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A Methodological Approach to Decision-Making Using Interval-Valued Neutrosophic Framework for Enhancing and Evaluating English Blended Teaching Quality

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Abstract: The future of blended English instruction in universities is promising, driven by ongoing technological advancements and the increasing diversity of educational needs. This teaching model is expected to better integrate the strengths of both online and in-person learning, providing students with more flexible and personalized learning experiences. By combining these two modalities, blended instruction can improve student motivation and engagement while allowing educators to continuously refine their teaching methods and materials based on real-time data and feedback. As a result, blended learning is projected to become a more widespread and preferred method of instruction in higher education. In terms of evaluating the quality of blended English teaching, multiple-attribute decision-making (MADM) techniques play an important role. Interval-valued neutrosophic sets (IVNSs) have been extensively used and studied in MADM for their ability to handle uncertainty and imprecision in decision-making processes. In this context, the ORESTE is applied under the IVNS framework for ranking the alternatives. This method is particularly useful for evaluating the quality of blended English instruction. A numerical example is provided in the paper to demonstrate its application in assessing the quality of blended teaching. The study concludes that the IVN-ORESTE method not only offers stability but also provides a degree of flexibility, which is crucial for adapting to the varying needs and conditions of higher education environments.

Keywords: Multiple attribute decision-making (MADM); IVNSs; IVN-ORESTE; Effect evaluation

1. Introduction

In the rapidly evolving landscape of higher education, blended learning has emerged as a significant trend, particularly because of its distinct educational advantages. In the context of university English instruction, this model merges traditional face-to-face classroom teaching with modern online platforms, creating a dynamic and flexible learning environment for students[1]. Often referred to as hybrid learning, blended learning integrates in-person teaching with digital experiences, optimizing educational resources and fusing learning activities across both online and offline environments. The primary goal of this approach is to enhance the effectiveness of teaching while improving the efficiency of student learning. In university English courses, blended learning typically involves a combination of video lectures, online forums, and interactive tasks, alongside conventional classroom interactions and discussions[2]. The widespread availability of internet technologies and mobile devices has facilitated the rapid adoption and expansion of blended learning across the globe. Many universities now implement this model as a strategic approach to improve both teaching quality and the overall learning experience. For instance, online platforms allow instructors to share instructional videos and supplementary materials, enabling students to access these resources anytime and anywhere, which promotes autonomous learning. Meanwhile, traditional classroom settings continue to offer opportunities for more direct face-to-face communication and in-depth discussions[3]. However, successfully implementing blended learning requires careful consideration of several key factors, including curriculum design, technological support, teacher training, and student acceptance. Effective curriculum design is crucial; it must ensure that online and offline activities are integrative and complementary, rather than simply existing side-by-side. Additionally, educational institutions need to provide reliable technical support, such as video conferencing tools and online discussion platforms, to facilitate smooth and uninterrupted teaching activities [4]. Blended learning has demonstrated significant advantages in enhancing student motivation, improving learning efficiency, and deepening learning engagement. Students can use online resources to engage in pre-learning or to review course materials, ensuring continuity and depth in their education. Simultaneously, face-to-face interactions in the classroom allow for timely feedback from instructors, helping students to better understand and master the course content. This balance between self-directed online learning and structured classroom interaction provides a more holistic educational experience[5]. Despite its benefits, blended learning also presents several challenges. A major obstacle is the seamless integration of online and offline instructional strategies, which requires careful planning to avoid fragmentation of the learning experience. Sustaining student interest and participation in both modes of instruction can also be difficult, especially when students face distractions in online environments[6]. Additionally, providing effective evaluation and feedback for student progress in a blended format requires new approaches that account for both digital and in-person learning activities. Furthermore, technical issues such as inconsistent internet access or software compatibility problems can diminish the quality of the teaching and learning experience[7]. As educational technologies continue to evolve, and as pedagogical philosophies shift, blended learning in university English instruction is poised for significant transformation. Future developments will likely incorporate cutting-edge technologies such as artificial intelligence and big data analytics, which can enhance the personalization and overall efficiency of teaching. These advancements will enable instructors to tailor learning experiences to individual student needs while utilizing data-driven insights to improve instructional strategies. Simultaneously, educators and researchers will continue to refine and optimize blended learning models to accommodate the diverse learning preferences of students, ensuring that this approach remains relevant in an ever-changing educational landscape. In conclusion, blended learning is increasingly becoming a central method for improving the quality and efficiency of university English education[8]. Through ongoing experimentation and scholarly research, this educational model is expected to reach its full potential, significantly enriching students' learning experiences in the years to come.

