Research Article

Partner Selection in a Virtual Enterprise: A Group Multiattribute Decision Model with Weighted Possibilistic Mean Values

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This paper proposes an extended technique for order preference by similarity to ideal solution (TOPSIS) for partner selection in a virtual enterprise (VE). The imprecise and fuzzy information of the partner candidate and the risk preferences of decision makers are both considered in the group multiattribute decision-making model. The weighted possibilistic mean values are used to handle triangular fuzzy numbers in the fuzzy environment. A ranking procedure for partner candidates is developed to help decision makers with varying risk preferences select the most suitable partners. Numerical examples are presented to reflect the feasibility and efficiency of the proposed TOPSIS. Results show that the varying risk preferences of decision makers play a significant role in the partner selection process in VE under a fuzzy environment.

1. Introduction

A virtual enterprise (VE) is a type of temporary alliance of independent, geographically dispersed organizations that aim to share skills and resources to exploit low-cost fast-changing market opportunities and achieve high-quality customer satisfaction [1–6]. VEs have become prevalent because of the increasing customer demands in the present global economy and the increasing complexity and diminishing life cycle of products. A VE is formed and dissolved by the appearance and disappearance of market opportunities, respectively.

A VE faces many important issues throughout its life cycle. Given the role of partners in the success of a VE, the proper selection of partners has received considerable research attention. Literature on partner selection can be divided into two categories.

The first literature category involves the information environment, wherein the verdicts of decision makers on candidate partners can be expressed in precise values. Various approaches have been proposed for VE partner selection. Talluri and Baker [7] proposed a two-phase mathematics

programming method. Wu et al. [8] developed an integer-programming method to minimize the transportation cost by geographic position and transportation approach. Ip et al. [1] described a risk-based partner selection problem and developed a mathematical programming model. Jarimo and Pulkkinen [9] presented a mixed-integer linear programming model to configure the virtual organization. Zhao et al. [10] developed a nonlinear integer-programming model to solve VE partner selection problems with precedence and due date constraints. Ng [11] proposed a weighted linear program to solve the multicriteria supplier selection problem. Other researchers simultaneously considered several factors such as cost, quality, credit, time, and risk for VE partner selection, thus making the partner selection problem for VE a type of multiattribute decision-making (MADM) problem. MADM methods, such as analytic hierarchy process (AHP), data envelopment analysis (DEA), and neural networks (NNs), have been developed to solve problems in VE partner selection. Sha and Che [12] developed a partner selection model based on AHP, multiattribute utility theory, and integer programming (IP) for multicriteria virtual integration; Sari et al. [13] applied the NN method to assess the performance

of a particular partner in a VE. Wu [14] combined DEA, decision trees, and NNs to assess supplier performance. Liou [15] proposed a hybrid model to help airline companies select suitable partners for strategic alliances.

In reality, the decision makers are generally unsure of their judgement on candidates because the information about these candidates is uncertain and vague [4]. Thus, the second literature category considers the real-life vagueness and uncertainty of the partner selection process. Such problems can only be resolved by fuzzy set theory. Mikhailov [16] developed a fuzzy preference programming method for VE partner selection. Kahraman et al. [17] applied fuzzy AHP to select the supplier that highly satisfies the determined criteria. Wang and Lin [18] developed a fuzzy hybrid decision-aid model to select the best partner. Golec and Kahya [19] proposed a fuzzy model for competency-based employee evaluation and selection. Guneri et al. [20] presented an integrated fuzzy and linear programming approach for selecting suppliers and presented a set of linguistic values that are expressed in trapezoidal fuzzy numbers to assess the weights and ratings of the supplier selection criteria. Moreover, Crispim and Souza [3, 21] applied a fuzzy TOPSIS algorithm to rank alternative VE configurations. Ye and Li [4] proposed two MADM models with interval values to solve partner selection problems with partial information. Ye [5] proposed an extended TOPSIS method with interval-valued intuitionistic fuzzy numbers. Tseng [22] used linguistic preferences to describe the weights of green supply chain criteria and applied grey and fuzzy set theories to rank alternatives. Shaw et al. [23] used fuzzy AHP and fuzzy multiobjective linear programming to select the suitable supplier for the development of a low carbon supply chain. Liao and Kao [24] proposed an integrated fuzzy TOPSIS and multichoice goal programming approach to select suppliers in a supply chain.

However, these previous studies did not consider the risk preferences of decision makers in their proposed methods. The existence of contradicting methods in practice reflects the varying risk preference and aversion to risk neutrality of managers, particularly when they are placed under an uncertain environment. Given that risk-averse and risk-prone decision makers behave differently under similar situations, the risk preferences of decision makers must be considered when setting applicable and tailored decisions.

This paper uses fuzzy set theory to solve the vague and uncertain problems in the partner selection process. In contrast to the studies in the second literature category, we consider the risk preferences of decision makers to develop a partner selection approach that is consistent with actual practices. An extended TOPSIS is proposed in this study. The proposed extended TOPSIS considers the imprecise and uncertain information of partner candidates and the risk preferences of decision makers in the group MADM model. Weighted possibilistic mean values are used to manage triangular fuzzy numbers and establish the proposed TOPSIS model.

The rest of the paper is organized as follows. Section 2 introduces the basic concepts on the possibilistic mean values of fuzzy numbers. Section 3 presents the group MADM problem with triangular fuzzy numbers. Section 4 outlines

the development of the extended TOPSIS. Section 5 presents an illustrative example. Section 6 summarizes the paper.

2. Possibilistic Mean Values of Fuzzy Numbers

In this section, we introduce some basic concepts related to possibilistic mean values of fuzzy numbers. First, we assume that a fuzzy number A is a fuzzy set of the real line ξ with a normal, fuzzy convex, and continuous membership function of bounded support. The family of fuzzy numbers can be denoted by $F(\xi)$. A γ -level set of a fuzzy number A is defined by $[A]^\gamma = \{t \in \xi | A(t) \geq \gamma\}$, as $\gamma > 0$, and $[A]^\gamma = \text{cl}\{t \in \xi | A(t) > 0\}$ (the closure of the support of A), as $\gamma = 0$ [25, 26].

Definition 1 (see [25, 26]). Let $A \in \xi$ be a fuzzy number with $[A]^\gamma = [a_1(\gamma), a_2(\gamma)]$, $\gamma \in [0, 1]$. The lower and upper possibilistic mean values of fuzzy number A with γ -level set can be defined as $M_*(A) = 2 \int_0^1 \gamma a_1(\gamma) d\gamma$ and $M^*(A) = 2 \int_0^1 \gamma a_2(\gamma) d\gamma$.

Definition 2 (see [25]). The interval-valued possibilistic mean of A can be defined as $M(A) = [M_*(A), M^*(A)]$. However, the crisp possibilistic mean value of A is defined as $\bar{M}(A) = (M_*(A) + M^*(A))/2$.

According to Definition 2, Zhang et al. [26] defined the weighted possibilistic mean of fuzzy number A as

$$\bar{M}(A; t) = (1 - t) M_*(A) + t M^*(A), \quad t \in [0, 1]. \quad (1)$$

If $t = 0$, then $\bar{M}(A; 0) = M_*(A)$; if $t = 1$, then $\bar{M}(A; 1) = M^*(A)$; if $t = 1/2$, then $\bar{M}(A; 1/2) = (M^*(A) + M_*(A))/2$. Obviously, for different t , we can give different importance to the lower and upper possibilistic mean values.

