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From Data to Decisions based on AI-Driven Insights: Intelligent Evaluation of English Translation Pedagogy in Higher Education under Interval Complex Neutrosophic Set

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Abstract: In the wake of rapid technological advancements, higher education institutions are increasingly exploring artificial intelligence (AI) for enhanced language pedagogy. This study delves into the intelligent evaluation of English translation teaching, leveraging AI-driven tools to provide real-time feedback, identify errors, and personalize instruction. Through a carefully structured Multi-Criteria Decision-Making (MCDM) model, we assess six innovative AI-powered alternatives using eight pedagogically relevant criteria. The goal is to identify the most effective solution that aligns with curricular standards and improves learning outcomes. The research aims to bridge data-driven technologies with humanistic language instruction. We use the interval complex neutrosophic set (ICNS) to deal with uncertainty and vague information. The ARAS method is used under the ICNS to rank the alternatives. The application is provided to show the validation of the proposed approach.

Keywords: Artificial Intelligence; Interval Complex Neutrosophic Set; English Translation; Higher Education.

1. Introduction

The integration of artificial intelligence into university English translation instruction is reshaping how teaching quality is assessed. Traditional assessment methods, though valuable, often lack scalability and real-time responsiveness, which are essential in addressing the individual learning trajectories of diverse students. AI, with its vast data-processing capability, presents a promising alternative for dynamic teaching evaluation[1], [2]. In translation courses, the need for nuanced feedback goes beyond grammatical correctness—it demands cultural sensitivity, contextual awareness, and semantic clarity. AI models, particularly those based on natural language processing (NLP), are now being designed to fulfill these complex needs, offering data-driven assessments that mimic human expertise[3], [4]. One major challenge, however, lies in defining the right indicators to measure AI's effectiveness in a pedagogical context. Metrics such as semantic accuracy, adaptability, and engagement levels are pivotal for understanding AI's true value in translation teaching. This study introduces a structured evaluation framework using MCDM techniques to weigh various AI tools against these educationally significant criteria. Moreover, the analysis captures the practical implications of AI deployment in the classroom. By measuring not just the outcomes but also the adaptability and pedagogical alignment of these tools, we ensure that the evaluation process is both holistic and aligned with institutional goals[5].

Student engagement is also a critical component, as AI systems are only effective when they can stimulate active learning. The Student Engagement Index included in the framework allows us to assess the motivational impact of each AI tool, providing a balanced perspective that considers both cognitive and affective factors in learning[6], [7]. Ultimately, the methodology seeks to ensure that AI doesn't just automate teaching evaluation but enriches it. By connecting intelligent systems with educational theory, the research contributes to a more personalized, responsive, and effective translation learning environment[8], [9].

As a generalization of the classical set, fuzzy set, and intuitionistic fuzzy set, Smarandache presented the Neutrosophic Set (NS). While the intuitionistic fuzzy set and fuzzy set do not function when the relations are uncertain, the neutrosophic set manages indeterminate data[10], [11]. Numerous domains, including decision-making issues, have effectively employed neutrophilic sets. Smarandache and Wang et al. introduced the idea of a single-valued neutrosophic set and gave its theoretical operations and properties since the neutrosophic set is hard to utilize directly in practical applications. However, in many real-world situations, interval forms—rather than actual numbers—may be a more appropriate way to display the degrees of truth, falsity, and indeterminacy of a given assertion[12], [13]. The Interval Neutrosophic Set (INS), which is defined by the degrees of truth, falsity, and indeterminacy whose values are intervals rather than real numbers, was presented by Wang et al. as a solution to this problem.[14], [15]

To better design and model real-life applications, recent NS and INS studies have focused on creating systems with complicated fuzzy sets. The "complex" feature allows for the simultaneous processing of periodicity and uncertainty information. A complex neutrosophic set (CNS), an extension form of both complex fuzzy and complex intuitionistic fuzzy sets, was proposed by Ali and Smarandache[16]. The redundant nature of uncertainty, incompleteness, indeterminacy, inconsistency, etc., in periodic data may be handled by the complicated neutrosophic set. The CNS has an advantage over the NS in that it gives the phase, an attribute degree that characterizes the amplitude, in addition to the membership degree that the NS provides and that is represented in the CNS by amplitude[17], [18].

2. Basic Concept

This section shows the basic concepts of the Interval Complex Neutrosophic Set (ICNS) and their operations[19], [20].

