Neutrosophic Sets and Systems, Vol. 83, 2025

University of New Mexico

Application of MCDM for Estimating Student Performance in University English Translation Courses under IndetermSoft Set

Qin Xu*

School of International Communication, Hunan Mass Media Vocational and Technical College, Changsha, Hunan, 410100, China

*Corresponding author, E-mail: juliaxu2022@163.com

Abstract: Evaluating student performance in university English translation courses is a complex process that requires a comprehensive assessment of multiple factors. Traditional assessment methods often fail to capture the nuances of translation quality, linguistic proficiency, and contextual adaptation. The application of Multi-Criteria Decision-Making (MCDM) methodologies offers a structured and systematic approach to estimating student performance based on diverse and interdependent criteria. By integrating MCDM, universities can develop a more objective, data-driven framework for evaluating translation skills while ensuring fair and consistent grading practices. This study uses two MCDM methods such as CRITIC method to compute the criteria weights and the RAFSI method to rank the alternatives. We use the IndetermSoft set to deal with indeterminacy in the values of the criteria. These methods are applied into a case study with eight criteria and seven alternatives.

Keywords: IndetermSoft Set; MCDM Methodology; English Translation Courses; Student Performance.

1. Introduction

In the evolving landscape of higher education, evaluating student performance in university English translation courses remains a significant challenge. Traditional grading systems primarily rely on subjective assessments from instructors, leading to inconsistencies and potential biases. Translation is a multi-dimensional skill that involves linguistic accuracy, cultural adaptability, fluency, and technical proficiency, requiring a more holistic evaluation approach[1], [2]. To enhance the objectivity and reliability of assessments, universities are increasingly adopting data-driven decision-making models such as Multi-Criteria Decision-Making (MCDM). MCDM allows for the systematic analysis of multiple performance indicators, enabling a fairer and more comprehensive evaluation of translation skills. The complexity of translation evaluation arises from the interplay of various qualitative and quantitative factors. For instance, a student's ability to accurately convey meaning may be compromised by their lack of cultural awareness or improper use of terminology. Similarly, grammatical precision does not necessarily equate to fluency or effective communication[3], [4]. Traditional assessment models often fail to consider these interdependencies, resulting in an incomplete evaluation of a student's true translation capabilities. By applying MCDM techniques, educators can rank and prioritize different aspects of translation performance, ensuring a well-rounded and consistent assessment.

One of the primary benefits of MCDM in translation assessment is its ability to integrate multiple perspectives into the decision-making process. Unlike conventional grading systems that rely heavily on individual instructor judgments, MCDM can incorporate peer reviews, automated translation assessment tools, and self-evaluation reports. This multi-source evaluation method minimizes subjectivity and allows for a more balanced and fair representation of student performance. Additionally, MCDM can help educators identify specific areas where students need improvement, enabling targeted interventions to enhance their translation skills[5], [6].

Another key advantage of MCDM is its adaptability to different translation contexts and course structures. Depending on the course objectives, instructors can assign varying weights to different criteria, such as linguistic accuracy, comprehension, or technical terminology usage. This flexibility makes MCDM a highly effective tool for translation education, as it accommodates diverse learning goals and student capabilities. Moreover, the inclusion of automated translation evaluation tools in MCDM frameworks enhances the efficiency of assessments, reducing the workload for instructors while maintaining a high level of accuracy and fairness[7], [8].

Despite its advantages, the implementation of MCDM in student performance evaluation presents certain challenges. The selection and weighting of criteria require careful consideration to ensure a balanced assessment framework[9], [10]. Additionally, integrating technology-based evaluation tools with human judgment necessitates a robust methodology to prevent biases and inconsistencies. Educators must also address the computational complexity of MCDM models, ensuring that the decision-making process remains transparent and interpretable for both students and faculty. Overcoming these challenges will be crucial in maximizing the effectiveness of MCDM in translation education[11], [12].

The future of translation education lies in the continuous refinement of assessment methodologies to better align with real-world translation demands. As universities adopt more advanced MCDM techniques, there is an opportunity to enhance the accuracy and fairness of student evaluations. Research is needed to explore the optimal combination of MCDM models, automated assessment tools, and instructor-led evaluations to achieve the best outcomes. Ultimately, the integration of MCDM in translation education not only improves assessment quality but also prepares students for the complexities of professional translation work[13], [14].

2. Proposed Model

This section shows the steps of the proposed model to show the criteria weights and ranking of the alternatives.

CRITIC Method

This part shows the steps of the CRITIC method.

Create the decision matrix.

Normalize the decision matrix

The decision matrix is normalized such as:

$$r_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}; i = 1, \ldots, m; j = 1, \ldots, n \quad (1)$$

$$r_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+}; i = 1, \ldots, m; j = 1, \ldots, n \quad (2)$$

Calculate the correlation coefficient (ρ_{jk}).