Researchers have focused on the computing of different approximations of fuzzy numbers, within which triangular fuzzy numbers and trapezoidal fuzzy numbers are the most popular fuzzy analysis methods. In this paper, we use triangular fuzzy numbers to express the judgments of decision makers on the information of the candidates. Let A be a triangular fuzzy number with center a , left width $\alpha > 0$, and right width $\beta > 0$; that is, $A = (a - \alpha, a, a + \beta)$. According to Definition 2, a γ -level set of the fuzzy number A can easily be computed as

$$[A]^\gamma = [a - (1 - \gamma)\alpha, a + (1 - \gamma)\beta], \quad \forall \gamma \in [0, 1]. \quad (2)$$

According to Definition 1, we can get

$$\begin{aligned} M_*(A) &= 2 \int_0^1 \gamma (a - (1 - \gamma)\alpha) d\gamma = a - \frac{\alpha}{3}, \\ M^*(A) &= 2 \int_0^1 \gamma (a + (1 - \gamma)\beta) d\gamma = a + \frac{\beta}{3}. \end{aligned} \quad (3)$$

Therefore, the interval-valued possibilistic mean value and crisp possibilistic mean value of A can be written as

$$\begin{aligned} M(A) &= \left[a - \frac{\alpha}{3}, a + \frac{\beta}{3} \right], \\ \overline{M}(A) &= a + \frac{\beta - \alpha}{6}. \end{aligned} \quad (4)$$

Finally, the weighted possibilistic mean value of fuzzy number A is computed as

$$\overline{M}(A; t) = a + \frac{t\beta - (1-t)\alpha}{3}, \quad t \in [0, 1]. \quad (5)$$

3. Partner Selection Problem Description and Notations

Let us consider a core enterprise getting a bid for a large project consisting of several subprojects. The core enterprise cannot complete the whole project only by its own ability. Therefore, the core enterprise has to select partners and form a VE to complete the project. The partner selection problem of a VE is described as follows: $X = \{X_i \mid i = 1, \dots, n\}$ represents a finite set of possible candidates, $B = \{B_j \mid j = 1, \dots, m\}$ represents a finite set of attributes according to the desirability judgment on a candidate.

Assuming the candidates' information is imprecise and fuzzy, the decision maker $DM\#k$ ($k = 1, 2, \dots, K$) utilizes a triangular fuzzy number $\tilde{a}_{ij}^k$ with center a_{ij}^k , left-width $\alpha_{ij}^k > 0$, and right-width $\beta_{ij}^k > 0$; that is, $\tilde{a}_{ij}^k = (a_{ij}^k - \alpha_{ij}^k, a_{ij}^k, a_{ij}^k + \beta_{ij}^k)$ to evaluate candidate X_i with respect to attribute B_j . Let $\tilde{A}^k = [\tilde{a}_{ij}^k]_{n \times m}$ be the decision matrix in the form of triangular fuzzy numbers. Then the group MADM problem with triangular fuzzy numbers can be expressed in matrix format as follows:

$$\tilde{A}^k = \begin{bmatrix} \tilde{a}_{11}^k & \tilde{a}_{12}^k & \dots & \tilde{a}_{1m}^k \\ \tilde{a}_{21}^k & \tilde{a}_{22}^k & \dots & \tilde{a}_{2m}^k \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1}^k & \tilde{a}_{n2}^k & \dots & \tilde{a}_{nm}^k \end{bmatrix}. \quad (6)$$

Each decision maker $DM\#k$ ($k = 1, 2, \dots, K$) will elicit weights for attribute B_j as ω_j^k , where $j = 1, 2, \dots, m$. ω_j^k ($j = 1, 2, \dots, m$) belongs to $[0, 1]$ and sums to one [18]; that is,

$$0 \leq \omega_j^k \leq 1, \quad j = 1, 2, \dots, m, \quad \sum_{j=1}^m \omega_j^k = 1. \quad (7)$$

The values of different attributes have different dimensions. Thus, the fuzzy decision matrix $\tilde{A}^k = [\tilde{a}_{ij}^k]_{n \times m}$ ($k = 1, 2, \dots, K$) should be standardized with matrix $\tilde{A}^{t^k}$ in order to reduce disturbance in the final results. Let $\tilde{A}^{t^k} = [\tilde{a}_{ij}^{t^k}]_{n \times m}$ be the standardized decision matrix in the form of triangular fuzzy numbers, where $\tilde{a}_{ij}^{t^k} = (a_{ij}^{t^k} - \alpha_{ij}^{t^k}, a_{ij}^{t^k}, a_{ij}^{t^k} + \beta_{ij}^{t^k})$.

In general, there are two attribute categories for candidates: benefit type and cost type. The higher the benefit type

value is, the better it will be. It is opposite for the cost type. We describe the normalized formula for triangular fuzzy numbers of the benefit type as follows:

$$\begin{aligned} (a_{ij}^{t^k} - \alpha_{ij}^{t^k}) &= \frac{(a_{ij}^k - \alpha_{ij}^k)}{\sqrt{\sum_{i=1}^n (a_{ij}^k + \beta_{ij}^k)^2}}, \\ a_{ij}^{t^k} &= \frac{a_{ij}^k}{\sqrt{\sum_{i=1}^n (a_{ij}^k)^2}}, \\ (a_{ij}^{t^k} + \beta_{ij}^{t^k}) &= \frac{(a_{ij}^k + \beta_{ij}^k)}{\sqrt{\sum_{i=1}^n (a_{ij}^k - \alpha_{ij}^k)^2}}. \end{aligned} \quad (8)$$

Similarly, the formula for the triangular fuzzy number of the cost type is described as follows:

$$\begin{aligned} (a_{ij}^{t^k} - \alpha_{ij}^{t^k}) &= \frac{1/(a_{ij}^k + \beta_{ij}^k)}{\sqrt{\sum_{i=1}^n (1/(a_{ij}^k - \alpha_{ij}^k))^2}}, \\ a_{ij}^{t^k} &= \frac{1/a_{ij}^k}{\sqrt{\sum_{i=1}^n (1/a_{ij}^k)^2}}, \\ (a_{ij}^{t^k} + \beta_{ij}^{t^k}) &= \frac{1/(a_{ij}^k - \alpha_{ij}^k)}{\sqrt{\sum_{i=1}^n (1/(a_{ij}^k + \beta_{ij}^k))^2}}. \end{aligned} \quad (9)$$

Now the triangular fuzzy number $\tilde{a}_{ij}^{t^k} = (a_{ij}^{t^k} - \alpha_{ij}^{t^k}, a_{ij}^{t^k}, a_{ij}^{t^k} + \beta_{ij}^{t^k})$ is the normalized form of triangular fuzzy number $\tilde{a}_{ij}^k = (a_{ij}^k - \alpha_{ij}^k, a_{ij}^k, a_{ij}^k + \beta_{ij}^k)$.

According to formula (5), we can get the weighted possibilistic mean value of triangular fuzzy number $\tilde{a}_{ij}^{t^k} = (a_{ij}^{t^k} - \alpha_{ij}^{t^k}, a_{ij}^{t^k}, a_{ij}^{t^k} + \beta_{ij}^{t^k})$ as follows:

$$\overline{M}(\tilde{a}_{ij}^{t^k}; t^k) = a_{ij}^{t^k} + \frac{t^k \beta_{ij}^{t^k} - (1 - t^k) \alpha_{ij}^{t^k}}{3}, \quad t^k \in [0, 1], \quad (10)$$

where t^k reflects the decision maker $DM\#k$'s risk preference coefficient; a larger t^k implies more risk-prone decision maker, whereas a smaller t^k indicates a more risk-averse decision maker. Specially, $t^k = 0$, $t^k = 0.5$, and $t^k = 1$ represent that the decision maker is extremely risk averse, risk neutral, and extremely risk prone, respectively.

Let $\overline{M}(\tilde{A}^{t^k}; t^k) = [\overline{M}(\tilde{a}_{ij}^{t^k}; t^k)]_{n \times m}$, $t^k \in [0, 1]$, be the decision matrix with the weighted possibilistic mean value of triangular fuzzy number, where $\overline{M}(\tilde{a}_{ij}^{t^k}; t^k) = a_{ij}^{t^k} + (t^k \beta_{ij}^{t^k} - (1 - t^k) \alpha_{ij}^{t^k})/3$.

