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A Refined Dual-Valued Neutrosophic COPRAS-Based Approach for Holistic Evaluation of English Teaching Standards

Peng Tong[1]*, Bin Xie[2]

[1]Nanchang Institute of Science and Technology, Nanchang, 330108, Jiangxi, China

[2]Jiujiang University, Jiujiang, 332005, Jiangxi, China

*Corresponding author, E-mail: 13767061850@163.com; guohechu@ncpu.edu.cn

Abstract

The evaluation of college English teaching (CET) quality helps to improve teaching standards, ensure the achievement of teaching objectives, and enhance students' language skills and overall competence. Through feedback from evaluations, teachers can refine their teaching methods, optimize course design, and meet students' needs. Additionally, teaching quality evaluation promotes the professional development of teachers, facilitates the rational allocation of educational resources, and ensures effective teaching outcomes. The evaluation of CET quality in vocational colleges in the new era involves the multiple-attribute decision-making (MADM) process. Currently, COPRAS methods are employed to address Multi-Attribute Decision-Making (MADM) challenges. To handle uncertain data in this evaluation, double-valued neutrosophic sets (DVNSs) have been introduced. This study proposes the double-valued neutrosophic number combined COPRAS (DVNN-COPRAS) technique, utilizing the DVNN, to address the MADM problem under DVNSs. A numerical study focused on CET quality evaluation is conducted to validate the proposed method.

Keywords: Multiple-attribute decision-making (MADM); DVNSs; COPRAS technique; CET quality evaluation

1. Introduction

The evaluation of university English teaching quality holds significant importance, directly influencing teaching effectiveness and the development of students' language skills. First, teaching quality evaluation helps educational administrators and teachers understand the actual outcomes of classroom instruction, identifying strengths and weaknesses in teaching, thus enabling targeted improvements. Through a well-structured evaluation system, teachers can better assess students' proficiency in various areas such as language knowledge, listening, speaking, reading, and writing, allowing them to adjust teaching methods and content to enhance classroom efficiency. Second, teaching quality evaluation ensures that educational objectives are achieved. The goal of university English courses is not only to improve students' language abilities but also to cultivate their cross-cultural communication skills, critical thinking, and independent learning capabilities. Through quality evaluation, the degree to which these goals are met can be measured, ensuring that course design and teaching practices align with the expected outcomes. Finally, teaching quality evaluation promotes professional development and innovation among teachers. Continuous feedback and reflection enable teachers to optimize teaching strategies, adopt new educational concepts and technologies, and improve their teaching skills. Additionally, evaluation results provide data support for schools to formulate teaching reform policies, contributing to systematic improvements in English teaching. Therefore, the evaluation of university English teaching quality is essential not only for student development but also for the enhancement of the entire educational system.

In 1965, Zadeh [1] introduced the pioneering theory of fuzzy sets (FSs) to handle various types of uncertainty. The concept of "neutrosophy" refers to the study of neutral thought, which distinguishes it from fuzzy and intuitionistic fuzzy logic and sets. Neutrosophic logic, introduced by Florentin [2], evaluates each proposition using three components: a degree of truth (T), a degree of indeterminacy (I), and a degree of falsity (F). In 2005, Wang, Smarandache, Zhang, and Sunderraman [3] introduced the concept of Single-Valued Neutrosophic Sets (SVNSs). In this framework, the truth, indeterminacy, and falsity degrees of each element are confined to the standard unit interval [0, 1]. SVNSs generalize several key concepts, including classical sets, fuzzy sets, intuitionistic fuzzy sets, and paraconsistent sets, expanding the range of tools available for addressing complex real-world problems[4-9]. The purpose of MADM is to assist decision-makers in selecting the optimal choice when faced with multiple conflicting attributes or criteria [9-12]. In real-world problems, decisions often involve various factors such as quality, cost, and efficiency, which may have conflicting or difficult-to-quantify relationships. MADM provides a systematic approach to comprehensively consider these factors, helping decision-makers balance pros and cons and choose the option that best aligns with overall objectives [2, 13, 14]. The significance of MADM lies in its broad applicability. It can be applied in various fields, such as engineering management, economics, environmental protection, healthcare, and supply chain management. MADM methods not only provide a systematic and transparent decision-making process but also enhance the scientific and rational nature of decisions [15-17]. By assigning weights to different attributes and ranking alternatives, MADM effectively avoids personal bias, ensuring fairness in the decision-making process. Moreover, MADM can handle complex and uncertain information environments[18-20]. Particularly when dealing with vague, incomplete, or uncertain data, MADM methods introduce tools such as fuzzy sets, grey system theory, or neutrosophic sets to offer more flexible solutions[14, 21]. Therefore, MADM plays a crucial role in improving decision quality, reducing decision risk, and optimizing resource allocation. The evaluation of CET quality falls within the realm of MADM. Recently, researchers have leveraged the TODIM and GRA [22] techniques to tackle MADM challenges in this area. Additionally, DVNSs [23] have been introduced to handle uncertain data during the evaluation process.

In this study, we utilize the DVNN-COPRAS technique to address MADM problems involving DVNSs. To validate this approach, we conduct a numerical study focused on CET quality evaluation. The primary objectives and motivations of this study are: (1) Using mean to determine weight values under DVNSs; (2) Implementing the DVNN-COPRAS technique to effectively manage MADM; (3) Conducting a numerical example to demonstrate the effectiveness of the DVNN-COPRAS technique in evaluating CET quality.

