Improving Teaching Quality Assessment in Smart Classrooms for English Majors: An Integrated Double-Valued Neutrosophic Decision-Making Model

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Abstract: The evaluation of multimedia-based college English teaching aims to assess the impact of multimedia technology on teaching quality and student learning outcomes. With the introduction of multimedia, classroom interactivity is enhanced, and students' interest and engagement are increased. Additionally, multimedia provides more opportunities for self-directed learning, helping students reinforce knowledge outside the classroom. However, the evaluation must focus on the alignment of technology with teaching objectives and whether the use of multimedia truly improves students' language skills and classroom efficiency. The evaluation of smart classroom teaching quality for English majors in universities is a multi-attribute decision-making (MADM) problem. Recently, methods such as the TOPSIS approach have been applied to tackle these challenges. Double-Valued Neutrosophic Sets (DVNSs) are used to represent fuzzy data in the evaluation process. In this study, a Double-Valued Neutrosophic Number TOPSIS (DVNN-TOPSIS) approach is proposed to address MADM problems involving DVNSs. Finally, a numerical case study on the quality evaluation of smart classroom teaching for English majors is provided to demonstrate the effectiveness of the DVNN-TOPSIS approach.

Keywords: MADM; DVNSs; TOPSIS approach; Smart classroom teaching

1. Introduction

The evaluation of multimedia-based college English teaching aims to comprehensively assess the impact of multimedia technology on teaching quality and student learning outcomes. By incorporating rich audio, video, and image resources, multimedia teaching makes the classroom more dynamic and engaging, enhancing students' interest and participation. Additionally, the interactive nature of multimedia fosters better communication between teachers and students, optimizing the classroom feedback mechanism. Moreover, multimedia teaching offers students more opportunities for independent learning, allowing them to use online resources for review and further study, thereby reinforcing classroom knowledge. However, evaluating teaching effectiveness requires not only examining whether multimedia technology improves students' language skills but also considering its alignment with teaching objectives and its actual contribution to classroom efficiency. Effective multimedia teaching should seamlessly integrate technology with course content, avoiding distractions and ensuring that the desired teaching goals are achieved. The quality evaluation of smart classroom teaching for English majors in universities is MADM problem. Recently, the MCDM approach [1, 2] and TOPSIS approach [3] have been applied to handle such problems.

1.1 Motivation of this study

The TOPSIS method combines the advantages of both and TOPSIS, offering the following three key benefits:

I. **It balances the decision-maker's subjective preferences with objective data analysis**. TOPSIS objectively evaluates the relative merits of alternatives by calculating their distances from the ideal and negative ideal solutions.

II. **It excels in handling complex and uncertain decision-making environments**. TOPSIS, through the construction of ideal solutions, effectively resolves multi-dimensional decision problems, providing clear ranking results. This makes the TOPSIS method highly effective in complex scenarios, applicable to decision analysis across various fields.

III. **It is easy to implement and widely applicable**. The computational process of TOPSIS is relatively simple, making it easy to understand and execute. Together, they create a method that can be employed in complex system evaluations, such as in education or technology assessments, and can be easily implemented using common computational tools, making it practical for real-world applications. Double-Valued Neutrosophic Sets (DVNSs) [4] have been employed to represent fuzzy data during the quality evaluation process.

DVNSs offer significant advantages in evaluating the effectiveness of multimedia-based college English teaching.

I. First, they handle uncertainty and ambiguity, accurately representing fuzzy data in the evaluation process.

II. Second, DVNS simultaneously considers truth, indeterminacy, and falsity, providing more comprehensive evaluation results.

III. Lastly, DVNS is flexible and applicable to complex evaluation scenarios, assisting decision-makers in making more rational judgments when faced with uncertainty and ambiguous information.

In this study, we propose the DVNN-TOPSIS approach to solve MADM problems with DVNSs. Finally, a numerical study on the quality evaluation of smart classroom teaching for English majors is presented to validate the effectiveness of the DVNN-TOPSIS model.

1.2 Organization of this study

The structure of this paper is as follows: Section 2 introduces DVNSs. In Section 3, the DVNN-TOPSIS method, incorporating entropy, is proposed within the DVNS framework. Section 4 presents a case study illustrating the quality evaluation of smart classroom teaching for English majors, accompanied by a comparative analysis. Finally, Section 5 offers concluding remarks.