4. An Extended TOPSIS Approach with Weighted Possibilistic Mean Values for Partner Selection

Yoon [27] developed a TOPSIS for multiattribute decision making. Now, TOPSIS is widely applied across different areas among numerous MADM methods and has received interest from both researchers and practitioners [28]. Hwang and Yoon [29] originally proposed TOPSIS to select the best candidate with a finite number of criteria. Kuo et al. [30] applied fuzzy SAW and fuzzy TOPSIS to select the location of an international distribution center in Asia Pacific. Liao and Kao [24] used fuzzy TOPSIS to select supplier in supply chain management. Boran et al. [31] employed an intuitionistic fuzzy TOPSIS approach to select a sales manager. Behzadian et al. [28] conducted a state-of-the-art literature review on TOPSIS research. Tian et al. [32] developed fuzzy TOPSIS model via chi-square test for information source selection. In this paper, we proposed a new extended TOPSIS method with weighted possibilistic mean values to solve partner selection problem of a VE.

Based on the TOPSIS concept, the chosen candidate should have the shortest distance from the positive ideal partner solution (PIPS) and the farthest distance from the negative ideal partner solution (NIPS). Hence, we identify PIPS $\overline{M}(\tilde{A}^{\kappa}; t^{\kappa})^+$ and NIPS $\overline{M}(\tilde{A}^{\kappa}; t^{\kappa})^-$ for each decision maker as follows:

$$\begin{aligned} & \overline{M}(\tilde{A}^{\kappa}; t^{\kappa})^+ \\ &= (\overline{M}(\tilde{a}_1^{\kappa}; t^{\kappa})^+, \overline{M}(\tilde{a}_2^{\kappa}; t^{\kappa})^+, \overline{M}(\tilde{a}_3^{\kappa}; t^{\kappa})^+, \dots, \overline{M}(\tilde{a}_m^{\kappa}; t^{\kappa})^+), \\ & \overline{M}(\tilde{A}^{\kappa}; t^{\kappa})^- \\ &= (\overline{M}(\tilde{a}_1^{\kappa}; t^{\kappa})^-, \overline{M}(\tilde{a}_2^{\kappa}; t^{\kappa})^-, \overline{M}(\tilde{a}_3^{\kappa}; t^{\kappa})^-, \dots, \overline{M}(\tilde{a}_m^{\kappa}; t^{\kappa})^-), \end{aligned} \quad (11)$$

where $\overline{M}(\tilde{a}_{ij}^{\kappa}; t^{\kappa})^+ = \max_i \overline{M}(\tilde{a}_{ij}^{\kappa}; t^{\kappa})$, $\overline{M}(\tilde{a}_{ij}^{\kappa}; t^{\kappa})^- = \min_i \overline{M}(\tilde{a}_{ij}^{\kappa}; t^{\kappa})$, $i = 1, 2, \dots, n$.

By using the m -dimensional Euclidean distance, the separation of each candidate from the PIPS $\overline{M}(\tilde{A}^{\kappa}; t^{\kappa})^+$ for the decision maker DM# κ is given as

$$\begin{aligned} & d_i^{\kappa+}(t^{\kappa}) \\ &= \sqrt{\sum_{j=1}^m (\overline{M}(\tilde{a}_{ij}^{\kappa}; t^{\kappa}) - \overline{M}(\tilde{a}_{ij}^{\kappa}; t^{\kappa})^+)^2 \omega_j}, \quad i = 1, 2, \dots, n. \end{aligned} \quad (12)$$

Similarly, the separation of each candidate from the NIPS $\overline{M}(\tilde{A}^{\kappa}; t^{\kappa})^-$ for the decision maker DM# κ is given as

$$\begin{aligned} & d_i^{\kappa-}(t^{\kappa}) \\ &= \sqrt{\sum_{j=1}^m (\overline{M}(\tilde{a}_{ij}^{\kappa}; t^{\kappa}) - \overline{M}(\tilde{a}_{ij}^{\kappa}; t^{\kappa})^-)^2 \omega_j}, \quad i = 1, 2, \dots, n. \end{aligned} \quad (13)$$

A closeness coefficient is defined to determine the ranking of all candidates once $d_i^{\kappa+}(t^{\kappa})$ and $d_i^{\kappa-}(t^{\kappa})$ of each candidate X_i for decision maker DM# κ is calculated.

The relative closeness of the candidate X_i for decision maker DM# κ is defined as

$$\begin{aligned} \mu_i^{\kappa}(t^{\kappa}) &= \frac{d_i^{\kappa-}(t^{\kappa})}{d_i^{\kappa-}(t^{\kappa}) + d_i^{\kappa+}(t^{\kappa})}, \quad i = 1, 2, \dots, n, \\ \kappa &= 1, 2, \dots, K, \quad t^{\kappa} \in [0, 1]. \end{aligned} \quad (14)$$

Obviously, for decision maker DM# κ , the candidate X_i is closer to the PIPS and farther from the NIPS as $\mu_i^{\kappa}(t^{\kappa})$ approaches to 1. Hence, according to the closeness coefficient, the ranking of all candidates can be determined, and decision maker DM# κ selects the best one among a set of feasible candidates.

In addition, the group separation measure of each candidate is combined through an operation $\otimes$ for all decision makers DM# κ ($\kappa = 1, 2, \dots, K$). The two group separation measures of the PIPS and NIPS, $\overline{M}(\tilde{A}^{\kappa}; t^{\kappa})^+$ and $\overline{M}(\tilde{A}^{\kappa}; t^{\kappa})^-$, respectively, can be computed by the following formulas [4, 33]:

$$\begin{aligned} D_i^+ &= d_i^{1+}(t^1) \otimes d_i^{2+}(t^2) \\ &\quad \dots \otimes d_i^{\kappa+}(t^{\kappa}) \dots \otimes d_i^{K+}(t^K) \text{ for candidate } i, \\ D_i^- &= d_i^{1-}(t^1) \otimes d_i^{2-}(t^2) \\ &\quad \dots \otimes d_i^{\kappa-}(t^{\kappa}) \dots \otimes d_i^{K-}(t^K) \text{ for candidate } i. \end{aligned} \quad (15)$$

Here, we take the geometric mean operation to combine all individual separation measures by the following formulas:

$$\begin{aligned} D_i^+ &= \left(\prod_{\kappa=1}^K d_i^{\kappa+}(t^{\kappa}) \right)^{1/K} \text{ for candidate } i, \\ D_i^- &= \left(\prod_{\kappa=1}^K d_i^{\kappa-}(t^{\kappa}) \right)^{1/K} \text{ for candidate } i. \end{aligned} \quad (16)$$

Hence, the relative closeness of the candidate X_i is defined as

$$\mu_i = \frac{D_i^-}{D_i^- + D_i^+}, \quad i = 1, 2, \dots, n. \quad (17)$$

The procedure to find out the best partner with the extended TOPSIS method for group MADM with weighted possibilistic mean values is developed as follows.

Step 1. Make up a group decision-making team $E = \{\text{DM\#1}, \text{DM\#2}, \dots, \text{DM\#}\kappa, \dots, \text{DM\#}K\}$.

Step 2. Generate a set of possible candidates for subproject $X = \{X_i \mid i = 1, \dots, n\}$.

TABLE 1: The decision matrix with triangular fuzzy numbers and weights of six attributes for each decision maker.

