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Adaptability Evaluation of Vocational Education and Economic Development Under the Bipolar Neutrosophic Sets

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Abstract: This study suggests a decision-making methodology to evaluate the risks in vocational education and economic development. This problem has different criteria and alternatives which must be evaluated. This evaluation can include uncertainty in the evaluation process. So, we use the bipolar neutrosophic sets (BNSs) to deal with uncertainty and vague data. The BNSs are extensions of the neutrosophic sets. We used two decision-making methods for the evaluation of risks in vocational education and economic development such as BWM to compute the criteria weights and the COPRAS method to rank the alternatives based on a set of criteria. This study uses nine criteria and six alternatives. The results show that Public Vocational Training Institutions is the best alternative and the Corporate Training and Upskilling Programs is the worst alternative.

Keywords: Bipolar Neutrosophic Sets (BNSs); Vocational Education and Economic Development; Uncertainty; BWM; COPRAS.

1. Introduction

Zadeh was the first to introduce fuzzy set theory. Any value inside the unit closed interval [0,1] can be used to represent the degree of membership that an object has in the set according to fuzzy set theory. Neutosophy, a field of philosophy that studies genesis, character, and extent of neutralities as well as their relationships to various intellectual spectrums, was first presented by Smarandache. Smarandache and Wang et al. devised single-valued neutrosophic sets, which take the value from the subset of [0,1], to more easily apply neutrosophic sets to real-life issues[1], [2]. A single-valued neutrosophic set is hence an example of a neutrosophic set and can be practically applied to real-world issues, particularly in decision support. Bipolar neutrosophic sets, are an extension of bipolar fuzzy sets[3], [4]. The process of selecting the best option with the maximum degree of attainment from a group of options that are defined by several competing criteria is known as multi-criteria decision-making or MCDM. One of the most significant areas of decision-making theory is MCDM. In terms of the problem's solution space, MCDM problems are typically classified as either continuous or discrete. Multi-objective decision-making (MODM) techniques are applied to continuous issues. In contrast, multi-attribute decision-making (MADM) techniques are used to handle discrete problems[5], [6]. However, MCDM is frequently used to describe the discrete MCDM in the literature that is currently available, which is why we use it in this paper as well.

This study proposes a novel approach to multi-criteria decision-making (MCDM) problems: the best-worst method (BWM). To choose the best alternative or alternatives in an MCDM situation, several options are assessed based on a variety of factors. BWM states that the decision-maker first determines the best (i.e., most desirable, most important) and worst (i.e., least desirable, least important) criteria[7], [8].

Then, each of these two criteria (best and worst) is compared pairwise with the other criteria. To ascertain the weights of various criteria, a maximin problem is then developed and resolved. The same procedure is used to determine the alternatives' weights according to other parameters. The best option is chosen based on the final scores of the alternatives, which are obtained by adding the weights from several sets of criteria and alternatives[9], [10].

The following is how the article is planned: The background theory, along with some initial thoughts on bipolar neutrosophic numbers and the suggested model, is explained in Section 2. A case study is presented in Section 3 to validate the BWM–COPRAS method's applicability. The sensitivity analysis is acknowledged in Section 4. Finally, we offer some observations to round up our investigation.

2. Bipolar Neutrosophic BWM Method and COPRAS Method

Definition 1. The bipolar neutrosophic sets (BNSs) can be defined as[11], [12], [13]:

$$B=\left\{c,\left(T_B^{+}(c),I_B^{+}(c),F_B^{+}(c),T_B^{-}(c),I_B^{-}(c),F_B^{-}(c)\right)c\in C\right\} \tag{1}$$

$$T_B^{+}(c),I_B^{+}(c),F_B^{+}(c):C\rightarrow[0,1] \tag{2}$$

$$T_B^{-}(c),I_B^{-}(c),F_B^{-}(c):C\rightarrow[-1,0] \tag{3}$$

Definition 2. Let two bipolar neutrosophic numbers (BNNs) such as:

$$A_1=\{T_1^{+}(c),I_1^{+}(c),F_1^{+}(c),T_1^{-}(c),I_1^{-}(c),F_1^{-}(c)\}$$

$$A_2=\{T_2^{+}(c),I_2^{+}(c),F_2^{+}(c),T_2^{-}(c),I_2^{-}(c),F_2^{-}(c)\}$$

$$A_1\cup A_2=\begin{pmatrix}\max\left(T_1^{+}(c),T_2^{+}(c)\right),\frac{I_1^{+}(c)+I_2^{+}(c)}{2},\\ \min\left(F_1^{+}(c),F_2^{+}(c)\right),\min\left(T_1^{-}(c),T_2^{-}(c)\right),\frac{I_1^{-}(c)+I_2^{-}(c)}{2},\\ \max\left(F_1^{-}(c),F_2^{-}(c)\right)\end{pmatrix} \tag{4}$$

Definition 3. Some operations of BNSs

$$a_1 + a_2 = \begin{pmatrix} T_1^+(c) + T_2^+(c) - T_1^+(c)T_2^+(c), \\ I_1^+(c)I_2^+(c), \\ F_1^+(c)F_2^+(c), \\ -T_1^-(c)T_2^-(c), \\ -\left(-I_1^-(c) - I_2^-(c) - I_1^-(c)I_2^-(c)\right), \\ -\left(-F_1^-(c) - F_2^-(c) - F_1^-(c)F_2^-(c)\right) \end{pmatrix} \quad (5)$$

$$a_1 a_2 = \begin{pmatrix} T_1^+(c)T_2^+(c), I_1^+(c) + I_2^+(c) - I_1^+(c)I_2^+(c) + \\ F_1^+(c) + F_2^+(c) - F_1^+(c)F_2^+(c), \\ -\left(-T_1^-(c) - T_2^-(c) - T_1^-(c)T_2^-(c)\right), \\ -I_1^-(c)I_2^-(c), \\ -F_1^-(c)F_2^-(c) \end{pmatrix} \quad (6)$$

$$\theta a_1 = \begin{pmatrix} \left(1 - \left(1 - T_1^+(c)\right)\right)^\theta, \\ \left(I_1^+(c)\right)^\theta, \\ \left(F_1^+(c)\right)^\theta, \\ -\left(-\left(T_1^-(c)\right)^\theta\right), \\ -\left(-\left(I_1^-(c)\right)^\theta\right), \\ -\left(1 - \left(1 - F_1^-(c)\right)\right)^\theta \end{pmatrix} \quad (7)$$

$$a_1^\theta = \begin{pmatrix} \left(T_1^+(c)\right)^\theta, \\ \left(1 - \left(1 - I_1^+(c)\right)\right)^\theta, \\ \left(1 - \left(1 - F_1^+(c)\right)\right)^\theta, \\ -\left(1 - \left(1 - T_1^-(c)\right)\right)^\theta, \\ -\left(-\left(I_1^-(c)\right)^\theta\right) \\ -\left(-\left(F_1^-(c)\right)^\theta\right) \end{pmatrix} \quad (8)$$

Definition 4. The score function of BNSs can be computed such as:

$$S(a_1) = \frac{\begin{pmatrix} T_1^+(c)+1-I_1^+(c)+1-F_1^+(c)+ \\ 1+T_1^-(c)-I_1^-(c)-F_1^-(c) \end{pmatrix}}{6} \quad (10)$$

Then the steps of the BWM and COPRAS methods under a neutrosophic environment are presented in Fig. 1.