The ICNS has three membership values such as $T_{S^-}, I_{S^-}, and\ F_{S^-}$

$$T_{S^-}: X \to T^{[0,1]} \times R, T_{S^-} = t_{S^-}(x) \cdot e^{j\alpha w_{S^-}(x)} \tag{1}$$

$$I_{S^-}: X \to T^{[0,1]} \times R, I_{S^-} = i_{S^-}(x) \cdot e^{j\beta \theta_{S^-}(x)} \tag{2}$$

$$F_{S^-}: X \to T^{[0,1]} \times R, F_{S^-} = f_{S^-}(x) \cdot e^{j\gamma \vartheta_{S^-}(x)} \tag{3}$$

$T^{[0,1]}$ presents the set of intervals Neutrosophic, R is a real number.

$$S^- = \left\{ \left(\frac{\begin{matrix} T_{S^-}(x) = t_{S^-}(x) \cdot e^{j\alpha w_{S^-}(x)}, \\ I_{S^-}(x) = i_{S^-}(x) \cdot e^{j\beta \theta_{S^-}(x)}, \\ F_{S^-}(x) = f_{S^-}(x) \cdot e^{j\gamma \vartheta_{S^-}(x)} \end{matrix}}{x} \right); x \in X \right\} \tag{4}$$

Let two intervals complex Neutrosophic set such as:

$$T_{A^-}(x) = t_{A^-}(x) \cdot e^{j\alpha w_{A^-}(x)}, I_{A^-}(x) = i_{A^-}(x) \cdot e^{j\beta \theta_{A^-}(x)}, F_{A^-}(x) = f_{A^-}(x) \cdot e^{j\gamma \vartheta_{A^-}(x)} \tag{5}$$

$$T_{B^-}(x) = t_{B^-}(x) \cdot e^{j\alpha w_{B^-}(x)}, I_{B^-}(x) = i_{B^-}(x) \cdot e^{j\beta \theta_{B^-}(x)}, F_{B^-}(x) = f_{B^-}(x) \cdot e^{j\gamma \vartheta_{B^-}(x)} \tag{6}$$

The union of A and B is

$$T_{A^- \cup B^-}(x) = [\inf t_{A^- \cup B^-}(x), \sup t_{A^- \cup B^-}(x)] \cdot e^{j\pi w_{A^- \cup B^-}(x)} \tag{7}$$

$$I_{A^- \cup B^-}(x) = [\inf i_{A^- \cup B^-}(x), \sup i_{A^- \cup B^-}(x)] \cdot e^{j\pi \theta_{A^- \cup B^-}(x)} \tag{8}$$

$$F_{A^- \cup B^-}(x) = [\inf f_{A^- \cup B^-}(x), \sup f_{A^- \cup B^-}(x)] \cdot e^{j\pi \vartheta_{A^- \cup B^-}(x)} \tag{9}$$

$$\inf t_{A^- \cup B^-}(x) = \vee(\inf t_{A^-}(x), \inf t_{B^-}(x)) \tag{10}$$

$$\sup t_{A^- \cup B^-}(x) = \vee(\sup t_{A^-}(x), \sup t_{B^-}(x)) \tag{11}$$

$$\inf i_{A^- \cup B^-}(x) = \wedge(\inf i_{A^-}(x), \inf i_{B^-}(x)) \tag{12}$$

$$\sup i_{A^- \cup B^-}(x) = \wedge(\sup i_{A^-}(x), \sup i_{B^-}(x)) \tag{13}$$

$$\inf f_{A^- \cup B^-}(x) = \wedge(\inf f_{A^-}(x), \inf f_{B^-}(x)) \tag{14}$$

$$\sup f_{A^- \cup B^-}(x) = \wedge(\sup f_{A^-}(x), \sup f_{B^-}(x)) \tag{15}$$

The intersection of A and B is

$$T_{A^- \cap B^-}(x) = [\inf t_{A^- \cap B^-}(x), \sup t_{A^- \cap B^-}(x)] \cdot e^{j\pi w_{A^- \cap B^-}(x)} \tag{16}$$

$$I_{A^- \cap B^-}(x) = [\inf i_{A^- \cap B^-}(x), \sup i_{A^- \cap B^-}(x)] \cdot e^{j\pi \theta_{A^- \cap B^-}(x)} \tag{17}$$

$$F_{A^- \cap B^-}(x) = [\inf f_{A^- \cap B^-}(x), \sup f_{A^- \cap B^-}(x)] \cdot e^{j\pi\vartheta_{A^- \cap B^-}(x)} \quad (18)$$

$$\inf t_{A^- \cap B^-}(x) = \wedge(\inf t_{A^-}(x), \inf t_{B^-}(x)) \quad (19)$$

$$\sup t_{A^- \cap B^-}(x) = \wedge(\sup t_{A^-}(x), \sup t_{B^-}(x)) \quad (20)$$

$$\inf i_{A^- \cap B^-}(x) = \vee(\inf i_{A^-}(x), \inf i_{B^-}(x)) \quad (21)$$

$$\sup i_{A^- \cap B^-}(x) = \vee(\sup i_{A^-}(x), \sup i_{B^-}(x)) \quad (22)$$

$$\inf f_{A^- \cap B^-}(x) = \vee(\inf f_{A^-}(x), \inf f_{B^-}(x)) \quad (23)$$

$$\sup f_{A^- \cap B^-}(x) = \vee(\sup f_{A^-}(x), \sup f_{B^-}(x)) \quad (24)$$

We show the steps of the ARAS method under the ICNS. Experts create the decision matrix using ICNS. These numbers are converted to crisp values. And then combined into a single matrix. The weights of criteria are computed using the average method.