The structure of this study is organized as follows: Section 2 introduces the DVNSs. Section 3 details the application of the DVNN-COPRAS technique under DVNSs. Section 4 presents a numerical example related to CET quality evaluation, along with a comparative analysis. Finally, Section 5 offers several remarks and conclusions.

2. Literature review

The evaluation of university English teaching quality is a comprehensive analysis of teaching effectiveness and student learning outcomes. Its core lies in assessing the teaching methods of instructors, the design of course content, and the improvement of students' language abilities. The evaluation process typically employs various methods such as student surveys, classroom observations, and analysis of teaching outcomes. Student feedback is a crucial reference factor, as it directly reflects the actual effectiveness of the teaching. Additionally, the evaluation of teaching quality also focuses on the professional development of teachers and the utilization of teaching resources. Through a scientific evaluation system, universities can identify strengths and weaknesses in teaching, thereby optimizing course design, enhancing teaching quality, and ultimately promoting the overall development of students and the cultivation of an international perspective. Since 2014, research on the quality of college English teaching has deepened and diversified. He and Wu [24] were among the first to emphasize the necessity of reforming college English teaching, highlighting that reforms could enhance teaching efficiency and effectiveness while cultivating high-quality talents. Following this, drawing from the input-output hypothesis, Song and Xia [25] explored how optimizing input and strengthening output could improve vocabulary teaching, addressing students' challenges in memorizing vocabulary. Lin [26] proposed improving teaching quality and efficiency through reforms in educational philosophy, teaching methods, and quality management. By 2016, Zhao [27] developed a comprehensive evaluation system for college English teachers' classroom performance, integrating student, peer, and self-assessments to systematically enhance teaching quality. Gao [28] in the same year, studied participatory teaching models and constructed a quality evaluation system using the analytic hierarchy process to refine the assessment criteria for college English teaching. In 2017, the focus on reforms in college English teaching intensified. Li [29] emphasized the importance of building effective teaching models and cultivating students' self-learning abilities. Meanwhile, Ma [30] advocated for innovative teaching approaches to meet societal demands for English talents. Xu [31] comprehensively analyzed the effectiveness of ongoing teaching reforms and pointed out the pivotal role of these measures in improving teaching quality. By 2018, researchers turned their attention to the specific factors influencing the quality of college English teaching. Peng [32] analyzed multiple factors affecting teaching quality and proposed strategies for improvement. Focusing on student-centered learning, Guo [33] suggested enhancing teaching quality through feedback mechanisms. In 2019, drawing on the Outcome-Based Education (OBE) framework, Geng [34] proposed a comprehensive evaluation mechanism integrating formative and summative assessments. That same year, Zheng [35] conducted empirical research demonstrating that a chunk-based situational teaching model significantly improved spoken English proficiency. With the rise of online teaching, Gao, Yan and Kang [36] introduced a quality evaluation system tailored for SPOC-based online English teaching, advancing online teaching quality frameworks. In 2021, Lv [37] analyzed the issues in teaching English to international students at Huaqiao University and proposed strategies to improve teaching quality in this context. In 2022, Xu [38] constructed an internal quality assurance system for college English courses, emphasizing the pivotal role of teaching management. In recent years, formative assessment and blended learning have become research hotspots. He [39] examined the impact of formative assessment on the quality of blended teaching in college English, suggesting it facilitates positive teaching development. In the context of engineering education accreditation, Li [40] developed a quality monitoring and assurance system for college English teaching, stressing its importance in enhancing the English proficiency of engineering students.

2. Preliminaries

Kandasamy [23] launched the DVNSs.

Definition 1 [23]. The DVNSs are launched:

$$CA=\left\{\left(\theta,CT_A\left(\theta\right),CIT_A\left(\theta\right),CIF_A\left(\theta\right),CF_A\left(\theta\right)\right)\middle|\theta\in\Theta\right\}. \tag{1}$$

With truth-membership $CT_A\left(\theta\right)$, $CIT_A\left(\theta\right)$ stands for indeterminacy leaning for $CT_A\left(\theta\right)$, $LIF_A\left(\theta\right)$ stands for indeterminacy leaning for $LT_A\left(\theta\right)$ and falsity-membership $CF_A\left(\theta\right)$, $CT_A\left(\theta\right),CIT_A\left(\theta\right),CIF_A\left(\theta\right),CF_A\left(\theta\right)\in\left[0,1\right]$, $0\le CT_A\left(\theta\right)+CIT_A\left(\theta\right)+CIF_A\left(\theta\right)+CF_A\left(\theta\right)\le 4$.

The DVNN is launched as $CA=\left(CT_A,CIT_A,CIF_A,CF_A\right)$, where $CT_A,CIT_A,CIF_A,CF_A\in\left[0,1\right]$, $0\le CT_A+CIT_A+CIF_A+CF_A\le 4$.