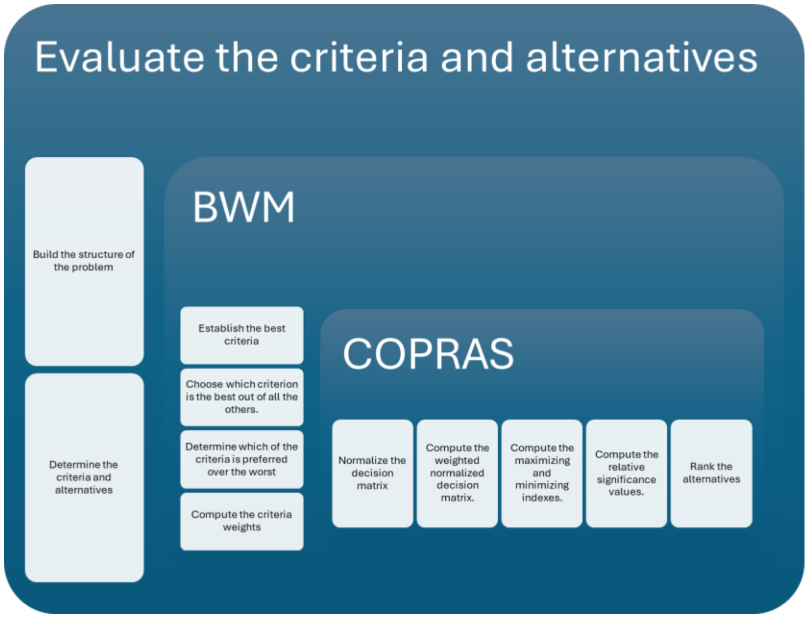

Figure 1. Suggested method.

We applied the steps of the BWM[14], [15].

A) Build the structure of the problem.

The structure of this problem is presented.

B) Determine the criteria and alternatives.

The list of experts and decision-makers determines the criteria and alternatives based on their experience.

C) Establish the best criteria (such as the most important or desirable) and the worst criteria (such as the least important or least attractive).

The decision-maker determines the best and worst criteria overall in this stage. At this point, no comparison is made.

D) Choose which criterion is the best out of all the others.

$A_B = \left(a_{B_1}, a_{B_2}, \dots, a_{B_n}\right)$

Where a_{B_j} refers the preference of the best criterion B over the criterion j.

$a_{B_B} = 1$

E) Determine which of the criteria is preferred over the worst. The outcome of the Vector of Others-to-Worst is obtained.

F) Compute the criteria weights.

$$\min \max_j \left\{\left|\frac{w_B}{w_j} - a_{B_j}\right|\right\}, \left|\frac{w_j}{w_W} - a_{j_W}\right| \tag{11}$$

$\sum_j w_j = 1$

$w_j \geq 0 \; for \; all \; j$

G) This phase applies the COPRAS method to rank the alternatives[16], [17]. Build the decision matrix.

H) Normalize the decision matrix.

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{12}$$

I) Compute the weighted normalized decision matrix.

$$q_{ij} = r_j r_{ij} \tag{13}$$

J) Compute the maximizing and minimizing indexes.

For positive criteria.

$$D_{+i} = \sum_{j=1}^{g} q_{ij} \tag{14}$$

For negative criteria.

$$D_{-i} = \sum_{j=g+1}^{n} q_{ij} \tag{15}$$

K) Compute the relative significance values.

$$Z_i = D_{+i} + \frac{\sum_{i=1}^{m} D_{-i}}{D_{-i} \sum_{i=1}^{m} 1/D_{-i}} \tag{16}$$

L) Rank the alternatives

3. Case Study

This study proposed the DM approach for the evaluation of Risk Areas in Vocational Education and Economic Development. Four experts have evaluated the criteria and alternatives. This study gathers nine criteria and six alternatives to be evaluated. Fig. 2. shows the criteria and alternatives in this study.

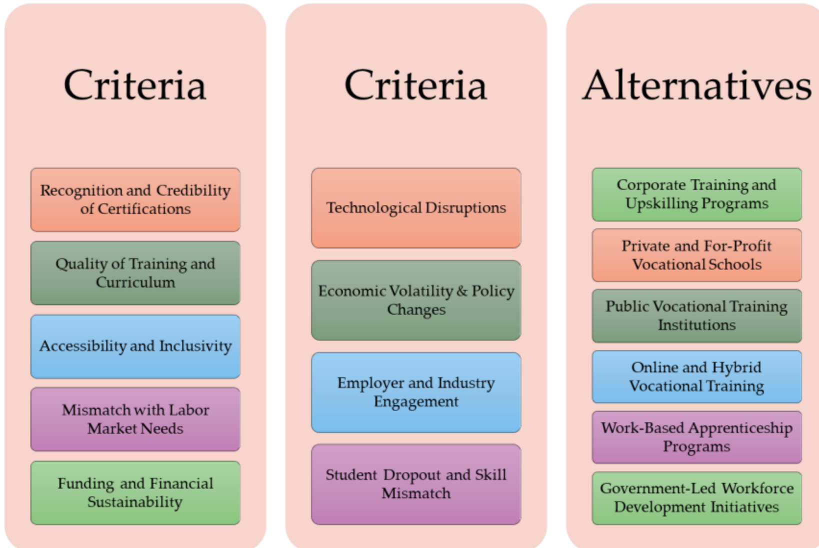

Figure .2. The criteria and alternatives.

