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AN INTEGRATED MULTI CRITERIA GROUP DECISION-MAKING MODEL APPLYING FUZZY TOPSIS-CRITIC METHOD WITH UNKNOWN WEIGHT INFORMATION

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Abstract. *It is well known that the weights of decision makers (DMs) and criteria play an important role in multi criteria group decision-making problems (MCGDM). A major problem is how to capture and deal with the qualitative and uncertainty weight information when facing a complex decision-making context. Considering the unknown expert weight and the difference in the proportion of subjective and objective weights of the criteria, this paper presents an integrated fuzzy model that combines the technique in order of preference by similarity to ideal solution (TOPSIS) and criteria importance through inter-criteria correlation (CRITIC) with unknown weight information. Firstly, the weights of DMs are obtained by the extended TOPSIS method, which implies that the influence on the decision results differs from each decision maker. Secondly, in order to simultaneously consider the conflict and contrast intensity of criteria, the CRITIC method is used to reflect the amount of decision-making information contained in each criterion, that is, the objective weight of the criterion is obtained. Afterwards, combined with the optimal weights determined by the uniformity entropy theory, a novel hybrid assessment model combining subjective and objective weights is proposed. Finally, after weighing the fuzzy comprehensive decision matrix, the traditional TOPSIS method is applied to ranking the alternatives and selecting the optimal one. A numerical example of sustainable supply chain risk evaluation is used to demonstrate the effectiveness of the proposed model based on the extended TOPSIS-CRITIC method and entropy theory.*
Keywords: TOPSIS-CRITIC model, Integrated weight, Multiple criteria group decision-making, Entropy theory

1. **Introduction.** Multi criteria decision-making, as an efficient application tool in the domain of decision-making science and technology research, has been frequently applied to solving real-life situations under uncertainty and developed rapidly in recent years. However, the diversity of decision-making problems and the complexity of the environment analysis make a single method insufficient to deal with the challenges in all fields. In addition, there exist different preferences of decision-making for solving the same decision-making problem due to their knowledge ability, background experience, and social status [1], which in turn brings with the difference and correlation among decision-making indicators and strategies, and finally determines the optimal ranking of the plans in the real case. For example, when experts evaluate the risk management of supply chain enterprises, DMs who focus on environmental indicators and experts who hold a larger opinion of the influence caused by the manufacturing stage will have a different degree of influence on

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the final result. Reasonable expert weight determination methods have always been one of the focuses of current research; however, in some papers [2,3], such weights are aggregated by arithmetic mean or their improved form and all the DMs have the same importance when making decisions. Therefore, based on the consideration of the different experts preferences, each DM should be assigned different decision weights in the process of processing decision information.

How to propose an innovative approach to integrate differential expert weights has attracted the interest of many scholars. For example, an intuitionistic fuzzy set-based model [4] is constructed to determine the weights of experts from the perspective of the hesitancy degrees and correlation coefficient characteristics of expert evaluation information when making decisions, merely considers the changes in the information characteristics of the decision-making environment and lacks a comprehensive measure of the excessively subjective or objective limitations of the decision-making, nevertheless. Wu et al. [5] obtained the weights of experts through the trusted third partners (TTPs) of the expert trust network, considering the lack of decision information that may be caused by multiple information environment in the form of trust, distrust, hesitancy, and inconsistency. Qiu et al. [6] established an intuitionistic mapping aggregation model for deriving unknown expert weights by calculating the shortest Euclidean distance between expert preference points based on plant growth simulation algorithm (PGSA). Furthermore, there are also some scholars who utilize method such as fuzzy AHP [7], deviation measures-based [8] and TOPSIS [9] to obtain the weights of DMs or criteria in MCGDM problems.

The traditional TOPSIS method was first proposed by Hwang and Yoon [10], the main idea of which is to simultaneously consider the distances to both positive ideal solution (PIS) and negative ideal solution (NIS), and the preference order of alternatives is ranked according to their closeness coefficient, as well as a combination of these two distance measures [1]. However, in addition to intuitively ranking the alternatives through closeness coefficient, this method rarely involves the determination of expert weights, nor can it conclude the weights of criteria in MCGDM problem; hence it is mostly applied in combination with other techniques. Among them, in view of the subjectivity that may exist in the evaluation of experts in the decision-making process, a CRITIC method based on the contrast intensity and conflict characteristics between criteria to obtain the weight of decision information was developed [11], which objectively shows the relevance and difference of decision indicators. Fu and Chu [12] used TOPSIS to rank the relevant criteria for measuring the level of regional development based on the combined weighting of the improved CRITIC and entropy method, while taking account of the subjectivity and objectivity of attribute weights. However, the information of the linguistic variables of the evaluation index system is in the form of crisp number, which has certain limitations that may not fully express the decision-making preferences of the decision maker when dealing with vague and uncertain decision information. In order to better deal with uncertainty, some scholars have begun to improve the expression of decision information. On the basis of the crisp number, fuzzy number, intuitionistic fuzzy number expressing decision information variables in traditional research, Abdel-Basset and Mohamed [3] innovatively introduced plithogenic set to the analysis of multi-criteria decision-making problems, and through the TOPSIS-CRITIC method, a risk management decision-making model is constructed, which enables the acquisition of decision weights and the ranking of alternatives complement to each other. However, this model does not take account of the differences in preference characteristics of experts that may occur during decision-making and the use of arithmetic averaging to integrate subjective and objective weights of criteria may produce subjective randomness decision-making errors, which limits the credibility of decision-making results. Aiming at the dilemma of insufficient implementation methods to improve ELV reverse logistics in the context of circular economy, Wang et al. [13] combined TOPSIS and DEA methods, which have a similar relationship with the ideal solution distance characteristic. However, completely objective decision-making results ignore the consideration of DMs who may lack the support of specific professional knowledge or relevant research background, which may easily lead to the omission of decision-making information.

The aforementioned methods focus on the difference of expert weights and the integration of subjective and objective criteria weights, enriching and developing the research depth of alternative selection and ranking of MCGDM problems. However, there are also some shortcomings and limitations, which are stated as follows. 1) The increase in the complexity of decision-making problems makes previous studies either lack of simultaneous consideration of the subjective differences in expert weights and uncertain objective evaluation information of decision opinions, or it is too cumbersome to sort the optimal alternative, in absence of complete scientific decision-making in the selecting stage after obtaining the weights of experts and criteria, which neglect the relevance degree to the ideal alternative. 2) Most researches disregard the differences of knowledge background, skills, interests of different DMs and assume all the members have the same weight in the aggregation of individual decisions. 3) Some existing ranking methods are extremely unstable for weight changes when the information partially known or completely unknown, the calculation steps of which are also too redundant to provide effective solutions under complex circumstances.

The contribution and innovation of this paper mainly lie in the expansion of the depth of understanding for solving MCGDM problems under uncertain environment and can be summarized as follows. 1) To fully reflect the inconsistencies and differences of weights caused by the unique characteristics of DMs in decision-making activities, this paper proposes an extended TOPSIS feature measure to derive the weights of DMs based on the classical TOPSIS, which implies the TOPSIS method is employed twice, the first time is used for the weight acquisition of experts, and then the integrated expert decision matrix is constructed to select the optimal alternative on the basis of closeness coefficient through the second application of the traditional TOPSIS. 2) This paper constructs a combined weight determination model under fuzzy environment that contains both the subjective and objective weights of the criteria on the basis of the uniformity entropy theory, rather than average their proportion, the outstanding advantages of which are that they can not only account the proportion of each weight in the integrated criteria weight but also eliminate the imprecise influence of subjective empowerment sufficiently. 3) The extended TOPSIS-CRITIC model is established under uncertain fuzzy environment to enhance the flexibility of DMs in the real MCGDM problem. The decision-making process of the model proposed is easy to implement and very stable to weight changes.

The remainder of this paper is organized as follows. In the next section, we briefly recall and recapitulate some of the fundamental concepts and operations related to fuzzy set, CRITIC method and uniformity entropy theory. In Section 3, the general steps in the decision analysis process of the extended TOPSIS-CRITIC model are detailed. In Section 4, an illustrative example about the evaluation of enterprise sustainable supply chain risk management is presented to illustrate the effectiveness and practicality of the developed methods. In Section 5, a comprehensive sensitivity analysis and comparative analysis of the results obtained via our proposed method are presented to verify the superiorities and robustness. Finally in Section 6, the concluding remarks and future research planning are given.

2. Preliminaries.

2.1. Fuzzy theory. The analysis object of MCGDM problem mainly includes a class of things with uncertain scope and boundary. Such an either-or relationship becomes a kind of membership relationship, which is falling into the fuzzy set. Fuzzy theory, proposed by Zadeh [14], can solve the alternatives ranking problem according to the evaluation criteria and the lack of accuracy in assigning the different importance weights of criteria. The role of fuzzy theory in decision-making process is to transform linguistic variables into numerical variables and some of the basic definitions are as follows.

Definition 2.1. [14] *Let X be a universal set of elements, with a generic element in X denoted by x, $X = \{x\}$, such that the fuzzy set can be defined as*

$$\widetilde{A} = \{\langle x, \mu_A(x)\rangle | x \in X\} \tag{1}$$

where function $\mu_{\widetilde{A}}$: $X \to [0,1]$ is called the membership function of the fuzzy set $\widetilde{A}$, $\mu_{\widetilde{A}}(x) \in [0,1]$ denotes the corresponding membership degree of element x to the universal set $\widetilde{A}$.