The assessment matrix is normalized as:

$$q_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \quad (25)$$

The weighted assessment matrix is computed as:

$$u_{ij} = q_{ij} w_j \quad (26)$$

Obtain the optimality function

$$O_i = \sum_{j=1}^{n} u_{ij} \quad (27)$$

Obtain the utility degree

$$R_i = \frac{O_i}{Z_o} \quad (28)$$

Z_o presents to the optimality value of R_i

3. Results

This paper shows the results of the proposed approach by presenting the criteria weights and ranking the alternatives. This study uses eight criteria and six alternatives as in Fig 1.

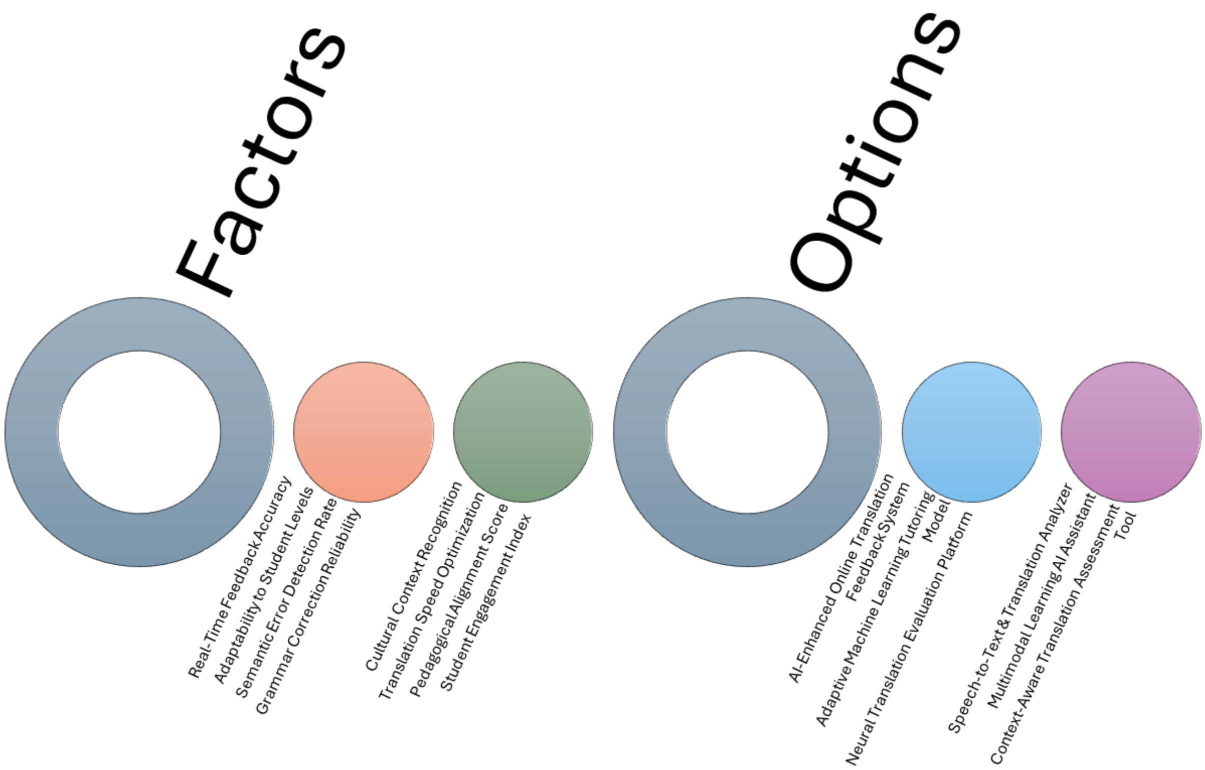

Fig 1. Factors and options.

Four experts created the decision matrix using the ICNS as shown in Tables 1-3. The decision matrices are combined into a single matrix as in Fig 3. Then we obtain the criteria weights as in Fig 4.

Table 1. The first ICNS.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_7
A_1	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])

A_2	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])
A_3	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)
A_4	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])
A_5	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])
A_6	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])

Table 2. The second ICNS.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_7
A_1	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])
A_2	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])
A_3	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.7, 0.8]ejπ$^{[1.1,1.2]}$, [0.2, 0.3]ejπ$^{[0.8,0.9]}$, [0.1, 0.2]ejπ$^{[0.6,0.7]}$)
A_4	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])

A5	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)
A6	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])

Table 3. The third ICNS.

	C1	C2	C3	C4	C5	C6	C7	C7
A1	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])
A2	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])
A3	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)
A4	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])
A5	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])
A6	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])

Table 4. The fourth ICNS.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_7
A_1	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])
A_2	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.6, 0.7]EJΠ[0.9,1.0], [0.4, 0.5]EJΠ[0.9,1.0], [0.3, 0.4]EJΠ[0.7,0.8])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])
A_3	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])
A_4	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)	([0.4, 0.5]EJΠ[0.8,0.9], [0.5, 0.6]EJΠ[0.9,1.0],[0.4, 0.5]EJΠ[0.8,0.9])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)	([0.7, 0.8]ej$\pi^{[1.1,1.2]}$, [0.2, 0.3]ej$\pi^{[0.8,0.9]}$, [0.1, 0.2]ej$\pi^{[0.6,0.7]}$)
A_5	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])
A_6	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])	([0.1, 0.2]EJΠ[0.7,0.8], [0.7, 0.8]EJΠ[0.9,1.0], [0.6, 0.7]EJΠ[1.0,1.1])	([0.3, 0.4]EJΠ[0.8,0.9], [0.6, 0.7]EJΠ[1.0,1.1], [0.5, 0.6]EJΠ[0.9,1.0])