A) We invited four experts to evaluate the criteria and alternatives.

B) We collected nine criteria and six alternatives.

C) Then we establish the best criteria and the worst criteria.

D) Then we choose which criterion is the best out of all the others.

E) Then we determine which of the criteria is preferred over the worst.

F) Then we computer the criteria weights as shown in Fig. 3.

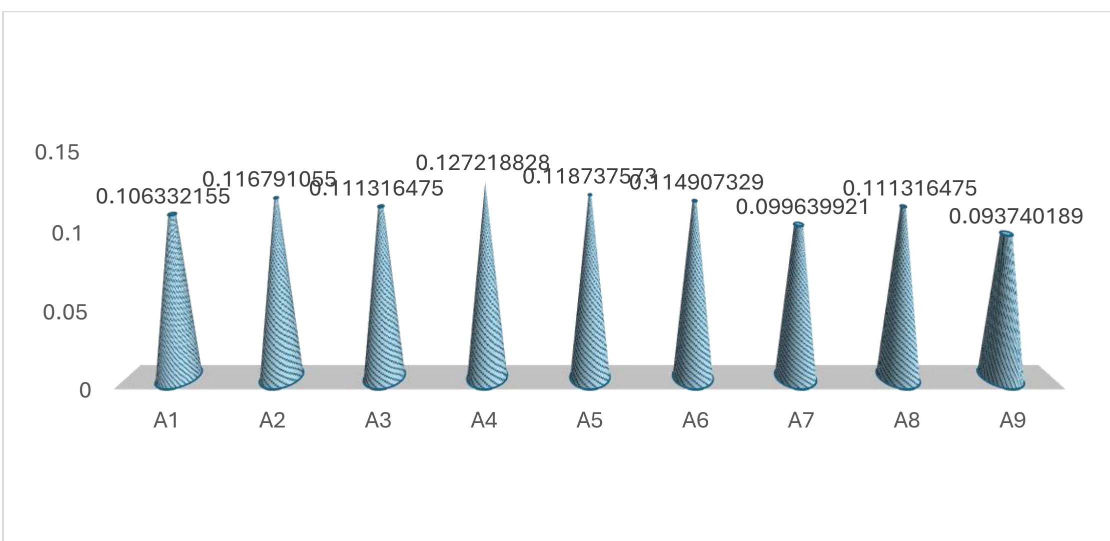

Figure 3. Criteria weights.

G) We build the decision matrix between the criteria and alternatives. We used the BNNs to evaluate the decision matrix as shown in Tables 1-4. Then we apply the score function to obtain one number. Then we combined these numbers into a single matrix.

Table 1. The first BNNs

	A_1	A_2	A_3	A_4	A_5	A_6
C_1	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)
C_2	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)
C_3	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)
C_4	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)
C_5	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)
C_6	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)
C_7	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)
C_8	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)
C_9	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)

Table 2. The second BNNs

	A_1	A_2	A_3	A_4	A_5	A_6
C_1	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)
C_2	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)
C_3	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)
C_4	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)
C_5	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)
C_6	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)
C_7	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)
C_8	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)
C_9	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)

Table 3. The third BNNs

	A_1	A_2	A_3	A_4	A_5	A_6
C_1	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)
C_2	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)
C_3	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)
C_4	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)

C_5	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)
C_6	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)
C_7	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)
C_8	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)
C_9	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)

Table 4. The fourth BNNs

	A_1	A_2	A_3	A_4	A_5	A_6
C_1	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)
C_2	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)
C_3	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)
C_4	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)
C_5	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)
C_6	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)
C_7	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.6,0.4,0.4,-0.3,-0.2,-0.3)	(0.1,0.4,0.4,-0.1,-0.3,-0.5)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.5,0.4,0.3,-0.4,-0.3,-0.3)
C_8	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.1,0.4,0.3,-0.1,-0.2,-0.3)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.4,0.3,0.3,-0.1,-0.2,-0.3)
C_9	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.4,0.1,0.4,-0.1,-0.2,-0.5)	(0.2,0.4,0.4,-0.1,-0.4,-0.5)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)	(0.7,0.3,0.2,-0.4,-0.2,-0.1)	(0.8,0.2,0.1,-0.3,-0.2,-0.4)

H) Then we used Eq. (12) to normalize the decision matrix as shown in Table 5.

