NSS

Neutrosophic Sets and Systems, Vol. 85, 2025

University of New Mexico

IndetermSoft Set for Artificial Intelligence Solutions for Teaching Competition Plans Assessment in Colleges

Xun Lin[1]*, Xiaoli Feng[2]

[1]Chuzhou Vocational and Technical College, Chuzhou, 239000, China

[2]Hefei Preschool Education College, Hefei, Anhui, 230013, China

*Corresponding author, E-mail: 13855020123@163.com

Abstract: Artificial Intelligence (AI) is becoming a key factor in transforming conventional educational institutions in the age of digital transformation. The review and assessment of college teaching competition plans, a field that has hitherto relied on human judgment, is one of the newer uses. By utilizing AI, assessments might become more transparent, data-driven, and uniform. This study investigates how AI-based solutions might improve feedback quality, streamline the assessment process, and assist teachers in honing their pedagogical approaches. Our goal is to provide an effective framework for assessing teaching competition strategies by examining contemporary AI approaches and how they have been modified for use in educational settings. We use the IndetermSoft Set to solve the indeterminacy in the criteria values. We use the multi-criteria decision making (MCDM) method to show the ranks of alternatives. We use the COBRA method as a MCDM to rank the alternatives.

Keywords: IndetermSoft Set; Artificial Intelligence; Teaching Competition Plans; Education; Colleges.

1. Introduction

New possibilities for enhancing teaching methods at all levels, especially in higher education, have been brought about by the development of AI technology. College teaching contests provide a forum for showcasing cutting-edge teaching strategies, but their assessment systems frequently have issues with scalability, consistency, and fairness. One of the most important steps toward a more methodical and objective review procedure is the use of AI techniques for evaluating these contests[1], [2]. Conventional techniques for assessing teaching competition plans mostly depend on expert panels that use arbitrary criteria, which might result in discrepancies. The results may vary depending on the assessors' own biases, experience, and criteria for making judgments[3]. By evaluating lesson plans using established criteria, AI provides an option that guarantees a more impartial and repeatable evaluation. The capacity of AI to manage intricate and multifaceted evaluation tasks is one of its most important contributions to this discipline. Submissions to teaching competitions may be examined from a variety of angles, including originality, instructional design, engagement strategy, and learning results, using machine learning techniques, natural language processing (NLP), and predictive analytics[4], [5]. The time and effort required for comprehensive examinations can be significantly decreased by these capabilities.

Real-time feedback production is another benefit of using AI into teaching plan assessment. AI systems, in contrast to manual review, can quickly pinpoint areas of strength and development and provide thorough recommendations. In addition to offering participants practical insights, this kind of dynamic feedback promotes a culture of ongoing pedagogical practice development.

But there are obstacles to overcome when integrating AI technology into educational assessment. It is important to carefully address issues like data privacy, model openness, and the danger of relying too much on automated evaluations[6], [6]. A hybrid approach is necessary for effective integration, one in which AI enhances human judgment rather than takes its place, guaranteeing that subtle facets of high-quality instruction are not missed.

The creation of thorough evaluation criteria is another essential component in the implementation of AI-based assessment systems. The criteria must be clear, reflective of many teaching philosophies, and adaptable to various educational environments for AI models to function efficiently. To create these frameworks, educators and technologists must work together.

Promising outcomes are shown by successful case studies from organizations that have tested AI-based evaluation systems[7], [8]. AI can revolutionize the assessment of teaching competition plans, as evidenced by increased evaluation accuracy, participant happiness, and richer feedback content. These early adopters offer insightful information for broader college deployment.

This study offers a methodical strategy for implementing AI solutions for competition plan evaluation instruction in colleges considering these advancements[9], [10]. We hope to provide a useful resource for organizations wishing to update and improve their teaching evaluation systems by examining different AI models, assessing their efficacy, and describing workable implementation options.

2. IndetermSoft Set Model

Between 2018-2024 Smarandache [https://fs.unm.edu/TSS/] introduced six new types of soft sets: HyperSoft Set, IndetermSoft Set, IndetermHyperSoft Set, SuperHyperSoft Set, TreeSoft Set, ForestSoft Set[11], [12], [13], [14], [15]. This study uses the IndetermSoft set to solve the uncertainty in the criteria values. The IndetermSoft set is used with the MCDM approach to compute the criteria weights and ranking the alternatives. Smarandache developed different sets[11], [12].

K is a non-empty subset of Y, Y is a discourse universe, and P(K) is the powerset of K. Suppose that D is a set of its values and that and is an attribute. D function F: D → (K) pertaining to the values of one or more attributes is known as an IndetermSoft Set (Function); set A contains some ambiguity[13], [14].

P(K) has some indeterminacy. Alternatively, if at least one attribute value v ∈ D, then F(v) = indeterminate (uncertain, ambiguous, or not unique). or any mix of those three situations.

An IndetermSoft Set is a soft set that contains a given quantity of indeterminate (ambiguous, uncertain, alternate, conflicting) data or techniques, according to Smarandache.

We show the steps of the COBRA methodology to rank the alternatives.