2. Literature review

MADM refers to a class of decision-making methods used to evaluate and select among multiple alternatives based on several attributes or criteria [5, 6]. It is widely applied in complex decision-making scenarios such as project evaluation, supplier selection, and investment decisions, assisting decision-makers in making optimal choices when faced with multidimensional information [7, 8]. The core of MADM lies in how to manage the importance of various attributes and the performance of alternatives under different attributes [9, 10]. First, decision problems typically involve multiple attributes (or criteria) that need to be considered, which can be either quantitative or qualitative. Second, different attributes may carry different levels of importance, so each attribute needs to be assigned a weight to reflect its relative significance in the decision-making process. Several methods are commonly used in MADM, including TOPSIS [3] and MCDM [11]. TOPSIS [3] ranks alternatives by calculating their distances from the ideal and negative ideal solutions. One key advantage of MADM is its flexibility, as it can handle different types of information (such as quantitative and qualitative data) and incorporate the subjective preferences of decision-makers. However, MADM also faces challenges, especially when dealing with a large number of attributes or conflicting opinions among decision-makers, which can increase the complexity of the decision-making process. In summary, MADM provides a systematic decision-making approach, helping decision-makers make rational choices in complex, multi-dimensional environments. In 1986, Atanassov [12] developed the intuitionistic fuzzy sets, incorporating hesitation into the existing membership and non-membership degrees. Later, Kandasamy [4] introduced Double-Valued Neutrosophic Sets (DVNSs) to enhance the representation of fuzziness with help of Neutrosophic Sets [13-15].

The evaluation of multimedia-based college English teaching aims to comprehensively assess the impact of multimedia technology on the teaching process and learning outcomes. By incorporating multimedia, the traditional teaching model has been transformed, making the classroom more engaging and flexible. Multimedia allows teachers to present content in a more vivid manner, which significantly improves students' attention and motivation to learn. Additionally, the instant feedback and interactive features provided by multimedia enhance communication and interaction between teachers and students, optimizing the dynamic feedback mechanism of the classroom. Multimedia teaching also offers students more opportunities for self-directed learning. With access to various online resources, students can engage in extracurricular study and review, reinforcing the content learned in class. Moreover, the use of multimedia broadens the channels through which knowledge is conveyed, exposing students to diverse language contexts and cultural backgrounds, thus improving their practical language skills. However, despite the many advantages of multimedia technology in teaching, evaluating its effectiveness requires considering its alignment with teaching objectives and the potential challenges or distractions it may introduce into the learning process. Ultimately, the improvement in teaching outcomes depends not only on the use of technology but also on how effectively it is integrated into the overall instructional design. Tang and Wu [16] explored how to combine multimedia teaching with differentiated teaching based on multiple intelligence theory to improve English learning efficiency in independent colleges and found that this combination effectively enhanced students' English proficiency in such institutions. Cui [17] examined how to create a good psychological environment in English classrooms under multimedia teaching, emphasizing its importance in improving teaching outcomes and suggesting relevant strategies. Liu and Niu [18] proposed optimizing multimedia teaching modes in college English based on constructivist theory. They argued that students are active constructors of knowledge, and teachers should promote autonomous learning through contextual teaching and collaborative activities. Li [19] pointed out that while multimedia teaching makes English classes more dynamic and effective, challenges remain in integrating it with traditional teaching methods. Wang [20] explored the application of metacognitive theory in network-based multimedia teaching, suggesting that metacognitive strategies help students monitor and regulate their learning, thereby improving outcomes. Liu [21] proposed combining traditional recitation strategies with multimedia teaching to optimize English instruction, particularly enhancing language retention. Zhang [22] studied innovative strategies for multimedia teaching in college English, highlighting that multimedia enhances student engagement and improves teaching efficiency but also poses challenges related to technology and teacher competence. Dai [23] analyzed the application of multimedia-based learning apps, using the "Gaci APP" as an example, and suggested that such tools can address shortcomings in traditional teaching by offering innovative features that improve learning outcomes. Ling [24] examined the reform of English teaching modes in the context of multimedia, arguing that multimedia technology can enrich teaching content, optimize the environment, and improve overall teaching quality. Gao [25] discussed the necessity of reforming college English teaching in the multimedia network environment, proposing innovative teaching methods to meet the modern demands of English education. Finally, Wang [26] analyzed the innovative paths for college English teaching from the perspective of new media technologies, suggesting that such technologies can drive teaching reforms and improve students' comprehensive English abilities.

3. Preliminaries

Kandasamy [4] put forward the DVNSs.

Definition 2 [4]. The DVNSs is put forward:

$$DA=\left\{\left(x,DT_A\left(x\right),DIT_A\left(x\right),DIF_A\left(x\right),DF_A\left(x\right)\right)\middle|x\in X\right\} \quad (1)$$

with $DT_A\left(x\right)$ is truth-membership, $DIT_A\left(x\right)$ is listed as indeterminacy leaning for truth-membership, $DIF_A\left(x\right)$ is listed as indeterminacy leaning for falsity-membership indeterminacy-membership, $DF_A\left(x\right)$ is listed as falsity-membership, $DT_A\left(x\right),DIT_A\left(x\right),DIF_A\left(x\right),DF_A\left(x\right)\in\left[0,1\right]$, $0\le DT_A\left(x\right)+DIT_A\left(x\right)+DIF_A\left(x\right)+DF_A\left(x\right)\le 4$.

The DVNN is listed as: $DA=\left(DT_A,DIT_A,DIF_A,DF_A\right)$, $DT_A,DIT_A,DIF_A,DF_A\in\left[0,1\right]$, $0\le DT_A+DIT_A+DIF_A+DF_A\le 4$.