The correlation coefficient is computed between the criteria.

Calculate the standard deviation (ε_j)

Calculate the index c

$$C_j = \varepsilon_j \sum_{k=1}^{n} \left(1 - \rho_{jk}\right) \quad (3)$$

Calculate the criteria weights.

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \quad (4)$$

Then we apply the steps of the RAFSI method to rank the alternatives.

Calculate the ideal $\left(B_j\right)^A$ and non-ideal $\left(B_j\right)^C$ values.

Obtain criterion intervals for each entry. $B_1 = 0.1, B_{2_c} = 0.9$

$$g_m\left(x_{ij}\right) = \frac{B_{2_c} - B_1}{\left(B_j\right)^A - \left(B_j\right)^C} x_{ij} + \frac{\left(B_j\right)^A B_1 - B_{2_c}\left(B_j\right)^C}{\left(B_j\right)^A - \left(B_j\right)^C} \quad (5)$$

Calculate the harmonic and arithmetic means

$$K = \frac{2}{\frac{1}{B_1} + \frac{1}{B_{2_c}}} \quad (6)$$

$$K = \frac{B_1 + B_{2_c}}{2} \quad (7)$$

Normalize the decision matrix

$$R_{ij} = \frac{x_{ij}}{2B} \quad (8)$$

$$R_{ij} = \frac{K}{2x_{ij}} \quad (9)$$

Calculate the criteria function

$$S(B_i) = \sum_{j=1}^{n} w_j R_{ij} \quad (10)$$

Rank the alternatives.

2. IndetermSoft Set

In 2022, Smarandache created the IndetermSoft Set. Let H be a non-empty subset of U, P(H) be the powerset of H, and U be a universe of discourse. Assume that the values of an attribute, a, are collected in A[15], [16].

The definition of IndetermSoft is thus F: A→ P(H). If at least one attribute-value v∈A exists such that F(v) = indeterminate (unclear, incomplete, conflicting, or not unique), then the set is set if: i) the set A includes some indeterminacy; ii) the set P(H) contains some indeterminacy; iv) any two or all three of the requirements.

3. Results and Discussion

This section shows the results of the proposed approach to compute the criteria weights and ranking the alternatives. This study uses eight criteria and seven alternatives. The criteria are: Linguistic Accuracy (Excellent, Poor), Translation Fluency (Highly Fluent), Cultural Adaptation (Strong), Terminology Usage (Precise), Grammar and Syntax (Minor Errors), Comprehension and Interpretation (Deep Understanding), Use of Translation Techniques (Diverse and Effective). The alternatives are: Analytical Rubric-Based Assessment, Peer Review and Feedback System, Instructor Evaluation and Grading, Automated Translation Quality Assessment Tools, Self-Assessment and Reflection Reports, Real-Time Translation Performance Testing, Hybrid Model Combining Automated and Human Evaluation. Then we apply the steps of the two MCDM methods.

CRITIC Method

Three experts and decision makers have created the decision matrix. They used scale between 0.1 to 0.9. Then we combine the decision matrix into a single matrix. We have indeterminacy in the first criterion. We have two values, such as Excellent and Poor. So, we use the concept of the IndetermSoft Set to deal with this indeterminacy. First, we use excellent value, then we use the poor value, then we use both values

We normalize the decision matrix using Eq. (1) as shown in Table 1.

Then we obtain ρ_{jk} values as shown in Table 2.

Then we compute ε_j values.

Then we compute the C index using Eq. (3).

Then we compute the criteria weights using Eq. (4) as shown in Fig 1.

Table 1. The normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0	0	0.137708	0.345734	0.288679	0.626298	1	0
A_2	0.595135	1	1	0.396329	0	0.088235	0	0.292761
A_3	0.115552	0.036994	0.642329	0.306052	0.486792	0.00346	0.290118	0.374799
A_4	0.246742	0.371098	0	0	0.413208	0	0.076858	0.500268
A_5	1	0.316763	0.891867	0	0.320755	1	0.119932	1
A_6	0.291051	0.306358	0.761553	1	1	0.843137	0.486064	0.500268
A_7	0.158123	0.246628	0.35305	0.537698	0.339623	0.401961	0.228885	0.374799

Table 2. The correlation between criteria.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	1	0.517881	0.677593	-0.34164	-0.24925	0.403378	-0.57669	0.80329
C_2	0.517881	1	0.519476	0.007643	-0.44074	-0.24731	-0.64159	0.108284
C_3	0.677593	0.519476	1	0.244922	-0.03039	0.263343	-0.39288	0.42204
C_4	-0.34164	0.007643	0.244922	1	0.609101	0.256575	0.327886	-0.3093
C_5	-0.24925	-0.44074	-0.03039	0.609101	1	0.370107	0.270347	0.180956
C_6	0.403378	-0.24731	0.263343	0.256575	0.370107	1	0.375359	0.418399
C_7	-0.57669	-0.64159	-0.39288	0.327886	0.270347	0.375359	1	-0.58468
C_8	0.80329	0.108284	0.42204	-0.3093	0.180956	0.418399	-0.58468	1