The decision matrix is developed by experts and decision makers. Let experts evaluate the criteria and alternatives. We integrate these criteria and alternatives into a single matrix.

Compute the criteria weights.

The weights of criteria are computed using the average method.

Normalize the decision matrix.

$$A_{ij} = \frac{r_{ij}}{\max r_{ij}} \tag{1}$$

Compute the weighted decision matrix.

$$H_{ij} = W_j A_{ij} \tag{2}$$

Compute the distance values from ideal solutions

$$D_j = \max H_{ij}\ ;\ D_j = \min H_{ij} \text{ for positive criteria} \tag{3}$$

$$A_j = \min q_{ij}\ ; B_j = \max q_{ij} \text{for positive criteria} \tag{4}$$

$$Q_j = \frac{\sum_{i=1}^{m} H_{ij}}{m} \tag{5}$$

Determine the distance to positive and cost criteria

$$T(D_j) = \sqrt{\sum_{j=1}^{n} (D_j - H_{ij})^2} \tag{6}$$

$$T(A_j) = \sqrt{\sum_{j=1}^{n} (A_j - H_{ij})^2} \tag{7}$$

$$T(Q_j) = \sqrt{\sum_{j=1}^{n} (Q_j - H_{ij})^2} \tag{8}$$

Determine the final distance

$$T_i = \frac{T(D_j) - T(A_j) - T(Q_j)}{3} \quad (9)$$

Order the alternatives

3. Application

We implemented the steps of the proposed approach for Artificial Intelligence Solutions for Teaching Competition Plans Assessment in Colleges. We use eight criteria and seven alternatives. This study has indeterminacy in the first and second criterion. So the IndetermSoft set is used to solve this indeterminacy. We have seven plans such as: Integrative Learning Project Plan, AI-Enhanced Interactive Lecture Strategy, Flipped Classroom Model for STEM Subjects, Gamification-Based Language Learning Plan, Problem-Based Learning with IoT Applications, Cross-Disciplinary Collaborative Workshop Series, Data-Driven Personalized Learning Paths Design. We have eight criteria such as:

- Innovation and Creativity {High, Medium, Low}
- Alignment with Educational Objectives {Excellent, Good, Fair}
- Feasibility of Implementation {Practical, Moderate, Challenging}
- Technological Integration {High, Medium, Low}
- Pedagogical Soundness {Strong, Adequate, Weak}
- Scalability Across Courses {Highly Scalable, Partially Scalable, Limited}
- Assessment Methods and Tools {Comprehensive, Sufficient, Basic}
- Student Engagement Potential {High, Medium, Low}

We select the criteria values such as:

- $C1$: $\{High, Medium, Low\}$
- $C2$: $\{Excellent, Good, Fair\}$
- $C3$: $\{Practical\}$
- $C4$: $\{High\}$
- $C5$: $\{Strong\}$
- $C6$: $\{Highly\ Scalable\}$
- $C7$: $\{Comprehensive\}$
- $C8$: $\{High\}$

So, we divide the criteria values into different sets such as:

- Set 1: C1: {High}, C2: {Excellent}, C3: {Practical}, C4: {High}, C5: {Strong}, C6: {Highly Scalable}, C7: {Comprehensive}, C8: {High}.
- Set 2: C1: { High, Medium}, C2: { Excellent,}, C3: {Practical}, C4: {High}, C5: {Strong}, C6: {Highly Scalable}, C7: {Comprehensive}, C8: {High}.
- Set 3: C1: { High, Medium, and Low}, C2: { Excellent }, C3: {Practical}, C4: {High}, C5: {Strong}, C6: {Highly Scalable}, C7: {Comprehensive}, C8: {High}.

- Set 4: C1: { High }, C2: {Excellent}, C3: {Practical}, C4: {High}, C5: {Strong}, C6: {Highly Scalable}, C7: {Comprehensive}, C8: {High}.
- Set 5: C1: { High }, C2: { Excellent, Good}, C3: {Practical}, C4: {High}, C5: {Strong}, C6: {Highly Scalable}, C7: {Comprehensive}, C8: {High}.
- Set 6: C1: { High }, C2: { Excellent, Good, Fair }, C3: {Practical}, C4: {High}, C5: {Strong}, C6: {Highly Scalable}, C7: {Comprehensive}, C8: {High}.

Let three experts evaluate the criteria and alternatives to build the decision matrix. We combine these value into a single matrix. We compute the criteria weights such as:

- $C1 = 0.121142278$
- $C2 = 0.116289651$
- $C3 = 0.110285161$
- $C4 = 0.129811627$
- $C5 = 0.133473736$
- $C6 = 0.127446054$
- $C7 = 0.131094911$
- $C8 = 0.130456582$

Set 1 results described such as:

Normalize the decision matrix using eq.(1) as shown in Fig 1.

Compute the weighted decision matrix using eq. (2) as shown in Fig 2.

Compute the distance values from ideal solutions using eqs. (3,4, and 5).

Determine the distance to positive and cost criteria using eqs. (6, 7, and 8) as shown in Figs 3,4, and 5.