Definition 2[23]. Let $CA=\left(CT_A,CIT_A,CIF_A,CF_A\right)$ be DVNN, score value (SV) is launched:

$$SV\left(CA\right)=\frac{\left(2+CT_A+CIT_A-CIF_A-CF_A\right)}{4},\ SV\left(CA\right)\in\left[0,1\right]. \tag{2}$$

Definition 3[23]. Let $CA=\left(CT_A,CIT_A,CIF_A,CF_A\right)$ be DVNN, accuracy value (AV) is launched:

$$AV\left(CA\right)=\frac{\left(CT_A+CIT_A+CIF_A+CF_A\right)}{4},\ AV\left(CA\right)\in\left[0,1\right]\ . \tag{3}$$

The order is launched for DVNNs.

Definition 4[23]. Let $CA=\left(CT_A,CIT_A,CIF_A,CF_A\right)$ and $CB=\left(CT_B,CIT_B,CIF_B,CF_B\right)$, $SV\left(CA\right)=\frac{\left(2+CT_A+CIT_A-CIF_A-CF_A\right)}{4}$, $SV\left(CB\right)=\frac{\left(2+CT_B+CIT_B-CIF_B-CF_B\right)}{4}$, $AV\left(CA\right)=\frac{\left(CT_A+CIT_A+CIF_A+CF_A\right)}{4}$, $AV\left(CB\right)=\frac{\left(CT_B+CIT_B+CIF_B+CF_B\right)}{4}$, if $SV\left(CA\right)<SV\left(CB\right)$, $CA<CB$; if $SV\left(CA\right)=SV\left(CB\right)$, (1)if $AV\left(CA\right)=AV\left(CB\right)$, $CA=CB$; (2) if $AV\left(CA\right)<AV\left(CB\right)$, $CA<CB$.

Definition 5[23]. Let $CA=\left(CT_A,CIT_A,CIF_A,CF_A\right)$ and $CB=\left(CT_B,CIT_B,CIF_B,CF_B\right)$ be DVNNs, the operations are launched:

(1) $CA \oplus CB = \left(CT_A + CT_B - CT_A CT_B, CIT_A + CIT_B - CIT_A CIT_B, CIF_A CIF_B, CF_A CF_B\right);$
(2) $CA \otimes CB = \left(CT_A CT_B, CIT_A CIT_B, CIF_A + CIF_B - CIF_A CIF_B, CF_A + CF_B - CF_A CF_B\right);$
(3) $\lambda CA = \left(1-\left(1-CT_A\right)^{\lambda}, 1-\left(1-CIT_A\right)^{\lambda}, \left(CIF_A\right)^{\lambda}, \left(CF_A\right)^{\lambda}\right), \lambda > 0;$
(4) $\left(CA\right)^{\lambda} = \left(\left(CT_A\right)^{\lambda}, \left(CIT_A\right)^{\lambda}, 1-\left(1-CIF_A\right)^{\lambda}, 1-\left(1-CF_A\right)^{\lambda}\right), \lambda > 0.$

Definition 6[23]. Let $CA = \left(CT_A, CIT_A, CIF_A, CF_A\right)$ and $CB = \left(CT_B, CIT_B, CIF_B, CF_B\right)$, the DVNN Hamming distance (DVNNHD) and DVNN Euclidean distance (DVNNED) between $CA = \left(CT_A, CIT_A, CIF_A, CF_A\right)$ and $CB = \left(CT_B, CIT_B, CIF_B, CF_B\right)$ is launched:

$$DVNNHD\left(CA, CB\right) = \frac{1}{4}\left(\left|CT_A - CT_B\right| + \left|CIT_A - CIT_B\right| + \left|CIF_A - CIF_B\right| + \left|CF_A - CF_B\right|\right) \tag{4-a}$$

$$DVNNED\left(CA, CB\right) = \sqrt{\frac{1}{4}\left(\left|CT_A - CT_B\right|^2 + \left|CIT_A - CIT_B\right|^2 + \left|CIF_A - CIF_B\right|^2 + \left|CF_A - CF_B\right|^2\right)} \tag{4-b}$$

3. The DVNN-COPRAS technique for MADM

This section shows the steps of the proposed method under the DVNNs to show the strength of the proposed method. The COPRAS method is used to rank the alternatives in MADM problems. The steps of the COPRAS method under DVNNs are shown as follows:

1. Experts evaluate the criteria and alternatives.

Three experts evaluated the criteria and alternatives using the DVNNs.

2. Obtain crisp values.

We used the score function to obtain crisp values.

3. Combine crisp values into one matrix.

4. Obtain the criteria weights.

The criteria weights are determined through the one matrix with crips values.

5. Normalize the crisp values of DVNN.

$$N_{ij} = \frac{t_{ij}}{\sum_{i=1}^{m} t_{ij}} \tag{5}$$

Where $i = 1,2,\dots,m; j = 1,2,\dots,n$

6. Determine the values of the weighted normalized decision matrix

$$K_{ij} = w_j * N_{ij} \tag{6}$$

7. Determine the maximizing and minimizing indexes for positive (g) and negative criteria (n-g)

$$S_{+i} = \sum_{j=1}^{g} K_{ij} \tag{7}$$

$$S_{-i} = \sum_{j=g+1}^{n} K_{ij} \tag{8}$$

8. Compute the relative significant values.

$$A_i = S_{+i} + \frac{\sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \frac{1}{S_{-i}}} \tag{9}$$