Definition 2.2. [14] *Suppose that $\widetilde{A}$ is a trapezoidal fuzzy number and can be represented as $\widetilde{A} = [a_1, a_2, a_3, a_4]$, where a_1, a_2, a_3, a_4 are definite values, such that the membership function of $\widetilde{A}$ can be defined as*

$$\mu_{\widetilde{A}}(x) = \begin{cases} \dfrac{x - a_1}{a_2 - a_1} & a_1 \le x \le a_2 \\ 1 & a_1 \le x \le a_2 \\ \dfrac{a_4 - x}{a_4 - a_3} & a_3 \le x \le a_4 \\ 0 & otherwise \end{cases} \tag{2}$$

Definition 2.3. [11] *Suppose that $\widetilde{A} = [a_1, a_2, a_3, a_4]$ and $\widetilde{B} = [b_1, b_2, b_3, b_4]$ are two trapezoidal fuzzy numbers ($a_1 \ge 0$, $b_1 \ge 0$), k is a crisp number, and then the arithmetic operations, including addition, subtraction, multiplication, and division can be defined as follows:*

$$\widetilde{A} \oplus \widetilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3, a_4 + b_4)$$
$$\widetilde{A} + k = (a_1 + k, a_2 + k, a_3 + k, a_4 + k) \tag{3}$$

$$\widetilde{A} \ominus \widetilde{B} = (a_1 - b_4, a_2 - b_3, a_3 - b_2, a_4 - b_1)$$
$$\widetilde{A} - k = (a_1 - k, a_2 - k, a_3 - k, a_4 - k) \tag{4}$$

$$\widetilde{A} \otimes \widetilde{B} = (a_1 \times b_1, a_2 \times b_2, a_3 \times b_3, a_4 \times b_4)$$
$$\widetilde{A} \times k = \begin{cases} (a_1 \times k, a_2 \times k, a_3 \times k, a_4 \times k) & if\ k > 0 \\ (a_4 \times k, a_3 \times k, a_2 \times k, a_1 \times k) & if\ k < 0 \end{cases} \tag{5}$$

$$\widetilde{A} \oslash \widetilde{B} = \left(\frac{a_1}{b_4}, \frac{a_2}{b_3}, \frac{a_3}{b_2}, \frac{a_4}{b_1}\right) \tag{6}$$

Definition 2.4. [15] *Suppose that $\widetilde{A} = [a_1, a_2, a_3, a_4]$ is a trapezoidal fuzzy number, and then the defuzzification operation of the fuzzy numbers (convert into crisp numbers) can be defined as the following equation:*

$$\kappa\left(\widetilde{A}\right) = \frac{1}{3}\left(a_1 + a_2 + a_3 + a_4 - \frac{a_3a_4 - a_1a_2}{(a_3 + a_4) - (a_1 + a_2)}\right) \tag{7}$$

Definition 2.5. [11] *Suppose that* $\widetilde{A} = [a_1, a_2, a_3, a_4]$ *and* $\widetilde{B} = [b_1, b_2, b_3, b_4]$ *are two trapezoidal fuzzy numbers* ($a_1 \geq 0$, $b_1 \geq 0$)*, and then the Hamming distance between them is defined as follows:*

$$d\left(\widetilde{A}, \widetilde{B}\right) = \sqrt{\frac{1}{4}\left|(a_1 - b_1)^2 + (a_2 - b_2)^2 + (a_3 - b_3)^2 + (a_4 - b_4)^2\right|} \tag{8}$$

2.2. **TOPSIS method.** The decision analysis of the technique in order of preference by similarity to ideal solution (TOPSIS method) basically focuses on constructing a multi criteria, multi-alternative decision-making problem and calculating the degree of closeness to the ideal solution. It has the characteristics of being able to better prioritize the various criteria of decision-making alternatives partial and overall, that has been widely used in MCGDM problems. According to this method, the optimal alternative is the closest one to the positive ideal solution and the farthest from the negative ideal solution [16,17], which can conveniently sort the various criteria of the alternatives.

2.3. **Fuzzy CRITIC method.** In this subsection, an essential MCGDM method called criteria importance through inter-criteria correlation (CRITIC), initially proposed by Diakoulaki et al. [18] will be introduced to determine the objective weights of criteria, which can reflect the amount of the decision-making information that is contained in each criterion. The characteristic of CRITIC is mainly to measure the objective weight from two aspects of criterion information: one is the contrast intensity, and the other is named conflict between criteria.

Let $\widetilde{x}_{ij} = (x_{ij1}, x_{ij2}, x_{ij3}, x_{ij4})$ denote the performance value in fuzzy environment of the ith alternative i according to the jth criterion j ($i = 1, 2, \ldots, m$; $j = 1, 2, \ldots, n$). The objective weight of criterion j can be represented by $\widetilde{w}_j = (w_{j1}, w_{j2}, w_{j3}, w_{j4})$. The set of beneficial criteria is shown by B, and N denotes the non-beneficial set. The main steps of CRITIC method are described as follows [11].

Step 1. Calculate the transformation performance values of criteria vectors. Since different attributes often have different dimensions and dimensional units, in order to eliminate the incommensurability, the criteria indicators should be transformed before decision-making, which can express the degree of how the alternative is close to the best performance criterion and far from the worst performance criterion.

$$x_{ijk}^T = \begin{cases} \dfrac{x_{ijk} - x_{jk}^-}{x_{jk}^* - x_{jk}^-}, & j \in B \\ \dfrac{x_{jk}^- - x_{ijk}}{x_{jk}^- - x_{jk}^*}, & j \in N \end{cases}, \quad x_{jk} = \left(x_{1jk}^T, x_{2jk}^T, \ldots, x_{njk}^T\right) \tag{9}$$

where x_{ijk}^T represents the transformed value of the kth element of $\widetilde{x}_{ij}$ ($k = 1, 2, 3, 4$), x_{jk} denotes the kth vector of criterion j, and x_{ij}^* and x_{ij}^- represent the ideal value and anti-ideal value for criterion j and kth element of $\widetilde{x}_{ij}$. If the criterion j is beneficial, then $x_{jk}^* = \max_i x_{ijk}$, and $x_{jk}^- = \min_i x_{ijk}$. Otherwise, we have $x_{jk}^* = \min_i x_{ijk}$ and $x_{jk}^- = \max_i x_{ijk}$.

Step 2. Determine the standard deviation σ_{jk} to evaluate the contrast intensity of each criterion separately for each vector x_{jk}.

Step 3. Conduct k (the number of alternatives) symmetric matrix with dimension $m \times m$ that represents the linear correlation coefficient between x_{jk} and $x_{j'k}$, the element of which is noted as $r_{jj'}^k$ ($j' = 1, 2, \ldots, n$, $k = 1, 2, 3, 4$). Especially, there is no correlation relationship between x_{jk} and $x_{j'k}$ if the values of elements within them are exactly selfsame, that is $r_{jj'}^k = 0$.

Step 4. Calculate the conflict of criteria and obtain the information measures combined with standard deviation σ_{jk} according to Equation (10):

$$H_{jk} = \sigma_{jk} \sum_{j'=1}^{m} \left(1 - r_{jj'}^{k}\right) \tag{10}$$

Step 5. Normalize the value of information conveyed by each criterion to obtain the objective weights of criteria according to the following equation:

$$w'_{jk} = \frac{H_{jk}}{\sum_{j'=1}^{m} H_{jj'}} \tag{11}$$

Step 6. Determine the fuzzy objective weights of criteria on the basis of the following equations (suppose that we have 4 alternatives in MCGDM problem):

$$\begin{aligned} &w_{jk}^{0} = w'_{jk'} \quad (k,\ k' = 1, 2, 3, 4) \\ &w_{j4}^{0} = \max_{k} w'_{jk}, \quad w_{j1}^{0} = \min_{k} w'_{jk} \end{aligned} \tag{12}$$

2.4. **Uniformity entropy theory.** In this subsection, the subjective weight and objective optimal weight of criteria are combined based on the concept of uniformity [19], which is extended from information entropy theory to facilitate the comparison and proportion analysis of kinds of weights. Entropy is a statistic that expresses the chaotic or ordered probability distribution of the system, while the entropy system, proposed by Shannon [20], presents a measure of the uncertainty or information nonuniformity about its actual structure.

If $q = (q_1, q_2, \ldots, q_n)$ is a finite probability distribution, then its Shannon entropy can be defined as the following equation

$$S(q) = -\sum_{i=1}^{n} q_i \log_2 q_i \tag{13}$$

From the definition of Shannon entropy: by replacing the probability distribution variate with the weight vector λ_k and normalizing Equation (13) at the same time, we can conclude the following definition of uniformity.

Definition 2.6. [20] *The uniformity of weight vector* $w = (w_1, w_2, \ldots, w_p)^T$ *on distribution can be defined as*

$$f(w) = -\frac{1}{\log_2 p} \sum_{k=1}^{p} w_k \log_2 w_k \tag{14}$$

The larger $f(w)$ *is, the more uniform the distribution of the weight vector* w *is. In particular, when the weight vector is a uniform distribution,* $f(w)$ *reaches its maximum of 1. It is not difficult to obtain the property* $0 < f(w) \leq 1$.

According to this character of uniformity, the synthesis process of two kinds of criterion weight information can be realized as the following steps.

Step 1. Calculate the uniformity of two kinds of criterion weight vector.

Suppose that $w_{ij}^{\phi} = \left(w_{ij1}^{\phi}, w_{ij2}^{\phi}, \ldots, w_{ijp}^{\phi}\right)^T$ represents the subjective weight vector of criterion C_j, alternative A_i, and then its uniformity can be denoted by $f\left(w_{ij}^{\phi}\right)$.

Suppose that $w_{ij}^{C} = \left(w_{ij1}^{C}, w_{ij2}^{C}, \ldots, w_{ijp}^{C}\right)^T$ represents the objective weight vector of criterion C_j, alternative A_i, and then its uniformity can be denoted by $f\left(w_{ij}^{C}\right)$.

Step 2. Calculate the proportion η_{ij} of the subjective weight of criterion w_{ij}^{ϕ} in the synthetic weight.

$$\eta_{ij} = \frac{1 - f\left(w_{ij}^{\phi}\right)}{1 - f\left(w_{ij}^{\phi}\right) + 1 - f\left(w_{ij}^{C}\right)} \tag{15}$$

Step 3. Calculate the aggregation weight w_j of expert k for criterion C_j, alternative A_i.

$$w_j = \eta_{ij} w_{ij}^{\phi} + (1 - \eta_{ij}) w_{ij}^{C} \tag{16}$$

Then we can construct an evaluation matrix according to the fuzzy number evaluation scale of the DM's evaluation of the criteria in all alternatives.