Decision maker	Candidate and weight	Cost (B_1)	Past performance (B_2)	Relationship closeness (B_3)	Completion probability (B_4)	Time (B_5)	Quality (B_6)
DM#1	C_1	(9, 11, 12)	(86, 89, 91)	(82, 83, 84)	(0.89, 0.90, 0.92)	(21, 23, 25)	(0.95, 0.96, 0.97)
	C_2	(10, 12, 14)	(87, 90, 93)	(84, 85, 86)	(0.88, 0.91, 0.92)	(23, 24, 25)	(0.96, 0.97, 0.98)
	C_3	(12, 13, 15)	(90, 93, 94)	(87, 88, 89)	(0.92, 0.93, 0.94)	(22, 23, 24)	(0.96, 0.97, 0.98)
	C_4	(14, 15, 16)	(92, 94, 95)	(91, 92, 94)	(0.95, 0.97, 0.98)	(18, 19, 21)	(0.97, 0.98, 0.99)
	Weight	0.10	0.25	0.15	0.20	0.14	0.16
DM#2	C_1	(9, 11, 13)	(88, 90, 92)	(79, 80, 82)	(0.90, 0.91, 0.92)	(23, 24, 25)	(0.96, 0.97, 0.98)
	C_2	(11, 12, 13)	(87, 89, 91)	(83, 84, 85)	(0.89, 0.90, 0.91)	(21, 22, 23)	(0.95, 0.96, 0.97)
	C_3	(12, 13, 14)	(90, 91, 92)	(86, 87, 88)	(0.92, 0.93, 0.94)	(22, 23, 24)	(0.96, 0.97, 0.98)
	C_4	(13, 14, 15)	(92, 93, 94)	(87, 89, 90)	(0.91, 0.92, 0.93)	(18, 19, 21)	(0.96, 0.97, 0.99)
	Weight	0.11	0.21	0.16	0.21	0.15	0.16
DM#3	C_1	(11, 12, 13)	(88, 89, 90)	(75, 76, 78)	(0.91, 0.92, 0.94)	(21, 22, 23)	(0.96, 0.97, 0.98)
	C_2	(12, 13, 14)	(87, 89, 90)	(76, 78, 80)	(0.90, 0.91, 0.92)	(20, 21, 23)	(0.95, 0.97, 0.98)
	C_3	(13, 14, 15)	(89, 90, 91)	(82, 84, 85)	(0.94, 0.95, 0.96)	(20, 21, 22)	(0.96, 0.98, 0.99)
	C_4	(14, 15, 17)	(88, 90, 92)	(84, 85, 86)	(0.93, 0.94, 0.95)	(18, 20, 21)	(0.97, 0.98, 0.99)
	Weight	0.09	0.26	0.14	0.19	0.17	0.15
DM#4	C_1	(12, 13, 14)	(87, 89, 90)	(76, 77, 78)	(0.88, 0.90, 0.91)	(21, 22, 23)	(0.94, 0.95, 0.96)
	C_2	(13, 14, 15)	(88, 89, 91)	(81, 82, 83)	(0.89, 0.90, 0.92)	(19, 21, 23)	(0.93, 0.94, 0.95)
	C_3	(16, 17, 18)	(87, 88, 89)	(84, 85, 86)	(0.95, 0.96, 0.97)	(20, 21, 22)	(0.94, 0.95, 0.96)
	C_4	(15, 16, 18)	(89, 90, 91)	(86, 87, 88)	(0.94, 0.95, 0.96)	(19, 21, 22)	(0.95, 0.96, 0.97)
	Weight	0.12	0.24	0.16	0.17	0.15	0.16

FIGURE 1: Decision hierarchy of the partner selection problem of a VE.

Step 3. Design a set of attributes $B = \{B_j \mid j = 1, \dots, m\}$.

Step 4. Construct the decision matrix $\tilde{A}^\kappa = [\tilde{a}_{ij}^\kappa]_{n \times m}$ with triangular fuzzy numbers.

Step 5. Each decision maker elicits weights for the attribute B_j as $\tilde{\omega}_j^\kappa$, where $j = 1, 2, \dots, m$.

Step 6. Compute normalized ratings. This step tries to transform various attribute dimensions into the nondimensional attributes, which allows comparison between the attributes. Formulas (8) and (9) are used for computing the normalized triangular fuzzy numbers $\tilde{a}_{ij}^{\prime\kappa} = (a_{ij}^{\prime\kappa} - \alpha_{ij}^{\prime\kappa}, a_{ij}^{\prime\kappa}, a_{ij}^{\prime\kappa} + \beta_{ij}^{\prime\kappa})$.

Step 7. Calculate weighted possibilistic mean value of triangular fuzzy number $\tilde{a}_{ij}^{\prime\kappa} = (a_{ij}^{\prime\kappa} - \alpha_{ij}^{\prime\kappa}, a_{ij}^{\prime\kappa}, a_{ij}^{\prime\kappa} + \beta_{ij}^{\prime\kappa})$ by using formula (10).

Step 8. Identify PIPS and NIPS by using formula (11).

Step 9. Compute separation measure between candidate and PIPS for each decision maker by using formula (12).

Step 10. Calculate separation measure between candidate and NIPS for each decision maker by using formula (13).

Step 11. Calculate the closeness coefficient of candidate X_i for the decision maker DM# κ by using formula (14).

TABLE 2: The normalized decision matrix with triangular fuzzy numbers for each decision maker.

Decision maker	Candidate	Cost (B_1)	Past performance (B_2)	Relationship closeness (B_3)	Completion probability (B_4)	Time (B_5)	Quality (B_6)
DM#1	C_1	(0.4519, 0.5638, 0.7779)	(0.4611, 0.4862, 0.5125)	(0.4642, 0.4766, 0.4880)	(0.4732, 0.4850, 0.5053)	(0.4145, 0.4776, 0.5611)	(0.4847, 0.4948, 0.5052)
	C_2	(0.3874, 0.5168, 0.7001)	(0.4664, 0.4917, 0.5238)	(0.4755, 0.4881, 0.4996)	(0.4679, 0.4904, 0.5053)	(0.4145, 0.4577, 0.5123)	(0.4849, 0.5000, 0.5104)
	C_3	(0.3616, 0.4771, 0.5835)	(0.4825, 0.5081, 0.5294)	(0.4925, 0.5054, 0.5170)	(0.4892, 0.5011, 0.5162)	(0.4318, 0.4776, 0.5355)	(0.4849, 0.5000, 0.5104)
	C_4	(0.3390, 0.4134, 0.5001)	(0.4932, 0.5135, 0.5350)	(0.5151, 0.5283, 0.5461)	(0.5051, 0.5227, 0.5382)	(0.4935, 0.5782, 0.6546)	(0.4949, 0.5051, 0.5156)
DM#2	C_1	(0.4234, 0.5638, 0.7599)	(0.4769, 0.4958, 0.5153)	(0.4577, 0.4702, 0.4892)	(0.4865, 0.4972, 0.5082)	(0.4145, 0.4529, 0.5022)	(0.4898, 0.5013, 0.5117)
	C_2	(0.4234, 0.5168, 0.6217)	(0.4715, 0.4903, 0.5097)	(0.4809, 0.4937, 0.5071)	(0.4810, 0.4918, 0.5027)	(0.4506, 0.4941, 0.5501)	(0.4847, 0.4961, 0.5065)
	C_3	(0.3932, 0.4771, 0.5699)	(0.4878, 0.5013, 0.5153)	(0.4982, 0.5114, 0.5250)	(0.4973, 0.5082, 0.5193)	(0.4318, 0.4726, 0.5251)	(0.4898, 0.5013, 0.5117)
	C_4	(0.3670, 0.4430, 0.5261)	(0.4986, 0.5123, 0.5265)	(0.5040, 0.5231, 0.5369)	(0.4919, 0.5027, 0.5138)	(0.4935, 0.5721, 0.6418)	(0.4898, 0.5013, 0.5170)
DM#3	C_1	(0.4771, 0.5618, 0.6609)	(0.4848, 0.4972, 0.5113)	(0.4556, 0.4701, 0.4915)	(0.4827, 0.4946, 0.5108)	(0.4273, 0.4765, 0.5286)	(0.4873, 0.4974, 0.5104)
	C_2	(0.4430, 0.5618, 0.6058)	(0.4793, 0.4972, 0.5113)	(0.4616, 0.4824, 0.5041)	(0.4774, 0.4892, 0.4999)	(0.4273, 0.4991, 0.5551)	(0.4822, 0.4974, 0.5104)
	C_3	(0.4134, 0.4816, 0.5592)	(0.4903, 0.5028, 0.5170)	(0.4981, 0.5195, 0.5357)	(0.4986, 0.5107, 0.5217)	(0.4667, 0.4991, 0.5551)	(0.4873, 0.5026, 0.5156)
	C_4	(0.3648, 0.4495, 0.5193)	(0.4848, 0.5028, 0.5227)	(0.5102, 0.5257, 0.5420)	(0.4933, 0.5053, 0.5162)	(0.4680, 0.5241, 0.6167)	(0.4924, 0.5026, 0.5156)
DM#4	C_1	(0.4929, 0.5734, 0.6646)	(0.4820, 0.5000, 0.5128)	(0.4533, 0.4648, 0.4766)	(0.4679, 0.4850, 0.4970)	(0.4282, 0.4827, 0.5353)	(0.4896, 0.5000, 0.5106)
	C_2	(0.4600, 0.5324, 0.6135)	(0.4875, 0.5000, 0.5185)	(0.4831, 0.4950, 0.5071)	(0.4732, 0.4850, 0.5025)	(0.4282, 0.5056, 0.5917)	(0.4844, 0.4947, 0.5053)
	C_3	(0.3834, 0.4384, 0.4985)	(0.4820, 0.4944, 0.5071)	(0.5010, 0.5131, 0.5254)	(0.5051, 0.5173, 0.5298)	(0.4477, 0.5056, 0.5621)	(0.4896, 0.5000, 0.5106)
	C_4	(0.3834, 0.4658, 0.5317)	(0.4931, 0.5056, 0.5185)	(0.5129, 0.5251, 0.5377)	(0.4990, 0.5119, 0.5243)	(0.4477, 0.5056, 0.5917)	(0.4848, 0.5052, 0.5196)