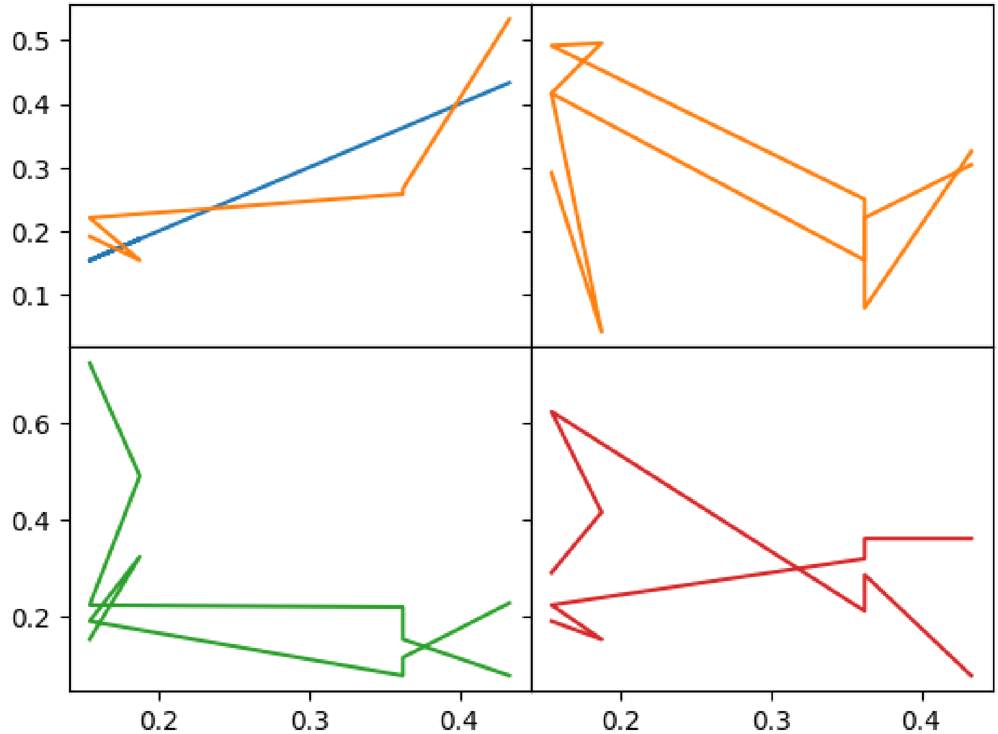

Fig 3. The aggregated decision matrix.

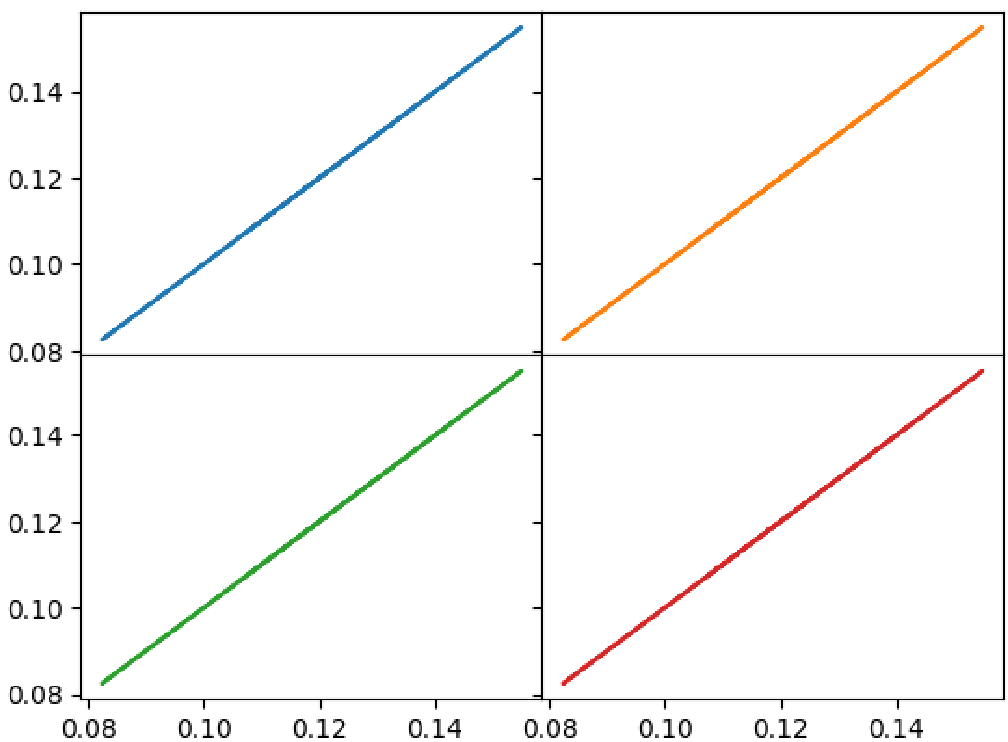

Fig 4. The factors are important.