9. Rank the alternatives. Figure 1. The criteria weights.

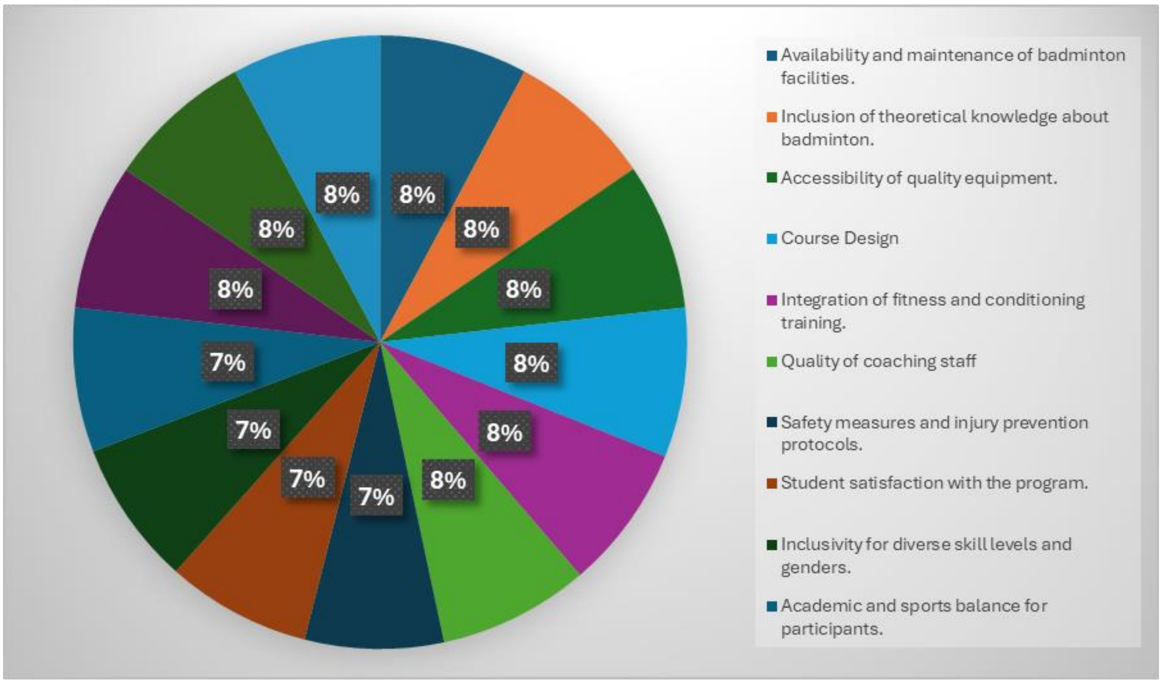

Figure 1. The criteria weights.

4. Numerical example and comparative analysis

The evaluation of college English teaching quality is a complex and multidimensional process aimed at comprehensively assessing teaching effectiveness and student learning outcomes. First, the core of the evaluation lies in course design, including the clarity of teaching objectives, the relevance of course content, and whether the selected textbooks meet students' actual needs. Secondly, the teaching methods and abilities of instructors are also crucial evaluation indicators. Excellent teachers not only need solid professional knowledge but also must employ diverse teaching techniques to stimulate students' interest and initiative in learning. Furthermore, student feedback is an essential component of evaluating teaching quality. Collecting students' opinions through surveys and discussion sessions can reveal the actual effectiveness of the teaching and identify existing issues. Students' academic performance and improvements in language skills are also key metrics; through examination results, language tests, and assessments of practical application abilities, the effectiveness of teaching can be objectively reflected. Teaching facilities and environment significantly impact teaching quality. Modern language laboratories, multimedia equipment, and a conducive learning atmosphere can effectively enhance teaching outcomes. The support and resource investment from the institution is equally important, including support for teacher training and development, as well as encouragement for teaching innovation. Lastly, the evaluation process should be ongoing and dynamic. Regular assessments of teaching quality can help identify problems and facilitate improvements. Through continuous feedback and adjustments, the quality of college English teaching can steadily improve, providing students with a higher quality education. The CET quality evaluation is MADM. Ten potential local applied undergraduate colleges are evaluated from 13 attributes.

Table 1. The DVNNs.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)
A_2	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.79, 0.43, 0.31, 0.91)
A_3	(0.83, 0.32, 0.21, 0.19)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)
A_4	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)
A_5	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)
A_6	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)
A_7	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.79, 0.43, 0.31, 0.91)	(0.52, 0.53, 0.31, 0.06)	(0.61, 0.43, 0.31, 0.17)	(0.52, 0.53, 0.31, 0.06)
A_8	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)
A_9	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.79, 0.43, 0.31, 0.91)
A_{10}	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.61, 0.43, 0.31, 0.17)
A_2	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)
A_3	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)
A_4	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)