TABLE 3: The normalized decision matrix with weighted possibilistic mean values for each decision maker.

Decision maker	t^k	Candidate	Cost (B_1)	Past performance (B_2)	Relationship closeness (B_3)	Completion probability (B_4)	Time (B_5)	Quality (B_6)
DM#1	$t^1 = 0$	C_1	0.5265	0.4778	0.4725	0.4811	0.4566	0.4914
		C_2	0.4737	0.4833	0.4839	0.4829	0.4433	0.4966
		C_3	0.4386	0.4995	0.5011	0.4972	0.4623	0.4966
		C_4	0.3886	0.5068	0.5239	0.5168	0.5499	0.5017
	$t^1 = 0.3$	C_1	0.5591	0.4830	0.4749	0.4843	0.4712	0.4935
		C_2	0.5049	0.4890	0.4863	0.4866	0.4531	0.4986
		C_3	0.4607	0.5042	0.5035	0.4999	0.4727	0.4986
		C_4	0.4047	0.5109	0.5270	0.5202	0.5660	0.5038
	$t^1 = 0.5$	C_1	0.5808	0.4864	0.4765	0.4864	0.4810	0.4949
		C_2	0.5258	0.4928	0.4879	0.4891	0.4596	0.5000
		C_3	0.4755	0.5074	0.5052	0.5017	0.4796	0.5000
		C_4	0.4155	0.5137	0.5291	0.5224	0.5768	0.5052
	$t^1 = 0.7$	C_1	0.6026	0.4898	0.4780	0.4885	0.4908	0.4962
		C_2	0.5466	0.4966	0.4895	0.4916	0.4661	0.5014
		C_3	0.4903	0.5105	0.5068	0.5035	0.4866	0.5014
		C_4	0.4262	0.5165	0.5312	0.5246	0.5875	0.5066
	$t^1 = 1.0$	C_1	0.6352	0.4950	0.4804	0.4917	0.5054	0.4983
		C_2	0.5779	0.5024	0.4920	0.4953	0.4759	0.5035
		C_3	0.5125	0.5152	0.5093	0.5062	0.4969	0.5035
		C_4	0.4423	0.5207	0.5343	0.5279	0.6036	0.5086
DM#2	$t^2 = 0$	C_1	0.5170	0.4895	0.4660	0.4936	0.4401	0.4975
		C_2	0.4857	0.4840	0.4894	0.4882	0.4796	0.4923
		C_3	0.4491	0.4968	0.5070	0.5045	0.4590	0.4975
		C_4	0.4177	0.5078	0.5168	0.4991	0.5459	0.4975
	$t^2 = 0.3$	C_1	0.5507	0.4933	0.4692	0.4958	0.4489	0.4996
		C_2	0.5055	0.4879	0.4921	0.4904	0.4896	0.4945
		C_3	0.4668	0.4995	0.5097	0.5067	0.4683	0.4996
		C_4	0.4336	0.5105	0.5200	0.5013	0.5607	0.5002
	$t^2 = 0.5$	C_1	0.5731	0.4959	0.4713	0.4973	0.4548	0.5011
		C_2	0.5187	0.4904	0.4938	0.4918	0.4962	0.4959
		C_3	0.4786	0.5014	0.5114	0.5082	0.4746	0.5011
		C_4	0.4442	0.5124	0.5222	0.5027	0.5706	0.5020
	$t^2 = 0.7$	C_1	0.5955	0.4985	0.4734	0.4987	0.4606	0.5026
		C_2	0.5320	0.4929	0.4956	0.4933	0.5028	0.4974
		C_3	0.4903	0.5032	0.5132	0.5097	0.4808	0.5026
		C_4	0.4548	0.5143	0.5244	0.5042	0.5805	0.5038
	$t^2 = 1.0$	C_1	0.6292	0.5023	0.4765	0.5009	0.4694	0.5048
		C_2	0.5518	0.4968	0.4982	0.4954	0.5128	0.4996
		C_3	0.5080	0.5060	0.5159	0.5119	0.4901	0.5048
		C_4	0.4707	0.5170	0.5277	0.5064	0.5953	0.5065

TABLE 3: Continued.

Decision maker	t^k	Candidate	Cost (B_1)	Past performance (B_2)	Relationship closeness (B_3)	Completion probability (B_4)	Time (B_5)	Quality (B_6)
DM#3	$t^3 = 0$	C_1	0.5336	0.4931	0.4652	0.4906	0.4601	0.4941
		C_2	0.4934	0.4912	0.4755	0.4852	0.4752	0.4924
		C_3	0.4589	0.4986	0.5124	0.5067	0.4817	0.4975
		C_4	0.4212	0.4968	0.5206	0.5013	0.5054	0.4992
	$t^3 = 0.3$	C_1	0.5520	0.4957	0.4688	0.4934	0.4702	0.4964
		C_2	0.5097	0.4944	0.4797	0.4875	0.4880	0.4952
		C_3	0.4734	0.5013	0.5161	0.5090	0.4925	0.5003
		C_4	0.4367	0.5006	0.5237	0.5036	0.5203	0.5015
	$t^3 = 0.5$	C_1	0.5642	0.4975	0.4712	0.4953	0.4770	0.4979
		C_2	0.5205	0.4966	0.4826	0.4890	0.4965	0.4971
		C_3	0.4832	0.5031	0.5186	0.5105	0.4997	0.5022
		C_4	0.4470	0.5031	0.5258	0.5051	0.5302	0.5030
	$t^3 = 0.7$	C_1	0.5765	0.4993	0.4736	0.4972	0.4837	0.4994
		C_2	0.5314	0.4987	0.4854	0.4905	0.5050	0.4989
		C_3	0.4929	0.5049	0.5212	0.5120	0.5070	0.5041
		C_4	0.4573	0.5056	0.5280	0.5067	0.5401	0.5046
	$t^3 = 1.0$	C_1	0.5949	0.5019	0.4772	0.5000	0.4939	0.5018
		C_2	0.5477	0.5019	0.4897	0.4928	0.5178	0.5018
		C_3	0.5075	0.5075	0.5249	0.5143	0.5178	0.5069
		C_4	0.4727	0.5094	0.5311	0.5089	0.5550	0.5069
DM#4	$t^4 = 0$	C_1	0.5465	0.4940	0.4609	0.4793	0.4645	0.4965
		C_2	0.5083	0.4958	0.4910	0.4810	0.4798	0.4913
		C_3	0.4201	0.4902	0.5090	0.5132	0.4863	0.4965
		C_4	0.4384	0.5014	0.5211	0.5079	0.4863	0.5018
	$t^4 = 0.3$	C_1	0.5637	0.4971	0.4633	0.4822	0.4752	0.4986
		C_2	0.5236	0.4989	0.4934	0.4840	0.4962	0.4934
		C_3	0.4316	0.4927	0.5115	0.5157	0.4978	0.4986
		C_4	0.4532	0.5040	0.5235	0.5103	0.5007	0.5039
	$t^4 = 0.5$	C_1	0.5752	0.4991	0.4648	0.4841	0.4824	0.5000
		C_2	0.5339	0.5010	0.4950	0.4859	0.5071	0.4948
		C_3	0.4393	0.4944	0.5131	0.5173	0.5054	0.5000
		C_4	0.4631	0.5057	0.5252	0.5120	0.5103	0.5053
	$t^4 = 0.7$	C_1	0.5866	0.5012	0.4664	0.4861	0.4895	0.5014
		C_2	0.5441	0.5031	0.4966	0.4879	0.5180	0.4962
		C_3	0.4469	0.4961	0.5147	0.5190	0.5130	0.5014
		C_4	0.4730	0.5074	0.5268	0.5136	0.5199	0.5067
	$t^4 = 1.0$	C_1	0.6038	0.5043	0.4687	0.4890	0.5002	0.5035
		C_2	0.5594	0.5062	0.4990	0.4908	0.5343	0.4983
		C_3	0.4585	0.4986	0.5172	0.5214	0.5245	0.5035
		C_4	0.4878	0.5099	0.5293	0.5160	0.5343	0.5088