The assessment matrix is normalized using eq. (25) as in Fig 5.

The weighted assessment matrix is computed using eq. (26) as in Fig 6.

Obtain the optimality function using eq. (27) as in Fig 7.

Obtain the utility degree using eq. (28) as in Fig 8.

Rank the alternatives as in Fig 9.

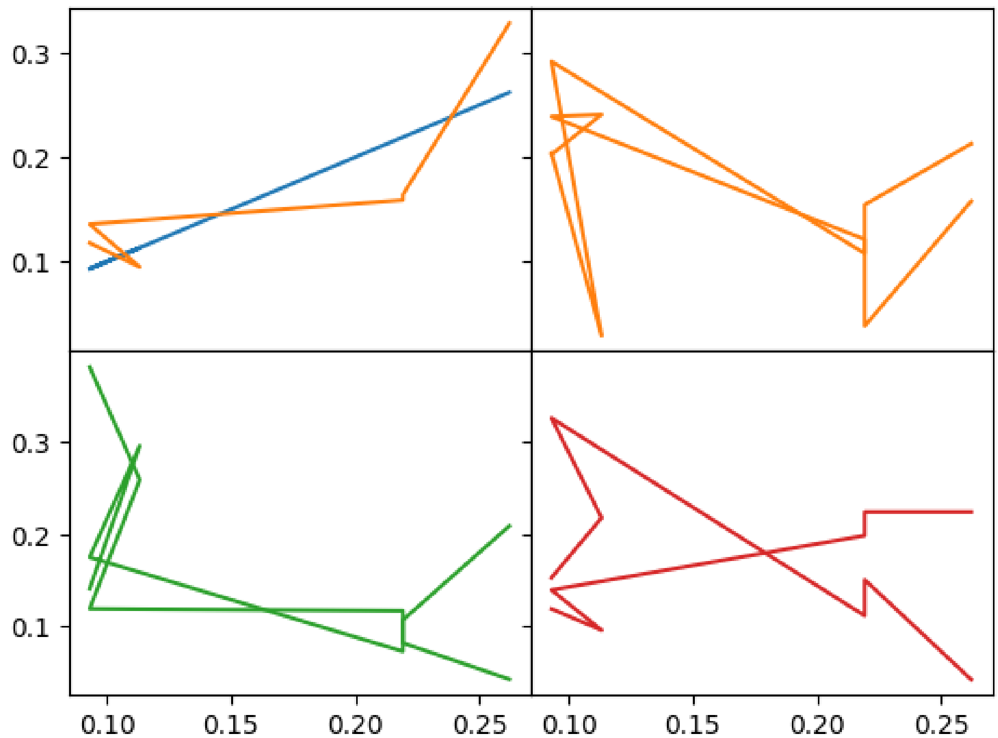

Fig 5. The normalized decision matrix.

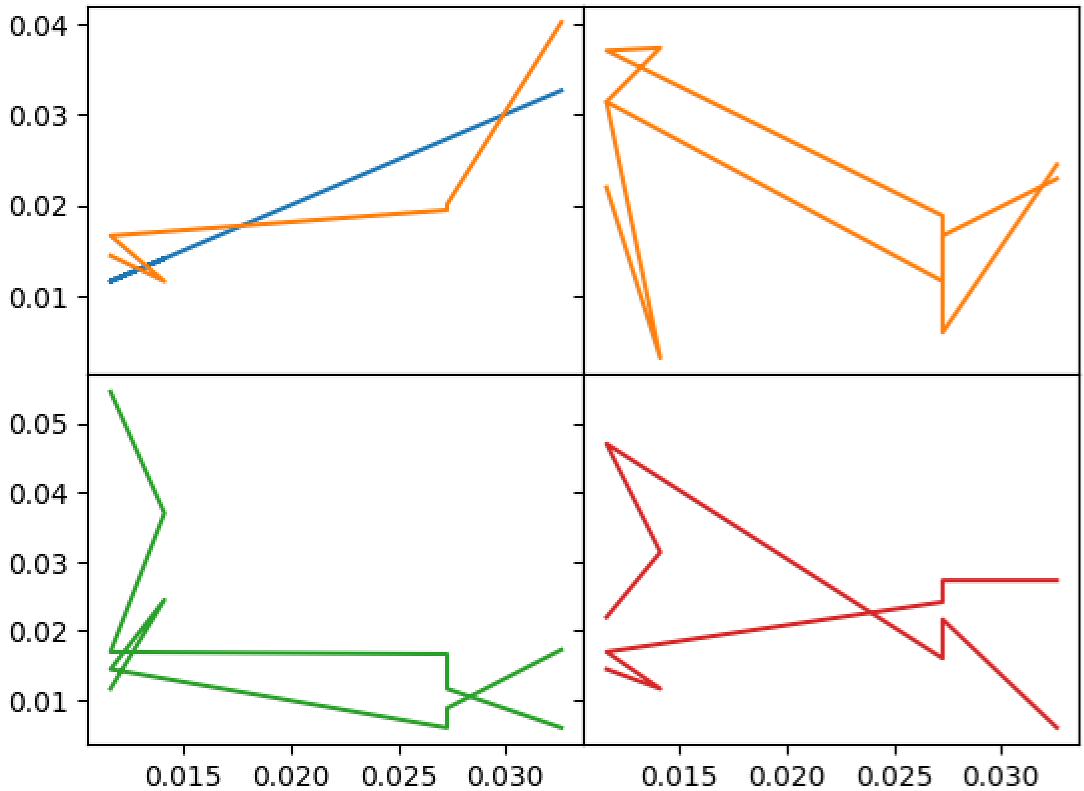

Fig 6. The weighted assessment matrix.