Smarandache [9] introduced neutrosophic sets (NSs), later refined by Wang et al. [10] into single-valued NSs (SVNSs), and further by Wang et al. [11] into interval-valued NSs (IVNSs) for MADM. IVNSs offer significant advantages in handling uncertainty and imprecision. First, IVNSs represent uncertainty through three independent parameters: truth-membership, falsity-membership, and indeterminacy-membership. This allows for a more flexible approach to dealing with complex and ambiguous decision-making environments. Unlike traditional fuzzy sets, IVNSs allow each parameter to be expressed as an interval, which enhances their ability to represent imprecise information. Second, IVNSs can simultaneously handle uncertainty, vagueness, and inconsistency, making them highly adaptable in areas such as multi-attribute decision-making, risk assessment, and complex system analysis. Additionally, by incorporating various neutrosophic logic operations, IVNSs provide flexibility in addressing different levels of subjective factors and objective conditions in the decision-making process. In summary, the primary advantages of IVNSs lie in their ability to comprehensively manage uncertain information and offer stable and reliable decision support in scenarios requiring precise evaluation of complex issues. This makes them particularly valuable in multi-attribute decision-making processes, especially when dealing with fuzziness and uncertainty. The English blended teaching quality evaluation is looked as MADM.

Roubens first presented the ORESTE approach at a conference in 1980, and it was later developed in an essay that same year. When a decision-maker gives an analyst a preliminary ranking of the traits for decision-making, ORESTE is utilized. Additionally, the best option—which has a variety of qualitative and quantitative characteristics—is chosen from the group of options. This method is frequently employed. Features of the ORESTE include It's among the compensatory techniques, Features ought to be autonomous, the qualitative attributes do not have to be transformed into quantitative attributes [12].

This study aims to propose the IVN-ORESTE method under IVNSs and apply it to practical MADM processes. The proposed method enhances decision-making by accommodating uncertainty and providing a more adaptable framework for evaluating alternatives in complex scenarios.

The structure of the remainder of this paper is organized as follows: Section 2 provides an in-depth discussion of IVNSs, explaining their fundamental concepts and applications. Section 3 focuses on the construction of the IVN-ORESTE method specifically for MADM scenarios, highlighting its flexibility and adaptability in complex decision environments. In Section 4, we present a numerical example that applies the IVN-ORESTE method to the evaluation of English blended teaching quality. This section includes a comprehensive case study. Finally, Section 5 concludes the paper, summarizing the key findings and contributions of the study, while also suggesting potential areas for future research and improvement in the application of IVNS-based decision-making techniques.

2. Preliminary

Definitions of NSs for additional computational analysis are presented in this section. In fact, Smarandache (1999) extended the IFS standard interval [0,1] by introducing neturosophic logic and NSs for the first time in literature [13-15].

2.1 Definition 1.

Let X be a space of points and $x \in X$, An NS A in X can be defined as truth $T_A(x)$, an indeterminacy $I_A(x)$, and falsity $F_A(x)$ membership function.