TABLE 4: PIPS and NIPS for each decision maker.

Decision maker	t^k	PIPS/NIPS	Cost (B_1)	Past performance (B_2)	Relationship closeness (B_3)	Completion probability (B_4)	Time (B_5)	Quality (B_6)
DM#1	$t^1 = 0$	PIPS	0.5265	0.5068	0.5239	0.5168	0.5499	0.5017
		NIPS	0.3886	0.4778	0.4725	0.4811	0.4433	0.4914
	$t^1 = 0.3$	PIPS	0.5591	0.5109	0.5270	0.5202	0.5660	0.5038
		NIPS	0.4047	0.4830	0.4749	0.4843	0.4531	0.4935
	$t^1 = 0.5$	PIPS	0.5808	0.5137	0.5291	0.5224	0.5768	0.5052
		NIPS	0.4155	0.4864	0.4765	0.4864	0.4596	0.4949
	$t^1 = 0.7$	PIPS	0.6026	0.5165	0.5312	0.5246	0.5875	0.5066
		NIPS	0.4262	0.4898	0.4780	0.4885	0.4661	0.4962
DM#2	$t^2 = 0$	PIPS	0.6352	0.5207	0.5343	0.5279	0.6036	0.5086
		NIPS	0.4423	0.4950	0.4804	0.4917	0.4759	0.4983
	$t^2 = 0.3$	PIPS	0.5170	0.5078	0.5168	0.5045	0.5459	0.4975
		NIPS	0.4177	0.4840	0.4660	0.4882	0.4401	0.4923
	$t^2 = 0.5$	PIPS	0.5507	0.5105	0.5200	0.5067	0.5607	0.5002
		NIPS	0.4336	0.4879	0.4692	0.4904	0.4489	0.4945
	$t^2 = 0.7$	PIPS	0.5731	0.5124	0.5222	0.5082	0.5706	0.5020
		NIPS	0.4442	0.4904	0.4713	0.4918	0.4548	0.4959
DM#3	$t^3 = 0$	PIPS	0.6026	0.5165	0.5312	0.5246	0.5875	0.5066
		NIPS	0.4262	0.4898	0.4780	0.4885	0.4661	0.4962
	$t^3 = 0.3$	PIPS	0.6292	0.5170	0.5277	0.5119	0.5953	0.5065
		NIPS	0.4707	0.4968	0.4765	0.4954	0.4694	0.4996
	$t^3 = 0.5$	PIPS	0.5336	0.4986	0.5206	0.5067	0.5054	0.4992
		NIPS	0.4212	0.4912	0.4652	0.4852	0.4601	0.4924
	$t^3 = 0.7$	PIPS	0.5520	0.5013	0.5237	0.5090	0.5203	0.5015
		NIPS	0.4367	0.4944	0.4688	0.4875	0.4702	0.4952
DM#4	$t^4 = 0$	PIPS	0.5642	0.5031	0.5258	0.5105	0.5302	0.5030
		NIPS	0.4470	0.4966	0.4712	0.4890	0.4770	0.4971
	$t^4 = 0.3$	PIPS	0.5765	0.5056	0.5280	0.5120	0.5401	0.5046
		NIPS	0.4573	0.4987	0.4736	0.4905	0.4837	0.4989
	$t^4 = 0.5$	PIPS	0.5949	0.5094	0.5311	0.5143	0.5550	0.5069
		NIPS	0.4727	0.5019	0.4772	0.4928	0.4939	0.5018
	$t^4 = 0.7$	PIPS	0.5465	0.5014	0.5211	0.5132	0.4863	0.5018
		NIPS	0.4201	0.4902	0.4609	0.4793	0.4645	0.4913

Step 12. Rank the preference order of all candidates according to the closeness coefficient and select the best partner for decision maker DM# k .

Step 13. Aggregate the separation measure for the group by using formula (16).

Step 14. Calculate the closeness coefficient of candidate X_i for the group by using formula (17).

Step 15. Rank the preference order of all candidates according to the closeness coefficient and select the best one.

TABLE 5: Separation measure for each decision maker.