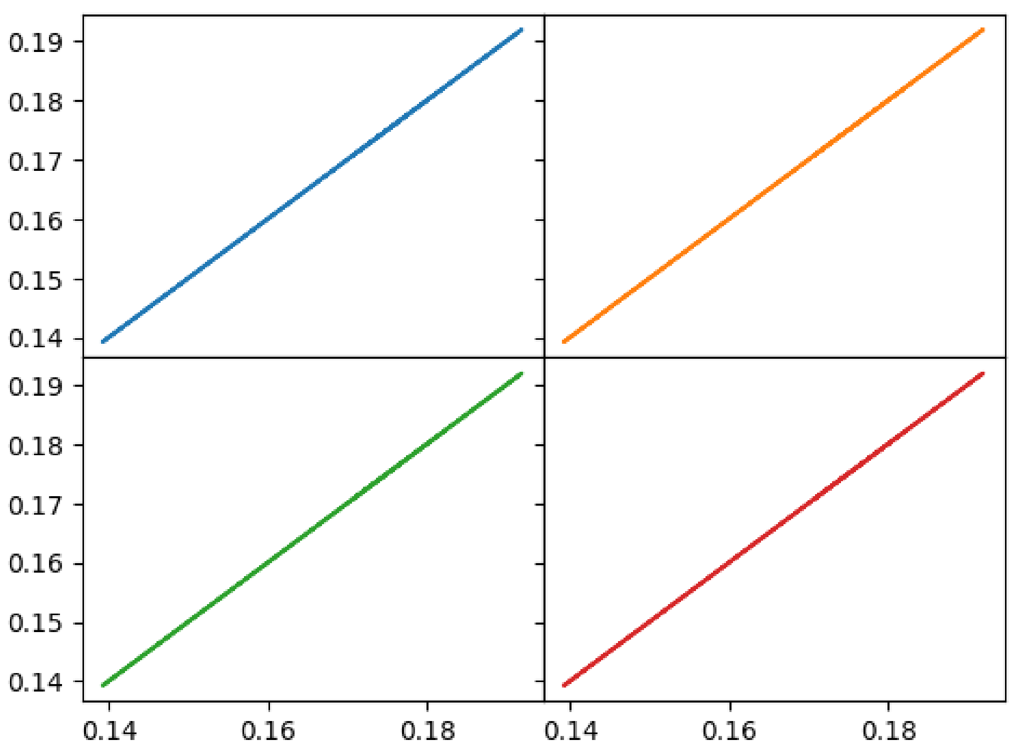

Fig 7. The optimality function.

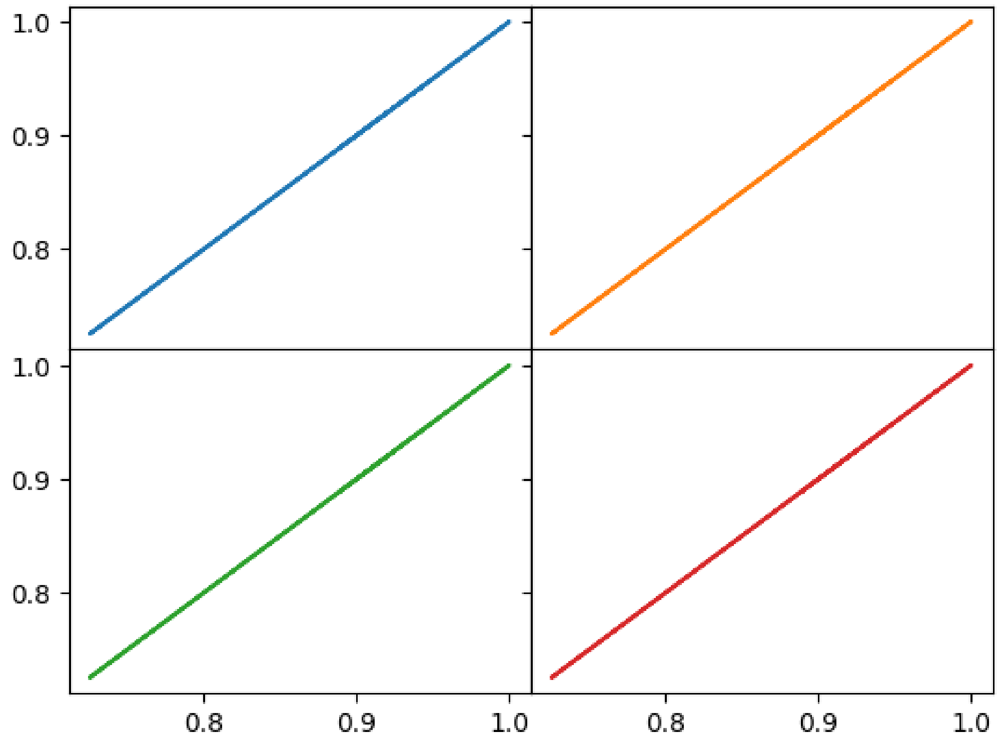

Fig 8. The utility degree.