Determine the final distance using eq. (9).

Order the alternatives.

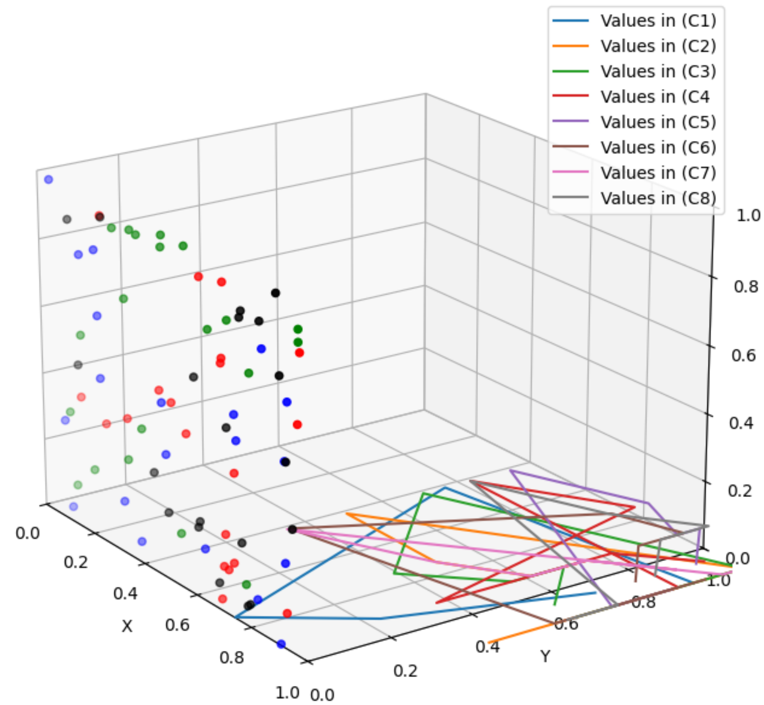

Fig 1. The normalized decision matrix.

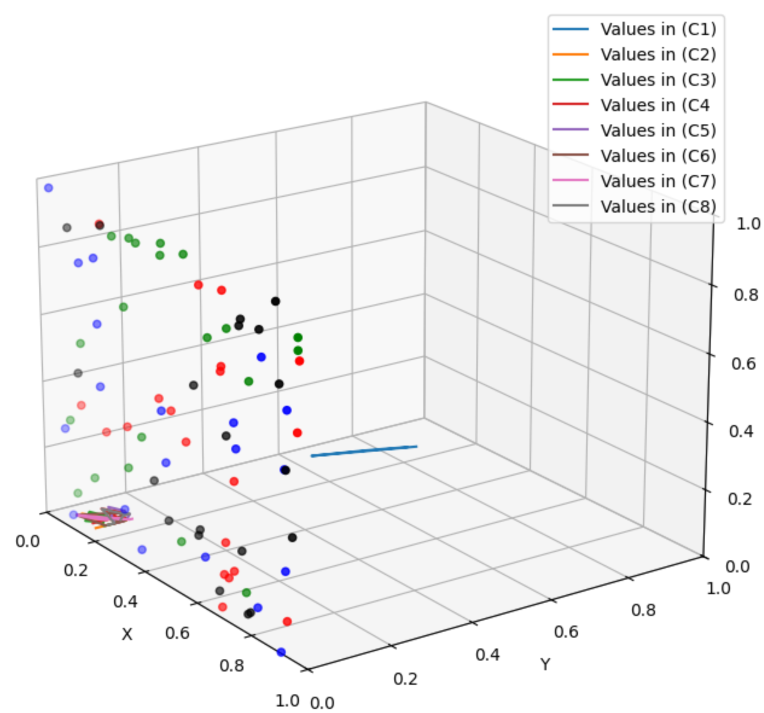

Fig 2. The weighted decision matrix.

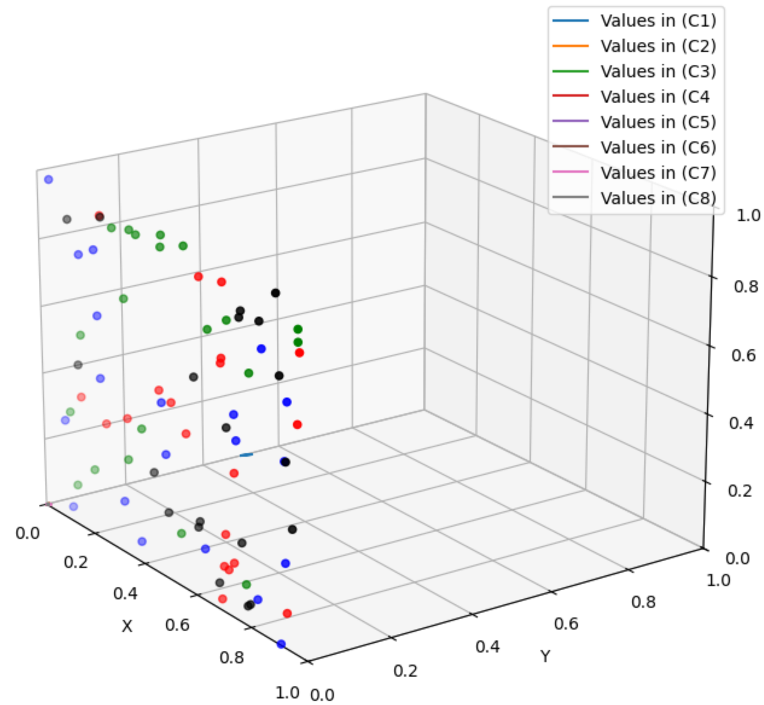

Fig 3. The values of $T(D_j)$.

