NSS

Neutrosophic Sets and Systems, Vol. 82, 2025

University of New Mexico

Comprehensive Analysis of Application of Multi-Criteria Decision-Making Methods with TreeSoft Set for Teaching Quality Improvement of College English Learning Process

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Abstract: The assessment of teaching quality in College English is a critical component of educational improvement, ensuring that language instruction meets the evolving needs of students in a globalized world. With the increasing integration of digital tools, interactive learning strategies, and student-centered pedagogies, assessing teaching effectiveness has become more complex and multidimensional. This study explores a structured evaluation framework that incorporates pedagogical innovation, student engagement, technological integration, and outcome-based assessment. By applying multi-criteria decision-making (MCDM) techniques, this research provides a systematic method to analyze the effectiveness of College English instruction. TreeSoft set is used to divide the main and sub criteria as a tree to show the relationships between the criteria and alternatives. Then in each sub criterion we compute the criteria weights and in main criteria. The SIWEC method is used to compute the criteria weights and the ARAS method is used to rank the alternatives.

Keywords: TreeSoft Set; MCDM Methods; Application of MCDM Issue; Teaching Quality; College English.

1. Introduction

The role of College English in higher education extends beyond linguistic proficiency; it serves as a bridge for students to engage in international communication, academic research, and professional development. As English continues to dominate as the global lingua franca, universities must ensure that their English programs equip students with essential language skills tailored to real-world applications. However, assessing the quality of College English teaching is not a straightforward process, as it involves multiple variables, including curriculum design, teaching methodology, technological integration, and student learning outcomes. This necessitates a robust and dynamic evaluation framework to measure teaching effectiveness accurately[1], [2]. With the advancement of digital technology, traditional English teaching methods are undergoing a paradigm shift. Conventional lecture-based instruction is being supplemented—or even replaced—by more interactive and student-centered approaches such as task-based learning, flipped classrooms, and AI-assisted language instruction. While these methodologies promise enhanced learning experiences, their effectiveness varies depending on institutional resources, student demographics, and pedagogical execution. Evaluating the impact of these instructional models requires a systematic analysis that considers both qualitative and quantitative indicators[3], [4].

Student engagement is another key determinant of teaching quality. In College English courses, engagement is not limited to classroom participation but extends to independent learning, collaborative projects, and language immersion opportunities. Factors such as motivation, interest in English learning, and the ability to apply language skills in real-life scenarios play a crucial role in determining the success of a course. A comprehensive evaluation model should, therefore, incorporate both student-centered and teacher-centered factors to provide a holistic picture of teaching effectiveness[2], [5].

Furthermore, assessment and feedback mechanisms are fundamental to improving teaching quality. Effective evaluation strategies include formative assessments, timely feedback, peer reviews, and self-assessments, all of which contribute to a more responsive and adaptive learning environment. In this regard, technology-enhanced assessments, such as AI-driven analytics and learning management systems, have emerged as valuable tools for tracking student progress and refining instructional strategies[6], [7]. These technological advancements need to be integrated into evaluation frameworks to ensure a data-driven approach to improving College English teaching.

Given the multidimensional nature of teaching quality evaluation, the use of multi-criteria decision-making (MCDM) methodologies offers a structured and objective approach to assessment. By assigning appropriate weights to various evaluation criteria, institutions can systematically compare different teaching models and identify best practices. Techniques ARAS and SIWEC models provide a solid foundation for analyzing diverse teaching methods and optimizing instructional strategies accordingly[8], [9].

Assessment the quality of College English teaching requires a comprehensive, data-driven approach that incorporates pedagogy, technology, student engagement, and assessment mechanisms. By leveraging MCDM techniques, universities can develop a structured evaluation framework that facilitates continuous improvement in English language education. This study aims to establish a reliable model for assessing teaching effectiveness and offers recommendations for enhancing College English instruction in higher education institutions.

The main contributions of this study are organized as follows:

We use the TreeSoft set to divide the main and sub criteria as tree, then we obtain the relation between the criteria.

We obtain the weights of the main and sub criteria by the SIWEC method. In each sub criterion we obtain the weights.

Then we obtain the global weights of all criteria.

We use the ARAS method to rank alternatives.

2. MCDM Methodology

This section displays the steps of the two MCDM methods under the TreeSoft set. We compute the criteria weights by the SIWEC method by dividing the criteria and sub criteria into tree, then we compute the criteria weights in each branch, and final we compute the global weights of each criterion. Then we rank the alternatives under these criteria weights.

TreeSoft Set

Let U be a universe of discourse and H is a non-empty subset of U, the powerset of H is a P(H)[10], [11]. then we let the set of attributes as Z and

$$Z = \{Z_1, Z_2, \dots Z_n\} \text{ and } n \geq 1 \tag{1}$$

We can form the sub attribute of Z as:

Attribute	Sub-attribute
Z_1	$\{Z_{1,1}, Z_{1,2}, \dots \dots ..\}$
Z_2	$\{Z_{2,1}, Z_{2,2}, \dots \dots ..\}$
Z_3	$\{Z_{3,1}, Z_{3,2}, \dots \dots ..\}$
..	..
Z_n	$\{Z_{n,1}, Z_{n,2}, \dots \dots ..\}$

The attributes can be presented at the first level, and the second level refers to the sub-attributes[12], [13]. Fig 1 shows an example of the TreeSoft set.