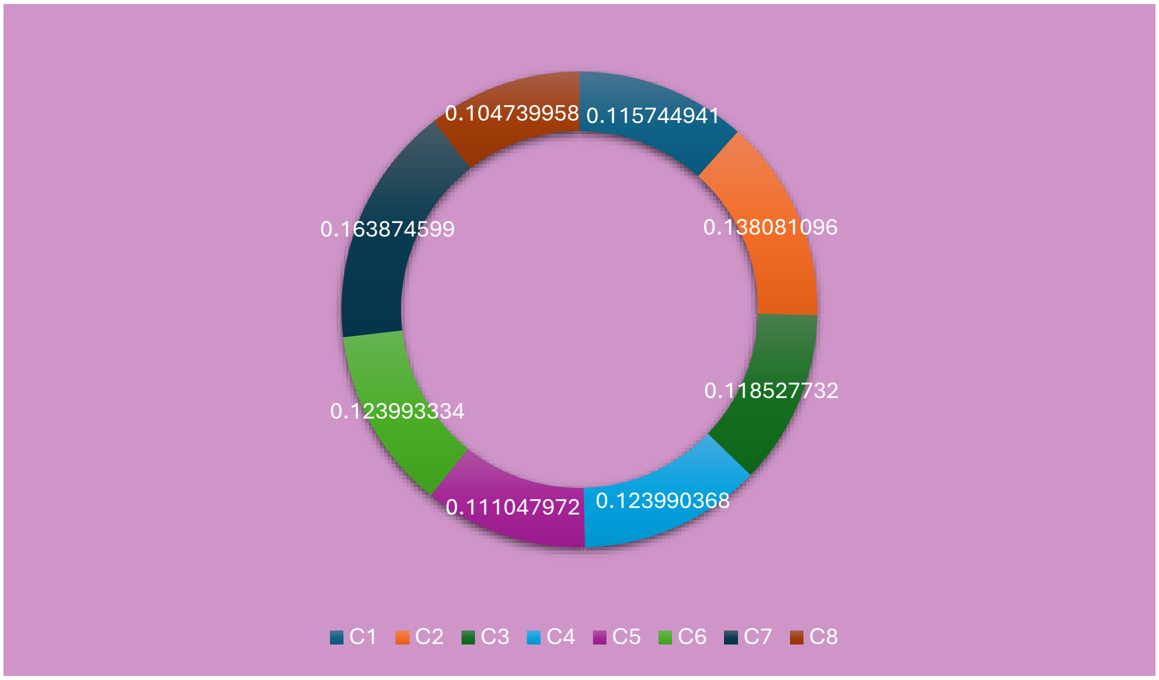

Fig 1. The criteria weights.

Poor Value.

We normalize the decision matrix using Eq. (1) as shown in Table 3.

Then we obtain ρ_{jk} values as shown in Table 4.

Then we compute ε_j values.

Then we compute the C index using Eq. (3).

Then we compute the criteria weights using Eq. (4) as shown in Fig 2.

Table 3. The normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0	0	0.137708	0.345734	0.288679	0.626298	1	0
A_2	0.501208	1	1	0.396329	0	0.088235	0	0.292761
A_3	0.562802	0.036994	0.642329	0.306052	0.486792	0.00346	0.290118	0.374799
A_4	0.562802	0.371098	0	0	0.413208	0	0.076858	0.500268
A_5	0.938406	0.316763	0.891867	0	0.320755	1	0.119932	1
A_6	1	0.306358	0.761553	1	1	0.843137	0.486064	0.500268
A_7	0.812802	0.246628	0.35305	0.537698	0.339623	0.401961	0.228885	0.374799

Table 4. The correlation between criteria.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	1	0.164628	0.487457	0.27399	0.49063	0.359939	-0.55599	0.783427
C_2	0.164628	1	0.519476	0.007643	-0.44074	-0.24731	-0.64159	0.108284
C_3	0.487457	0.519476	1	0.244922	-0.03039	0.263343	-0.39288	0.42204
C_4	0.27399	0.007643	0.244922	1	0.609101	0.256575	0.327886	-0.3093
C_5	0.49063	-0.44074	-0.03039	0.609101	1	0.370107	0.270347	0.180956
C_6	0.359939	-0.24731	0.263343	0.256575	0.370107	1	0.375359	0.418399
C_7	-0.55599	-0.64159	-0.39288	0.327886	0.270347	0.375359	1	-0.58468
C_8	0.783427	0.108284	0.42204	-0.3093	0.180956	0.418399	-0.58468	1