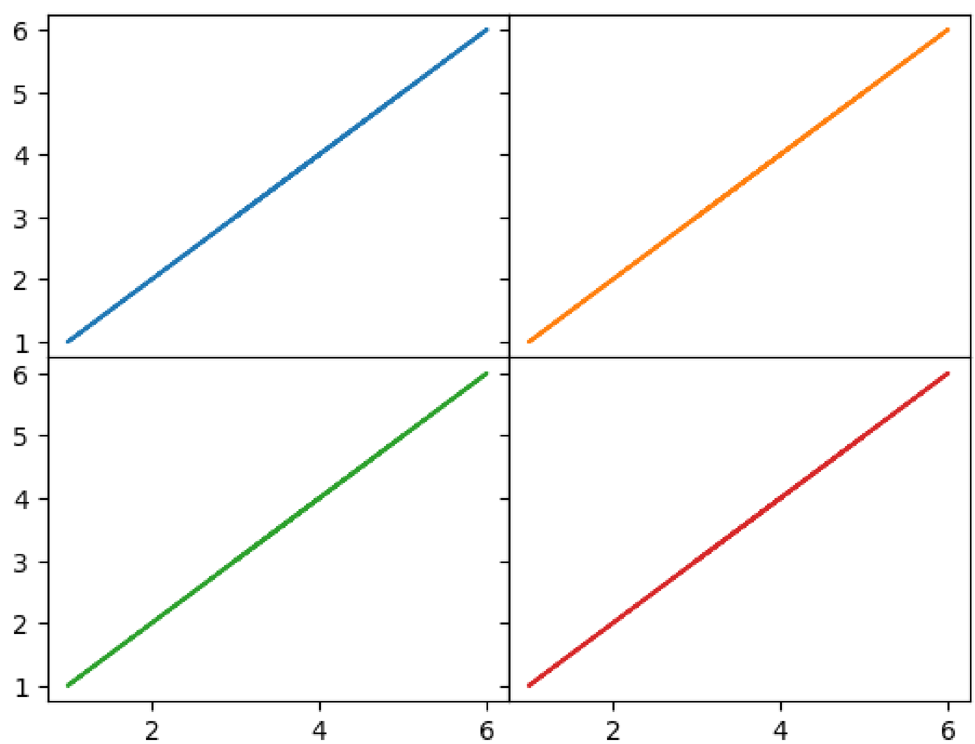

Fig 9. The rank of options.

Comparison between the proposed approach and other methods

This section compares the ARAS method with other MCDM methods such as TOPSIS, VIKOR, and MABAC methods. We show the core definitions of these methods, advantages and disadvantages.

ARAS method Ranks alternatives by comparing the normalized performance of each to an ideal (best possible) alternative.

- Normalize the decision matrix.
- Compute the weighted decision matrix.
- Determine the optimal alternative (ideal solution).
- Compute the utility degree of each alternative compared to the ideal.
- Rank the alternatives based on the highest utility scores.

Advantages:

- Simple, linear, and transparent.
- Consider the ideal solution.
- Easy to interpret and implement.

Disadvantages:

- Assumes additive utility, which may oversimplify some decision problems.
- Less sensitive to small changes in data compared to others like VIKOR.

TOPSIS: An alternative is better if it is closest to the ideal solution and farthest from the negative-ideal solution.

Steps:

- Normalize the decision matrix.
- Compute the weighted decision matrix.
- Determine ideal (best) and negative-ideal (worst) solutions.
- Calculate distances from both ideal and non-ideal solutions.
- Compute relative closeness.
- Rank alternatives based on the highest value in the closeness scores.

Advantages:

- Use the best and worst solutions.
- Widely used in MCDM issues.

Disadvantages:

- Rely heavily on Euclidean distance.
- Assuming criteria are independent.
- Sensitive to normalization methods.

VIKOR: Focuses on ranking and selecting from alternatives based on closeness to the ideal and a compromise solution between maximum group utility and individual regret.

Steps:

- Normalize the decision matrix.
- Identify best and worst values for each criterion.
- Compute the S and R indexes
- Compute the score value of each alternative.
- The alternatives are ranked based on the lowest score value.

Advantages:

- Dealing with decision-making under conflict.
- Balances group utility and individual regret.
- Suitable for complex problems where compromise is needed.

Disadvantages:

- More complex to compute.
- Requires assumptions about decision strategy (compromise vs ideal).
- Sensitive to score value calculation weights.

MABAC: Assesses alternatives based on their distance from a border approximation area (i.e., a reference region derived from weighted attribute values).