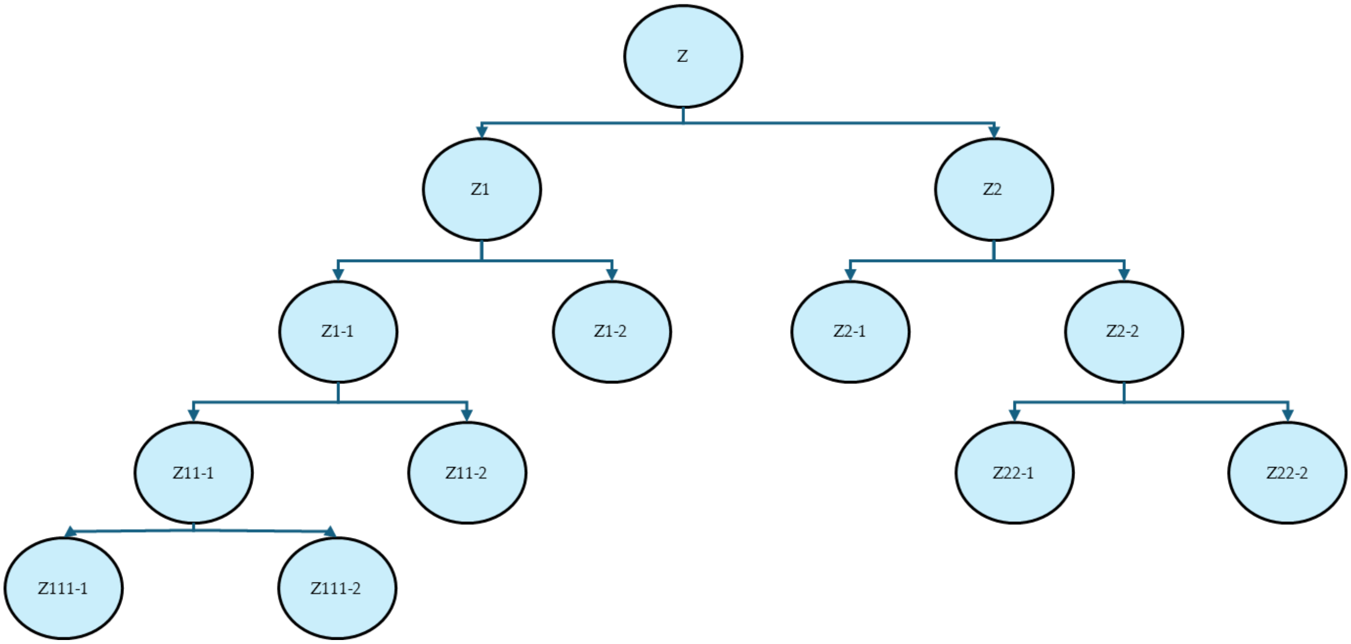

Fig 1. Example of TreeSoft set.

SIWEC Approach

The SIWEC method is used to compute the criteria weights. The steps of this method are organized as follows:

Create the assessment matrix.

Let experts and decision makers evaluate the criteria and alternatives to build the decision matrix.

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \quad (2)$$

Normalize the decision matrix.

$$x_{ij} = \frac{a_{ij}}{\max a_{ij}}; i = 1, \dots, m; j = 1, \dots, n \quad (3)$$

Compute the standard deviation.

The aim of this step is to obtain the standard deviation δ_j.

Multiply the standard deviation by the normalization values.

$$r_{ij} = x_{ij}\delta_j \quad (4)$$

Compute the sum results of the previous multiplication

$$d_j = \sum_{j=1}^{n} r_{ij} \quad (5)$$

Compute the criteria weights.

The criteria weights are computed as follows:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{6}$$

ARAS Method

The ARAS Method is used to rank the alternatives[14], [15].

The ARAS Method starts with the decision matrix between the criteria and the alternatives.

Normalize the decision matrix

$$k_{ij} = \frac{a_{ij}}{\sum_{i=1}^{m} a_{ij}} \tag{7}$$

Compute the weighted decision matrix.

$$q_{ij} = k_{ij} w_j \tag{8}$$

Compute the optimality function

$$E_i = \sum_{j=1}^{n} q_{ij} \tag{9}$$

Compute the utility degree

$$U_i = \frac{E_i}{V_o} \tag{10}$$

V_o refers to the optimality value of E_i

Final rank of the alternatives.

3. Application

This section shows an application of the proposed approach to show its validation. We obtained eight criteria, and eight alternatives present as eight colleges. Fig 2 shows the eight criteria their sub criteria.

