, Kopić, & Stević, 2019). Furthermore, we will extend the CoCoSo method to other fuzzy environments, such as neutrosophic linguistic context and probabilistic linguistic context, and combine the CoCoSo method with other MCDM methods such as the AHP and Best Worst Method to solve practical decision-making problems in wilder fields. In addition, we will consider using the ANFIS (Adaptive Neuro-Fuzzy Inference Systems) approach (Dahooie et al., 2019) to solve the decision-making problem in supply chain finance.

Notes

1. https://baike.baidu.com/item/供应链金融/9993766?fr=aladdin
2. https://wiki.mbalib.com/wiki/供应链金融

Disclosure statement

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