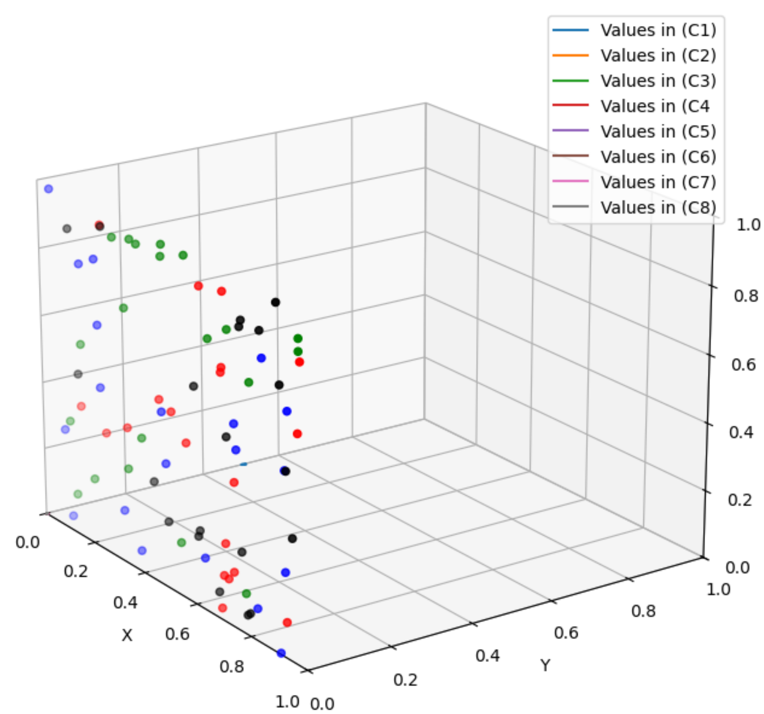

Fig 4. The values of $T(A_j)$.

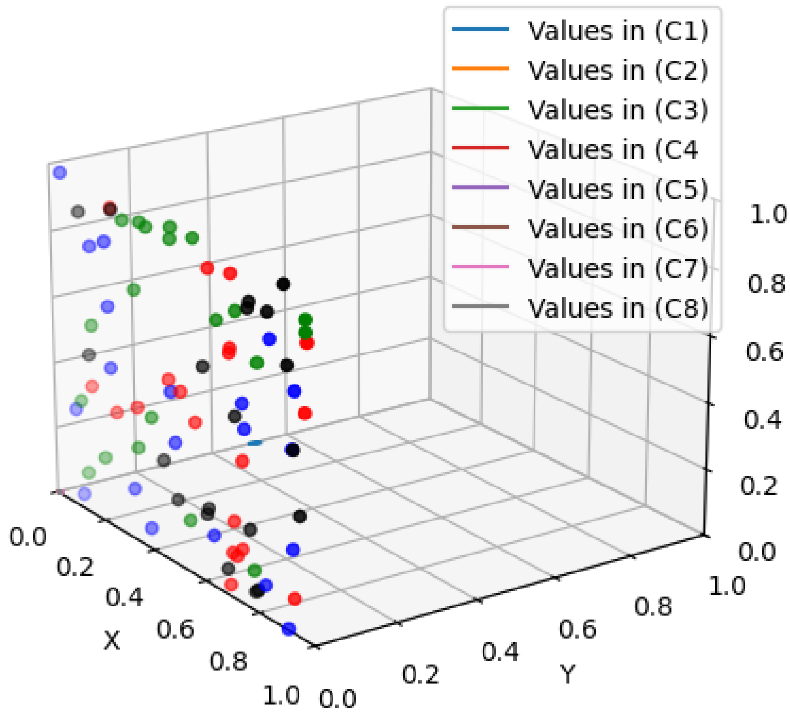

Fig 5. The values of $T(Q_j)$.

Set 2 results described such as:

Normalize the decision matrix using eq.(1) as shown in Fig 6.

Compute the weighted decision matrix using eq. (2) as shown in Fig 7.

Compute the distance values from ideal solutions using eqs. (3,4, and 5).

Determine the distance to positive and cost criteria using eqs. (6, 7, and 8) as shown in Figs 8,9, and 10.

Determine the final distance using eq. (9).

Order the alternatives.