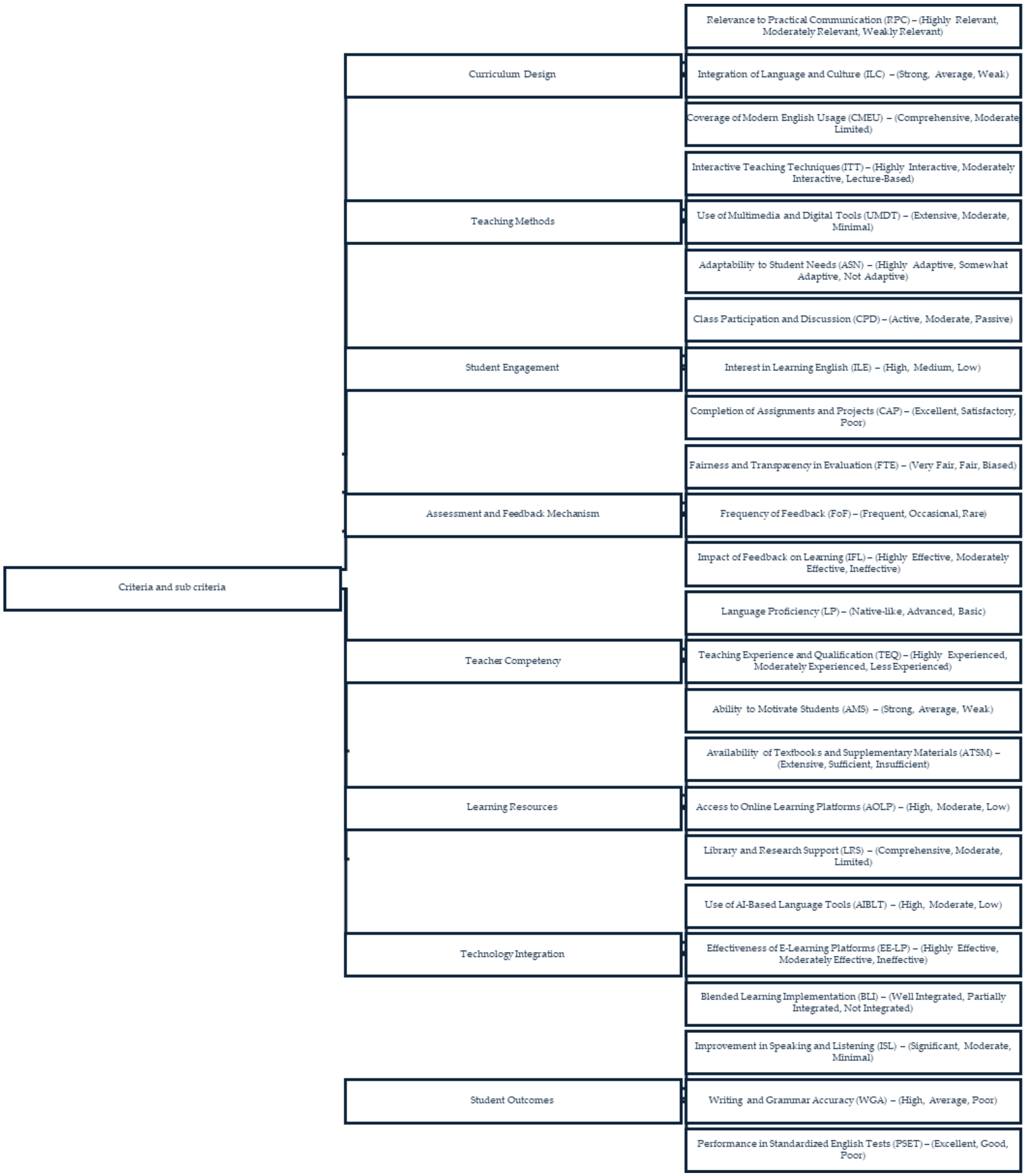

Fig 2. Eight criteria with sub criteria.

SIWEC Approach

In this section, we compute the weights of the main criteria, then we compute the weights of each sub criterion. Finally, we compute the criteria of global weights. We have eight main criteria, and each criterion has three sub criteria.

We created the decision matrix for the main criteria, sub criteria and global criteria. Three experts evaluated the criteria and alternatives based on scale between 0.1 to 0.9.

Eq. (3) is used to normalize the decision matrix as shown in Table 1.

Then we compute the standard deviation.

Then we multiply the standard deviation by the normalization values using Eq. (4) as shown in Table 2.

Then we compute the sum results of the previous multiplication using Eq. (5).

Then we compute the criteria weights using Eq. (6).

Table 1. Normalized decision matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.461748	0.401213	1	0.611037	0.391797	0.460139	0.478554	0.45571
A_2	0.589916	0.465819	0.234856	0.463154	1	0.529318	0.507641	0.326497
A_3	0.40579	0.722511	1	0.611037	0.358934	0.722511	1	0.465819
A_4	0.753821	0.337185	0.341632	0.531177	0.267682	0.492153	0.384782	0.78601
A_5	1	0.546072	0.604905	0.537735	0.411619	0.401791	0.589916	1
A_6	0.384782	0.609571	0.530955	0.734856	0.633804	0.711294	0.478554	0.369199
A_7	0.589916	1	0.292357	0.450817	0.53918	0.743308	0.471998	0.481465
A_8	0.39554	0.700607	0.325627	1	0.666667	1	0.671915	0.391103