A_5	(0.52, 0.53, 0.31, 0.06)	(0.61, 0.43, 0.31, 0.17)	(0.52, 0.53, 0.31, 0.06)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.79, 0.43, 0.31, 0.91)	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)
A_6	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)
A_7	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)	(0.83, 0.32, 0.21, 0.19)	(0.2, 0.54, 0.42, 0.55)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)
A_8	(0.61, 0.43, 0.31, 0.17)	(0.52, 0.53, 0.31, 0.06)	(0.61, 0.43, 0.31, 0.17)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)
A_9	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.79, 0.43, 0.31, 0.91)
A_{10}	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.83, 0.32, 0.21, 0.19)
A_2	(0.79, 0.43, 0.31, 0.91)	(0.79, 0.43, 0.31, 0.91)	(0.52, 0.53, 0.31, 0.06)	(0.79, 0.43, 0.31, 0.91)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)
A_3	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.83, 0.32, 0.21, 0.19)	(0.83, 0.32, 0.21, 0.19)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)
A_4	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)
A_5	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)
A_6	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)	(0.83, 0.32, 0.21, 0.19)	(0.2, 0.54, 0.42, 0.55)
A_7	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.52, 0.53, 0.31, 0.06)	(0.79, 0.43, 0.31, 0.91)	(0.79, 0.43, 0.31, 0.91)	(0.79, 0.43, 0.31, 0.91)	(0.52, 0.53, 0.31, 0.06)
A_8	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.83, 0.32, 0.21, 0.19)
A_9	(0.79, 0.43, 0.31, 0.91)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.52, 0.53, 0.31, 0.06)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)
A_{10}	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)	(0.79, 0.43, 0.31, 0.91)	(0.83, 0.32, 0.21, 0.19)	(0.52, 0.53, 0.31, 0.06)	(0.2, 0.54, 0.42, 0.55)	(0.2, 0.54, 0.42, 0.55)	(0.61, 0.43, 0.31, 0.17)	(0.61, 0.43, 0.31, 0.17)

1. Three DVNN matrices are built based on the opinions of three experts as shown in Table 1.

2. We obtain crisp values.

3. We combine crisp values into one matrix.

4. We obtain the criteria weights as shown in Figure 1.

5. Then we used Eq. (5) to normalize the crisp values of DVNN as shown in Table 2.

6. Then we used Eq. (6) to determine the values of the weighted normalized decision matrix

7. Then we used Eqs. (7 and 8) to determine the maximizing and minimizing.

8. Then we used Eq. (9) to compute the relative significant values.

9. Then we ranked the alternatives as shown in Figure 2.

Table 2. The normalized of crisp values of DVNNs.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
A_1	0.087986	0.115379	0.092288	0.089486	0.109792	0.116295	0.091968	0.106633	0.093833	0.078192	0.091811	0.117065	0.109281
A_2	0.094158	0.08122	0.114385	0.106701	0.096159	0.108261	0.097946	0.089719	0.08326	0.119423	0.109473	0.100175	0.093956
A_3	0.10765	0.118164	0.097487	0.109262	0.091762	0.074852	0.122471	0.11031	0.107342	0.098513	0.099548	0.103669	0.101977
A_4	0.104349	0.101745	0.080012	0.090909	0.100997	0.086411	0.103464	0.105898	0.084728	0.106759	0.105824	0.097408	0.086365
A_5	0.092579	0.08943	0.114385	0.111965	0.089856	0.110939	0.099019	0.094867	0.102937	0.101311	0.087578	0.082557	0.089086
A_6	0.106789	0.104384	0.099365	0.09788	0.117121	0.081336	0.106376	0.115752	0.1	0.101458	0.091811	0.104834	0.090089
A_7	0.091718	0.077848	0.106297	0.103429	0.087951	0.097124	0.107449	0.083395	0.11909	0.098365	0.10743	0.100175	0.115153
A_8	0.110234	0.101745	0.110919	0.095035	0.103782	0.105582	0.081392	0.093984	0.112775	0.099396	0.117647	0.111823	0.118161
A_9	0.08612	0.092215	0.108174	0.114668	0.099824	0.110939	0.097946	0.0781	0.077974	0.118392	0.111371	0.089255	0.085935
A_{10}	0.118415	0.117871	0.07669	0.080666	0.102756	0.108261	0.091968	0.121341	0.118062	0.078192	0.077507	0.09304	0.109997