I) Then we used Eq. (13) to compute the weighted normalized decision matrix as shown in Table 6.

Table 5. The normalized BNNs

	A_1	A_2	A_3	A_4	A_5	A_6
C_1	0.175393	0.170157	0.170157	0.162304	0.157068	0.164921
C_2	0.16245	0.183755	0.170439	0.173103	0.149134	0.161119
C_3	0.168865	0.172823	0.170185	0.162269	0.155673	0.170185
C_4	0.151967	0.176391	0.184532	0.162822	0.162822	0.161465
C_5	0.161725	0.16442	0.177898	0.167116	0.167116	0.161725
C_6	0.164675	0.162019	0.171315	0.163347	0.177955	0.160691
C_7	0.188158	0.169737	0.161842	0.155263	0.168421	0.156579
C_8	0.16732	0.169935	0.15817	0.16732	0.183007	0.154248
C_9	0.186962	0.168512	0.154982	0.177122	0.152522	0.159902

Table 6. The weighted normalized BNNs

	A_1	A_2	A_3	A_4	A_5	A_6

C1	0.01865	0.018093	0.018093	0.017258	0.016701	0.017536
C2	0.018973	0.021461	0.019906	0.020217	0.017418	0.018817
C3	0.018798	0.019238	0.018944	0.018063	0.017329	0.018944
C4	0.019333	0.02244	0.023476	0.020714	0.020714	0.020541
C5	0.019203	0.019523	0.021123	0.019843	0.019843	0.019203
C6	0.018922	0.018617	0.019685	0.01877	0.020448	0.018465
C7	0.018748	0.016913	0.016126	0.01547	0.016781	0.015602
C8	0.018626	0.018917	0.017607	0.018626	0.020372	0.01717
C9	0.017526	0.015796	0.014528	0.016603	0.014297	0.014989

J) Then we used Eq. (14) to compute the maximizing and minimizing indexes.

K) Then we used Eq. (16) to compute the relative significance values as shown in Table 7.

L) Then we ranked the alternatives as shown in Table 7 and Fig. 4.

Table 7. The rank of alternatives.

	D_{+i}	D_{-i}	Z_i	RANKS
A1	0.113301	0.017071	0.122083	1
A2	0.118766	0.013186	0.130135	5
A3	0.117711	0.009531	0.133441	6
A4	0.113647	0.012231	0.125904	3
A5	0.112982	0.011236	0.126324	4
A6	0.111474	0.011388	0.124638	2