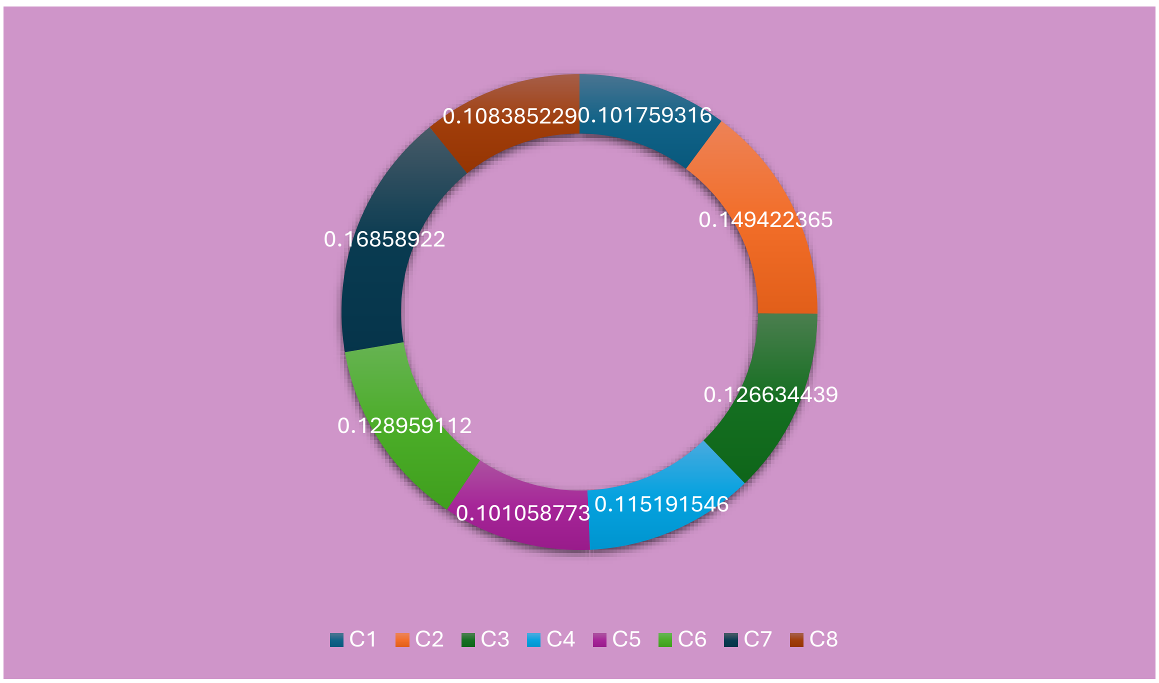

Fig 2. The criteria weights.

Excellent and Poor Value.

We normalize the decision matrix using Eq. (1) as shown in Table 5.

Then we obtain ρ_{jk} values as shown in Table 6.

Then we compute ε_j values.

Then we compute the C index using Eq. (3).

Then we compute the criteria weights using Eq. (4) as shown in Fig 3.

Table 5. The normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0	0	0.137708	0.345734	0.288679	0.626298	1	0

A_2	0.486805	1	1	0.396329	0	0.088235	0	0.292761
A_3	1	0.036994	0.642329	0.306052	0.486792	0.00346	0.290118	0.374799
A_4	0.056148	0.371098	0	0	0.413208	0	0.076858	0.500268
A_5	0.54183	0.316763	0.891867	0	0.320755	1	0.119932	1
A_6	0.214486	0.306358	0.761553	1	1	0.843137	0.486064	0.500268
A_7	0.230769	0.246628	0.35305	0.537698	0.339623	0.401961	0.228885	0.374799

Table 6. The correlation between criteria.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
C_1	1	0.022779	0.613311	-0.13643	-0.08449	-0.24448	-0.39373	0.289742
C_2	0.022779	1	0.519476	0.007643	-0.44074	-0.24731	-0.64159	0.108284
C_3	0.613311	0.519476	1	0.244922	-0.03039	0.263343	-0.39288	0.42204
C_4	-0.13643	0.007643	0.244922	1	0.609101	0.256575	0.327886	-0.3093
C_5	-0.08449	-0.44074	-0.03039	0.609101	1	0.370107	0.270347	0.180956
C_6	-0.24448	-0.24731	0.263343	0.256575	0.370107	1	0.375359	0.418399
C_7	-0.39373	-0.64159	-0.39288	0.327886	0.270347	0.375359	1	-0.58468
C_8	0.289742	0.108284	0.42204	-0.3093	0.180956	0.418399	-0.58468	1