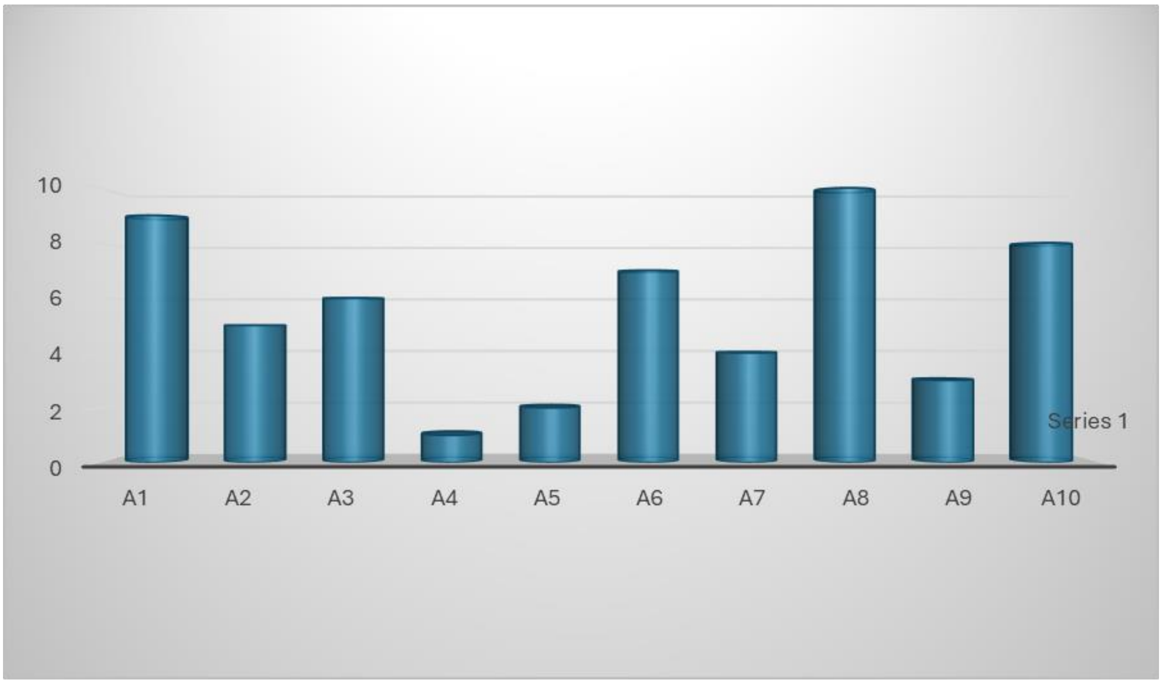

Figure 2. The rank of alternatives.

4.2 Sensitivity Analysis

This part changes the criteria weights by different cases to show the rank of alternatives under different weights. Figure 3 shows the different criteria weights. In the first case, we put all criteria with the same weights. Then we ranked the alternatives as shown in Figure 4. The results show our model is stable under different weights.

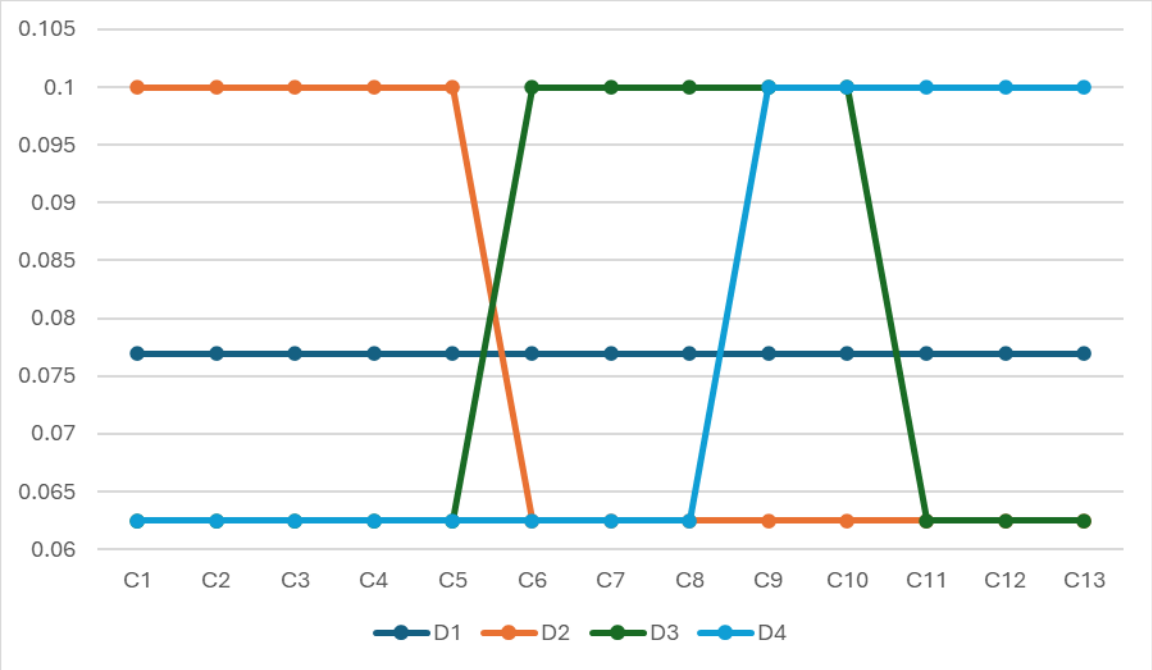

Figure 3. The different criteria weights.