3. **Multiple Criteria Decision-Making Based on the Extended Fuzzy TOPSIS-CRITIC Method.** In this section, we propose a model based on the extended TOPSIS-CRITIC method in accordance with the uniformity entropy theory to cope with MCGDM problems under fuzzy environment. The importance of this model is to comprehensively consider the weights of experts and criteria to improve the accuracy of the decision-making process and make the model more suitable for solving complex MCGDM practical problems. However, the traditional TOPSIS method only uses the distance scale to judge the positional relationship between the alternatives in the ordering stage during the decision-making process, ignoring the difference in the closeness of the decision-making experts' weights due to different preferences of knowledge ability and background, which has certain limitations. The extended TOPSIS method places emphasis on the difference in the closeness of expert weights by judging the local and overall distance scales from the positive and negative ideal decision, which can finally obtain the weights of DMs for decision-making problems in different contexts. CRITIC method can make up for the subjectivity generated by the preference of experts in the decision-making process, and obtain the objective weight of the decision matrix through the contrast intensity and conflicts of the criteria. Therefore, the CRITIC method and the extended TOPSIS in this paper can be regarded as complementary to each other in this article. On this basis, the integration weight is obtained through the uniformity distribution difference of the subjective and objective weights of criteria under the entropy system, which avoids the loss of decision information that may be caused by the weight integration through arithmetic mean and other techniques. Therefore, in order to be able to fully and objectively reflect the characteristics of various criteria, alternatives and their ranking results, this approach combines the advantages of uniformity entropy theory, extended TOPSIS and CRITIC method to provide a sturdy MCGDM model under fuzzy environment. Figure 1 shows the steps of the proposed approach and its details will be mentioned as below in this section.

Stage 1. Problem analysis stage.

Step 1. Suppose an MCGDM problem needs to be resolved. Let $A = \{A_1, A_2, \ldots, A_m\}$ be a collection of m alternatives, $C = \{C_1, C_2, \ldots, C_n\}$ denotes a set of n evaluation criteria, the vector set of criteria weights is represented by $w = (w_1, w_2, \ldots, w_n)$, where $0 \leq w_j \leq 1$, $\sum_{j=1}^{n} w_j = 1$. The number of decision makers is K and the collection is denoted by $D = \{DM_1, DM_2, \ldots, DM_K\}$, $\lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_K\}$ is the set of the weights of DMs, such that $0 \leq \lambda_k \leq 1$, $\sum_{k=1}^{K} \lambda_k = 1$. If the performance value of alternative A_i in regard to criterion C_j is represented by x_{ij}, the fuzzy decision matrix $(x_{ij})_{m*n}$ based on

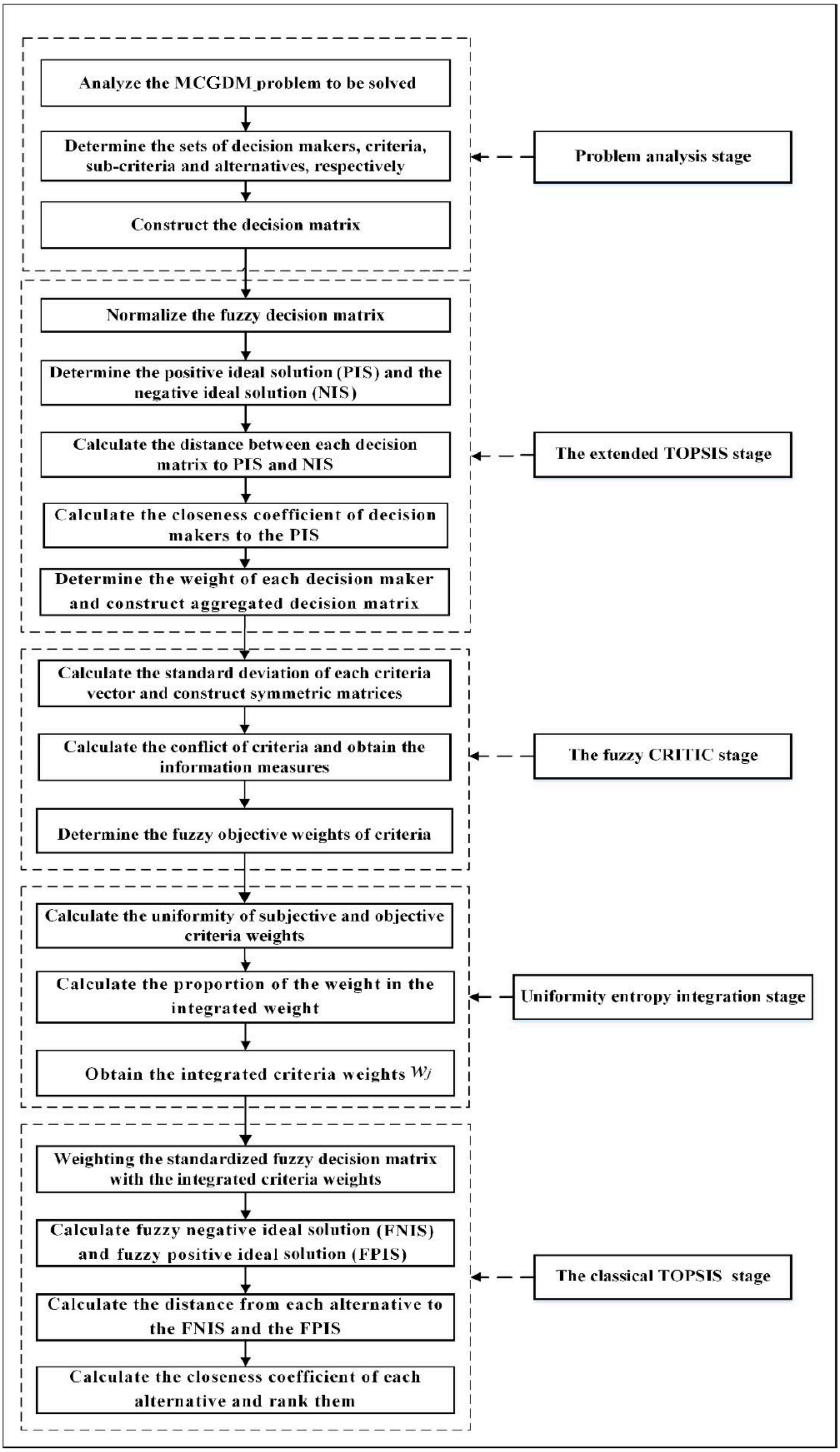

FIGURE 1. The conceptual framework of the proposed model

the linguistic scale of the criteria for the target alternative is offered by DMs as follows:

$$X^k = \left[x_{ij}^k\right]_{m\times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11}^k & x_{12}^k & \cdots & x_{1n}^k \\ x_{21}^k & x_{22}^k & \cdots & x_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1}^k & x_{m2}^k & \cdots & x_{mn}^k \end{bmatrix} \end{array} \tag{17}$$

Stage 2. The extended TOPSIS method to determine the weights of DMs.

Step 2. Obtain the normalized evaluation decision matrix. In order to ensure the criteria comparable and eliminate the interference of different influencing factors, the fuzzy evaluation matrix is normalized using Equation (18), the set of beneficial criteria is represented by B and the non-beneficial criteria is denoted by N. The normalized fuzzy decision matrix is shown in Equation (19).

$$\begin{aligned} y_{ij}^k &= \left(\frac{fx_{ij1}^k}{\max_i x_{ij}^k}, \frac{fx_{ij2}^k}{\max_i x_{ij}^k}, \frac{fx_{ij3}^k}{\max_i x_{ij}^k}, \frac{fx_{ij4}^k}{\max_i x_{ij}^k}\right) \quad j \in B \\ y_{ij}^k &= \left(\frac{\min_i x_{ij}^k}{fx_{ij1}^k}, \frac{\min_i x_{ij}^k}{fx_{ij2}^k}, \frac{\min_i x_{ij}^k}{fx_{ij3}^k}, \frac{\min_i x_{ij}^k}{fx_{ij4}^k}\right) \quad j \in N \end{aligned} \tag{18}$$

$$Y^k = \left[y_{ij}^k\right]_{m\times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} y_{11}^k & y_{12}^k & \cdots & y_{1n}^k \\ y_{21}^k & y_{22}^k & \cdots & y_{2n}^k \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1}^k & y_{m2}^k & \cdots & y_{mn}^k \end{bmatrix} \end{array} \tag{19}$$

Step 3. Determine the positive and the negative ideal solutions. The positive ideal solution (PIS) is defined as the average of all individual evaluation decision matrix, denoted by D^+

$$D^+ = \left[d_{ij}^+\right]_{m\times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} d_{11}^+ & d_{12}^+ & \cdots & d_{1n}^+ \\ d_{21}^+ & d_{22}^+ & \cdots & d_{2n}^+ \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1}^+ & d_{m2}^+ & \cdots & d_{mn}^+ \end{bmatrix} \end{array} \tag{20}$$

where $d_{ij}^+ = \frac{1}{k}\sum_{k=1}^K y_{ij}^k$, and the negative ideal solution (NIS) is divided into two parts: the left negative ideal decision

$$D^{-L} = \left[d_{ij}^{-L}\right]_{m\times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} d_{11}^{-L} & d_{12}^{-L} & \cdots & d_{1n}^{-L} \\ d_{21}^{-L} & d_{22}^{-L} & \cdots & d_{2n}^{-L} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1}^{-L} & d_{m2}^{-L} & \cdots & d_{mn}^{-L} \end{bmatrix} \end{array} \tag{21}$$

where $d_{ij}^{-L} = \min_k y_{ij}^k$, and the right negative ideal decision

$$D^{-R} = \left[d_{ij}^{-R}\right]_{m\times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} d_{11}^{-R} & d_{12}^{-R} & \cdots & d_{1n}^{-R} \\ d_{21}^{-R} & d_{22}^{-R} & \cdots & d_{2n}^{-R} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1}^{-R} & d_{m2}^{-R} & \cdots & d_{mn}^{-R} \end{bmatrix} \end{array} \tag{22}$$

where $d_{ij}^{-R} = \max_k y_{ij}^k$, which define the left and right maximum separation from the PIS.