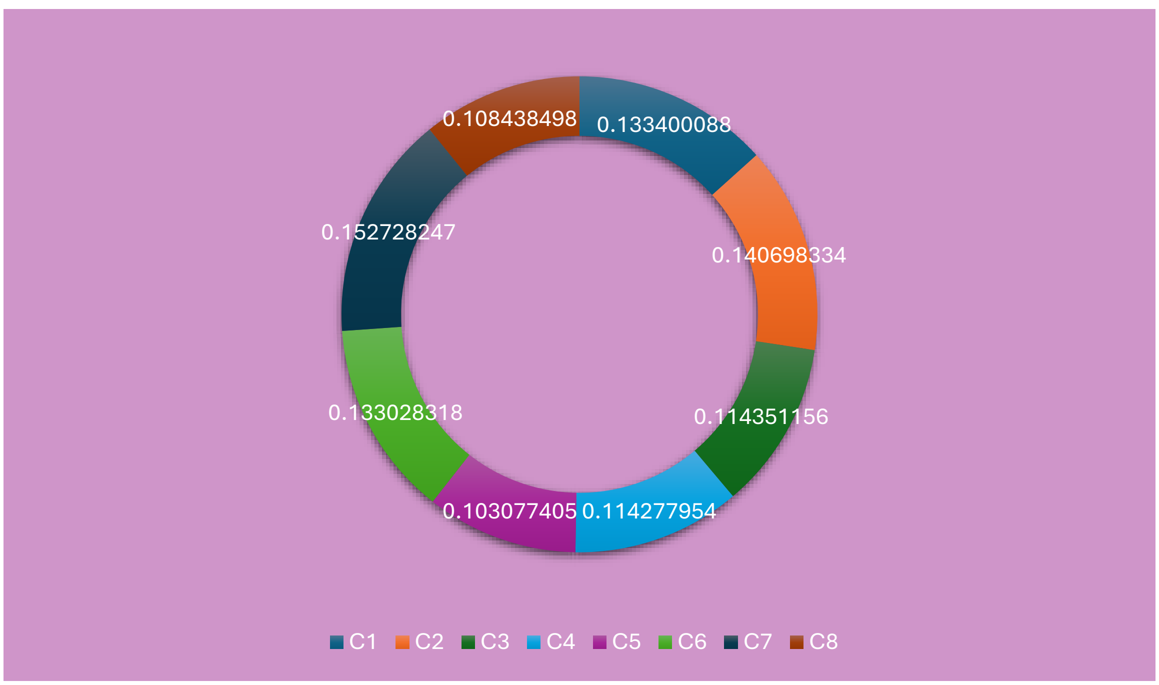

Fig 3. The criteria weights.

Then we apply the steps of the RAFSI method to rank the alternatives. We have indeterminacy in the first criterion. We have two values, such as Excellent and Poor. So, we use the concept of the

IndetermSoft Set to deal with this indeterminacy. First, we use excellent value, then we use the poor value, then we use both values. Then we applied the RAFSI method three times.

With Excellent Value.

We obtain the ideal and non-ideal values.

Then we obtain criterion intervals for each entry using Eq. (5) as shown in Table 7.

Then we calculate the harmonic and arithmetic means using Eq. (6 and 7).

Then we normalize the decision matrix using Eq. (8 and 9) as shown in Table 8.

Then we calculate the criteria function using Eq. (10) as shown in Table 9.

Table 7. The criterion intervals for each entry.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.1	0.1	0.210166	0.376587	0.330943	0.601038	0.9	0.1
A_2	0.576108	0.9	0.9	0.417063	0.1	0.170588	0.1	0.334209
A_3	0.192441	0.129595	0.613863	0.344841	0.489434	0.102768	0.332095	0.399839
A_4	0.297394	0.396879	0.1	0.1	0.430566	0.1	0.161486	0.500214
A_5	0.9	0.35341	0.813494	0.1	0.356604	0.9	0.195946	0.9
A_6	0.332841	0.345087	0.709242	0.9	0.9	0.77451	0.488851	0.500214
A_7	0.226499	0.297303	0.38244	0.530159	0.371698	0.421569	0.283108	0.399839

Table 8. Normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.025	0.025	0.052542	0.094147	0.082736	0.15026	0.225	0.025
A_2	0.144027	0.225	0.225	0.104266	0.025	0.042647	0.025	0.083552
A_3	0.04811	0.032399	0.153466	0.08621	0.122358	0.025692	0.083024	0.09996
A_4	0.074348	0.09922	0.025	0.025	0.107642	0.025	0.040372	0.125054
A_5	0.225	0.088353	0.203373	0.025	0.089151	0.225	0.048986	0.225
A_6	0.08321	0.086272	0.177311	0.225	0.225	0.193627	0.122213	0.125054
A_7	0.056625	0.074326	0.09561	0.13254	0.092925	0.105392	0.070777	0.09996