$$0- \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3+ \quad (1)$$

2.2 Definition 2.

We can define some operations of IVNN as:

$$\mu A = \left\{ \begin{array}{c} \left[1-\left(1-T_A^L(x)\right)^{\mu}, 1-\left(1-T_A^U(x)\right)^{\mu}\right], \\ \left[\left(\left(I_A^L(x)\right)^{\mu}, I_A^U(x)\right)^{\mu}\right], \\ \left[\left(\left(F_A^L(x)\right)^{\mu}, F_A^U(x)\right)^{\mu}\right] \end{array} \right\} \quad (2)$$

$$A^{\mu} = \left\{ \begin{array}{c} \left[\left(T_A^L(x)\right)^{\mu}\right], \\ \left[1-\left(1-I_A^L(x)\right)^{\mu}, 1-\left(1-I_A^U(x)\right)^{\mu}\right], \\ \left[1-\left(1-F_A^L(x)\right)^{\mu}, 1-\left(1-F_A^U(x)\right)^{\mu}\right] \end{array} \right\} \quad (3)$$

$$A + B = \left\{ \begin{array}{c} [T_A^L(x) + T_B^L(x) - T_A^L(x)T_B^L(x), T_A^U(x) + T_B^U(x) - T_A^U(x)T_B^U(x)], \\ [I_A^L(x)I_B^L(x), I_A^U(x)I_B^U(x)], \\ [F_A^L(x)F_B^L(x), F_A^U(x)F_B^U(x)] \end{array} \right\} \quad (4)$$

$$A - B = \left\{ \begin{array}{c} [T_A^L(x) - T_B^L(x), T_A^U(x) - T_B^U(x)], \\ \left[\max\left(I_A^L(x), I_B^L(x)\right), \max\left(I_A^U(x), I_B^U(x)\right)\right], \\ \left[\max\left(F_A^L(x), F_B^L(x)\right), \max\left(F_A^U(x), F_B^U(x)\right)\right] \end{array} \right\} \quad (5)$$

$$A + B = \left\{ \begin{array}{c} [T_A^L(x)T_B^L(x), T_A^U(x)T_B^U(x)], \\ [I_A^L(x) + I_B^L(x) - I_A^L(x)I_B^L(x), I_A^U(x) + I_B^U(x) - I_A^U(x)I_B^U(x)], \\ [F_A^L(x) + F_B^L(x) - F_A^L(x)F_B^L(x), F_A^U(x) + F_B^U(x) - F_A^U(x)F_B^U(x)] \end{array} \right\} \quad (6)$$

$$\frac{A}{B} = \left\{ \begin{array}{c} \left[\min\left\{\frac{T_A^L(x)}{T_B^L(x)}, \frac{T_A^L(x)}{T_B^U(x)}, \frac{T_A^U(x)}{T_B^L(x)}, \frac{T_A^U(x)}{T_B^U(x)}\right\}, \max\left\{\frac{T_A^L(x)}{T_B^L(x)}, \frac{T_A^L(x)}{T_B^U(x)}, \frac{T_A^U(x)}{T_B^L(x)}, \frac{T_A^U(x)}{T_B^U(x)}\right\}\right], \\ \min\left\{\frac{I_A^L(x)}{I_B^L(x)}, \frac{I_A^L(x)}{I_B^U(x)}, \frac{I_A^U(x)}{I_B^L(x)}, \frac{I_A^U(x)}{I_B^U(x)}\right\}, \max\left\{\frac{I_A^L(x)}{I_B^L(x)}, \frac{I_A^L(x)}{I_B^U(x)}, \frac{I_A^U(x)}{I_B^L(x)}, \frac{I_A^U(x)}{I_B^U(x)}\right\}, \\ \min\left\{\frac{F_A^L(x)}{F_B^L(x)}, \frac{F_A^L(x)}{F_B^U(x)}, \frac{F_A^U(x)}{F_B^L(x)}, \frac{F_A^U(x)}{F_B^U(x)}\right\}, \max\left\{\frac{F_A^L(x)}{F_B^L(x)}, \frac{F_A^L(x)}{F_B^U(x)}, \frac{F_A^U(x)}{F_B^L(x)}, \frac{F_A^U(x)}{F_B^U(x)}\right\} \end{array} \right\} \quad (7)$$