Definition 2. Let $DA=\left(DT_A,DIT_A,DIF_A,DF_A\right)$, the score value is constructed:

$$DSV\left(DA\right)=\frac{\left(2+DT_A+DIT_A-DIF_A-DF_A\right)}{4},\ DSV\left(DA\right)\in\left[0,1\right]. \quad (2)$$

Definition 3. Let $DA=\left(DT_A,DIT_A,DIF_A,DF_A\right)$, the accuracy value is constructed:

$$DAV\left(DA\right)=\frac{\left(DT_A+DIT_A+DIF_A+DF_A\right)}{4},\ DAV\left(DA\right)\in\left[0,1\right]\ . \quad (3)$$

The order between two DVNNs is put forward.

Definition 4. Let $DA=\left(DT_A,DIT_A,DIF_A,DF_A\right)$ and $DB=\left(DT_B,DIT_B,DIF_B,DF_B\right)$, let $DSV\left(DA\right)=\frac{\left(2+DT_A+DIT_A-DIF_A-DF_A\right)}{4}$ and $DSV\left(DB\right)=\frac{\left(2+DT_B+DIT_B-DIF_B-DF_B\right)}{4}$, and let $DAV\left(DA\right)=\frac{\left(DT_A+DIT_A+DIF_A+DF_A\right)}{4}$ and $DAV\left(DB\right)=\frac{\left(DT_B+DIT_B+DIF_B+DF_B\right)}{4}$, then if $DSV\left(DA\right)<DSV\left(DB\right)$, $DA<DB$; if $DSV\left(DA\right)=DSV\left(DB\right)$, Then (1)if $DAV\left(DA\right)=DAV\left(DB\right)$, $DA=DB$; (2) if $DAV\left(DA\right)<DAV\left(DB\right)$, $DA<DB$.

Definition 5[4]. $DA=\left(DT_A,DIT_A,DIF_A,DF_A\right)$, $DB=\left(DT_B,DIT_B,DIF_B,DF_B\right)$, the operations are constructed:

(1) $DA\oplus DB=\left(DT_A+DT_B-DT_ADT_B,DIT_A+DIT_B-DIT_ADIT_B,DIF_ADIF_B,DF_ADF_B\right)$;

(2) $DA\otimes DB=\left(DT_ADT_B,DIT_ADIT_B,DIF_A+DIF_B-DIF_ADIF_B,DF_A+DF_B-DF_ADF_B\right)$;

(3) $\lambda DA=\left(1-\left(1-DT_A\right)^{\lambda},1-\left(1-DIT_A\right)^{\lambda},\left(DIF_A\right)^{\lambda},\left(DF_A\right)^{\lambda}\right),\lambda>0;$

(4) $\left(DA\right)^{\lambda}=\left(\left(DT_A\right)^{\lambda},\left(DIT_A\right)^{\lambda},1-\left(1-DIF_A\right)^{\lambda},1-\left(1-DF_A\right)^{\lambda}\right),\lambda>0.$

Definition 6[4]. Let $DA=\left(DT_A, DIT_A, DIF_A, DF_A\right)$ and $DB=\left(DT_B, DIT_B, DIF_B, DF_B\right)$, then the normalized Euclidean distance between $DA=\left(DT_A, DIT_A, DIF_A, DF_A\right)$ and $DB=\left(DT_B, DIT_B, DIF_B, DF_B\right)$ is:

$$ED(DA, DB)=\sqrt{\frac{1}{4}\left(\begin{array}{l}\left|DT_A-DT_B\right|^2+\left|DIT_A-DIT_B\right|^2 \\ +\left|DIF_A-DIF_B\right|^2+\left|DF_A-DF_B\right|^2\end{array}\right)} \quad (4)$$

4. DVNN-TOPSIS approach

In MCDM, several alternatives can be assessed using number of criteria. MCDM can support the experts in the decision-making process. There are decision making issues that have several conflict criteria. So, the TOPSIS method used to rank alternatives by using the positive ideal solution (PIS) and negative ideal solution (NIS). Figure 1 shows the framework of the proposed method. The steps of the neutrosophic TOPSIS method include as follows:

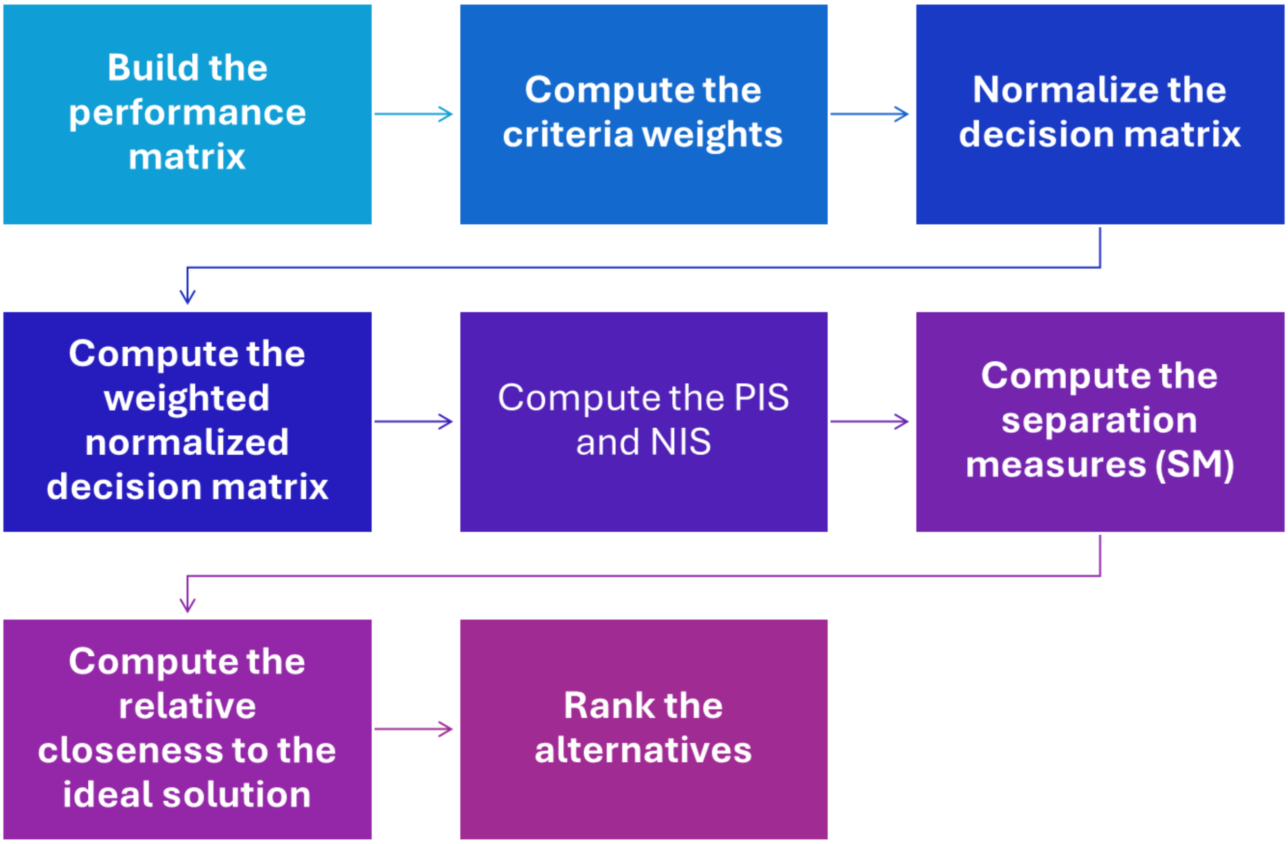

Figure 1. The steps of the TOPSIS method.

A. Build the performance matrix.

The performance matrix between criteria and alternatives $\boldsymbol{F_{ij}}$ where i refers to the number of alternatives and j refers to the number of criteria.

B. Compute the criteria weights.

The criteria weights are computed by using the average method.

C. Normalize the decision matrix.

The normalized performance matrix can be computed as:

$$\boldsymbol{u_{ij}} = \frac{\boldsymbol{F_{ij}}}{\sqrt{\sum_{j=1}^{m}(\boldsymbol{F_{ij}})^2}}, \quad \boldsymbol{j = 1, 2, 3, \ldots n; i = 1, 2, \ldots, m}$$

(5)

D. Compute the weighted normalized decision matrix.

The criteria weights are multiplied by the normalized decision matrix to obtain the weighted normalized decision matrix such as:

$$\boldsymbol{r_{ij}} = \boldsymbol{w_j} * \boldsymbol{u_{ij}} \tag{6}$$

E. Compute the PIS and NIS.

$$\boldsymbol{B^+} = \{\boldsymbol{B_1^+}, \ldots, \boldsymbol{B_n^+}\} = \left\{\left(\max_i \boldsymbol{r_{ij}}, \boldsymbol{j} \in \boldsymbol{J}\right)\left(\min_i \boldsymbol{r_{ij}}, \boldsymbol{j} \in \boldsymbol{J^*}\right)\right\}$$

(7)

$$\boldsymbol{B^-} = \{\boldsymbol{B_1^-}, \ldots, \boldsymbol{B_n^-}\} = \left\{\left(\min_i \boldsymbol{r_{ij}}, \boldsymbol{j} \in \boldsymbol{J}\right)\left(\max_i \boldsymbol{r_{ij}}, \boldsymbol{j} \in \boldsymbol{J^*}\right)\right\} \tag{8}$$

Where $\boldsymbol{J^*}$ refers to the cost criteria and $\boldsymbol{J}$ refers to the beneficial criteria.

F. Compute the separation measures (SM).

We compute the SM from PIS and NIS as:

$$\boldsymbol{d_i^+} = \left\{\sum_{j=1}^{n}\left(\boldsymbol{r_{ij}} - \boldsymbol{r_j^+}\right)^2\right\}^{\frac{1}{2}} \tag{9}$$

$$d_i^- = \left\{\sum_{j=1}^{n}\left(r_{ij} - r_j^-\right)^2\right\}^{\frac{1}{2}} \tag{10}$$

G. Compute the relative closeness to the ideal solution

$$T_i = \frac{d_i^-}{d_i^+ + d_i^-} \tag{11}$$

H. Rank the alternatives.

Rank the best alternatives based on T_i in descending order.