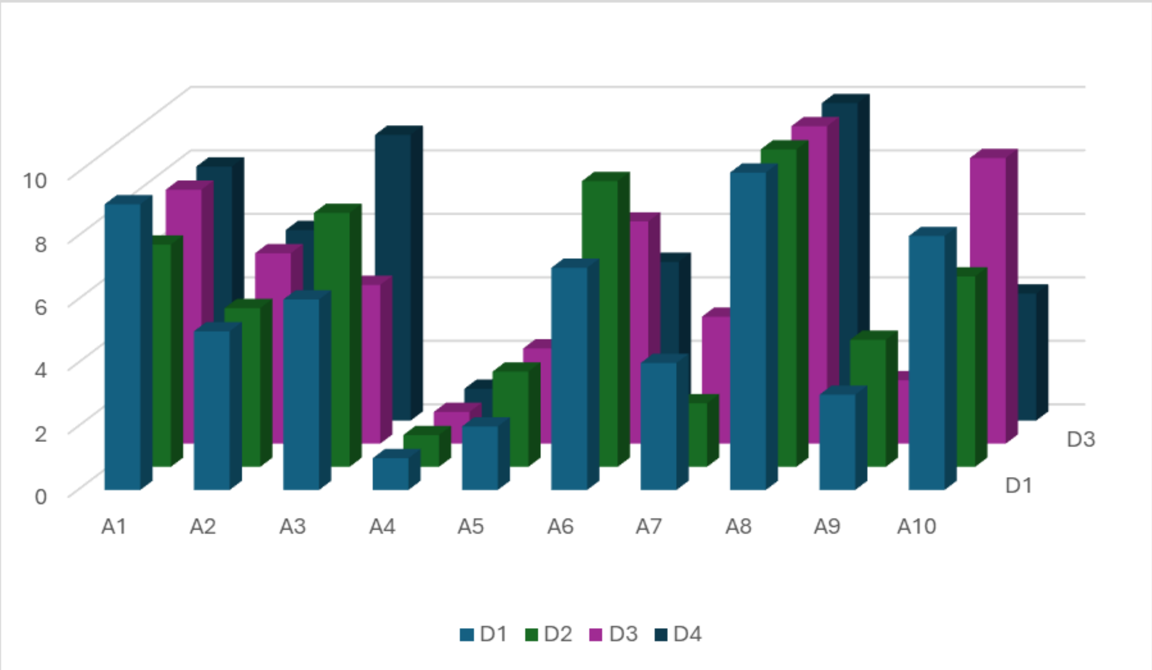

Figure 4. The rank of alternatives under different weights.

4.3. Comparative analysis

We compare our model with different MADM methods such as Taxonomy, CoCoSo, and VIKOR. We used the criteria weights from the proposed model. All methods are compared under the DVNN. Figure 5 shows the comparative ranks. We show the proposed model is strong compared to other methods.

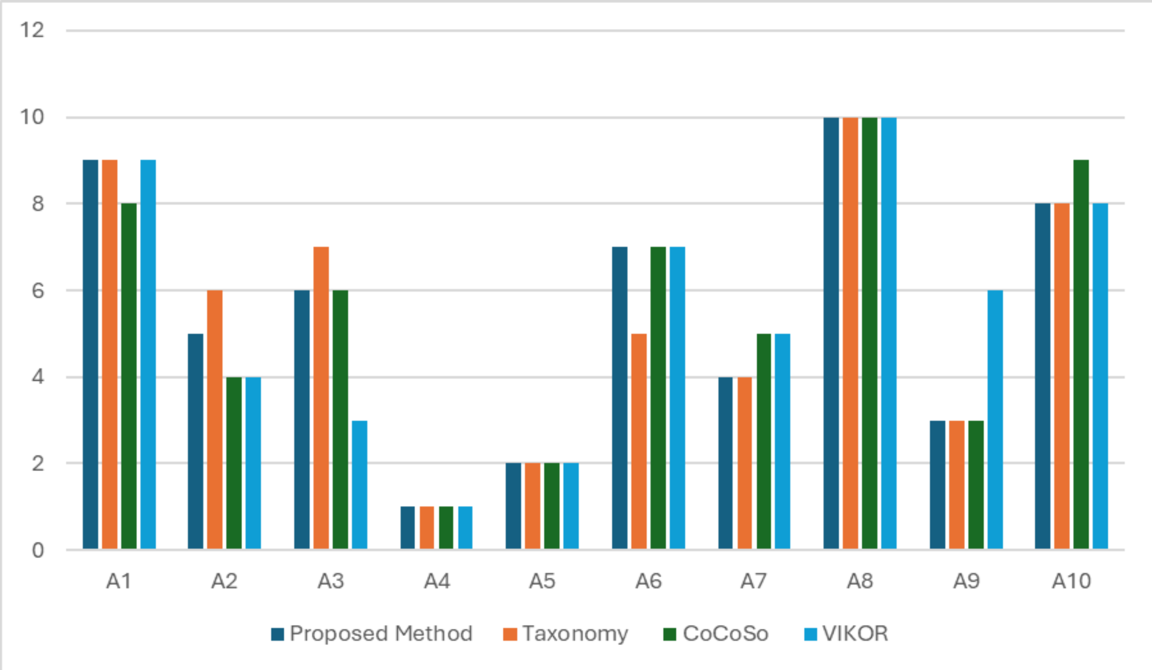

Figure 5. The comparative ranks.

5. Discussion analysis

When comparing the proposed DVNN-COPRAS technique with existing methods such as the DVNN-Taxonomy technique, DVNN-CoCoSo technique, and DVNN-VIKOR technique, the proposed method demonstrates significant advantages, though it also has some limitations. By analyzing these methods, we can better understand their disadvantages and the strengths and weaknesses of the proposed method. Some disadvantages of existing methods are outlined: The main drawback of the DVNN-Taxonomy Technique lies in its heavy reliance on subjective judgment when categorizing evaluation criteria. Although DVNN-Taxonomy can handle fuzzy and uncertain information, in complex multi-attribute decision-making problems, the process of defining classification standards may lead to inconsistent results. This is especially true when dealing with multi-dimensional, complex data, where the interrelationships between attributes may not be fully captured. While the DVNN-CoCoSo technique can address multi-attribute decision-making problems, its computational process is relatively complex and heavily dependent on the assignment of weights to evaluation criteria. This means that if the weight distribution is not reasonable, it could bias the final evaluation results. Additionally, the method's ability to handle uncertain data is limited, making it less effective in dealing with various types of uncertain information.