Step 4. Obtain the separation of each individual fuzzy evaluation matrix Y^k ($k = 1, 2, \ldots, K$) from the positive and the negative ideal solution S^{+k}, S^{-kL} and S^{-kR}.

$$S^{+k} = \sum_{i=1}^{m}\sum_{j=1}^{n} d\left(y_{ij}^k, d_{ij}^+\right)$$

$$S^{-kL} = \sum_{i=1}^{m}\sum_{j=1}^{n} d\left(y_{ij}^k, d_{ij}^{-L}\right)$$

$$S^{-kR} = \sum_{i=1}^{m}\sum_{j=1}^{n} d\left(y_{ij}^k, d_{ij}^{-R}\right) \tag{23}$$

Step 5. Calculate the closeness coefficient to PIS of each decision maker. Clearly, the larger the separations S^{-kL} and S^{-kR}, the better the decision of the kth DM. The closeness coefficient RC^k is defined to determine the ranking order of all DMs after the calculation of S^{+k}, S^{-kL} and S^{-kR}.

$$RC^k = \frac{S^{-kL} + S^{-kR}}{S^{+k} + S^{-kL} + S^{-kR}}; \quad RC^k \in [0, 1] \tag{24}$$

Step 6. Determine the weight of each DM. Based on the rank of closeness coefficient in Step 5, we can derive the order of all DMs. The weights of them can be defined as the following equation

$$\lambda_k = \frac{RC^k}{\sum_{k=1}^{K} RC^k} \tag{25}$$

such that $\lambda_k \geq 0$, $\sum_{k=1}^{K} \lambda_k = 1$.

Stage 3. Determine the subjective weights of criteria through the weights of DMs and calculate the objective weights of criteria utilizing the CRITIC method.

Step 7. With the acquisition of weights λ_k, the aggregated comprehensive decision matrix Y with different weights of DMs ($k = 1, 2, \ldots, K$) can be obtained as follows

$$Y = [y_{ij}]_{m\times n} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{m1} & y_{m2} & \cdots & y_{mn} \end{bmatrix} \end{array}$$

$$y_{ij} = \left(\frac{1}{\lambda_1} \overset{K}{\underset{p=1}{\oplus}} \widetilde{y}_{ij}^p + \frac{1}{\lambda_2} \overset{K}{\underset{p=1}{\oplus}} \widetilde{y}_{ij}^p + \cdots + \frac{1}{\lambda_K} \overset{K}{\underset{p=1}{\oplus}} \widetilde{y}_{ij}^p\right) \tag{26}$$

where $\widetilde{y}_{ij}^p$ denotes the performance value of criterion C_j ($1 \leq j \leq n$) in alternative A_i, assigned by the pth DM ($1 \leq p \leq n$).

Step 8. Determine the subjective criteria weights matrix as the following equations

$$W = \left[\widetilde{w}_j^s\right]_{1\times n}$$

$$\widetilde{w}_j^s = \left(\frac{1}{\lambda_1} \overset{K}{\underset{p=1}{\oplus}} \widetilde{w}_{jp}^s + \frac{1}{\lambda_2} \overset{K}{\underset{p=1}{\oplus}} \widetilde{w}_{jp}^s + \cdots + \frac{1}{\lambda_K} \overset{K}{\underset{p=1}{\oplus}} \widetilde{w}_{jp}^s \right) \tag{27}$$

where $\widetilde{w}_{jp}^s$ represents the subjective weight of criterion C_j $(1 \le j \le n)$, assigned by the pth $(1 \le p \le K)$ DM.

Step 9. Construct normalized subjective weight decision matrix for each criterion with inconsistent weights of DMs

$$\widetilde{w}_j^{sn} = \widetilde{w}_j^s \Big/ K \left(\overset{m}{\underset{j=1}{\oplus}} \widetilde{w}_j^s \right) \tag{28}$$

Step 10. The objective weights of criteria can be calculated by using Equations (9)-(12), shown in Subsection 2.3.

Stage 4. Integrate the subjective and objective weights of criteria.

Step 11. The normalized subjective weights of criteria obtained by the expert weights and the objective criteria weights of the decision matrix are integrated through the uniformity entropy theory method using Equations (13)-(16), whose result can be represented by $\widetilde{w}_j$.

Stage 5. Rank and select the optimal alternative applying the classical TOPSIS.

Step 12. Normalizing the fuzzy comprehensive decision matrix obtained in Step 5 using Equation (29), on this basis, combined with the integration matrix of criteria weights $\widetilde{w}_j$ calculate a weighted normalized comprehensive fuzzy decision matrix by means of Equation (30).

$$\begin{aligned}
&R = [\widetilde{r}_{ij}]_{m \times n} \\
&\widetilde{r}_{ij} = \left(\frac{y_{ij1}}{u_j}, \frac{y_{ij2}}{u_j}, \frac{y_{ij3}}{u_j}, \frac{y_{ij4}}{u_j} \right) \quad j \in B \\
&\widetilde{r}_{ij} = \left(\frac{l_j}{y_{ij4}}, \frac{l_j}{y_{ij3}}, \frac{l_j}{y_{ij2}}, \frac{l_j}{y_{ij1}} \right) \quad j \in N \\
&l_j = \min_i y_{ij1} \\
&u_j = \max_i y_{ij4} && (29) \\
&Z = [\widetilde{z}_{ij}]_{m \times n} \\
&\widetilde{z}_{ij} = \widetilde{w}_j \otimes \widetilde{r}_{ij} && (30)
\end{aligned}$$

Step 13. Determine the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) by means of Equations (31) and (32).

$$A^+ = \left(v_1^-, v_2^-, \ldots, v_n^-\right), \quad A^- = \left(v_1^+, v_2^+, \ldots, v_n^+\right) \tag{31}$$

$$v_j^+ = \begin{cases} \max_i z_{ij4}, & j \in B \\ \min_i z_{ij1}, & j \in N \end{cases}, \quad v_j^- = \begin{cases} \min_i z_{ij1}, & j \in B \\ \max_i z_{ij4}, & j \in N \end{cases} \tag{32}$$

where B is a set of beneficial criteria and N is a set of non-beneficial criteria.

Step 14. Calculate the relative Euclidean distance of each alternative from the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS) to measure the separation of alternative performance

$$d_i^+ = \sum_{j=1}^{n} d\left(\widetilde{z}_{ij}, v_j^+\right), \quad d_i^- = \sum_{j=1}^{n} d\left(\widetilde{z}_{ij}, v_j^-\right) \tag{33}$$

Step 15. Calculate the relative closeness coefficient of each alternative and arrange them in descending order, where the higher the value of closeness coefficient, the more preferred the decision-making alternative by DMs, and it can be seen as the recommended optimal alternative, the lower the coefficient is, the less recommended the alternative is for adoption.

$$C_i = \frac{d_i^-}{d_i^- + d_i^+} \tag{34}$$

4. **An Illustrative Example.** To illustrate the effectiveness and feasibility of the proposed model, in this section, a practical MCGDM example (adapted from Rostamzadeh et al. [11] where the authors used arithmetic mean to aggregate the criteria decision matrices and weights of DMs and our model is an improvement compared to it) concerns with the oil industry in Iran. Practitioners in this industry want to analyze the relevant factors that affect the industry's sustainable supply chain risk and select the optimal partner company (alternative) to enhance competitiveness. The specific stages and steps are described in detail below.

Stage 1. Problem analysis stage.

After the initial selection, four representative companies (A1, A2, A3, A4) are available as alternatives for evaluation. A group of three decision makers (D1, D2, D3) is constructed to select the optimal alternative and the most important influencing factor based on the linguistic variables for the ratings from seven scales (Very Low, Low, Medium Low, Medium, Medium High, High, Very High), which is shown in Table 1. Suppose the decision-making committee evaluates the sustainable supply chain risk management level of the four alternatives based on the following seven main criteria $C = \{C_1, C_2, \ldots, C_7\}$, where C_1 – environmental risks, C_2 – organizational risks, C_3 – sustainable supply risks, C_4 – sustainable production manufacturer/risks, C_5 – sustainable distribution risks, C_6 – sustainable recycling risks, C_7 – IT related risks. Among them, these seven main criteria are also divided into corresponding 6, 5, 8, 10, 7, 4, 4, a total of 44 sub-criteria, which contain almost all possible risk influencing factors in related research. The weights of decision makers and the weights of these criteria are unknown in this paper.

TABLE 1. Linguistic variables for the ratings

Importance linguistic variable	Code	Trapezoidal fuzzy numbers
Very Low	VL	$(0, 0, 0.1, 0.2)$
Low	L	$(0.1, 0.2, 0.2, 0.3)$
Medium Low	ML	$(0.2, 0.3, 0.4, 0.5)$
Medium	M	$(0.4, 0.5, 0.5, 0.6)$
Medium High	MH	$(0.5, 0.6, 0.7, 0.8)$
High	H	$(0.7, 0.8, 0.8, 0.9)$
Very High	VH	$(0.8, 0.9, 1, 1)$

Stage 2. The extended TOPSIS method to determine the weights of DMs.

The original importance weights of the criteria and the evaluation of each criterion in alternatives by DMs are stated in [11], where all DMs have the same weight. In this stage, the extended TOPSIS is applied to determining the inconsistent expert weights. After normalizing the fuzzy decision matrix through Equations (18) and (19), the positive ideal solution (PIS) and both parts of negative ideal solution are calculated by means of Equations (20)-(22), on which basis, the separation of each individual fuzzy decision matrix from the positive ideal decision S^{+k} and from both parts of the negative ideal decision S^{-kL} and S^{-kR} are obtained using Equation (23). Afterwards, for each expert, Equation (24) is used to calculate the relative closeness coefficient between them and PIS, the results of which are $RC_1^k = 0.66495$, $RC_2^k = 0.69516$, $RC_3^k = 0.71894$, respectively. Finally,

Table 2. The weights of the DMs

	RC^k	λ_k
D1	0.664950396	0.319834244
D2	0.695155573	0.334362621
D3	0.718940937	0.345803135

by comparing the coefficients of the individual and overall, the inconsistent weights of experts are obtained as $\lambda = (0.31983, 0.33436, 0.34580)$. Table 2 shows the specific results of DM weights.

Stage 3. Determine the subjective weight of criteria through the weights of DMs and calculate the objective weights of criteria utilizing the CRITIC method.