Decision maker	t^k	C_1	C_2	C_3	C_4
DM#1	$t^1 = 0$	$d_1^{1+} = 0.0458$	$d_2^{1+} = 0.0498$	$d_3^{1+} = 0.0450$	$d_4^{1+} = 0.0436$
		$d_1^{1-} = 0.0439$	$d_2^{1-} = 0.0275$	$d_3^{1-} = 0.0244$	$d_4^{1-} = 0.0497$
	$t^1 = 0.3$	$d_1^{1+} = 0.0462$	$d_2^{1+} = 0.0517$	$d_3^{1+} = 0.0487$	$d_4^{1+} = 0.0488$
		$d_1^{1-} = 0.0493$	$d_2^{1-} = 0.0322$	$d_3^{1-} = 0.0256$	$d_4^{1-} = 0.0516$
	$t^1 = 0.5$	$d_1^{1+} = 0.0465$	$d_2^{1+} = 0.0530$	$d_3^{1+} = 0.0511$	$d_4^{1+} = 0.0523$
		$d_1^{1-} = 0.0529$	$d_2^{1-} = 0.0354$	$d_3^{1-} = 0.0265$	$d_4^{1-} = 0.0529$
	$t^1 = 0.7$	$d_1^{1+} = 0.0468$	$d_2^{1+} = 0.0544$	$d_3^{1+} = 0.0537$	$d_4^{1+} = 0.0558$
		$d_1^{1-} = 0.0565$	$d_2^{1-} = 0.0386$	$d_3^{1-} = 0.0274$	$d_4^{1-} = 0.0542$
	$t^1 = 1.0$	$d_1^{1+} = 0.0472$	$d_2^{1+} = 0.0564$	$d_3^{1+} = 0.0574$	$d_4^{1+} = 0.0610$
		$d_1^{1-} = 0.0620$	$d_2^{1-} = 0.0433$	$d_3^{1-} = 0.0288$	$d_4^{1-} = 0.0562$
DM#2	$t^2 = 0$	$d_1^{2+} = 0.0467$	$d_2^{2+} = 0.0326$	$d_3^{2+} = 0.0410$	$d_4^{2+} = 0.0330$
		$d_1^{2-} = 0.0332$	$d_2^{2-} = 0.0288$	$d_3^{2-} = 0.0229$	$d_4^{2-} = 0.0473$
	$t^2 = 0.3$	$d_1^{2+} = 0.0488$	$d_2^{2+} = 0.0358$	$d_3^{2+} = 0.0458$	$d_4^{2+} = 0.0389$
		$d_1^{2-} = 0.0391$	$d_2^{2-} = 0.0300$	$d_3^{2-} = 0.0230$	$d_4^{2-} = 0.0493$
	$t^2 = 0.5$	$d_1^{2+} = 0.0501$	$d_2^{2+} = 0.0381$	$d_3^{2+} = 0.0491$	$d_4^{2+} = 0.0428$
		$d_1^{2-} = 0.0430$	$d_2^{2-} = 0.0308$	$d_3^{2-} = 0.0231$	$d_4^{2-} = 0.0506$
	$t^2 = 0.7$	$d_1^{2+} = 0.0515$	$d_2^{2+} = 0.0405$	$d_3^{2+} = 0.0525$	$d_4^{2+} = 0.0467$
		$d_1^{2-} = 0.0469$	$d_2^{2-} = 0.0316$	$d_3^{2-} = 0.0232$	$d_4^{2-} = 0.0520$
	$t^2 = 1.0$	$d_1^{2+} = 0.0536$	$d_2^{2+} = 0.0444$	$d_3^{2+} = 0.0577$	$d_4^{2+} = 0.0526$
		$d_1^{2-} = 0.0527$	$d_2^{2-} = 0.0329$	$d_3^{2-} = 0.0233$	$d_4^{2-} = 0.0540$
DM#3	$t^3 = 0$	$d_1^{3+} = 0.0290$	$d_2^{3+} = 0.0263$	$d_3^{3+} = 0.0247$	$d_4^{3+} = 0.0338$
		$d_1^{3-} = 0.0338$	$d_2^{3-} = 0.0229$	$d_3^{3-} = 0.0250$	$d_4^{3-} = 0.0290$
	$t^3 = 0.3$	$d_1^{3+} = 0.0301$	$d_2^{3+} = 0.0267$	$d_3^{3+} = 0.0263$	$d_4^{3+} = 0.0347$
		$d_1^{3-} = 0.0347$	$d_2^{3-} = 0.0235$	$d_3^{3-} = 0.0250$	$d_4^{3-} = 0.0302$
	$t^3 = 0.5$	$d_1^{3+} = 0.0309$	$d_2^{3+} = 0.0270$	$d_3^{3+} = 0.0275$	$d_4^{3+} = 0.0352$
		$d_1^{3-} = 0.0353$	$d_2^{3-} = 0.0239$	$d_3^{3-} = 0.0250$	$d_4^{3-} = 0.0311$
	$t^3 = 0.7$	$d_1^{3+} = 0.0318$	$d_2^{3+} = 0.0274$	$d_3^{3+} = 0.0287$	$d_4^{3+} = 0.0358$
		$d_1^{3-} = 0.0359$	$d_2^{3-} = 0.0243$	$d_3^{3-} = 0.0250$	$d_4^{3-} = 0.0319$
	$t^3 = 1.0$	$d_1^{3+} = 0.0332$	$d_2^{3+} = 0.0280$	$d_3^{3+} = 0.0305$	$d_4^{3+} = 0.0367$
		$d_1^{3-} = 0.0368$	$d_2^{3-} = 0.0250$	$d_3^{3-} = 0.0250$	$d_4^{3-} = 0.0333$
DM#4	$t^4 = 0$	$d_1^{4+} = 0.0294$	$d_2^{4+} = 0.0230$	$d_3^{4+} = 0.0445$	$d_4^{4+} = 0.0375$
		$d_1^{4-} = 0.0457$	$d_2^{4-} = 0.0352$	$d_3^{4-} = 0.0283$	$d_4^{4-} = 0.0329$
	$t^4 = 0.3$	$d_1^{4+} = 0.0298$	$d_2^{4+} = 0.0232$	$d_3^{4+} = 0.0464$	$d_4^{4+} = 0.0383$
		$d_1^{4-} = 0.0459$	$d_2^{4-} = 0.0352$	$d_3^{4-} = 0.0254$	$d_4^{4-} = 0.0303$
	$t^4 = 0.5$	$d_1^{4+} = 0.0300$	$d_2^{4+} = 0.0233$	$d_3^{4+} = 0.0477$	$d_4^{4+} = 0.0389$
		$d_1^{4-} = 0.0472$	$d_2^{4-} = 0.0364$	$d_3^{4-} = 0.0254$	$d_4^{4-} = 0.0308$
	$t^4 = 0.7$	$d_1^{4+} = 0.0304$	$d_2^{4+} = 0.0235$	$d_3^{4+} = 0.0491$	$d_4^{4+} = 0.0394$
		$d_1^{4-} = 0.0485$	$d_2^{4-} = 0.0376$	$d_3^{4-} = 0.0254$	$d_4^{4-} = 0.0313$
	$t^4 = 1.0$	$d_1^{4+} = 0.0309$	$d_2^{4+} = 0.0237$	$d_3^{4+} = 0.0511$	$d_4^{4+} = 0.0402$
		$d_1^{4-} = 0.0505$	$d_2^{4-} = 0.0395$	$d_3^{4-} = 0.0255$	$d_4^{4-} = 0.0322$

5. Numerical Example

We present a numerical example to illustrate our proposed approach. Four decision makers, namely, DM#1, DM#2, DM#3, and DM#4, from the core enterprise are selected to form the decision-making team. These decision makers are then tasked to select the best partner out of four candidates, namely, C_1 , C_2 , C_3 , and C_4 , in forming a new VE. The six attributes of each candidate, including cost (B_1), past performance (B_2), relationship closeness (B_3), completion

probability (B_4), time (B_5), and quality (B_6), are considered in the selection process. B_1 and B_5 are included in the cost-type attributes, whereas B_2 , B_3 , B_4 , and B_6 are included in the benefit-type attributes. Figure 1 shows the hierarchical structure of the partner selection problem, and Table 1 shows the decision matrix that contains the triangular fuzzy numbers and weights of the six attributes of each decision maker.

The selection process is conducted by the procedures outlined in Section 4. We calculate the normalized decision matrix of each decision maker with triangular fuzzy numbers,

TABLE 6: Closeness coefficient and ranking of each candidate for each decision maker.

Decision maker	Candidate	$t^k = 0$		$t^k = 0.3$		$t^k = 0.5$		$t^k = 0.7$		$t^k = 1.0$	
		$\mu_i^k(t^k)$	Ranking	$\mu_i^k(t^k)$	Ranking	$\mu_i^k(t^k)$	Ranking	$\mu_i^k(t^k)$	Ranking	$\mu_i^k(t^k)$	Ranking
DM#1	C_1	0.4892	2	0.5160	1	0.5322	1	0.5472	1	0.5676	1
	C_2	0.3554	3	0.3838	3	0.4002	3	0.4150	3	0.4346	3
	C_3	0.3520	4	0.3450	4	0.3411	4	0.3378	4	0.3337	4
	C_4	0.5327	1	0.5139	2	0.5030	2	0.4930	2	0.4797	2
DM#2	C_1	0.4154	3	0.4448	3	0.4615	2	0.4765	2	0.4960	2
	C_2	0.4689	2	0.4563	2	0.4474	3	0.4385	3	0.4254	3
	C_3	0.3586	4	0.3344	4	0.3198	4	0.3063	4	0.2882	4
	C_4	0.5887	1	0.5587	1	0.5416	1	0.5264	1	0.5066	1
DM#3	C_1	0.5385	1	0.5354	1	0.5330	1	0.5302	1	0.5257	1
	C_2	0.4647	3	0.4673	3	0.4689	3	0.4701	3	0.4717	3
	C_3	0.5031	2	0.4865	2	0.4759	2	0.4655	4	0.4506	4
	C_4	0.4620	4	0.4658	4	0.4685	4	0.4714	2	0.4758	2
DM#4	C_1	0.6085	1	0.6065	1	0.6109	1	0.6150	2	0.6204	2
	C_2	0.6048	2	0.6030	2	0.6095	2	0.6156	1	0.6245	1
	C_3	0.3890	4	0.3534	4	0.3473	4	0.3413	4	0.3327	4
	C_4	0.4669	3	0.4412	3	0.4419	3	0.4428	3	0.4447	3

TABLE 7: Aggregated separation measure, closeness coefficient, and ranking of candidates.