Table 2. The multiplication of the standard deviation by the normalization values.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.099165	0.085068	0.308736	0.109691	0.091468	0.09119	0.092254	0.106851
A_2	0.12669	0.098766	0.072509	0.083144	0.233457	0.1049	0.097861	0.076554
A_3	0.087147	0.153192	0.308736	0.109691	0.083796	0.143186	0.192776	0.109221
A_4	0.16189	0.071492	0.105474	0.095355	0.062492	0.097534	0.074177	0.184297
A_5	0.214759	0.115782	0.186756	0.096532	0.096095	0.079626	0.113722	0.234471
A_6	0.082636	0.129245	0.163925	0.131918	0.147966	0.140963	0.092254	0.086567
A_7	0.12669	0.212027	0.090261	0.080929	0.125875	0.147308	0.09099	0.11289
A_8	0.084946	0.148547	0.100533	0.179516	0.155638	0.198179	0.129529	0.091703

Then we apply the previous steps into each sub criterion. In the first sub criterion, we obtain the normalization values and multiplication of normalization and standard deviation as shown in Table 3.

Table 3. Values of first sub-criterion.

	C_1	C_2	C_3
A_1	0.611037	0.391797	0.460139
A_2	0.463154	1	0.529318
A_3	0.611037	0.358934	0.722511
A_4	0.531177	0.267682	0.492153
A_5	0.537735	0.411619	0.401791
A_6	0.734856	0.633804	0.711294
A_7	0.450817	0.53918	0.743308
A_8	1	0.666667	1
	C_1	C_2	C_3
A_1	0.109691	0.091468	0.09119
A_2	0.083144	0.233457	0.1049
A_3	0.109691	0.083796	0.143186
A_4	0.095355	0.062492	0.097534
A_5	0.096532	0.096095	0.079626
A_6	0.131918	0.147966	0.140963
A_7	0.080929	0.125875	0.147308
A_8	0.179516	0.155638	0.198179

Then we apply the previous steps into each sub criterion. In the second sub criterion, we obtain the normalization values and multiplication of normalization and standard deviation as shown in Table 4.

Table 4. Values of second sub-criterion.

	C_1	C_2	C_3
A_1	0.478554	0.45571	1
A_2	0.507641	0.326497	0.234856
A_3	1	0.465819	1
A_4	0.384782	0.78601	0.341632
A_5	0.589916	1	0.604905
A_6	0.478554	0.369199	0.530955
A_7	0.471998	0.481465	0.292357
A_8	0.671915	0.391103	0.325627
	C_1	C_2	C_3
A_1	0.092254	0.106851	0.308736
A_2	0.097861	0.076554	0.072509
A_3	0.192776	0.109221	0.308736
A_4	0.074177	0.184297	0.105474
A_5	0.113722	0.234471	0.186756
A_6	0.092254	0.086567	0.163925
A_7	0.09099	0.11289	0.090261
A_8	0.129529	0.091703	0.100533

Then we apply the previous steps into each sub criterion. In the third sub criterion, we obtain the normalization values and multiplication of normalization and standard deviation as shown in Table 5.

Table 5. Values of third sub-criterion.

	C_1	C_2	C_3
A_1	0.394745	0.401213	1
A_2	0.351582	0.423118	0.326497
A_3	0.383942	0.379838	0.390526
A_4	0.340827	0.347824	0.347824
A_5	1	0.347824	0.42254
A_6	0.394745	0.454602	0.326497
A_7	0.465109	1	0.379886
A_8	0.416886	0.700607	0.423118
	C_1	C_2	C_3
A_1	0.086119	0.092036	0.224671
A_2	0.076702	0.09706	0.073355
A_3	0.083762	0.087132	0.08774
A_4	0.074356	0.079789	0.078146
A_5	0.218164	0.079789	0.094933
A_6	0.086119	0.104283	0.073355
A_7	0.10147	0.229393	0.08535
A_8	0.090949	0.160714	0.095062

Then we apply the previous steps into each sub criterion. In the fourth sub criterion, we obtain the normalization values and multiplication of normalization and standard deviation as shown in Table 6.

Table 6. Values of fourth sub-criterion.

	C_1	C_2	C_3
A_1	0.555796	0.748162	1
A_2	0.888963	0.970178	0.409757
A_3	0.734689	0.908404	0.72387
A_4	0.487774	0.908404	0.576267
A_5	1	0.908404	0.495284
A_6	0.605091	0.908404	0.614379
A_7	0.734689	0.984745	0.338292
A_8	0.476103	1	0.37679
	C_1	C_2	C_3
A_1	0.105325	0.058712	0.218038
A_2	0.168461	0.076135	0.089343
A_3	0.139225	0.071287	0.157831
A_4	0.092434	0.071287	0.125648
A_5	0.189502	0.071287	0.107991
A_6	0.114666	0.071287	0.133958

A_7	0.139225	0.077278	0.07376
A_8	0.090223	0.078475	0.082154

Then we apply the previous steps into each sub criterion. In the fifth sub criterion, we obtain the normalization values and multiplication of normalization and standard deviation as shown in Table 7.

Table 7. Values of fifth sub-criterion.