Steps:

- Normalize and compute the weighted the decision matrix.
- Construct a border approximation area.
- Calculate distance of each alternative from the border.
- Rank the alternatives based on the alternative score.

Advantages:

- Handles benefit and cost criteria well.
- Offers stable ranking results.

Disadvantages:

- Less widely known or used compared to TOPSIS/VIKOR.
- Interpretation can be more technical.
- Sensitivity to criteria weighting.

4. Conclusions

This study offers a novel framework for evaluating the quality of English translation teaching in higher education through AI-powered tools. The proposed criteria and MCDM-based assessment approach highlight how AI can deliver nuanced, real-time insights while aligning with pedagogical goals. Among the alternatives assessed, context-aware and adaptive AI tools show the highest potential. As universities continue to adopt AI technologies, such frameworks will be essential in guiding strategic decisions that ensure educational quality, engagement, and long-term student success. We used the multicriteria decision making approach (MCDM) to deal with different criteria. We used eight criteria and six alternatives to be evaluated. The interval complex neutrosophic set (ICNS) is used to deal with uncertainty and vague information.

References

[1] Z. D. Zaghlool and M. A. Khasawneh, "Aligning translation curricula with technological advancements; Insights from artificial intelligence researchers and language educators," *Stud. Media Commun.*, vol. 12, no. 1, p. 58, 2023.

[2] A. Kundu and T. Bej, "Transforming EFL Teaching with AI: A Systematic Review of Empirical Studies," *Int. J. Artif. Intell. Educ.*, pp. 1–34, 2025.

[3] S. Xu, Y. Su, and K. Liu, "Investigating student engagement with AI-driven feedback in translation revision: A mixed-methods study," *Educ. Inf. Technol.*, pp. 1–27, 2025.

[4] T. P. Ruksana, "AI-Driven Pedagogy: Unveiling ChatGPT's Influence in Education," *J. Appl. Sci. Eng. Technol. Manag.*, vol. 2, no. 01, pp. 9–14, 2024.

[5] K. Ahmad *et al.*, "Data-driven artificial intelligence in education: A comprehensive

review," *IEEE Trans. Learn. Technol.*, vol. 17, pp. 12–31, 2023.

[6] R. J. Singh, "Transforming higher education: The power of artificial intelligence," *Int. J. Multidiscip. Res. Arts, Sci. Technol.*, vol. 1, no. 3, pp. 13–18, 2023.

[7] M. B. Saaida, "AI-Driven transformations in higher education: Opportunities and challenges," *Int. J. Educ. Res. Stud.*, vol. 5, no. 1, pp. 29–36, 2023.

[8] Y. E. Yesilyurt, "AI-enabled assessment and feedback mechanisms for language learning: Transforming pedagogy and learner experience," in *Transforming the language teaching experience in the age of AI*, IGI Global, 2023, pp. 25–43.

[9] T. K. Vashishth, V. Sharma, K. K. Sharma, B. Kumar, R. Panwar, and S. Chaudhary, "AI-driven learning analytics for personalized feedback and assessment in higher education," in *Using traditional design methods to enhance AI-driven decision making*, IGI Global Scientific Publishing, 2024, pp. 206–230.

[10] F. Smarandache and M. Jdid, "An Overview of Neutrosophic and Plithogenic Theories and Applications," 2023.

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

[12] S. Broumi and F. Smarandache, "Several similarity measures of neutrosophic sets," *Infin. Study*, vol. 410, no. 1, 2013.

[13] S. Pramanik, "Single-Valued Neutrosophic Set: An Overview," *Transdisciplinarity*, pp. 563–608, 2022.

[14] A. A. Salama and S. A. Alblowi, "Neutrosophic set and neutrosophic topological spaces," 2012.

[15] F. Smarandache, "Foundation of superhyperstructure & neutrosophic superhyperstructure," *Neutrosophic Sets Syst.*, vol. 63, pp. 367–381, 2024.

[16] M. Ali and F. Smarandache, "Complex neutrosophic set," *Neural Comput. Appl.*, vol. 28, pp. 1817–1834, 2017.

[17] L. Q. Dat, N. T. Thong, M. Ali, F. Smarandache, M. Abdel-Basset, and H. V. Long, "Linguistic approaches to interval complex neutrosophic sets in decision making," *IEEE access*, vol. 7, pp. 38902–38917, 2019.

[18] M. Ali, L. Q. Dat, L. H. Son, and F. Smarandache, "Interval complex neutrosophic set: Formulation and applications in decision-making," *Int. J. Fuzzy Syst.*, vol. 20, pp. 986–999, 2018.

[19] F. Al-Sharqi, A. Al-Quran, A. G. Ahmad, and S. Broumi, "Interval-valued complex neutrosophic soft set and its applications in decision-making," *Neutrosophic Sets Syst.*, vol. 40, no. 1, p. 9, 2021.

[20] F. Al-Sharqi and A. Al-Quran, "Similarity measures on interval-complex neutrosophic soft sets with applications to decision making and medical diagnosis under uncertainty," *Neutrosophic Sets Syst.*, vol. 51, pp. 495–515, 2022.

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