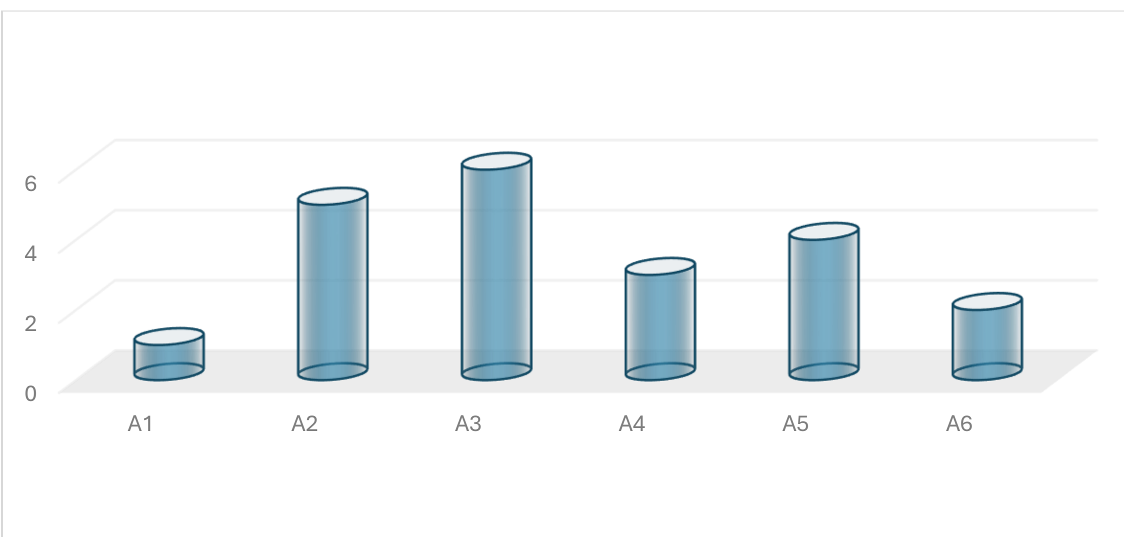

Fig. 4. Ranks of alternatives.

4. Analysis

This section shows the sensitivity analysis for changing the criteria weights based on the set of cases. Fig. 5. shows the criteria weights under different cases. In the first case, we put all criteria with the same weights. In each case, we increase the criteria weights by 15%. In the second case, we increase the first criterion by 15%. In the third case, we increase the second criterion with 15% weights.

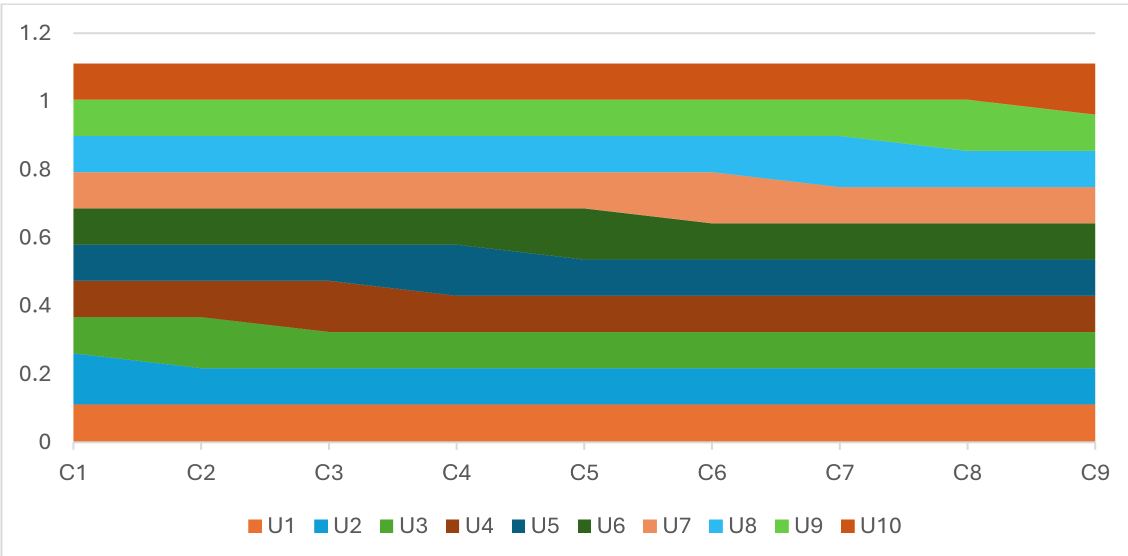

Figure 5. The various criteria weights.

Then we applied the COPRAS method under different criteria weights. We obtained the normalized decision matrix. Then we computed the weighted normalized decision matrix. Then we compute the relative significant values as shown in Table 8. Then ranked the alternatives as shown in Fig. 6. In all cases, we show the alternative 3 is the best and the alternative 1 is the worst.

Table 8. The relative significance values under different weights.