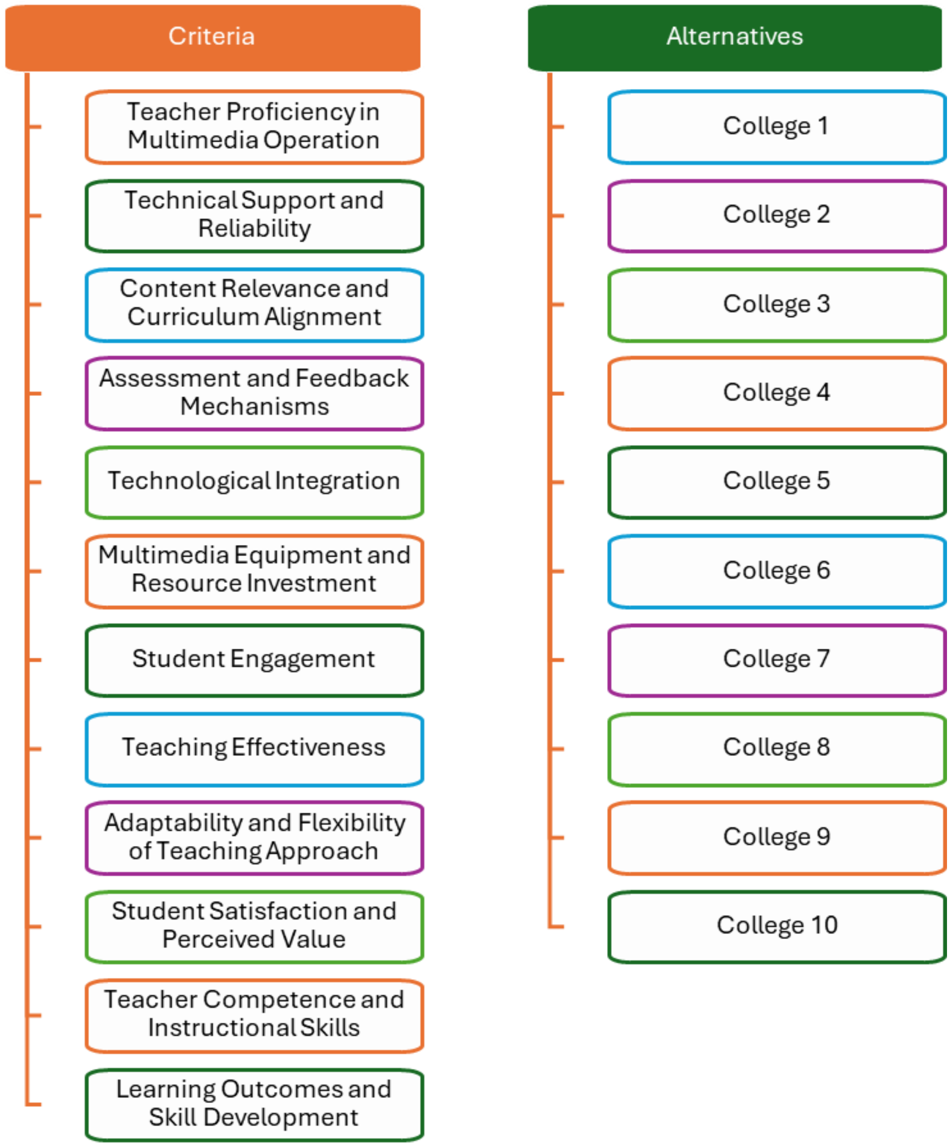

Figure 2. The criteria and alternatives.

5. Data analysis

This section shows the results of the proposed method under the neutrosophic sets.

5.1. Data analysis with quality evaluation of smart classroom teaching for English majors in universities

The evaluation of smart classroom teaching quality for college English is a systematic process designed to assess the effectiveness of multimedia technology in English instruction. With the rapid advancement of information technology, multimedia teaching has become a key tool in college English education, enriching content, enhancing classroom interaction, and stimulating students' interest in learning. However, to accurately and comprehensively evaluate its true effectiveness, a well-structured evaluation system is essential. At the core of evaluating smart classroom teaching quality is the establishment of clear and reasonable criteria. Common evaluation dimensions include the quality of teaching content (such as its depth and practicality), the innovation in teaching methods (including the effective use of multimedia and variety in instructional approaches), student engagement (such as participation in classroom activities and self-directed learning), resource utilization efficiency (such as the appropriate use of teaching materials, videos, and audio resources), teachers' instructional abilities (including pacing, communication, and classroom management), and students' learning outcomes (such as knowledge retention and language skill improvement). The selection of evaluation methods is equally critical. Common approaches include questionnaires, classroom observation, student feedback, and performance analysis. Questionnaires can capture students' perceptions and opinions on multimedia teaching, providing subjective insights. Classroom observation assesses how multimedia is practically implemented in teaching through both teacher behavior and student engagement. Additionally, analyzing students' exam performance offers a quantitative measure of multimedia's impact on learning outcomes. In practice, evaluation should blend both qualitative and quantitative methods. For instance, well-designed scoring standards can convert subjective student feedback into measurable data, while statistical analysis of academic performance offers an objective assessment of multimedia’s effects. Finally, the evaluation results should be shared with teachers and educational administrators, offering insights into the strengths and areas for improvement in current teaching practices. Teachers can use these results to refine their content and methods, optimizing their instructional design to further improve teaching quality. In conclusion, evaluating smart classroom teaching quality for college English is a comprehensive and systematic process. The goal is to apply scientific and effective evaluation methods to fully understand the impact of multimedia teaching, providing valuable insights for both educational decision-making and instructional enhancement. The quality evaluation of smart classroom teaching for English majors in universities is MADM.