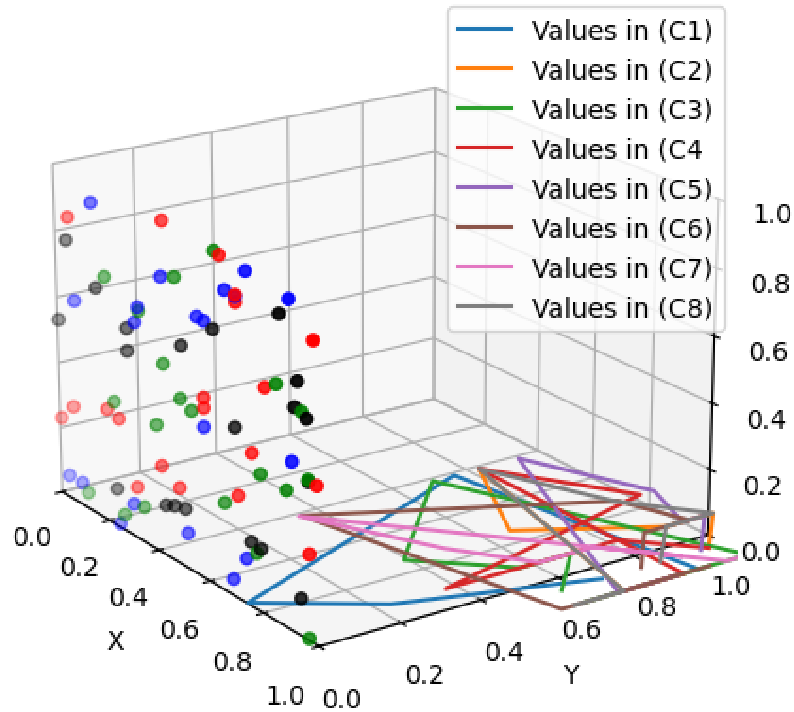

Fig 6. The normalized decision matrix.

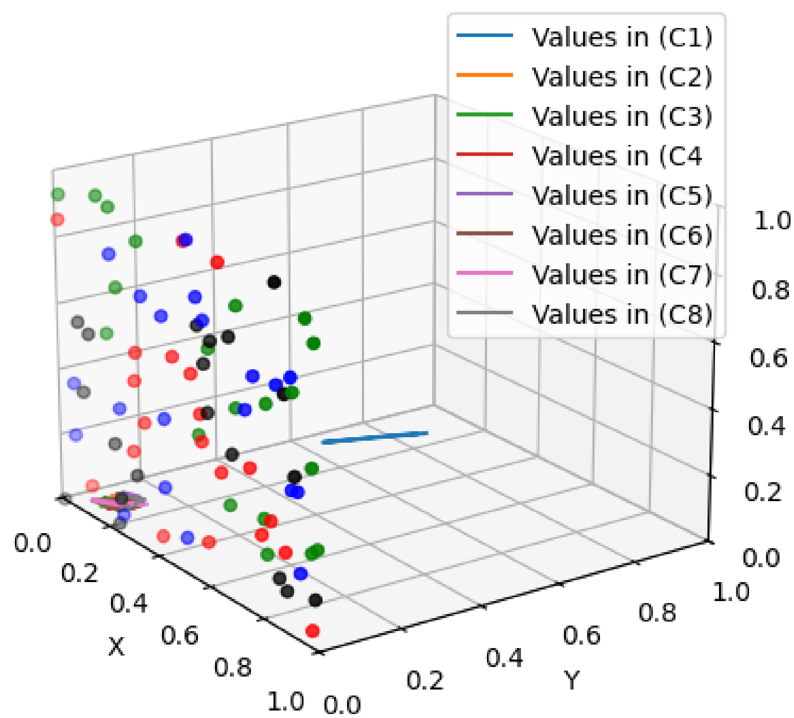

Fig 7. The weighted decision matrix.

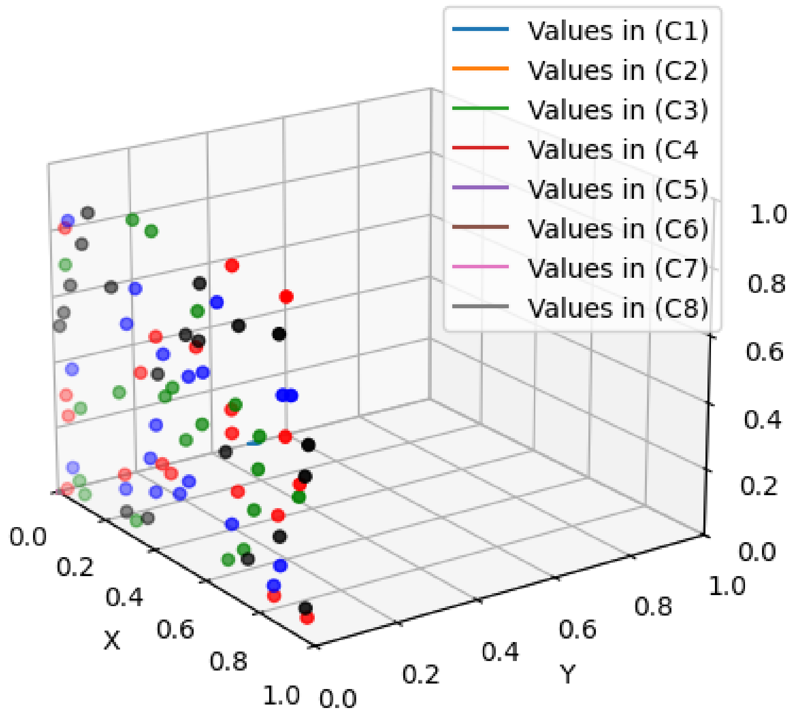

Fig 8. The values of $T(D_j)$.