	C_1	C_2	C_3
A_1	0.864214	0.30877	1
A_2	0.354118	1	0.489904
A_3	1	0.234856	0.744952
A_4	0.284132	1	0.514542
A_5	0.802453	0.53918	0.572043
A_6	0.30877	0.411619	0.53918
A_7	0.47338	0.76959	0.292357
A_8	0.317402	0.53918	0.325627
	C_1	C_2	C_3
A_1	0.251362	0.091133	0.227385
A_2	0.102997	0.295149	0.111397
A_3	0.290856	0.069318	0.169391
A_4	0.082641	0.295149	0.116999
A_5	0.233398	0.159138	0.130074
A_6	0.089807	0.121489	0.122602
A_7	0.137685	0.227144	0.066478
A_8	0.092318	0.159138	0.074043

Then we apply the previous steps into each sub criterion. In the sixth sub criterion, we obtain the normalization values and multiplication of normalization and standard deviation as shown in Table 8.

Table 8. Values of sixth sub-criterion.

	C_1	C_2	C_3
A_1	0.373139	0.390526	1
A_2	0.373139	0.369151	0.330024
A_3	0.330024	0.347824	0.373139
A_4	0.351582	0.326497	0.373139
A_5	1	0.347824	0.330024
A_6	0.405547	0.475929	0.373139
A_7	0.621752	1	0.308467
A_8	0.416886	0.700607	0.427689
	C_1	C_2	C_3
A_1	0.084821	0.092901	0.229487
A_2	0.084821	0.087816	0.075736
A_3	0.07502	0.082743	0.085631
A_4	0.079921	0.077669	0.085631

A_5	0.227318	0.082743	0.075736
A_6	0.092188	0.113217	0.085631
A_7	0.141335	0.237887	0.070789
A_8	0.094766	0.166665	0.098149

Then we apply the previous steps into each sub criterion. In the seventh sub criterion, we obtain the normalization values and multiplication of normalization and standard deviation as shown in Table 9.

Table 9. Values of seventh sub-criterion.

	C_1	C_2	C_3
A_1	0.326497	0.369199	1
A_2	0.636578	0.657905	0.234856
A_3	1	0.668592	0.744952
A_4	0.443915	0.743308	0.53918
A_5	0.78601	0.476507	0.374495
A_6	0.401213	0.609571	0.563818
A_7	0.615107	1	0.292357
A_8	0.41243	0.700607	0.325627
	C_1	C_2	C_3
A_1	0.074663	0.069025	0.26035
A_2	0.145572	0.123002	0.061145
A_3	0.228679	0.125	0.193948
A_4	0.101514	0.138968	0.140375
A_5	0.179744	0.089087	0.0975
A_6	0.091749	0.113965	0.14679
A_7	0.140662	0.186959	0.076115
A_8	0.094314	0.130985	0.084777

Then we apply the previous steps into each sub criterion. In the eighth sub criterion, we obtain the normalization values and multiplication of normalization and standard deviation as shown in Table 10.

Table 10. Values of eighth sub-criterion.

	C_1	C_2	C_3
A_1	0.630377	0.401213	0.98697
A_2	0.426865	0.498989	0.393311
A_3	0.463821	0.369777	0.64311
A_4	0.988329	0.434383	0.792765
A_5	1	0.679713	1
A_6	0.463154	0.609571	0.661786
A_7	0.71007	1	0.489607
A_8	0.476103	0.700607	0.545325
	C_1	C_2	C_3
A_1	0.14886	0.083792	0.21973
A_2	0.100802	0.104213	0.087563

A_3	0.109529	0.077227	0.143176
A_4	0.233389	0.09072	0.176494
A_5	0.236145	0.141956	0.222631
A_6	0.109372	0.127307	0.147334
A_7	0.167679	0.208847	0.109002
A_8	0.112429	0.14632	0.121406

Finally, we compute the global weights of the criteria as shown in Fig 3.