	U_1	U_2	U_3	U_4	U_5	U_6	U_7	U_8	U_9	U_{10}
A_1	0.124281	0.126517	0.125951	0.126232	0.125493	0.111815	0.126048	0.125238	0.126164	0.125253
A_2	0.132449	0.134099	0.134694	0.134216	0.134372	0.119047	0.133743	0.133822	0.134089	0.133849
A_3	0.135688	0.137196	0.137209	0.137198	0.137825	0.123541	0.137247	0.137155	0.136672	0.137522
A_4	0.128473	0.129953	0.130426	0.129952	0.129976	0.11529	0.129999	0.130667	0.130173	0.129686
A_5	0.129226	0.130444	0.130097	0.130383	0.130696	0.116048	0.131358	0.130766	0.131579	0.131528
A_6	0.12766	0.12929	0.129124	0.12952	0.129139	0.114259	0.129105	0.129851	0.128823	0.129661

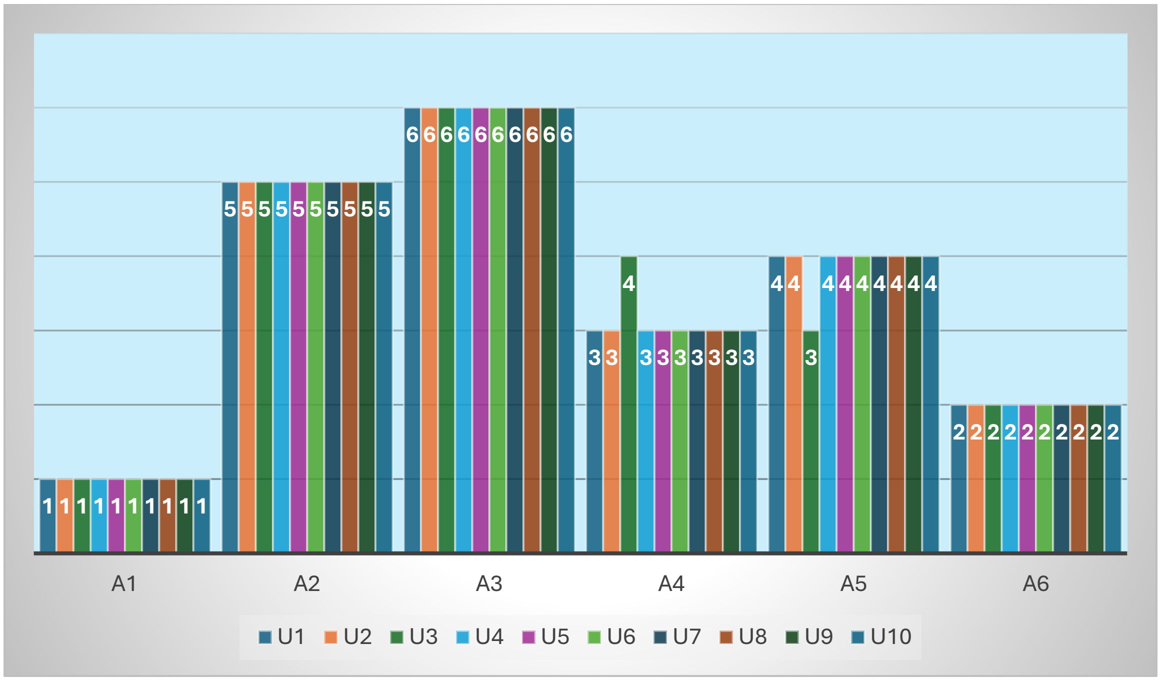

Figure 6. The rank of alternatives is based on a set of weights.

5. Conclusions

Two decision-making methods are used in this study to evaluate the risks of Vocational Education and Economic Development. BWM is used to compute the criteria weights. The COPRAS method is used to rank the alternatives. Two decision-making methods are used under the bipolar neutrosophic sets to deal with uncertainty in the evaluation. Four experts have evaluated the criteria and alternatives using the bipolar neutrosophic numbers to build the decision matrix. The results show the Mismatch with Labor Market Needs has the highest weights and the Student Dropout and Skill Mismatch has the lowest weights. Then we applied the COPRAS method to rank the alternatives. The results show alternative 3 is the best and alternative 1 is the worst. Then we applied the sensitivity analysis to show the stability of the ranks. We proposed ten cases in criteria weights. The results show the ranks of the alternatives are stable under different cases.

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References

[1] F. Smarandache, *A unifying field in logics: neutrosophic logic. Neutrosophy, neutrosophic set, neutrosophic probability: neutrsophic logic. Neutrosophy, neutrosophic set, neutrosophic probability*. Infinite Study, 2005.