Here, the weights of experts obtained in Stage 2 are used to calculate the aggregated fuzzy comprehensive decision matrix $\widetilde{w}_j^{sn}$ and the subjective weight of criteria $\widetilde{w}_j^{s}$. First, by using Equation (26), the original evaluation matrix of criteria and the weights of DMs are combined in order to acquire the aggregated fuzzy comprehensive evaluation matrix of each alternative. On this basis, bring the value of expert's weight into the fuzzy decision matrix evaluated by the expert for each criterion of alternative to calculate the subjective weights of criteria using Equation (27), the results of which are shown as the second column of Table 3. Finally, the normalized subjective weight decision matrix of each criterion is obtained by the process of Equation (28), as presented in the fourth column of Table 3.

After calculating the subjective weight of the decision criterion, the objective weights of the amount of information contained in the measurement criterion of the four alternatives A1, A2, A3, and A4 are obtained using Equations (9)-(12), the results of which are shown in the sixth column of Table 3.

Stage 4. Integrate the subjective and objective weights of criteria.

On the basis of the obtained subjective and objective weights of decision-making criteria, the subjective and objective weights are integrated through the uniformity entropy method in this stage. After the calculation by means of Equations (13)-(16), the obtained ratio is 0.493 for subjective weights of criteria and 0.507 for the objective one. Therefore, the proportion can be brought into the weight matrix in order to calculate the aggregated weights of criteria $\widetilde{w}_j$, the results of which are summarized in the eighth column of Table 3. In addition, the weight matrix obtained in Table 3 can be transformed into precise number by means of Equation (7), which is also reflected in the table in the form of "defuzzy".

Stage 5. Rank and select the optimal alternative applying the classical TOPSIS.

Since the decision-making criteria in this case are all benefit-based, the fuzzy comprehensive evaluation matrix with inconsistent expert weights will be first normalized by Equation (29). Afterwards, to aggregate normalized fuzzy matrix $\widetilde{r}_{ij}$ with the integrated weights of criteria $\widetilde{w}_j$ obtained in Stage 4, Equation (30) is used and the weighted normalized fuzzy comprehensive decision matrix $\widetilde{z}_{ij}$ is summarized in Table 4. On this basis, for each decision criterion and alternative, the set of fuzzy negative ideal solutions (FNIS) A^- and the set of fuzzy positive ideal solutions (FPIS) A^+ are obtained from Equations (31) and (32), as shown in the second and third columns of Table 5. The distance d_j^+ and d_j^- of each alternative to the FPIS and FNIS is calculated using Equation (33), which can help to measure the performance of the alternatives based on the FPIS and the FNIS as shown in Table 5. After the summation, the overall value of the four alternatives is obtained, that is $d_j^+ = (0.3809, 0.3276, 0.3973, 0.4116)$, $d_j^- = (0.3302, 0.3835, 0.3137, 0.2995)$.

TABLE 3. Subjective weights of criteria, normalized subjective weights of criteria, objective and aggregated weights of criteria

	Subjective weights		Normalized subjective weights		Objective weights		Aggregated weights	
	fuzzy	defuzzy	fuzzy	defuzzy	fuzzy	defuzzy	fuzzy	defuzzy
C11	(0,0,0.1,0.2)	0.078	(0,0,0.004,0.008)	0.003	(0.043,0.044,0.049,0.051)	0.047	(0.022,0.022,0.027,0.03)	0.025
C12	(0.033,0.067,0.133,0.233)	0.120	(0.001,0.003,0.005,0.009)	0.005	(0.016,0.016,0.029,0.032)	0.023	(0.009,0.009,0.017,0.02)	0.014
C13	(0.636,0.736,0.768,0.868)	0.752	(0.024,0.028,0.029,0.033)	0.028	(0.024,0.024,0.024,0.025)	0.024	(0.024,0.026,0.027,0.029)	0.026
C14	(0.767,0.867,0.933,0.967)	0.880	(0.029,0.033,0.035,0.036)	0.033	(0.024,0.024,0.028,0.03)	0.026	(0.026,0.028,0.032,0.033)	0.030
C15	(0.465,0.565,0.631,0.731)	0.598	(0.018,0.021,0.024,0.028)	0.023	(0.017,0.017,0.019,0.02)	0.018	(0.017,0.019,0.022,0.024)	0.020
C16	(0.167,0.267,0.333,0.433)	0.300	(0.006,0.01,0.013,0.016)	0.011	(0.023,0.023,0.03,0.031)	0.027	(0.015,0.017,0.021,0.024)	0.019
C1	(2.068,2.501,2.899,3.432)	2.728	(0.078,0.094,0.109,0.129)	0.103	(0.146,0.148,0.18,0.189)	0.166	(0.113,0.121,0.145,0.159)	0.135
C21	(0.732,0.832,0.864,0.932)	0.838	(0.028,0.031,0.033,0.035)	0.032	(0.017,0.018,0.018,0.018)	0.018	(0.022,0.025,0.025,0.027)	0.025
C22	(0.765,0.865,0.931,0.965)	0.879	(0.029,0.033,0.035,0.036)	0.033	(0.023,0.023,0.027,0.031)	0.026	(0.026,0.028,0.031,0.034)	0.030
C23	(0.264,0.364,0.432,0.532)	0.398	(0.01,0.014,0.016,0.02)	0.015	(0.017,0.017,0.023,0.024)	0.020	(0.013,0.015,0.02,0.022)	0.018
C24	(0.4,0.5,0.5,0.6)	0.500	(0.015,0.019,0.019,0.023)	0.019	(0.036,0.036,0.046,0.048)	0.041	(0.026,0.028,0.033,0.035)	0.030
C25	(0.569,0.669,0.735,0.835)	0.702	(0.021,0.025,0.028,0.031)	0.026	(0.017,0.017,0.017,0.017)	0.017	(0.019,0.021,0.022,0.024)	0.022
C2	(2.731,3.231,3.461,3.864)	3.317	(0.103,0.122,0.13,0.146)	0.125	(0.11,0.111,0.131,0.138)	0.122	(0.106,0.116,0.131,0.142)	0.124
C31	(0.132,0.232,0.264,0.364)	0.248	(0.005,0.009,0.01,0.014)	0.009	(0.016,0.016,0.017,0.017)	0.016	(0.01,0.012,0.013,0.015)	0.013
C32	(0.8,0.9,1,1)	0.922	(0.03,0.034,0.038,0.038)	0.035	(0.017,0.017,0.018,0.018)	0.017	(0.023,0.025,0.028,0.028)	0.026
C33	(0.569,0.669,0.735,0.835)	0.702	(0.021,0.025,0.028,0.031)	0.026	(0.017,0.017,0.019,0.02)	0.018	(0.019,0.021,0.023,0.025)	0.022
C34	(0.631,0.731,0.765,0.865)	0.748	(0.024,0.028,0.029,0.033)	0.028	(0.015,0.015,0.019,0.019)	0.017	(0.019,0.021,0.024,0.026)	0.023
C35	(0.432,0.532,0.564,0.664)	0.548	(0.016,0.02,0.021,0.025)	0.021	(0.023,0.023,0.024,0.031)	0.026	(0.02,0.022,0.023,0.028)	0.023
C36	(0.468,0.568,0.636,0.736)	0.602	(0.018,0.021,0.024,0.028)	0.023	(0.016,0.016,0.017,0.017)	0.016	(0.017,0.019,0.02,0.022)	0.019
C37	(0.7,0.8,0.8,0.9)	0.800	(0.026,0.03,0.03,0.034)	0.030	(0.023,0.023,0.026,0.027)	0.025	(0.025,0.027,0.028,0.03)	0.027
C38	(0.633,0.733,0.767,0.867)	0.750	(0.024,0.028,0.029,0.033)	0.028	(0.016,0.016,0.02,0.02)	0.018	(0.02,0.022,0.024,0.026)	0.023
C3	(4.365,5.165,5.531,6.231)	5.320	(0.164,0.195,0.208,0.235)	0.200	(0.142,0.143,0.16,0.168)	0.154	(0.153,0.168,0.184,0.201)	0.177
C41	(0.068,0.136,0.168,0.268)	0.162	(0.003,0.005,0.006,0.01)	0.006	(0.016,0.016,0.021,0.021)	0.018	(0.009,0.011,0.014,0.015)	0.012
C42	(0.264,0.364,0.432,0.532)	0.398	(0.01,0.014,0.016,0.02)	0.015	(0.015,0.015,0.016,0.016)	0.015	(0.013,0.015,0.016,0.018)	0.015
C43	(0.433,0.533,0.567,0.667)	0.550	(0.016,0.02,0.021,0.025)	0.021	(0.024,0.024,0.024,0.024)	0.024	(0.02,0.022,0.023,0.025)	0.022
C44	(0.765,0.865,0.931,0.965)	0.879	(0.029,0.033,0.035,0.036)	0.033	(0.02,0.021,0.021,0.021)	0.021	(0.025,0.027,0.028,0.029)	0.027
C45	(0.733,0.833,0.867,0.933)	0.840	(0.028,0.031,0.033,0.035)	0.032	(0.023,0.024,0.034,0.034)	0.029	(0.025,0.028,0.033,0.035)	0.030
C46	(0.467,0.567,0.633,0.733)	0.600	(0.018,0.021,0.024,0.028)	0.023	(0.022,0.022,0.035,0.035)	0.028	(0.02,0.022,0.029,0.031)	0.026
C47	(0.132,0.232,0.264,0.364)	0.248	(0.005,0.009,0.01,0.014)	0.009	(0.027,0.027,0.031,0.031)	0.029	(0.016,0.018,0.02,0.023)	0.019
C48	(0.8,0.9,1,1)	0.922	(0.03,0.025,0.038,0.038)	0.035	(0.016,0.017,0.018,0.018)	0.017	(0.023,0.025,0.028,0.028)	0.026
C49	(0.569,0.669,0.735,0.835)	0.702	(0.021,0.025,0.028,0.031)	0.026	(0.021,0.024,0.024,0.024)	0.023	(0.021,0.024,0.026,0.028)	0.025
C410	(0.633,0.733,0.767,0.867)	0.750	(0.024,0.028,0.029,0.033)	0.028	(0.023,0.023,0.028,0.029)	0.026	(0.023,0.025,0.029,0.031)	0.027
C4	(4.865,5.833,6.363,7.164)	6.051	(0.183,0.22,0.24,0.27)	0.228	(0.207,0.212,0.251,0.254)	0.231	(0.195,0.216,0.245,0.262)	0.230
C51	(0.1,0.2,0.2,0.3)	0.200	(0.004,0.008,0.008,0.011)	0.008	(0.016,0.016,0.017,0.022)	0.018	(0.01,0.012,0.013,0.017)	0.013
C52	(0.068,0.136,0.168,0.268)	0.162	(0.003,0.005,0.006,0.01)	0.006	(0.017,0.017,0.023,0.023)	0.020	(0.01,0.011,0.015,0.017)	0.013
C53	(0.732,0.832,0.864,0.932)	0.838	(0.028,0.031,0.033,0.035)	0.032	(0.03,0.031,0.044,0.044)	0.037	(0.029,0.031,0.038,0.04)	0.034
C54	(0.569,0.669,0.735,0.835)	0.702	(0.021,0.025,0.028,0.031)	0.026	(0.014,0.015,0.016,0.016)	0.015	(0.018,0.02,0.022,0.024)	0.021
C55	(0.633,0.733,0.767,0.867)	0.750	(0.024,0.028,0.029,0.033)	0.028	(0.025,0.025,0.029,0.029)	0.027	(0.024,0.026,0.029,0.031)	0.028
C56	(0.432,0.532,0.564,0.664)	0.548	(0.016,0.02,0.021,0.025)	0.021	(0.023,0.026,0.027,0.027)	0.025	(0.02,0.023,0.024,0.026)	0.023
C57	(0.132,0.232,0.264,0.364)	0.248	(0.005,0.009,0.01,0.014)	0.009	(0.028,0.028,0.033,0.034)	0.031	(0.017,0.019,0.022,0.024)	0.020
C5	(2.666,3.334,3.561,4.229)	3.448	(0.1,0.126,0.134,0.159)	0.130	(0.153,0.158,0.189,0.195)	0.174	(0.127,0.142,0.162,0.177)	0.152
C61	(0.732,0.832,0.864,0.932)	0.838	(0.028,0.031,0.033,0.035)	0.032	(0.023,0.023,0.024,0.025)	0.024	(0.025,0.027,0.028,0.03)	0.028
C62	(0.132,0.232,0.264,0.364)	0.248	(0.005,0.009,0.01,0.014)	0.009	(0.016,0.016,0.017,0.017)	0.016	(0.011,0.012,0.013,0.015)	0.013
C63	(0.567,0.667,0.733,0.833)	0.700	(0.021,0.025,0.028,0.031)	0.026	(0.016,0.016,0.018,0.018)	0.017	(0.019,0.021,0.023,0.025)	0.022
C64	(0.7,0.8,0.8,0.9)	0.800	(0.026,0.03,0.03,0.034)	0.030	(0.016,0.016,0.021,0.021)	0.018	(0.021,0.023,0.025,0.027)	0.024
C6	(2.131,2.531,2.661,3.029)	2.586	(0.08,0.095,0.1,0.114)	0.097	(0.071,0.071,0.079,0.081)	0.076	(0.076,0.083,0.09,0.097)	0.086
C71	(0.768,0.868,0.936,0.968)	0.882	(0.029,0.033,0.035,0.036)	0.033	(0.019,0.021,0.022,0.022)	0.021	(0.024,0.027,0.028,0.029)	0.027
C72	(0.433,0.533,0.567,0.667)	0.550	(0.016,0.02,0.021,0.025)	0.021	(0.017,0.017,0.017,0.017)	0.017	(0.016,0.018,0.019,0.021)	0.019
C73	(0.733,0.833,0.867,0.933)	0.840	(0.028,0.031,0.033,0.035)	0.032	(0.022,0.022,0.028,0.029)	0.026	(0.025,0.027,0.03,0.032)	0.029
C74	(0.7,0.8,0.8,0.9)	0.800	(0.026,0.03,0.03,0.034)	0.030	(0.014,0.014,0.015,0.015)	0.015	(0.02,0.022,0.023,0.024)	0.022
C7	(2.635,3.035,3.17,3.468)	3.072	(0.099,0.114,0.119,0.131)	0.116	(0.072,0.074,0.083,0.084)	0.078	(0.085,0.094,0.101,0.107)	0.097