A. We built the performance matrix between criteria and alternatives by using double valued neitrosophic number. Then we used the score function to obtain single number and combined into single matrix. We used 12 criteria and 10 alternatives as shown in Figure 2. Three experts are involved to evaluate the criteria and alternatives.

B. We compute the criteria weighs as shown in Figure 3. Criterion 8 has the highest weight and criterion 10 has the lowest weight.

C. Eq. (5) is used to normalize the decision matrix as shown in Table 1.

D. Eq. (6) is used to compute the weighted normalized decision matrix as shown in Table 2.

E. Eq. (7,8) are used to compute the PIS and NIS.

F. Eqs. (9 and 10) are used to compute the SM as shown in Table 3.

G. Eq. (11) is used to compute the relative closeness to the ideal solution

H. Rank the alternatives as shown in Figure 4.

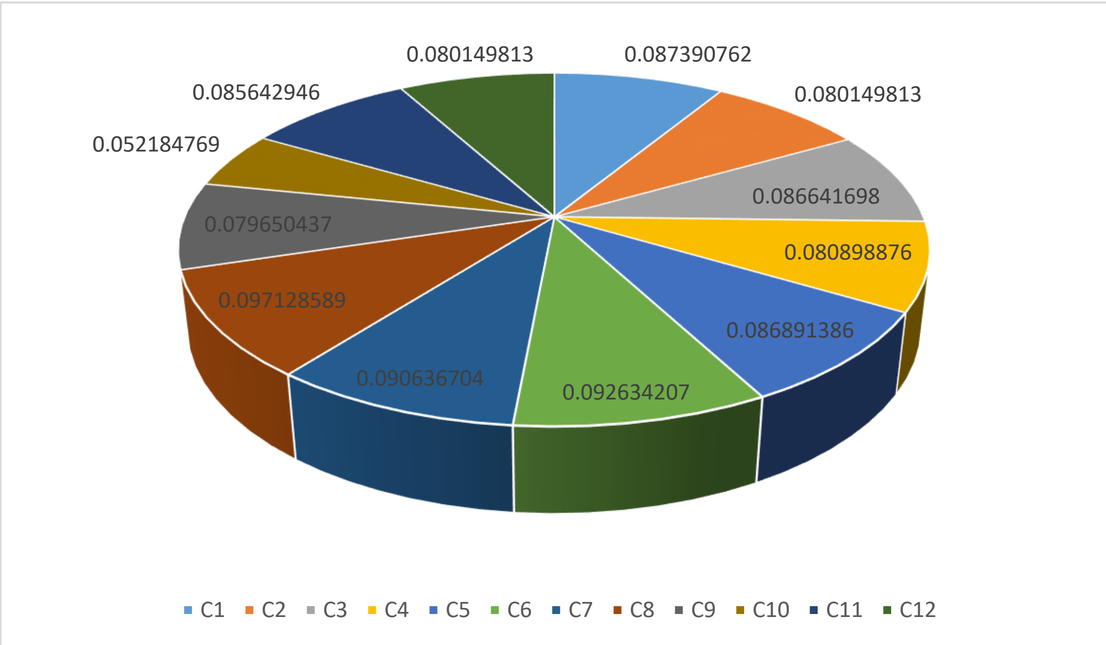

Figure 3. The criteria weights.