Table 9. Criteria function values.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.002894	0.003452	0.006228	0.011673	0.009188	0.018631	0.036872	0.002618
A_2	0.01667	0.031068	0.026669	0.012928	0.002776	0.005288	0.004097	0.008751
A_3	0.005569	0.004474	0.01819	0.010689	0.013588	0.003186	0.013605	0.01047
A_4	0.008605	0.0137	0.002963	0.0031	0.011953	0.0031	0.006616	0.013098
A_5	0.026043	0.0122	0.024105	0.0031	0.0099	0.027899	0.008028	0.023566
A_6	0.009631	0.011912	0.021016	0.027898	0.024986	0.024009	0.020028	0.013098
A_7	0.006554	0.010263	0.011332	0.016434	0.010319	0.013068	0.011599	0.01047

With Poor Value.

We obtain the ideal and non-ideal values.

Then we obtain criterion intervals for each entry using Eq. (5) as shown in Table 10.

Then we calculate the harmonic and arithmetic means using Eq. (6 and 7).

Then we normalize the decision matrix using Eq. (8 and 9) as shown in Table 11.

Then we calculate the criteria function using Eq. (10) as shown in Table 12.

Table 10. The criterion intervals for each entry.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.1	0.1	0.210166	0.376587	0.330943	0.601038	0.9	0.1
A_2	0.500966	0.9	0.9	0.417063	0.1	0.170588	0.1	0.334209
A_3	0.550242	0.129595	0.613863	0.344841	0.489434	0.102768	0.332095	0.399839
A_4	0.550242	0.396879	0.1	0.1	0.430566	0.1	0.161486	0.500214
A_5	0.850725	0.35341	0.813494	0.1	0.356604	0.9	0.195946	0.9
A_6	0.9	0.345087	0.709242	0.9	0.9	0.77451	0.488851	0.500214
A_7	0.750242	0.297303	0.38244	0.530159	0.371698	0.421569	0.283108	0.399839

Table 11. Normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.025	0.025	0.052542	0.094147	0.082736	0.15026	0.225	0.025
A_2	0.125242	0.225	0.225	0.104266	0.025	0.042647	0.025	0.083552
A_3	0.13756	0.032399	0.153466	0.08621	0.122358	0.025692	0.083024	0.09996
A_4	0.13756	0.09922	0.025	0.025	0.107642	0.025	0.040372	0.125054
A_5	0.212681	0.088353	0.203373	0.025	0.089151	0.225	0.048986	0.225
A_6	0.225	0.086272	0.177311	0.225	0.225	0.193627	0.122213	0.125054
A_7	0.18756	0.074326	0.09561	0.13254	0.092925	0.105392	0.070777	0.09996

Table 12. Criteria function values.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.002544	0.003736	0.006654	0.010845	0.008361	0.019377	0.037933	0.00271
A_2	0.012744	0.03362	0.028493	0.012011	0.002526	0.0055	0.004215	0.009056
A_3	0.013998	0.004841	0.019434	0.009931	0.012365	0.003313	0.013997	0.010834
A_4	0.013998	0.014826	0.003166	0.00288	0.010878	0.003224	0.006806	0.013554
A_5	0.021642	0.013202	0.025754	0.00288	0.009009	0.029016	0.008259	0.024387
A_6	0.022896	0.012891	0.022454	0.025918	0.022738	0.02497	0.020604	0.013554
A_7	0.019086	0.011106	0.012108	0.015267	0.009391	0.013591	0.011932	0.010834

With Excellent and Poor Value.

We obtain the ideal and non-ideal values.

Then we obtain criterion intervals for each entry using Eq. (5) as shown in Table 13.

Then we calculate the harmonic and arithmetic means using Eq. (6 and 7).

Then we normalize the decision matrix using Eq. (8 and 9) as shown in Table 14.

Then we calculate the criteria function using Eq. (10) as shown in Table 15. Then we obtain the final ranks of the alternatives as shown in Fig 4.