When comparing the proposed DVNN-COPRAS technique with existing methods three advantages of the proposed method are outlined: (1) More Effective Handling of Uncertain Data:

The DVNN-COPRAS technique, by incorporating Double-Valued Neutrosophic Numbers (DVNNs), is more effective in dealing with uncertain data. In multi-attribute decision-making processes, the introduction of DVNNs allows for more precise and robust results when handling fuzzy and uncertain information, thereby reducing information loss during the decision-making process. (2) Dual Distance Measures Enhance Decision Accuracy: The proposed method employs both Hamming distance and Euclidean distance under DVNN, which enables a more comprehensive assessment of the differences between attributes. This dual distance measure approach increases the flexibility and adaptability of the method, allowing it to better reflect the relationships between various attributes in different decision-making scenarios, ultimately improving decision accuracy. Relatively Higher Computational Efficiency: Compared to methods, the DVNN-COPRAS technique strikes a balance between computational complexity and efficiency. In multi-dimensional evaluation contexts, this method converges to reasonable results more quickly, making it particularly efficient when dealing with large datasets.

6. Conclusion

College English teaching quality evaluation is a crucial method for assessing the effectiveness of English instruction in higher education, aiming to comprehensively understand and enhance teaching quality. The evaluation typically includes aspects such as teacher proficiency, curriculum design, teaching resources, and student learning outcomes. Assessing teaching methods, classroom management, and the scientific and practical aspects of teaching content, helps teachers continually improve their strategies. In terms of curriculum design, the evaluation should focus on the systematic and cutting-edge nature of courses to ensure students acquire comprehensive and up-to-date knowledge. The richness and accessibility of teaching resources, such as textbooks, courseware, and online materials, are also key indicators. Evaluating student learning outcomes involves examining exam scores, language application skills, learning motivation, and satisfaction. By integrating these factors, college English teaching quality evaluation not only identifies issues in teaching but also provides a basis for educational reform, thereby promoting continuous improvement in teaching quality and cultivating well-rounded talents with international competitiveness. The evaluation of CET quality involves MADM. Currently, the COPRAS technique is employed to address Multi-Attribute Decision Making (MADM) problems. To handle uncertainty in this evaluation, the Dempster-Shafer Theory (DVNSs) is used as a characterization method. This study developed the DVNN-COPRAS technique, to tackle MADM challenges under DVNSs. To demonstrate the effectiveness of the proposed approach, a numerical example focusing on the evaluation of CET quality is provided. The key contributions of this study are constructed: (1) Utilizing the mean method to determine weight values under DVNSs; (2) Applying the DVNN-COPRAS technique to efficiently address MADM challenges and (3) Validating the DVNN-COPRAS method through a numerical example related to CET quality assessment.

7. Research limitations and future research directions:

Although this paper proposes an innovative method combining Double-Valued Neutrosophic Numbers with COPRAS (DVNN-COPRAS) for evaluating College English Teaching (CET) quality, its effectiveness is validated through a numerical study, several limitations exist:

(1) Method complexity: While the introduction of Double-Valued Neutrosophic Sets (DVNSs) and multiple distance measures (Hamming distance and Euclidean distance) allows for handling uncertain data, it increases the computational complexity. For practical applications, especially for decision-makers in the educational field, overly complex mathematical models might limit the method's widespread adoption.

(2)Limited empirical validation: The paper validates the proposed method through a numerical study, but the scope of empirical validation is limited. Only through real-world educational scenarios and large-scale sample data can the applicability and generalizability of the method be further confirmed.

(3) Dependence on subjective judgments: Although the double-valued neutrosophic set can deal with uncertainty, the evaluation process still depends on subjective judgment, particularly in the assignment of weights to evaluation criteria. Different evaluators may assign varying weights to the same criteria, which could lead to inconsistent results.

To address the current study's limitations, future research can focus on the following three directions:

(1) Simplifying the model to enhance practicality: Future studies could explore ways to simplify the current DVNN-COPRAS method, or incorporate more intuitive, user-friendly tools to reduce the computational complexity and increase its applicability in real-world teaching evaluations. For instance, machine learning or other data-driven algorithms could be integrated to automatically optimize the evaluation process and minimize human intervention.

(2) Large-Scale Empirical Validation: Further research could conduct large-scale, diverse empirical studies to validate the proposed method in different educational contexts, including various types of institutions, courses, and student groups. By collecting and analyzing extensive data, researchers can ensure the method's reliability and generalizability across different settings. Additionally, real-world feedback could be used to fine-tune the model's parameters.

(3) Incorporating Objective Data to Reduce Subjectivity: Future research could consider integrating more objective data, such as learning analytics, student performance metrics, and classroom interaction data, alongside the subjective evaluation system. By combining objective data with subjective assessments, the accuracy and consistency of the evaluation results could be further improved, minimizing biases from subjective judgment.

By addressing these research limitations and exploring the aforementioned directions, the proposed CET quality evaluation method could be more widely applied and further optimized, providing more effective and practical tools for multi-attribute decision-making in education.

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