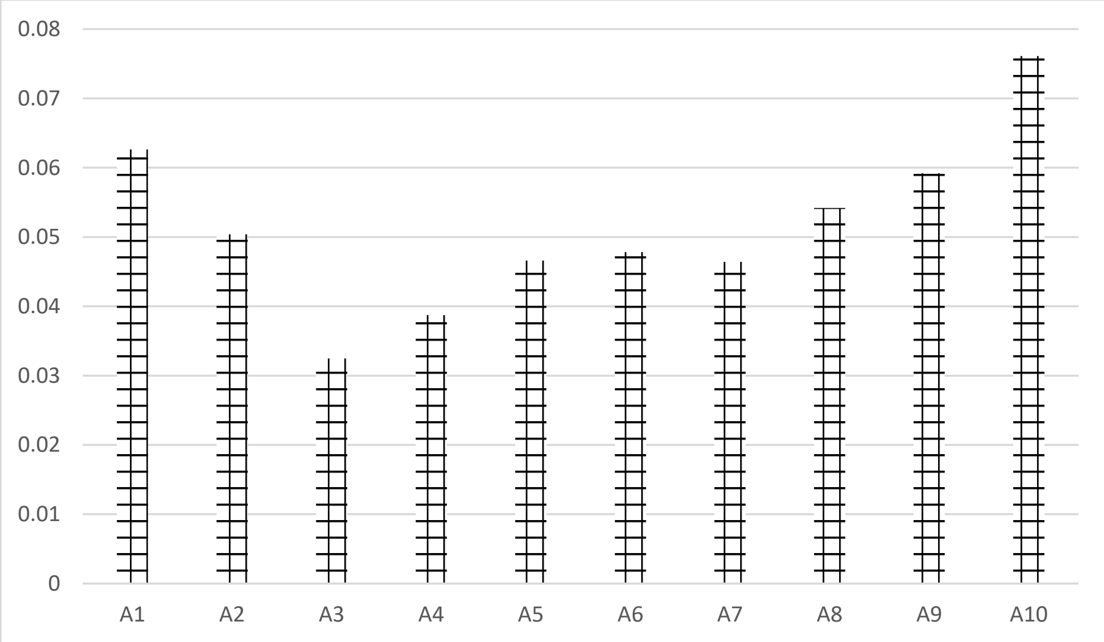

Figure 4. The rank of alternatives.

Table 1. The normalized decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	0.346043932	0.51032	0.30729	0.386478	0.35525	0.156332	0.123445	0.191364	0.027586	0.038922	0.488251	0.359253
A_2	0.354484028	0.24571	0.324849	0.046009	0.195388	0.436085	0.320958	0.398675	0.422981	0.428138	0.248408	0.479003
A_3	0.362924123	0.349664	0.30729	0.322065	0.310844	0.419629	0.427944	0.29502	0.321833	0.518956	0.334066	0.322406
A_4	0.295403356	0.330763	0.359968	0.441689	0.390775	0.279752	0.222202	0.310967	0.321833	0.441112	0.282671	0.442157
A_5	0.405124603	0.274061	0.482884	0.220844	0.195388	0.287981	0.419714	0.382728	0.285052	0.337321	0.188448	0.331618
A_6	0.337603836	0.321313	0.28973	0.358872	0.301963	0.353805	0.296269	0.29502	0.128733	0.285426	0.385461	0.193444
A_7	0.346043932	0.302412	0.30729	0.294459	0.2842	0.329121	0.213972	0.350834	0.3862	0.129739	0.334066	0.28556
A_8	0.354484028	0.24571	0.158035	0.285257	0.301963	0.287981	0.320958	0.310967	0.358614	0.090817	0.334066	0.239502
A_9	0.059080671	0.311862	0.324849	0.377276	0.381894	0.197472	0.197512	0.223258	0.285052	0.350295	0.316935	0.221078
A_{10}	0.092841055	0.141756	0.184374	0.24845	0.373013	0.304437	0.444403	0.342861	0.395395	0.090817	0.025697	0.082904

Table 2. The weighted normalized decision matrix

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	0.030241043	0.040902	0.026624	0.031266	0.030868	0.014482	0.011189	0.018587	0.002197	0.002031	0.041815	0.028794
A_2	0.030978629	0.019694	0.028145	0.003722	0.016978	0.040396	0.029091	0.038723	0.033691	0.022342	0.021274	0.038392
A_3	0.031716216	0.028026	0.026624	0.026055	0.02701	0.038872	0.038787	0.028655	0.025634	0.027082	0.02861	0.025841
A_4	0.025815524	0.026511	0.031188	0.035732	0.033955	0.025915	0.02014	0.030204	0.025634	0.023019	0.024209	0.035439
A_5	0.035404148	0.021966	0.041838	0.017866	0.016978	0.026677	0.038041	0.037174	0.022705	0.017603	0.016139	0.026579
A_6	0.029503456	0.025753	0.025103	0.029032	0.026238	0.032774	0.026853	0.028655	0.010254	0.014895	0.033012	0.015504
A_7	0.030241043	0.024238	0.026624	0.023821	0.024695	0.030488	0.019394	0.034076	0.030761	0.00677	0.02861	0.022888
A_8	0.030978629	0.019694	0.013692	0.023077	0.026238	0.026677	0.029091	0.030204	0.028564	0.004739	0.02861	0.019196

A_9	0.005163105	0.024996	0.028145	0.030521	0.033183	0.018293	0.017902	0.021685	0.022705	0.01828	0.027143	0.017719
A_{10}	0.00811345	0.011362	0.015974	0.020099	0.032412	0.028201	0.040279	0.033302	0.031493	0.004739	0.002201	0.006645