$$A^{-1} = \begin{Bmatrix} \left[\left(T_A^L(x)\right)^{-1}, \left(T_A^U(x)\right)^{-1}\right], \\ \left[\left(I_A^L(x)\right)^{-1}, \left(I_A^U(x)\right)^{-1}\right], \\ \left[\left(F_A^L(x)\right)^{-1}, \left(F_A^U(x)\right)^{-1}\right] \end{Bmatrix} \quad (8)$$

$$\frac{A}{\mu} = \begin{Bmatrix} \left[\min\left(\frac{T_A^L(x)}{\mu}, 1\right), \min\left(\frac{T_A^U(x)}{\mu}, 1\right)\right], \\ \left[\min\left(\frac{I_A^L(x)}{\mu}, 1\right), \min\left(\frac{I_A^U(x)}{\mu}, 1\right)\right], \\ \left[\min\left(\frac{F_A^L(x)}{\mu}, 1\right), \min\left(\frac{F_A^U(x)}{\mu}, 1\right)\right] \end{Bmatrix} \quad (9)$$

3. MADM approach

This section shows the steps of the IVNN-ORESTE for ranking the alternatives [16-17].

Step 1. Build the decision matrix

The decision matrix is built based on the opinions of experts and decision makers.

$$T = \begin{pmatrix} t_{11} & \cdots & t_{1n} \\ \vdots & \ddots & \vdots \\ t_{m1} & \cdots & t_{mn} \end{pmatrix} \quad (10)$$

Step 2. We used the IVNN to evaluate the criteria and alternatives.

Step 3. Apply the score function.

The score function is applied to obtain crisp values.

Step 4. Combine the decision matrix.

Step 5. Compute the criteria weights.

The criteria weights are computed using the average method.

Step 6. Obtain the position matrix.

The position matrix is obtained by ranking the alternatives based on the decision matrix and criteria.

Step 7. Obtain the block distance of each alternative.

$$d(0, A_{ij}) = \gamma t_{ij}(\gamma) + (1-\gamma)t_j \quad (11)$$

Where $0 < \gamma < 1$

Step 8. Compute the block distance of each alternative in the position matrix is computed to build the block distance matrix.

Step 9. Rank the alternatives.

The alternatives are ranked based on:

$$d(0, A_{ij}) \le d(0, A_{i \cdot j}), R(A_{ij}) \le R(A_{ij}) \le R(A_{i \cdot j}) \quad (12)$$

The total rank of alternatives is:

$$R(A_i) = \sum_{j=1}^{n} R(A_{ij}) \quad (13)$$

4. Case and comparative study

The evaluation of blended English language teaching quality in universities spans several key dimensions, including course content, instructional methods, student engagement, and the integration of technology. At the heart of this assessment lies the development of course content, which plays a critical role in the effectiveness of blended learning environments. An ideal blended teaching approach seamlessly merges online and in-person components, ensuring that both complement each other rather than replicate content. Typically, online components involve video lectures, discussion forums, and digital resources that support self-paced learning outside the traditional classroom. Educators must carefully design these online materials, tailoring them to the specific needs of the digital environment rather than simply duplicating classroom content. For example, video lectures should be concise, information-rich, and crafted to engage learners with shorter attention spans typically found in online settings. Innovative teaching methodologies are also essential for enhancing the quality of blended learning. Instructors are encouraged to adopt dynamic, participatory activities that foster deeper student engagement. Virtual group discussions, live Q&A sessions, and other interactive elements can significantly boost student motivation and participation. Additionally, the use of technology to provide immediate feedback on student performance is crucial. Timely feedback not only helps students gauge their progress but also enables them to adjust their learning strategies in real-time, thus enhancing educational outcomes. Student engagement, another vital indicator of blended learning quality, is often a reflection of teaching effectiveness. High levels of engagement suggest that students are actively involved and able to learn autonomously. To promote engagement, educators can design tasks that are both relevant and suitably challenging, as well as offer personalized learning paths that cater to individual student needs. Continuous adjustment of teaching methods, based on student feedback and learning data, is also essential for maintaining high engagement levels and improving overall teaching quality. The application of technology is another cornerstone of successful blended learning. Learning Management Systems (LMS), interactive tools, and a variety of online resources can significantly improve teaching quality and student outcomes. To maximize the benefits of these technologies, schools should ensure that they are user-friendly and accessible. Furthermore, teachers should receive adequate technical training to effectively incorporate these tools into their teaching practices. Finally, structured assessment and feedback mechanisms are crucial for maintaining and improving the quality of blended teaching. A systematic approach to assessment should be established to monitor both the teaching process and learning outcomes. Regular feedback from students and educators should be gathered, focusing not only on academic performance but also on the overall learning experience. This feedback helps refine teaching content, course design, and instructional methods. In conclusion, the quality of blended English teaching in universities is a multi-dimensional evaluation system. It encompasses course content, teaching methods, student engagement, the effective use of technology, and ongoing assessment and feedback. By continuously optimizing these aspects, educators can significantly improve teaching effectiveness, ensuring students achieve their best possible learning outcomes. The evaluation of blended teaching quality constitutes a MADM process. Ten possible English Colleges are evaluated through 14 attributes:

1. Teaching Effectiveness

- The ability of the blended teaching approach to improve student learning outcomes, comprehension, and language proficiency.

2. Student Engagement

- The extent to which students are actively involved and participate in both online and in-class activities.

3. Curriculum Design

- The alignment of course content, learning objectives, and assessment methods with the blended learning model.

4. Technology Integration

- The seamless and effective use of digital tools and platforms to support teaching and learning.

5. Assessment of Quality

- The ability of assessments (formative and summative) to measure learning outcomes accurately and provide meaningful feedback.

6. Teacher Competence

- The skills and preparedness of instructors to deliver blended teaching effectively, including their ability to use technology and manage hybrid classrooms.

7. Resource Availability

- Accessibility and quality of instructional materials, such as videos, slides, e-books, and online exercises.

8. Student Satisfaction

- Perceptions of students regarding the quality of teaching, course structure, and overall learning experience.

9. Flexibility

- The degree to which the blended teaching model accommodates different learning paces, styles, and schedules.

10. Interaction Quality

- The effectiveness of interactions between students and teachers, as well as peer-to-peer communication in online and offline settings.

11. Feedback Mechanism

- Timeliness, quality, and relevance of feedback provided to students on their performance.

12. Technological Accessibility

- Availability and ease of use of technological tools and platforms for students and teachers, including access to reliable internet.

13. Innovation in Pedagogy

- Implementation of innovative teaching methods such as gamification, flipped classrooms, and collaborative projects.

14. Monitoring and Evaluation

- Systems in place to regularly monitor and evaluate the effectiveness of the blended teaching approach and make data-driven improvements.

The IVNN-ORESTE method is illustrated for evaluation of blended teaching quality under IVNSs.

Step 1. Eq. (10) is used to build the decision matrix. Three experts are building the decision matrix using the IVNN as shown in Table 1. The decision matrix is built between 14 criteria and ten alternatives.

Step 2. Set of IVNN are used for building the decision matrix.

Step 3. The score function was applied to convert the IVNN into single number.

Step 4. The mean method was used to combine three decision matrices into one.

Step 5. The criteria weights are computed as shown in Figure 1.

We show the Teaching Effectiveness criterion has the highest weight equal to 0.07762, followed by the Student Engagement with weight equal to 0.07609, and Curriculum Design criterion with weight equal to 0.0749. we show the Monitoring and Evaluation has the lowest weight.