Finally, by using Equation (34), the closeness coefficient of the four alternatives can be obtained as $C_i = (0.4644, 0.5393, 0.4412, 0.4211)$. According to the principle that the higher the degree of closeness to the positive ideal solution, the better the alternative, and the company can be ranked as A2 > A1 > A3 > A4. Therefore, A2 company has the highest level of sustainable supply chain risk management, and this alternative should be selected as the optimal one.

Table 4. The weighted normalized fuzzy comprehensive decision matrix

	A1	A2	A3	A4
C11	(0.005,0.007,0.018,0.03)	(0.002,0.005,0.012,0.023)	(0.007,0.015,0.018,0.03)	(0.007,0.015,0.018,0.03)
C12	(0.002,0.003,0.011,0.019)	(0.003,0.005,0.012,0.02)	(0.003,0.006,0.01,0.019)	(0.003,0.006,0.01,0.019)
C13	(0.018,0.022,0.024,0.029)	(0.018,0.022,0.024,0.029)	(0.016,0.02,0.022,0.027)	(0.018,0.022,0.024,0.029)
C14	(0.017,0.021,0.024,0.029)	(0.02,0.024,0.03,0.032)	(0.018,0.023,0.025,0.03)	(0.021,0.025,0.032,0.033)
C15	(0.013,0.016,0.02,0.024)	(0.013,0.017,0.019,0.024)	(0.011,0.014,0.017,0.022)	(0.012,0.016,0.018,0.023)
C16	(0.007,0.011,0.016,0.022)	(0.008,0.012,0.015,0.021)	(0.006,0.01,0.014,0.02)	(0.009,0.013,0.018,0.024)
C21	(0.015,0.019,0.02,0.024)	(0.018,0.022,0.024,0.027)	(0.016,0.02,0.021,0.025)	(0.015,0.019,0.02,0.024)
C22	(0.018,0.023,0.027,0.032)	(0.019,0.024,0.026,0.033)	(0.018,0.022,0.025,0.031)	(0.02,0.025,0.029,0.034)
C23	(0.007,0.01,0.014,0.019)	(0.009,0.012,0.017,0.022)	(0.007,0.011,0.016,0.021)	(0.007,0.01,0.014,0.019)
C24	(0.015,0.019,0.024,0.031)	(0.014,0.019,0.024,0.031)	(0.015,0.02,0.027,0.034)	(0.018,0.023,0.028,0.035)
C25	(0.012,0.015,0.017,0.021)	(0.013,0.017,0.021,0.024)	(0.012,0.015,0.017,0.021)	(0.012,0.015,0.017,0.021)
C31	(0.006,0.009,0.01,0.014)	(0.007,0.009,0.012,0.015)	(0.006,0.008,0.009,0.013)	(0.006,0.008,0.009,0.013)
C32	(0.017,0.021,0.024,0.026)	(0.019,0.023,0.028,0.028)	(0.016,0.02,0.022,0.025)	(0.018,0.022,0.026,0.027)
C33	(0.004,0.009,0.011,0.016)	(0.011,0.016,0.019,0.025)	(0.008,0.012,0.015,0.021)	(0.008,0.012,0.015,0.021)
C34	(0.012,0.016,0.018,0.023)	(0.013,0.017,0.02,0.026)	(0.008,0.012,0.016,0.021)	(0.007,0.011,0.013,0.018)
C35	(0.015,0.018,0.02,0.028)	(0.015,0.018,0.02,0.027)	(0.014,0.018,0.018,0.026)	(0.015,0.018,0.02,0.028)
C36	(0.005,0.008,0.011,0.015)	(0.011,0.014,0.018,0.022)	(0.007,0.01,0.011,0.015)	(0.007,0.01,0.011,0.015)
C37	(0.016,0.021,0.022,0.028)	(0.017,0.022,0.024,0.03)	(0.017,0.022,0.024,0.03)	(0.014,0.019,0.021,0.027)
C38	(0.011,0.015,0.018,0.023)	(0.011,0.016,0.02,0.026)	(0.007,0.012,0.014,0.019)	(0.007,0.012,0.014,0.019)
C41	(0.005,0.008,0.01,0.013)	(0.005,0.008,0.012,0.015)	(0.004,0.007,0.009,0.012)	(0.005,0.007,0.01,0.014)
C42	(0.007,0.01,0.012,0.016)	(0.007,0.011,0.013,0.018)	(0.007,0.01,0.012,0.016)	(0.006,0.009,0.01,0.014)
C43	(0.012,0.016,0.019,0.024)	(0.014,0.018,0.02,0.025)	(0.014,0.018,0.02,0.025)	(0.011,0.015,0.017,0.021)
C44	(0.019,0.024,0.026,0.029)	(0.019,0.024,0.026,0.029)	(0.015,0.019,0.022,0.026)	(0.018,0.022,0.025,0.028)
C45	(0.018,0.023,0.029,0.035)	(0.016,0.02,0.028,0.033)	(0.016,0.02,0.028,0.033)	(0.017,0.022,0.026,0.032)
C46	(0.011,0.016,0.025,0.031)	(0.011,0.016,0.025,0.031)	(0.012,0.017,0.023,0.029)	(0.011,0.016,0.025,0.031)
C47	(0.003,0.007,0.009,0.017)	(0.006,0.012,0.015,0.023)	(0.006,0.012,0.015,0.023)	(0.003,0.007,0.009,0.016)
C48	(0.017,0.022,0.025,0.027)	(0.018,0.023,0.027,0.028)	(0.015,0.019,0.022,0.025)	(0.017,0.022,0.025,0.027)
C49	(0.013,0.018,0.021,0.026)	(0.016,0.021,0.024,0.028)	(0.016,0.022,0.023,0.028)	(0.012,0.016,0.017,0.021)
C410	(0.014,0.019,0.021,0.028)	(0.015,0.02,0.024,0.031)	(0.015,0.02,0.024,0.031)	(0.013,0.018,0.023,0.03)
C51	(0.007,0.009,0.011,0.017)	(0.007,0.01,0.011,0.017)	(0.006,0.009,0.01,0.015)	(0.006,0.009,0.01,0.015)
C52	(0.006,0.008,0.011,0.015)	(0.006,0.009,0.013,0.017)	(0.005,0.008,0.01,0.013)	(0.007,0.009,0.012,0.016)
C53	(0.017,0.024,0.031,0.039)	(0.01,0.016,0.027,0.035)	(0.017,0.024,0.031,0.04)	(0.01,0.017,0.02,0.028)
C54	(0.012,0.015,0.017,0.021)	(0.014,0.018,0.019,0.024)	(0.011,0.014,0.016,0.02)	(0.011,0.015,0.018,0.022)
C55	(0.014,0.02,0.024,0.031)	(0.007,0.012,0.017,0.024)	(0.006,0.011,0.014,0.02)	(0.009,0.014,0.015,0.022)
C56	(0.014,0.019,0.021,0.026)	(0.013,0.018,0.02,0.024)	(0.012,0.017,0.018,0.023)	(0.012,0.017,0.019,0.023)
C57	(0.008,0.013,0.018,0.024)	(0.009,0.014,0.016,0.022)	(0.009,0.014,0.016,0.022)	(0.009,0.014,0.016,0.022)
C61	(0.017,0.022,0.026,0.03)	(0.018,0.023,0.025,0.03)	(0.018,0.023,0.025,0.03)	(0.014,0.019,0.02,0.024)
C62	(0.004,0.007,0.009,0.012)	(0.007,0.01,0.011,0.015)	(0.005,0.008,0.009,0.013)	(0.004,0.006,0.007,0.011)
C63	(0.005,0.009,0.011,0.017)	(0.009,0.014,0.018,0.025)	(0.006,0.01,0.014,0.02)	(0.007,0.012,0.013,0.018)
C64	(0.014,0.018,0.02,0.025)	(0.015,0.019,0.022,0.027)	(0.01,0.014,0.018,0.022)	(0.01,0.014,0.018,0.022)
C71	(0.014,0.019,0.022,0.026)	(0.019,0.024,0.026,0.029)	(0.018,0.023,0.024,0.023)	(0.015,0.02,0.021,0.025)
C72	(0.01,0.014,0.016,0.02)	(0.011,0.015,0.017,0.021)	(0.009,0.013,0.014,0.018)	(0.007,0.01,0.012,0.016)
C73	(0.017,0.022,0.026,0.032)	(0.017,0.022,0.027,0.032)	(0.017,0.022,0.026,0.032)	(0.017,0.022,0.027,0.032)
C74	(0.01,0.014,0.016,0.021)	(0.013,0.018,0.019,0.024)	(0.007,0.011,0.012,0.017)	(0.008,0.012,0.015,0.02)