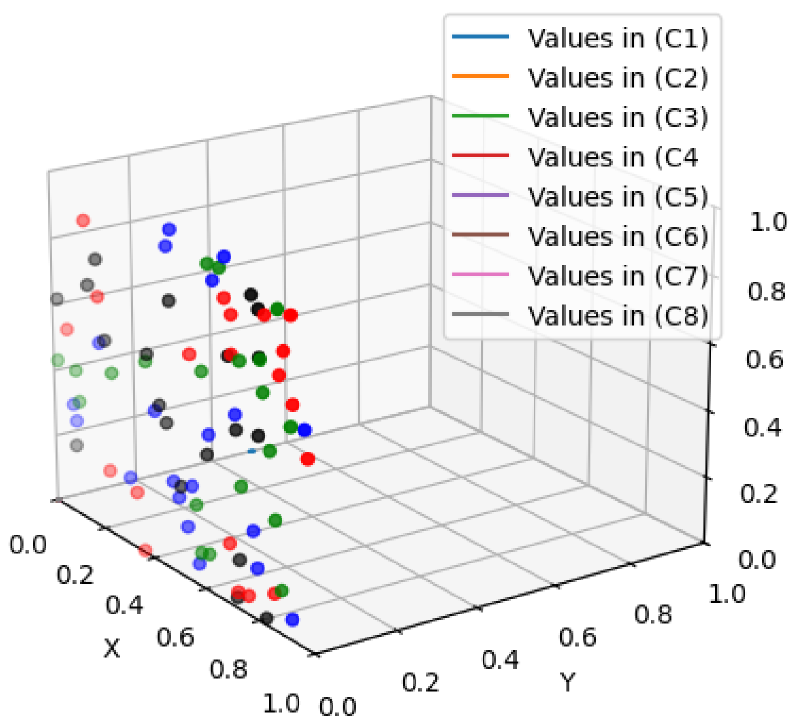

Fig 9. The values of $T(A_j)$.

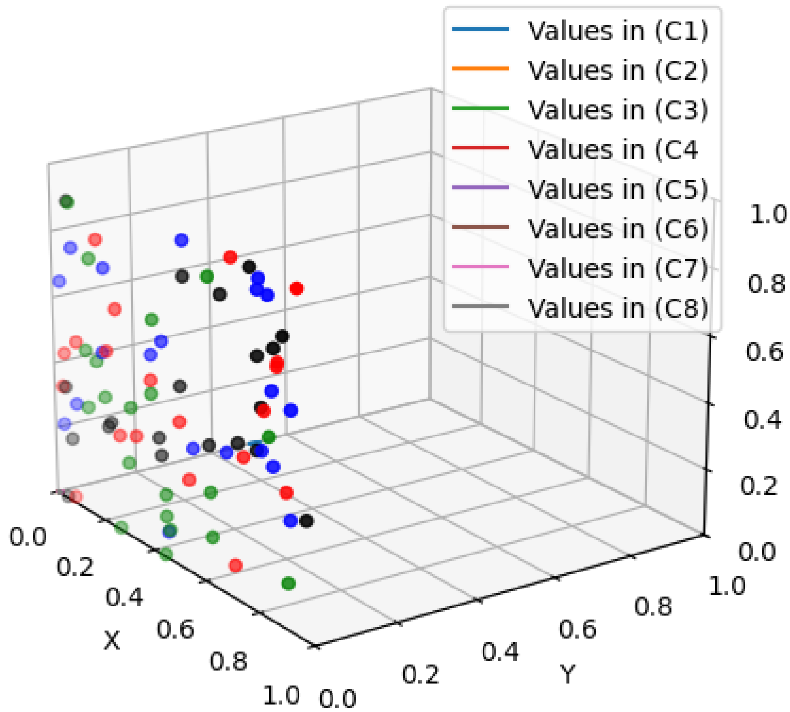

Fig 10. The values of $T(Q_j)$.

Set 3 results described such as:

Normalize the decision matrix using eq.(1) as shown in Fig 11.

Compute the weighted decision matrix using eq. (2) as shown in Fig 12.

Compute the distance values from ideal solutions using eqs. (3,4, and 5).

Determine the distance to positive and cost criteria using eqs. (6, 7, and 8) as shown in Figs 13,14, and 15.

Determine the final distance using eq. (9).

Order the alternatives.