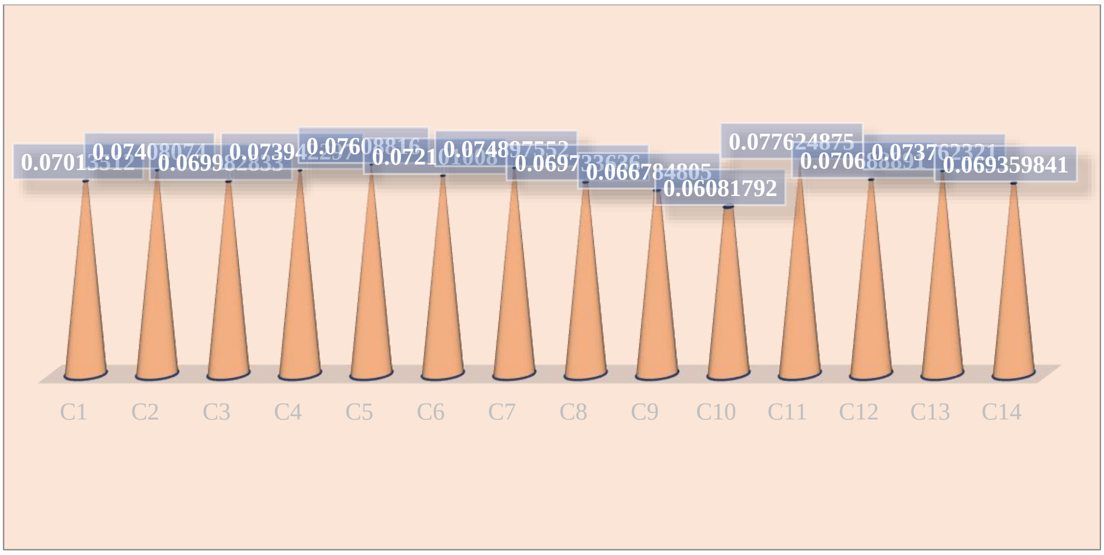

Figure 1. The criteria weights.

Table 1. The 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}	C_{13}	C_{14}
A_1	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])
A_2	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])
A_3	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.6,0.7],[0.4,0.5],[0.3,0.4])
A_4	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.7,0.8],[0.2,0.3],[0.2,0.3])
A_5	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.8,0.9],[0.1,0.2],[0.1,0.2])
A_6	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.1,0.2],[0.1,0.2],[0.8,0.9])
A_7	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.2,0.3],[0.3,0.4],[0.7,0.8])
A_8	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])
A_9	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.4,0.5],[0.5,0.6],[0.5,0.6])
A_{10}	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])
	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}	C_{14}
A_1	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])
A_2	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])
A_3	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.5,0.5],[0.6,0.7],[0.4,0.5])
A_4	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.3,0.4],[0.4,0.5],[0.6,0.7])
A_5	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])
A_6	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])
A_7	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])
A_8	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])
A_9	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.2,0.3],[0.3,0.4],[0.7,0.8])
A_{10}	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])
	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}	C_{14}
A_1	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.5],[0.6,0.7],[0.4,0.5])
A_2	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.4,0.5],[0.5,0.6],[0.5,0.6])
A_3	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])
A_4	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])
A_5	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])
A_6	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])
A_7	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.2,0.3],[0.3,0.4],[0.7,0.8])
A_8	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.1,0.2],[0.1,0.2],[0.8,0.9])
A_9	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.4,0.5],[0.5,0.6],[0.5,0.6])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.2,0.3],[0.3,0.4],[0.7,0.8])
A_{10}	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.5,0.5],[0.6,0.7],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.3,0.4],[0.4,0.5],[0.6,0.7])	([0.2,0.3],[0.3,0.4],[0.7,0.8])	([0.1,0.2],[0.1,0.2],[0.8,0.9])	([0.8,0.9],[0.1,0.2],[0.1,0.2])	([0.7,0.8],[0.2,0.3],[0.2,0.3])	([0.6,0.7],[0.4,0.5],[0.3,0.4])	([0.5,0.6],[0.5,0.6],[0.4,0.5])	([0.3,0.4],[0.4,0.5],[0.6,0.7])

Step 6. We obtained the position matrix.

Step 7. Then we obtain the block distance of each alternative using Eq. (11).

Step 8. Then we computed the block distance of each alternative in the position matrix is computed to build the block distance matrix.