5. **Parameter Analysis and Comparative Analysis.**

5.1. **Parameter sensitivity analysis.**

For the reason that different parameters are involved in the proposed method of obtaining the alternative decision ranking, an inherent situation is considered that even a subtle change of parameter may have a great impact on the result. Therefore, in order to verify the stability of the proposed method and control the influence of the parameter function in MCGDM, the parameter of weight η_{ij} is

TABLE 5. FNIS, FPIS, and distances of each alternative from them

	FNIS	FPIS	d_i^-				d_i^+			
			A1	A2	A3	A4	A1	A2	A3	A4
C11	0.0024	0.0297	0.013	0.008	0.015	0.015	0.015	0.019	0.012	0.012
C12	0.0018	0.0204	0.007	0.008	0.008	0.008	0.012	0.011	0.011	0.011
C13	0.0156	0.0286	0.007	0.007	0.006	0.007	0.006	0.006	0.007	0.006
C14	0.0165	0.0329	0.006	0.01	0.007	0.011	0.01	0.006	0.009	0.005
C15	0.0108	0.0240	0.007	0.008	0.005	0.006	0.006	0.006	0.008	0.007
C16	0.0061	0.0238	0.008	0.008	0.006	0.01	0.01	0.01	0.011	0.008
C21	0.0147	0.0267	0.005	0.008	0.006	0.005	0.007	0.004	0.006	0.007
C22	0.0175	0.0337	0.008	0.008	0.006	0.009	0.008	0.008	0.01	0.007
C23	0.0067	0.0218	0.006	0.008	0.007	0.006	0.01	0.007	0.008	0.009
C24	0.0145	0.0354	0.008	0.008	0.01	0.012	0.013	0.013	0.011	0.009
C25	0.0117	0.0242	0.005	0.007	0.005	0.005	0.008	0.005	0.008	0.008
C31	0.0057	0.0154	0.004	0.005	0.003	0.003	0.005	0.005	0.006	0.006
C32	0.0163	0.0276	0.006	0.008	0.005	0.007	0.006	0.003	0.007	0.005
C33	0.0044	0.0254	0.006	0.014	0.01	0.01	0.015	0.007	0.011	0.011
C34	0.0069	0.0259	0.010	0.012	0.007	0.005	0.009	0.007	0.012	0.014
C35	0.0137	0.0278	0.006	0.006	0.005	0.006	0.008	0.008	0.009	0.008
C36	0.0046	0.0223	0.005	0.012	0.006	0.006	0.013	0.006	0.012	0.012
C37	0.0140	0.0304	0.008	0.009	0.01	0.006	0.009	0.007	0.007	0.01
C38	0.0074	0.0261	0.009	0.011	0.006	0.006	0.009	0.008	0.013	0.013
C41	0.0044	0.0154	0.005	0.006	0.004	0.005	0.006	0.005	0.007	0.006
C42	0.0060	0.0178	0.005	0.006	0.005	0.004	0.007	0.005	0.007	0.008
C43	0.0112	0.0248	0.007	0.008	0.008	0.005	0.007	0.006	0.006	0.009
C44	0.0149	0.0287	0.009	0.009	0.005	0.008	0.004	0.004	0.008	0.006
C45	0.0155	0.0347	0.011	0.009	0.009	0.008	0.009	0.01	0.01	0.011
C46	0.0113	0.0315	0.009	0.01	0.009	0.009	0.011	0.011	0.011	0.011
C47	0.0029	0.0227	0.006	0.011	0.011	0.006	0.014	0.009	0.009	0.014
C48	0.0149	0.0279	0.008	0.009	0.005	0.008	0.005	0.004	0.008	0.005
C49	0.0117	0.0277	0.008	0.01	0.01	0.005	0.008	0.006	0.006	0.011
C410	0.0129	0.0310	0.008	0.01	0.01	0.008	0.01	0.008	0.008	0.01
C51	0.0063	0.0167	0.005	0.005	0.004	0.004	0.006	0.005	0.007	0.007
C52	0.0054	0.0166	0.005	0.006	0.004	0.005	0.006	0.005	0.007	0.006
C53	0.0102	0.0396	0.018	0.012	0.018	0.009	0.012	0.018	0.012	0.021
C54	0.0105	0.0237	0.006	0.008	0.005	0.006	0.007	0.005	0.009	0.007
C55	0.0058	0.0308	0.017	0.009	0.007	0.009	0.008	0.016	0.018	0.016
C56	0.0119	0.0260	0.008	0.007	0.006	0.006	0.006	0.007	0.008	0.008
C57	0.0084	0.0239	0.007	0.007	0.007	0.007	0.008	0.008	0.008	0.008
C61	0.0145	0.0302	0.009	0.01	0.01	0.005	0.006	0.006	0.006	0.011
C62	0.0037	0.0153	0.004	0.007	0.005	0.003	0.007	0.004	0.006	0.008
C63	0.0047	0.0245	0.006	0.012	0.008	0.008	0.014	0.008	0.012	0.012
C64	0.0100	0.0272	0.009	0.011	0.006	0.006	0.008	0.007	0.011	0.011
C71	0.0145	0.0290	0.006	0.01	0.009	0.006	0.009	0.005	0.006	0.009
C72	0.0071	0.0212	0.008	0.009	0.007	0.004	0.006	0.005	0.008	0.01
C73	0.0173	0.0321	0.007	0.007	0.007	0.007	0.008	0.008	0.008	0.008
C74	0.0070	0.0245	0.008	0.012	0.005	0.007	0.009	0.006	0.013	0.011

discussed in this section. Firstly, on the basis that the weights of DMs $\lambda = (0.31983, 0.33436, 0.34580)$ obtained in this paper remain unchanged, a sensitivity analysis of the parameters η_{ij} reflecting the subjective preferences of experts in the process of integrating subjective and objective weights of criteria is carried out, where $0 \leq \eta_{ij} \leq 1$, 11 values of weights parameter were taken at interval 0.1 and vary from 0 to 1, and the sensitivity of closeness coefficient C_i to the parameter η_{ij} based on the proposed method can be shown in Figure 2. From the analysis of the graph, it is evident that, whatever the value of η_{ij}, the best optimal coefficient value is reported by A2 in all phase, followed by A1 and A3, the order of which remains unchanged, that is A2 > A1 > A3 > A4. It is also noticed that, with the increasing of η_{ij}, the values of A1, A3 and A4 all show a decreasing trend, and the gap between them and A2 gradually increases, which implies that as the subjective preference of DMs becomes stronger, A2 is more favored. To sum up, the ranking of five alternatives has not been changed with the significant increase of weight parameter η_{ij}, but shows some stability, which means the proposed extended TOPSIS-CRITIC method is not so sensitive to the weights parameter, that is, the decision result is relatively stable.