Case	Decision maker	t^k	Candidate	Aggregated positive separation measure	Aggregated negative separation measure	μ_i	Ranking
Case no. 1	DM#1	$t^1 = 0.0$	C_1	$D_1^+ = 0.0367$	$D_1^- = 0.0387$	0.5132	1
	DM#2	$t^2 = 0.0$	C_2	$D_2^+ = 0.0315$	$D_2^- = 0.0282$	0.4728	3
	DM#3	$t^3 = 0.0$	C_3	$D_3^+ = 0.0377$	$D_3^- = 0.0251$	0.3995	4
	DM#4	$t^4 = 0.0$	C_4	$D_4^+ = 0.0368$	$D_4^- = 0.0387$	0.5128	2
Case no. 2	DM#1	$t^1 = 0.3$	C_1	$D_1^+ = 0.0377$	$D_1^- = 0.0418$	0.5260	1
	DM#2	$t^2 = 0.3$	C_2	$D_2^+ = 0.0327$	$D_2^- = 0.0299$	0.4774	3
	DM#3	$t^3 = 0.3$	C_3	$D_3^+ = 0.0406$	$D_3^- = 0.0247$	0.3783	4
	DM#4	$t^4 = 0.3$	C_4	$D_4^+ = 0.0399$	$D_4^- = 0.0391$	0.4949	2
Case no. 3	DM#1	$t^1 = 0.5$	C_1	$D_1^+ = 0.0384$	$D_1^- = 0.0441$	0.5348	1
	DM#2	$t^2 = 0.5$	C_2	$D_2^+ = 0.0336$	$D_2^- = 0.0312$	0.4816	3
	DM#3	$t^3 = 0.5$	C_3	$D_3^+ = 0.0426$	$D_3^- = 0.0250$	0.3693	4
	DM#4	$t^4 = 0.5$	C_4	$D_4^+ = 0.0419$	$D_4^- = 0.0400$	0.4887	2
Case no. 4	DM#1	$t^1 = 0.0$	C_1	$D_1^+ = 0.0381$	$D_1^- = 0.0414$	0.5210	1
	DM#2	$t^2 = 0.3$	C_2	$D_2^+ = 0.0326$	$D_2^- = 0.0293$	0.4735	3
	DM#3	$t^3 = 0.5$	C_3	$D_3^+ = 0.0392$	$D_3^- = 0.0244$	0.3745	4
	DM#4	$t^4 = 0.7$	C_4	$D_4^+ = 0.0195$	$D_4^- = 0.0393$	0.5007	2
Case no. 5	DM#1	$t^1 = 0.3$	C_1	$D_1^+ = 0.0388$	$D_1^- = 0.0442$	0.5326	1
	DM#2	$t^2 = 0.5$	C_2	$D_2^+ = 0.0336$	$D_2^- = 0.0312$	0.4815	3
	DM#3	$t^3 = 0.7$	C_3	$D_3^+ = 0.0433$	$D_3^- = 0.0248$	0.3641	4
	DM#4	$t^4 = 1.0$	C_4	$D_4^+ = 0.0417$	$D_4^- = 0.0405$	0.4929	2
Case no. 6	DM#1	$t^1 = 0.7$	C_1	$D_1^+ = 0.0390$	$D_1^- = 0.0463$	0.5427	1
	DM#2	$t^2 = 0.7$	C_2	$D_2^+ = 0.0345$	$D_2^- = 0.0325$	0.4850	2
	DM#3	$t^3 = 0.7$	C_3	$D_3^+ = 0.0446$	$D_3^- = 0.0252$	0.3609	4
	DM#4	$t^4 = 0.7$	C_4	$D_4^+ = 0.0438$	$D_4^- = 0.0410$	0.4834	3
Case no. 7	DM#1	$t^1 = 1.0$	C_1	$D_1^+ = 0.0401$	$D_1^- = 0.0496$	0.5529	1
	DM#2	$t^2 = 1.0$	C_2	$D_2^+ = 0.0359$	$D_2^- = 0.0344$	0.4895	2
	DM#3	$t^3 = 1.0$	C_3	$D_3^+ = 0.0476$	$D_3^- = 0.0256$	0.3492	4
	DM#4	$t^4 = 1.0$	C_4	$D_4^+ = 0.0467$	$D_4^- = 0.0425$	0.4767	3

FIGURE 2: The change of ranking of candidates with the change of t^1 for decision maker DM#1.

FIGURE 3: The change of ranking of candidates with the change of t^2 for decision maker DM#2.

as well as the normalized decision matrix for each decision maker with weighted possibilistic mean values; the results are shown in Tables 2 and 3.

We identify the PIPS and NIPS of each decision maker by using (11); the results are shown in Table 4. The positive and negative separation measures between each candidate for each decision maker are calculated by using (12) and (13), respectively; the results are shown in Table 5.

The closeness coefficient is used to determine the preference order of each candidate for each decision maker; the results are shown in Table 6 and Figures 2, 3, 4, and 5.

For DM#1, the candidates are ranked as $C_4 > C_1 > C_2 > C_3$ when $t^1 = 0$ ($> =$ superior to) but are ranked as $C_1 > C_4 > C_2 > C_3$ when $t^1 = 0.3, 0.5, 0.7, 1.0$. For DM#2, the candidates are ranked as $C_4 > C_2 > C_1 > C_3$ when $t^2 = 0$ or 0.3 but are ranked as $C_4 > C_1 > C_2 > C_3$ when $t^2 = 0.5, 0.7, 1.0$. Therefore, C_1 is identified as the best candidate for DM#3, and C_1 or C_2 may be chosen as the partner for DM#4.

Decision makers may experience problems in reaching a consensus during a group decision-making process. Therefore, these decision makers must combine their assessments to form a highly reasonable evaluation. We obtain the aggregated group separation measures of all candidates by using (16); the results are shown in Table 7. The aggregated closed closeness coefficients and ranking of all candidates are calculated by using (17); the results are shown in Table 7 and Figure 6. C_1 is identified as the best candidate in all four cases.

FIGURE 4: The change of ranking of candidates with the change of t^3 for decision maker DM#3.

FIGURE 5: The change of ranking of candidates with the change of t^4 for decision maker DM#4.

6. Discussions and Conclusions

We have proposed an extended TOPSIS for partner selection in a VE. Different from traditional methods, our proposed method considers the varying risk preferences of decision makers. We also use weighted possibilistic mean values to manage candidate information formed by triangular fuzzy numbers.

We perform sensitivity analyses by using a wide range of risk preference coefficient t of decision makers to determine the effects of risk preferences on candidate rank. The value of t may range between zero and one, which covers three categories, namely, extremely risk averse, risk neutral, and extremely risk prone. Our numerical examples show that the ranking of candidates changes with the shifting risk preferences of decision makers. For example, for the first decision maker (DM#1), the fourth candidate (C_4) is selected as the best partner when DM#1 is extremely risk averse ($t^1 = 0$) and the first candidate (C_1) is selected as the best partner when DM#1 is less risk averse, risk neutral, or extremely risk prone ($t^1 = 0.3, 0.5, 0.7$, or 1). Other decision makers exhibit the same behavior in their selections. These observations confirm that the risk preferences of decision makers must be considered to produce results that closely reflect real-life practices. Our proposed approach can guide the core enterprise of a VE in selecting a suitable partner, particularly during situations when decision makers exhibit varying risk preferences.

FIGURE 6: The change of ranking of candidates with different risk preference combination cases for the group decision making.

Our extended TOPSIS method may also be applied for other purposes, such as for performance evaluation and for the selection of green suppliers, information systems, facility locations, construction technique alternatives, and human resource arrangements. Future research may investigate the group MADM model with the weighted possibilistic mean values of trapezoidal fuzzy numbers and include the weighted possibilistic variance of fuzzy numbers in the MADM model.

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