Table 3. The SM values.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}
A_1	2.66577E-05	0	0.000231	1.99E-05	9.53E-06	0.000672	0.000846	0.000405	0.000992	0.000628	0	9.21E-05
A_2	1.95852E-05	0.00045	0.000187	0.001025	0.000288	0	0.000125	0	0	2.25E-05	0.000422	0
A_3	1.36008E-05	0.000166	0.000231	9.37E-05	4.82E-05	2.32E-06	2.23E-06	0.000101	6.49E-05	0	0.000174	0.000158
A_4	9.19417E-05	0.000207	0.000113	0	0	0.00021	0.000406	7.26E-05	6.49E-05	1.65E-05	0.00031	8.72E-06
A_5	0	0.000359	0	0.000319	0.000288	0.000188	5.01E-06	2.4E-06	0.000121	8.98E-05	0.000659	0.00014
A_6	3.48182E-05	0.000229	0.00028	4.49E-05	5.96E-05	5.81E-05	0.00018	0.000101	0.000549	0.000149	7.75E-05	0.000524
A_7	2.66577E-05	0.000278	0.000231	0.000142	8.58E-05	9.82E-05	0.000436	2.16E-05	8.58E-06	0.000413	0.000174	0.00024
A_8	1.95852E-05	0.00045	0.000792	0.00016	5.96E-05	0.000188	0.000125	7.26E-05	2.63E-05	0.000499	0.000174	0.000368
A_9	0.000914521	0.000253	0.000187	2.72E-05	5.96E-07	0.000489	0.000501	0.00029	0.000121	7.75E-05	0.000215	0.000427
A_{10}	0.000744782	0.000873	0.000669	0.000244	2.38E-06	0.000149	0	2.94E-05	4.83E-06	0.000499	0.001569	0.001008

The three advantages of DVNN-TOPSIS approach for evaluating the quality of smart classroom teaching for English majors are outlined:

(1) Enhanced ability to handle fuzzy information: Based on DVNSs, this method provides a more precise way to represent uncertainty and fuzziness. Compared to traditional methods, DVNSs can handle membership, non-membership, and hesitation information simultaneously, making decision-making in fuzzy environments more comprehensive and reasonable.

(2)Integration of the strengths of TOPSIS: The DVNN -TOPSIS method combines the strengths of both TOPSIS. TOPSIS evaluates alternatives based on their distances from ideal and negative-ideal solutions. The combination leads to more robust and rational results.

(3) High adaptability to complex decision environments: This method is particularly suited for multi-attribute, multi-criteria decision-making scenarios, such as smart classroom teaching evaluations. It can process fuzzy information under various attributes and preferences, producing reasonable results even in complex environments, making it highly adaptable and widely applicable.

5. Conclusion

The evaluation of smart classroom teaching quality in college English is a systematic process aimed at assessing the impact of multimedia technology in teaching. The evaluation involves multiple dimensions, including the richness and practicality of teaching content, the innovation of teaching methods, student engagement, and the efficiency of resource utilization. By combining qualitative and quantitative evaluation methods, such as questionnaires, classroom observation, and student performance analysis, it provides a comprehensive reflection of the impact of multimedia teaching on student learning outcomes. Additionally, the evaluation must consider the investment in multimedia equipment and the teacher's technical proficiency to ensure the efficient use and optimal allocation of teaching resources. Ultimately, the evaluation of teaching effectiveness provides scientific evidence for improving instructional design and enhancing teaching quality, contributing to the continuous development of college English education. The quality evaluation of smart classroom teaching for English majors in universities is MADM. DVNSs are used as an effective tool for representing fuzzy data in the quality evaluation of smart classroom teaching for English majors in universities. In this study, the DVNN-TOPSIS approach is proposed to handle MADM under DVNSs. Finally, a numerical study on the quality evaluation of smart classroom teaching for English majors is conducted to validate the DVNN-TOPSIS model.

Based on the content of this study, future research can delve into the following three directions: (1) Expanding the application areas of the decision model: Although the DVNN-TOPSIS method performed well in evaluating the quality of smart classroom teaching for English majors, its application scope can be further expanded. Future studies could apply this model to other disciplines' smart teaching quality evaluations, corporate management decision-making, healthcare optimization, and more, to verify its applicability and effectiveness in different contexts. This would provide richer data support for the model's use across a wide range of fields. (2) Incorporating additional uncertainty-handling methods: While DVNSs are effective at handling fuzzy information, more complex decision environments may involve even greater uncertainty or fuzziness. Future research could consider integrating other uncertainty-handling methods, such as interval numbers, grey system theory, or stochastic fuzzy sets, to further enhance the model's ability to process complex information. These extended methods would improve the model's robustness in dynamic and uncertain environments. (3) Optimizing computational efficiency and algorithm performance: As the scale and complexity of decision problems increase, computational efficiency and performance become critical issues. Future studies could focus on improving the algorithm design of the DVNN-TOPSIS method, optimizing its computational complexity, and enhancing its ability to handle large-scale datasets. Additionally, leveraging machine learning and artificial intelligence techniques to develop intelligent optimization algorithms could further improve the method's computational efficiency and decision-making speed. By pursuing these research directions, the DVNN-TOPSIS method can be further enhanced in terms of its broad applicability and decision-support capabilities, providing more comprehensive and efficient solutions for complex decision-making problems.

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