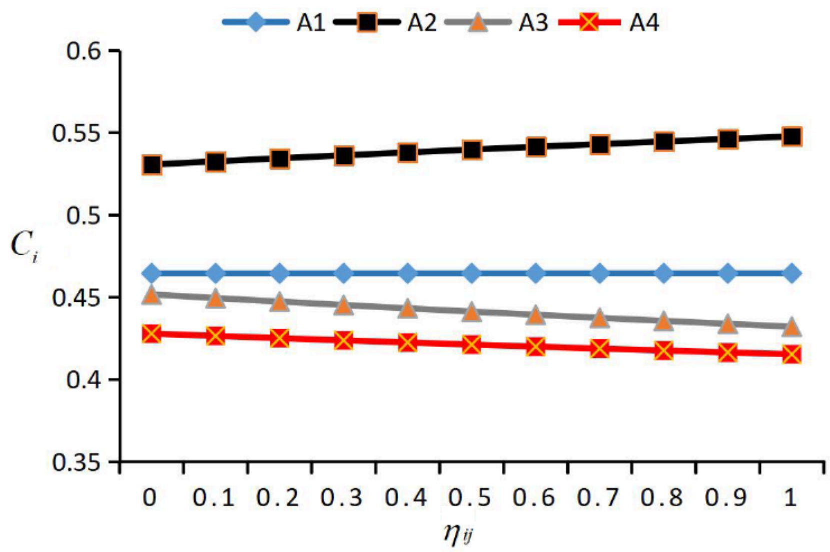

FIGURE 2. The closeness coefficient sensitivity to values of weights parameter

The determination of criteria weights is one of the core issues studied in this paper and next we will analyze the impact of weight parameter on the aggregated weights of main criteria. Similar to the previous analysis between the closeness coefficient and weights parameter, here we adjust 11 values of η_{ij} in the range of $[0, 1]$ and set 0.1 as the step length in order to figure out the influence of weights parameter to the weights of main criteria. The values of weights of seven sub-criteria in this paper for 11 different parameters are shown in Figure 3. Based on the results from Figure 3, we can conclude that, with the weight parameter varying from 0 to 1, the obtained weights of main criteria are not as stable as closeness coefficient, and some changes have taken place. For most criteria, even a small change of the weight parameter may result in obvious trend changes in the weights of criteria. When the weights parameter gradually increases, the values of criteria C1 (environmental risks) and C5 (sustainable distribution risks), all show a decreasing trend and the difference in numerical value is increasing. However, it should be noticed that regardless of the value of weight parameter, the weight of main criterion C4 (sustainable production/manufacturer risks) is always the optimal one and shows a stable trend, which means that the related risks about sustainable production are the

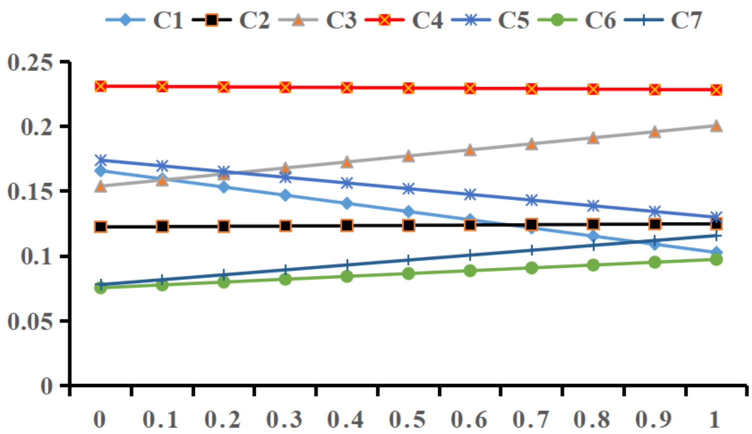

Figure 3. The combined weights sensitivity to values of weights parameter

most important in the activities of SCF and need to be handled carefully to avoid risks while achieving optimal production goals. The weights of main criteria C3, C6 and C7 all show a gradual increase trend, especially for the value of C3 (sustainable supply risks), based on which, we can make targeted risk prevention policies.

5.2. **Comparative analysis and discussion.** In this subsection, we will illustrate the effectiveness and superiority of the extended uniformity entropy theory TOPSIS-CRITIC by analyzing and comparing the relationship and differences between the proposed model and other existing relevant methods [11,21,22] under fuzzy environment. The decision result of the proposed method is compared based on the data from the example in Section 4 with other methods, the ranking of which is shown in Table 6.

Table 6. The comparison of the rankings of alternatives using different methods

	TODIM method in [21]	Dominance value	The proposed method	C_i	Method in [11]	C_i	GHM operator method in [22]	Score value
A1	3	0.7809	2	0.4644	2	0.4637	2	0.7448
A2	4	0	1	0.5393	1	0.5404	1	0.7984
A3	2	0.9296	3	0.4412	3	0.4414	3	0.7308
A4	1	1	4	0.4211	4	0.4207	4	0.7164

Firstly, we compare with the method [11] of the actual example sources in this paper, which also takes advantages of the TOPSIS-CRITIC but ignores the weights of DMs and the proportion of subjective, objective weights of criteria in the integrated processing. In addition, the acquisition of comprehensive decision matrix is different from the average decision matrix obtained on the basis of arithmetic mean of the importance weight of the criteria assessed by DMs in [11]. The proposed method in this paper not only integrates the advantages of considering the subjective decision preferences and differential characteristics of DMs, but also involves the different amounts of information contained in each criterion during the decision process and the characteristics of combining objectivity and subjectivity. As can be seen from Table 6, the ranking result obtained by the extended TOPSIS-CRITIC and the classical TOPSIS-CRITIC method is almost the same. The optimal one is A2 while A4 ranks the last, which implies that the proposed method can not only obtain reasonable and reliable accuracy results, but also comprehensively take account of the characteristics of decision makers and criteria weights, hence more suitable for application in practical MCGDM problems.

Secondly, characterized by considering the psychological behavior of DM, an MCGDM method named TODIM is applied for comparison with the proposed method. The dominance value of TODIM, as shown in Table 6, indicates that A4 is the optimal alternative, whereas it ranks the last among the proposed method and the other ranking results are completely opposite compared to our method. The difference is caused by a number of reasons. First, the determination of objective weights of criteria and the different preference of DMs are not involved in [21], which may cause bias in decision-making results. What is more, the TODIM method needs to define the reference attribute that has the highest importance weight, which may lead to over-absolute extreme results and disturb the evaluation information of experts. The proposed method ranks from the perspective of the closest to the positive ideal solution and the farthest from the negative ideal solution, which is more in line with actual decision-making in application.

Finally, we continue to compare our model of Section 4 with the GHM (geometric Heronian mean) operator method proposed by [22]. We will take account of the proposed aggregation method, which takes account of the weights of DMs and the proportion of subjective and objective criteria in the weight of integration, versus selected methods well-known from the literature, which ignore the differences between decision makers, as well as the differences of subjective and objective weight of criteria. For the comparison we use the following definition of the operator method.

Definition 5.1. [23] *Let $p, q \geq 0$ and p, q do not take the value 0 simultaneously. a_i $(i = 1, 2, \ldots, n)$ is a collection of nonnegative numbers. If trapezoidal fuzzy set satisfies the following equation:*

$$GHM^{p,q}(a_1, a_2, \ldots, a_n) = \frac{1}{p+q}\left(\prod_{i=1,j=1}^{n}(pa_i + qa_j)^{\frac{2}{n(n+1)}}\right) \tag{35}$$

then GHM is called the geometric Heronian mean (GHM) for trapezoidal fuzzy set.

On the basis of the weighted normalized fuzzy comprehensive decision matrix obtained from the integration of weights with the fuzzy evaluation matrix, the GHM operator is applied to calculating the score values of alternatives, the results of which are summarized in the last column of Table 6. It can be observed that the ranking results obtained by the proposed method and the GHM operator are identical, that is, A2 > A1 > A3 > A4, the sustainable supply chain risk management level of A2 is considered to be the best by DMs and the relevant risk management plan of the A1 company should be appropriately upgraded. Although the two methods have their own advantages, the operator-based method requires a lot of complicated calculations and is easy to cause the loss of decision-making information. It is also worth noting that the proposed method can not only obtain reasonable and reliable results, but also is very stable in response to sensitive changes, hence more suitable for application in practical MCGDM problems. In addition, the decision-making information contained in the proposed model is more extensive, and the distance scale of the ideal solution is also based on the linguistic variable of the uncertainty of the DM's preference, which can be adapted to decision-making needs of different backgrounds.

From the above comparative analysis, it can be seen that the decision-making model proposed in this paper is more suitable for dealing with MCGDM problems in which the preference of experts is unknown and the subjective and objective weights are fuzzy under complex environment.

6. **Conclusion.** In this paper, a novel weight-driven MCGDM model considering the unique characteristics of DMs and the proportion of subjective, objective weights in the integration criteria weight under trapezoidal fuzzy set environment is established based on the idea of uniformity entropy theory and extended TOPSIS-CRITIC method. This approach has all the advantages of fuzzy theory, TOPSIS-CRITIC method and uniformity entropy method. Firstly, take the characteristic differences of decision makers into consideration, which have been disregarded in most related research. Secondly, make full use of the characteristics of the CRITIC method to measure the amount of information contained in the criteria, and objectively obtain the weights of criteria in decision-making. On the basis of the theory of uniformity entropy, we construct a combined weight model under fuzzy environment that takes consideration of both the subjective and objective weights of the criteria, the outstanding advantages of which are that they can not only account the influence of decision makers' subjective decision preferences but also remain the objective decision information based on related calculations sufficiently. Finally, due to the integration of weight determination method, the proposed model can obtain the weights of DMs, objective weights of criteria, alternative closeness coefficient and ranking results under fuzzy, uncertain decision-making environment and meet the needs and preferences of different decision makers in practical problems.

An illustrative example has been conducted in the field of sustainable SCF risk management that the proposed method is confirmed to be applicable and scientific. The effectiveness and feasibility of the model have been demonstrated with sensitivity analysis and comparation analysis, which also reduces the potential risks caused by improper alternative selection to a certain extent.

Although this paper has enriched the theoretical system of MCGDM under uncertain environment, there are also some limitations that are worthy of future research. The established model only discusses the case where the evaluation value of criteria and alternatives is in the form of fuzzy numbers, they may not fully reflect all aspects of the complex relationship between the criteria of the research objects, which may lead to deviations in the results to a certain extent. In addition, the description of the related methods for determining the subjective criteria weights is slightly thin and not exhaustive enough. In the future, it is necessary to further extend the current research, focusing on how to reasonably express MCGDM opinions when the criterion value is presented in the form of mixed, uncertain information such as hesitation and linguistic variables, for solving the practical problems through appropriate weight determination and ranking methods. It is worth noting that the proposed method can be made applicable to other decision-related industries and problems, such as blockchain operational risk analysis, credit system evaluation and city happiness index rankings.

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