Step 9. Then we ranked the alternatives using Eq. (13) as shown in Figure 2. We show the alternative 5 is the best and alternative 8 is the worst.

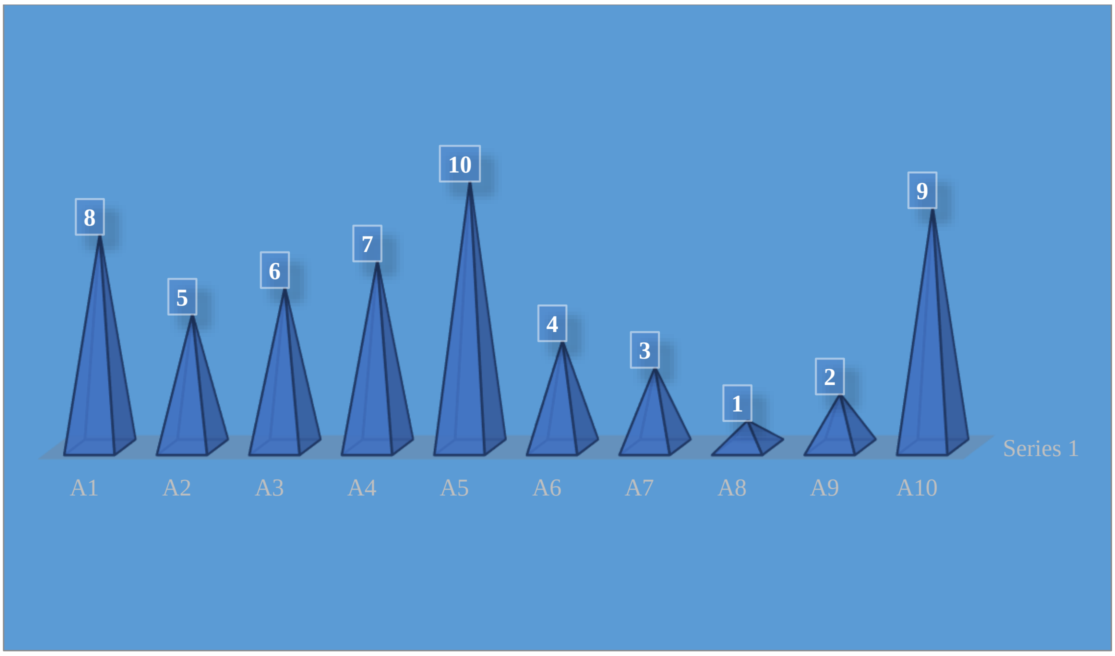

Figure 2. The rank of alternatives.

4.1. Comparative study

Then, the IVN- ORESTE approach is compared with INN-VIKOR approach [18], INN-CODAS approach[19], INN-EDAS approach [20] and INN-TODIM approach [21]. The comparative results are conducted in Figure 3.