Table 13. The criterion intervals for each entry.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.1	0.1	0.210166	0.376587	0.330943	0.601038	0.9	0.1
A_2	0.489444	0.9	0.9	0.417063	0.1	0.170588	0.1	0.334209
A_3	0.9	0.129595	0.613863	0.344841	0.489434	0.102768	0.332095	0.399839
A_4	0.144919	0.396879	0.1	0.1	0.430566	0.1	0.161486	0.500214
A_5	0.533464	0.35341	0.813494	0.1	0.356604	0.9	0.195946	0.9
A_6	0.271589	0.345087	0.709242	0.9	0.9	0.77451	0.488851	0.500214
A_7	0.284615	0.297303	0.38244	0.530159	0.371698	0.421569	0.283108	0.399839

Table 14. Normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.025	0.025	0.052542	0.094147	0.082736	0.15026	0.225	0.025
A_2	0.122361	0.225	0.225	0.104266	0.025	0.042647	0.025	0.083552
A_3	0.225	0.032399	0.153466	0.08621	0.122358	0.025692	0.083024	0.09996
A_4	0.03623	0.09922	0.025	0.025	0.107642	0.025	0.040372	0.125054
A_5	0.133366	0.088353	0.203373	0.025	0.089151	0.225	0.048986	0.225
A_6	0.067897	0.086272	0.177311	0.225	0.225	0.193627	0.122213	0.125054
A_7	0.071154	0.074326	0.09561	0.13254	0.092925	0.105392	0.070777	0.09996

Table 15. Criteria function values.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.003517	0.002859	0.006004	0.009704	0.011006	0.022949	0.024399	0.002711
A_2	0.017216	0.025729	0.025713	0.010747	0.003326	0.006513	0.002711	0.00906
A_3	0.031657	0.003705	0.017538	0.008886	0.016277	0.003924	0.009003	0.010839
A_4	0.005097	0.011346	0.002857	0.002577	0.014319	0.003818	0.004378	0.013561
A_5	0.018764	0.010103	0.023241	0.002577	0.01186	0.034364	0.005312	0.024399
A_6	0.009553	0.009865	0.020263	0.023192	0.029931	0.029572	0.013253	0.013561
A_7	0.010011	0.008499	0.010926	0.013662	0.012362	0.016096	0.007675	0.010839

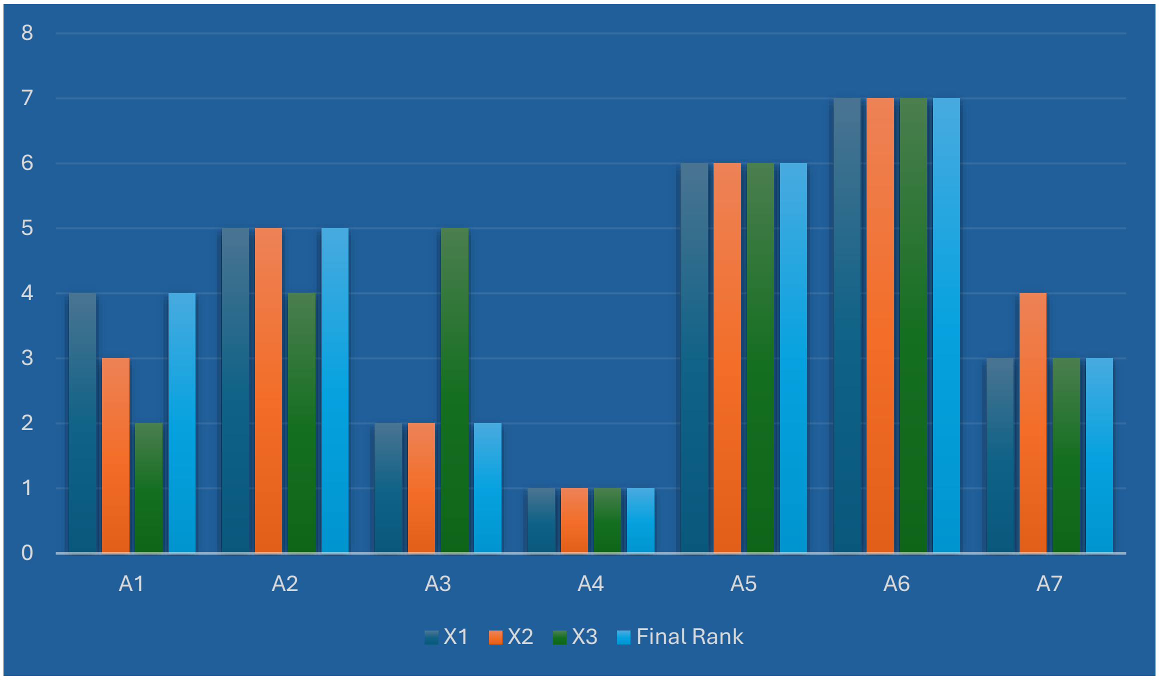

Fig 4. The final ranks of the alternatives.