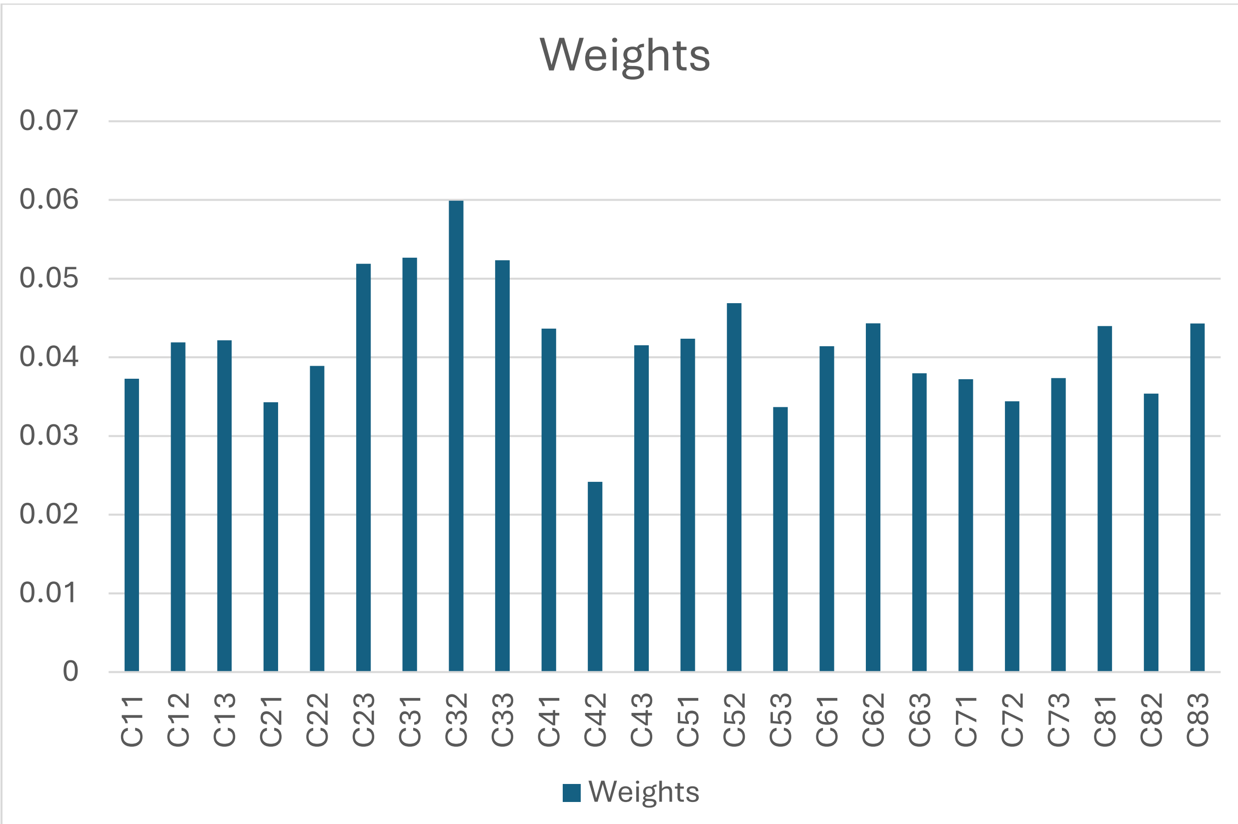

Fig 3. Global weights of the criteria.

ARAS Method

Then we build the decision matrix for all sub criteria. Then we apply the steps of the ARAS method.

Eq. (7) is used to normalize the decision matrix as shown in Table 11.

Eq. (8) is used to compute the weighted decision matrix as shown in table 12.

Eq. (9) is used to compute the optimality function

Eq. (10) is used to compute the utility degree. Final we ranked the alternatives as shown in Fig 4.

Table 11. Normalization values.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
C11	0.100785	0.12876	0.088571	0.164535	0.218268	0.083986	0.12876	0.086334
C12	0.083884	0.097391	0.151059	0.070497	0.11417	0.127446	0.209075	0.146479
C13	0.230929	0.054235	0.230929	0.078893	0.13969	0.122613	0.067514	0.075197
C21	0.123696	0.093759	0.123696	0.10753	0.108857	0.148762	0.091262	0.202437
C22	0.091763	0.234209	0.084066	0.062694	0.096405	0.148443	0.126281	0.15614
C23	0.090927	0.104598	0.142774	0.097254	0.079397	0.140558	0.146884	0.197608
C31	0.104411	0.110757	0.218181	0.083952	0.128708	0.104411	0.102981	0.146599
C32	0.106579	0.076359	0.108943	0.183827	0.233874	0.086346	0.112602	0.091469
C33	0.106182	0.106182	0.112499	0.106182	0.194856	0.115664	0.136282	0.122152
C41	0.098942	0.104344	0.093671	0.085776	0.085776	0.112108	0.246608	0.172775
C42	0.234831	0.076672	0.162015	0.08419	0.099226	0.154497	0.089209	0.099361
C43	0.135744	0.102891	0.09741	0.094669	0.08373	0.163251	0.100151	0.222154
C51	0.112616	0.221207	0.086387	0.081659	0.076941	0.074588	0.154979	0.191623
C52	0.109295	0.125728	0.174155	0.092761	0.087683	0.082618	0.090233	0.237527
C53	0.125152	0.122049	0.17304	0.095268	0.089919	0.098093	0.128787	0.167691
C61	0.126883	0.093882	0.114833	0.11171	0.117648	0.189119	0.093882	0.152043
C62	0.1075	0.111975	0.144438	0.101876	0.235096	0.083996	0.128776	0.086344
C63	0.071924	0.085421	0.133249	0.133249	0.147636	0.10162	0.201307	0.125594
C71	0.194951	0.0803	0.144908	0.144908	0.160554	0.102187	0.089704	0.082487
C72	0.101831	0.077186	0.101831	0.192381	0.085401	0.182092	0.077186	0.182092
C73	0.087637	0.22368	0.074676	0.083767	0.179492	0.120604	0.111397	0.118747
C81	0.059707	0.093728	0.177074	0.078606	0.153392	0.124059	0.114588	0.198846
C82	0.09656	0.085902	0.094165	0.201774	0.135575	0.125225	0.125225	0.135575
C83	0.099619	0.078371	0.097041	0.171823	0.218602	0.114584	0.134464	0.085496