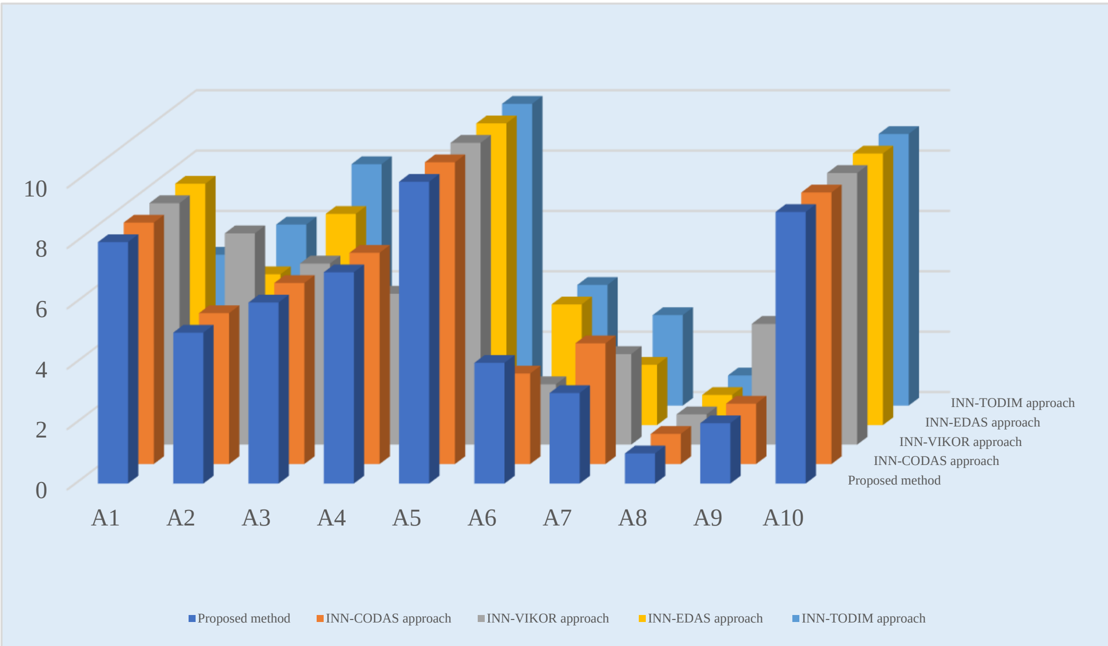

Figure 3. The comparative analysis.

In accordance with correlation coefficients information between the INN-VIKOR approach

[18], INN-CODAS approach[19], INN-EDAS approach [20], INN-TODIM approach [21] is 0.90303, 987879, 975758, 915152,, respectively. Compared the final results of IVN- ORESTE approach with INN-VIKOR approach [18], INN-CODAS approach[19], INN-EDAS approach [20], INN-TODIM approach [21], the illustrated results are slightly different and the illustrated best college and worst college is same. This validation confirms that the IVN-ORESTE method is both reasonable and effective. The primary advantages of the proposed IVN- ORESTE approach are: (1) criteria are independent; (2) It is no need to change the qualitative criteria into quantitative criteria. Moreover, the IVN-ORESTE allows decision-makers the flexibility to adjust parameters based on personal preferences, risk tolerance, and other subjective considerations. This adaptability enables decision-makers to tailor the decision-making process to better align with their specific needs and satisfaction. As a result, the method provides a more personalized and context-sensitive approach to decision-making, ensuring that the final ranking reflects the unique priorities of the decision maker. Overall, the IVN-ORESTE method offers a robust framework for decision-making, combining analytical rigor with flexibility, making it highly suitable for complex MADM situations where both objectivity and subjective preferences need to be considered.

5. Conclusion

Blended English teaching at the university level integrates traditional classroom instruction with digital learning platforms, creating a dynamic and flexible educational model. This approach leverages a variety of educational resources and technological tools to enhance both the efficiency and quality of instruction. Through online learning, students can access course materials at any time and from any location, which significantly increases the flexibility of the learning process. This not only fosters independent learning but also allows students to pace their studies according to individual needs and schedules. At the same time, offline classroom teaching remains essential for fostering direct teacher-student interaction. In-person discussions and activities help deepen students' understanding of complex concepts, reinforce knowledge, and provide immediate feedback. The blended teaching model is particularly well-suited for language learning, as it combines the benefits of autonomous learning with those of interactive communication. For example, students can engage in language exercises, quizzes, and simulation tests via online platforms, while face-to-face sessions enhance their speaking and listening skills through active participation and real-time interaction. Moreover, this hybrid model also helps students develop digital literacy and adaptability, essential skills in today's technology-driven work environments. By navigating between online and offline modes of learning, students are better prepared for the demands of modern professional settings, where digital competence is increasingly important. Blended learning thus not only improves academic outcomes but also equips students with practical skills for their future careers. In evaluating the quality of blended English teaching, MADM techniques are employed. In this study, we ORESTE method to IVNSs and introduce the IVN-ORESTE, specifically designed for MADM applications. An illustrative example is provided to demonstrate the evaluation of English blended teaching quality using this method.

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