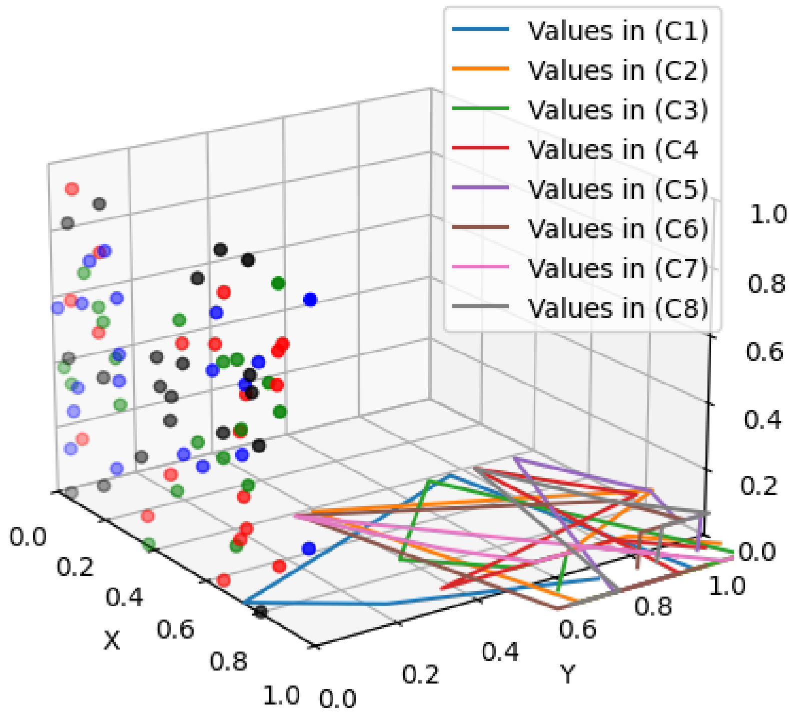

Fig 11. The normalized decision matrix.

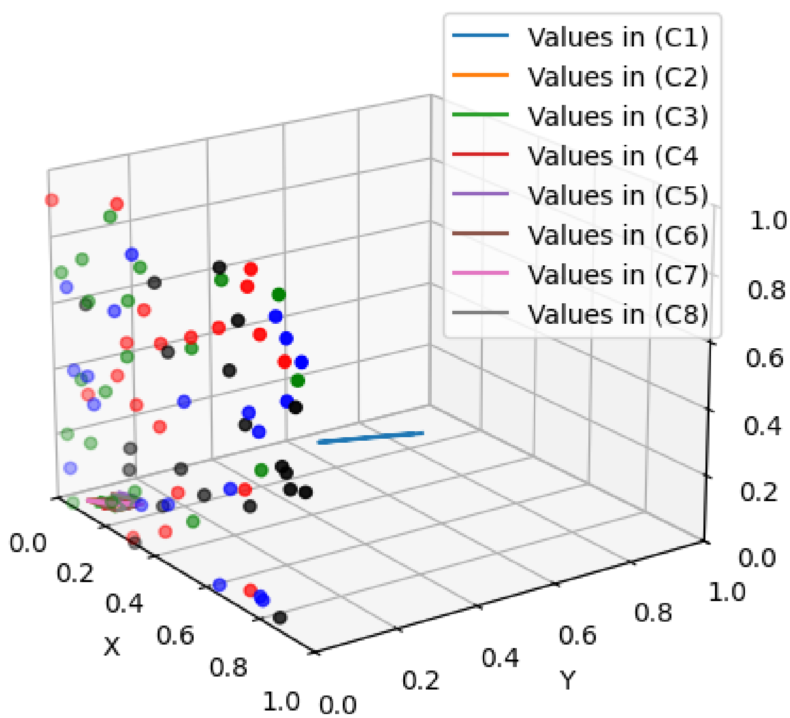

Fig 12. The weighted decision matrix.

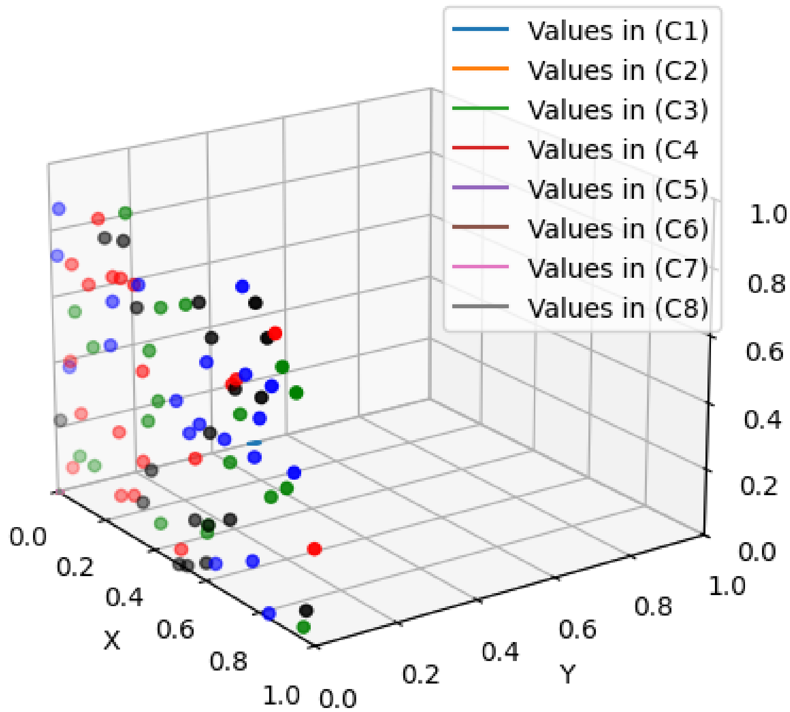

Fig 13. The values of $T(D_j)$.