Table 12. Weighted normalization values.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8
C11	0.003758	0.004801	0.003302	0.006135	0.008138	0.003131	0.004801	0.003219
C12	0.003516	0.004082	0.006331	0.002954	0.004785	0.005341	0.008762	0.006139
C13	0.009737	0.002287	0.009737	0.003327	0.00589	0.00517	0.002847	0.003171
C21	0.004242	0.003215	0.004242	0.003687	0.003733	0.005101	0.003129	0.006942
C22	0.00357	0.009113	0.003271	0.002439	0.003751	0.005776	0.004913	0.006075
C23	0.004718	0.005427	0.007408	0.005046	0.00412	0.007293	0.007621	0.010253
C31	0.005498	0.005832	0.011489	0.004421	0.006778	0.005498	0.005423	0.00772
C32	0.006385	0.004574	0.006526	0.011013	0.014011	0.005173	0.006746	0.00548
C33	0.005557	0.005557	0.005888	0.005557	0.010198	0.006053	0.007132	0.006393
C41	0.004319	0.004555	0.004089	0.003744	0.003744	0.004894	0.010765	0.007542
C42	0.00568	0.001855	0.003919	0.002036	0.0024	0.003737	0.002158	0.002403
C43	0.005638	0.004274	0.004046	0.003932	0.003478	0.006781	0.00416	0.009228
C51	0.004772	0.009373	0.00366	0.00346	0.00326	0.00316	0.006567	0.00812
C52	0.005125	0.005895	0.008166	0.00435	0.004111	0.003874	0.004231	0.011138
C53	0.004216	0.004111	0.005829	0.003209	0.003029	0.003304	0.004338	0.005648

C61	0.005256	0.003889	0.004756	0.004627	0.004873	0.007833	0.003889	0.006298
C62	0.004764	0.004962	0.0064	0.004514	0.010418	0.003722	0.005706	0.003826
C63	0.002731	0.003243	0.005059	0.005059	0.005605	0.003858	0.007643	0.004768
C71	0.007255	0.002989	0.005393	0.005393	0.005975	0.003803	0.003338	0.00307
C72	0.003503	0.002655	0.003503	0.006618	0.002938	0.006264	0.002655	0.006264
C73	0.003274	0.008357	0.00279	0.00313	0.006706	0.004506	0.004162	0.004437
C81	0.002625	0.004121	0.007786	0.003456	0.006745	0.005455	0.005038	0.008743
C82	0.003417	0.00304	0.003332	0.00714	0.004797	0.004431	0.004431	0.004797
C83	0.004413	0.003472	0.004299	0.007612	0.009684	0.005076	0.005957	0.003787

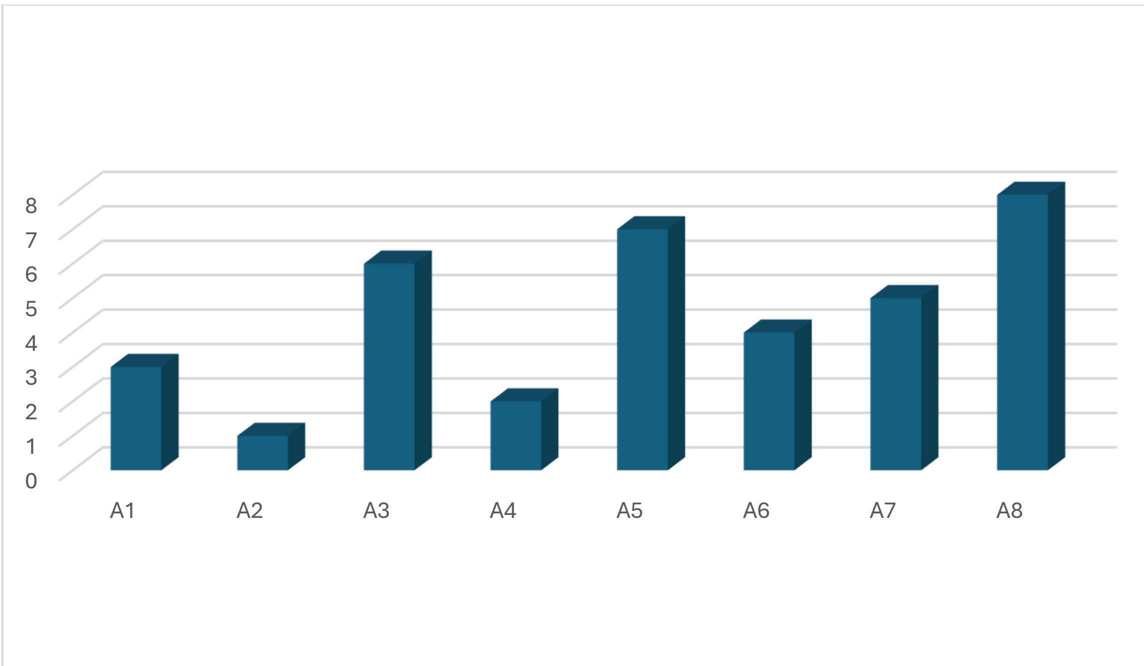

Fig 4. Ranks of alternatives.