4. Conclusions

The application of Multi-Criteria Decision-Making (MCDM) in evaluating student performance in English translation courses represents a significant advancement in academic assessment. By incorporating multiple evaluation criteria, MCDM ensures a more comprehensive, objective, and fair assessment framework. While challenges exist in implementing MCDM, its benefits in enhancing evaluation accuracy, minimizing subjectivity, and improving student learning outcomes are undeniable. As translation education continues to evolve, the adoption of MCDM methodologies will play a crucial role in shaping the future of performance assessment, ensuring that students receive a holistic evaluation that aligns with industry and academic expectations. This study used two MCDM methods for this evaluation. We used the CRITIC method to compute the criteria weights and the RAFSI method to rank the alternatives. These methods are used with the IndetermSoft set to deal with indeterminacy. Then we obtain the final ranks of the alternatives. The results show alternative 6 is the best and alternative 4 is the worst.

References

[1] Y. Guerra-Macías and S. Tobón, "Development of transversal skills in higher education programs in conjunction with online learning: relationship between learning strategies, project-based pedagogical practices, e-learning platforms, and academic performance," *Heliyon*, vol. 11, no. 2, 2025.

[2] J. Xu and Q. Wang, "Applying neural machine translation and ChatGPT in the teaching of business English writing," *Transl. Translanguaging Multiling. Context.*, vol. 11, no. 1, pp. 88–110, 2025.

[3] Y. Jiang and J.-E. Peng, “Exploring the relationships between learners’ engagement, autonomy, and academic performance in an English language MOOC,” *Comput. Assist. Lang. Learn.*, vol. 38, no. 1–2, pp. 71–96, 2025.

[4] M. C. P. Igwe and M. A. D. Ligaya, “Students’ Performance in English: Effects of Teachers’ Leadership Behavior and Students’ Motivation.,” *J. Educ. Learn.*, vol. 19, no. 1, pp. 91–102, 2025.

[5] J. Su, H. Liu, Y. Chen, N. Zhang, and J. Li, “A novel multi-criteria decision making method to evaluate green innovation ecosystem resilience,” *Eng. Appl. Artif. Intell.*, vol. 139, p. 109528, 2025.

[6] W. Ho, X. Xu, and P. K. Dey, “Multi-criteria decision making approaches for supplier evaluation and selection: A literature review,” *Eur. J. Oper. Res.*, vol. 202, no. 1, pp. 16–24, 2010.

[7] B. Mohamed and M. Marzouk, “Post-adaptive reuse evaluation of heritage buildings using multi-criteria decision-making techniques,” *J. Build. Eng.*, vol. 99, p. 111485, 2025.

[8] I. Oubrahim and N. Sefiani, “An integrated multi-criteria decision-making approach for sustainable supply chain performance evaluation from a manufacturing perspective,” *Int. J. Product. Perform. Manag.*, vol. 74, no. 1, pp. 304–339, 2025.

[9] A. U. R. Bajwa, C. Siriwardana, W. Shahzad, and M. A. Naeem, “Material selection in the construction industry: a systematic literature review on multi-criteria decision making,” *Environ. Syst. Decis.*, vol. 45, no. 1, pp. 1–22, 2025.

[10] A. Hassan Ali, A. Farouk Kineber, N. Elshaboury, M. Arashpour, and A. Osama Daoud, “Analysing multifaceted barriers to modular construction in sustainable building projects: a comprehensive evaluation using multi-criteria decision making,” *Int. J. Constr. Manag.*, vol. 25, no. 1, pp. 1–17, 2025.

[11] Z.-F. Hou, K.-M. Lee, K.-L. Keung, and J.-Y. Huang, “A Novel Multi-Criteria Decision-Making Framework of Vehicle Structural Factor Evaluation for Public Transportation Safety,” *Appl. Sci.*, vol. 15, no. 6, p. 3045, 2025.

[12] H. Wang, Y. Ju, and C. Porcel, “Energy internet project evaluation in circular economy practices: A novel multi-criteria decision-making framework with flexible linguistic expressions based on multi-granularity cloud-rough set,” *Comput. Ind. Eng.*, p. 110890, 2025.

[13] M. Gandomzadeh *et al.*, “Dust mitigation methods and multi-criteria decision-making cleaning strategies for photovoltaic systems: Advances, challenges, and future directions,” *Energy Strateg. Rev.*, vol. 57, p. 101629, 2025.

[14] Y. Zhu, H. Wan, L.-A. Carlos, J. Ye, and S. Zeng, “Evaluating digital maturity in specialized enterprises: a multi-criteria decision-making approach,” *Int. Entrep. Manag. J.*, vol. 21, no. 1, pp. 1–22, 2025.

[15] F. Smarandache, *Introducción a los conjuntos IndetermSoft e IndetermHyperSoft*, vol. 3. Infinite Study, 2022.

[16] F. Smarandache, "Aplicaciones prácticas de indetermsoft set e indetermhypersoft set e introduccion a treesoft set como una extension del multisoft set," *Neutrosophic Comput. Mach. Learn. ISSN 2574-1101*, vol. 25, pp. 1–8, 2023.

Received: Nov. 1, 2024. Accepted: March 30, 2025