[2] F. Smarandache, “Neutrosophic set is a generalization of intuitionistic fuzzy set, inconsistent intuitionistic fuzzy set (picture fuzzy set, ternary fuzzy set), pythagorean fuzzy set, spherical fuzzy set, and q-rung orthopair fuzzy set, while neutrosophication is a generalization of regret theory, grey system theory, and three-ways decision (revisited),” *J. new theory*, no. 29, pp. 1–31, 2019.

[3] J. Zhan, M. Akram, and M. Sitara, “Novel decision-making method based on bipolar neutrosophic information,” *Soft Comput.*, vol. 23, pp. 9955–9977, 2019.

[4] M. Abdel-Basset, M. Mohamed, M. Elhoseny, F. Chiclana, and A. E.-N. H. Zaied, “Cosine similarity measures of bipolar neutrosophic set for diagnosis of bipolar disorder diseases,” *Artif. Intell. Med.*, vol. 101, p. 101735, 2019.

[5] B. Singha, D. L. Kamble, R. K. Sahu, S. Narendranath, and R. I. Badiger, “Optimization of measured mechanical characteristics of selective microwave hybrid heating processed Inconel 625/SS 304 weldments using multi-objective JAYA algorithm coupled with multi-attributes decision making R-method,” *Measurement*, vol. 240, p. 115553, 2025.

[6] X. Liu, P. Ren, Z. Xu, and W. Xie, “Evolutive multi-attribute decision making with online consumer reviews,” *Omega*, vol. 131, p. 103225, 2025.

[7] S. Guo and H. Zhao, “Fuzzy best-worst multi-criteria decision-making method and its applications,” *Knowledge-based Syst.*, vol. 121, pp. 23–31, 2017.

[8] M. Akbari *et al.*, “Identification of the groundwater potential recharge zones using MCDM models: full consistency method (FUCOM), best worst method (BWM) and analytic hierarchy process (AHP),” *Water Resour. Manag.*, vol. 35, pp. 4727–4745, 2021.

[9] F. Ecer, “Sustainability assessment of existing onshore wind plants in the context of triple bottom line: a best-worst method (BWM) based MCDM framework,” *Environ. Sci. Pollut. Res.*, vol. 28, no. 16, pp. 19677–19693, 2021.

[10] J. Rezaei, “Best-worst multi-criteria decision-making method,” *Omega*, vol. 53, pp. 49–57, 2015.

[11] V. Ulucay, A. Kilic, I. Yildiz, and M. Şahin, *A new approach for multi-attribute decision-making problems in bipolar neutrosophic sets*. Infinite Study, 2018.

[12] V. Ulucay, I. Deli, and M. Şahin, “Similarity measures of bipolar neutrosophic sets and their application to multiple criteria decision making,” *Neural Comput. Appl.*, vol. 29, pp. 739–748, 2018.

[13] I. Deli, M. Ali, and F. Smarandache, “Bipolar neutrosophic sets and their application based on multi-criteria decision making problems,” in *2015 International conference on advanced mechatronic systems (ICAMechS)*, Ieee, 2015, pp. 249–254.

[14] F. Nawaz, M. R. Asadabadi, N. K. Janjua, O. K. Hussain, E. Chang, and M. Saberi, “An MCDM method for cloud service selection using a Markov chain and the best-worst method,” *Knowledge-Based Syst.*, vol. 159, pp. 120–131, 2018.

[15] A. R. A. Ghaffar, M. R. Nadeem, and M. G. Hasan, “Cost-benefit analysis of shale

development in India: A best-worst method based MCDM approach," *J. King Saud Univ.*, vol. 33, no. 8, p. 101591, 2021.

[16] B. Vytautas, B. Marija, and P. Vytautas, "Assessment of neglected areas in Vilnius city using MCDM and COPRAS methods," *Procedia Eng.*, vol. 122, pp. 29–38, 2015.

[17] Y. Ayrim, K. D. Atalay, and G. F. Can, "A new stochastic MCDM approach based on COPRAS," *Int. J. Inf. Technol. Decis. Mak.*, vol. 17, no. 03, pp. 857–882, 2018.

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