4. Conclusions, Implications and Future Works

MCDM methods are used in this study to deal with different criteria and alternatives. Three experts are evaluated the criteria and alternatives based on their opinions. They used a scale between 0.1 to 0.9. Two MCDM methods are used in this study such as SIWEC method to compute the criteria weights and the ARAS method to rank the alternatives. We used the TreeSoft set to deal with different criteria and sub-criteria. We divided the main criteria into eight branches and each branch we computed the criteria weights. Then we obtain the global weights of this study. The results show alternative 8 is the best and alternative 2 is the worst.

The evaluation of teaching quality in College English must go beyond conventional assessment methods to embrace a holistic, multidimensional approach. This research highlights the necessity of integrating pedagogical innovation, student engagement, and technological advancements into a structured evaluation framework. By implementing MCDM methodologies, universities can ensure a more objective and data-driven assessment of teaching effectiveness.

Findings from this study emphasize the importance of adaptive teaching methods, formative feedback, and technology-enhanced assessments in improving student outcomes. The shift toward digital learning tools, AI-driven instruction, and interactive pedagogies requires educators to continuously refine their strategies to meet the evolving needs of students. A systematic evaluation framework enables institutions to identify strengths and weaknesses, allowing for targeted improvements in College English programs.

Future research should explore the long-term impact of digital and hybrid learning environments on English language acquisition. Additionally, comparative studies across different educational contexts can provide deeper insights into effective teaching practices. As higher education continues to evolve, a well-structured evaluation mechanism will be instrumental in ensuring that College English instruction remains relevant, engaging, and effective for diverse learners.

References

[1] Z. Wu, H. Li, X. Zhang, Z. Wu, and S. Cao, "Teaching quality assessment of college English department based on factor analysis," *Int. J. Emerg. Technol. Learn.*, vol. 16, no. 23, pp. 158–170, 2021.

[2] Z. Xie and Z. Su, "Evaluation of college English classroom teaching quality dependent on triangular fuzzy number," *Int. J. Electr. Eng. Educ.*, p. 00207209211002075, 2021.

[3] H. Liu, R. Chen, S. Cao, and H. Lv, "Evaluation of college English teaching quality based on grey clustering analysis," *Int. J. Emerg. Technol. Learn.*, vol. 16, no. 2, pp. 173–187, 2021.

[4] Q. Wang, "Research on teaching quality evaluation of college english based on the CODAS method under interval-valued intuitionistic fuzzy information," *J. Intell. Fuzzy Syst.*, vol. 41, no. 1, pp. 1499–1508, 2021.

[5] X. Wang, "Design and implementation of college English teaching quality evaluation system based on analytic hierarchy process," in *2020 international conference on computers, information processing and advanced education (CIPAE)*, IEEE, 2020, pp. 213–216.

[6] Y. Jiang, J. Zhang, and C. Chen, "Research on a new teaching quality evaluation method based on improved fuzzy neural network for college English," *Int. J. Contin. Eng. Educ. Life Long Learn.*, vol. 28, no. 3–4, pp. 293–309, 2018.

[7] N. Li, "A fuzzy evaluation model of college English teaching quality based on analytic hierarchy process," *Int. J. Emerg. Technol. Learn.*, vol. 16, no. 2, pp. 17–30, 2021.

[8] M. Sun, Y. Li, and B. He, "Study on a quality evaluation method for college English classroom teaching," *Futur. Internet*, vol. 9, no. 3, p. 41, 2017.

[9] L. Qian, "Research on college english teaching and quality evaluation based on data mining technology," *J. Appl. Sci. Eng.*, vol. 26, no. 4, pp. 547–556, 2022.

[10] T. Fujita and F. Smarandache, *Neutrosophic TreeSoft Expert Set and ForestSoft Set*. Infinite Study, 2025.

[11] A. Elsayed, "TrS-RAM: Leveraging Novel MCDM Techniques for Evaluating Sustainability of Fuel Cell Vehicles Based on Tree Soft Technique," *HyperSoft Set Methods Eng.*, vol. 1, pp. 46–58, 2024.

[12] S. F. AL-baker, I. El-henawy, and M. Mohamed, "Pairing New Approach of Tree Soft with MCDM Techniques: Toward Advisory an Outstanding Web Service Provider Based on QoS Levels," *Neutrosophic Syst. with Appl.*, vol. 14, pp. 17–29, 2024.

[13] F. Smarandache, *Practical applications of IndetermSoft Set and IndetermHyperSoft Set and introduction to TreeSoft Set as an extension of the MultiSoft Set*. Infinite Study, 2022.

[14] E. K. Zavadskas and Z. Turskis, "A new additive ratio assessment (ARAS) method in multicriteria decision-making," *Technol. Econ. Dev. Econ.*, vol. 16, no. 2, pp. 159–172, 2010.

[15] N. Liu and Z. Xu, "An overview of ARAS method: Theory development, application extension, and future challenge," *Int. J. Intell. Syst.*, vol. 36, no. 7, pp. 3524–3565, 2021.

Received: Oct 27, 2024. Accepted: March 14, 2025