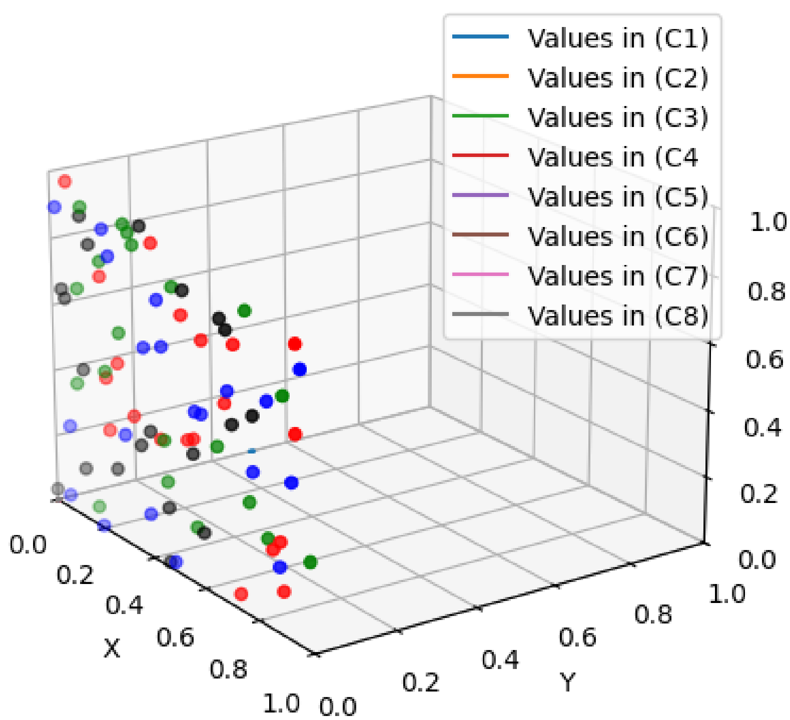

Fig 14. The values of $T(A_j)$.

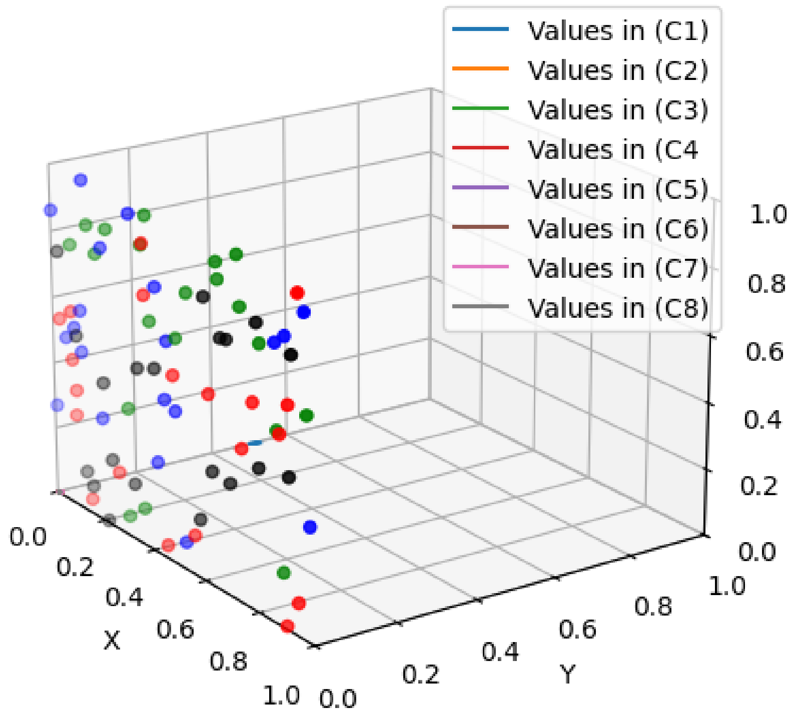

Fig 15. The values of $T(Q_j)$.

Set 4 results described such as:

Normalize the decision matrix using eq.(1) as shown in Fig 16.

Compute the weighted decision matrix using eq. (2) as shown in Fig 17.

Compute the distance values from ideal solutions using eqs. (3,4, and 5).

Determine the distance to positive and cost criteria using eqs. (6, 7, and 8) as shown in Figs 18,19, and 20.

Determine the final distance using eq. (9).

Order the alternatives.

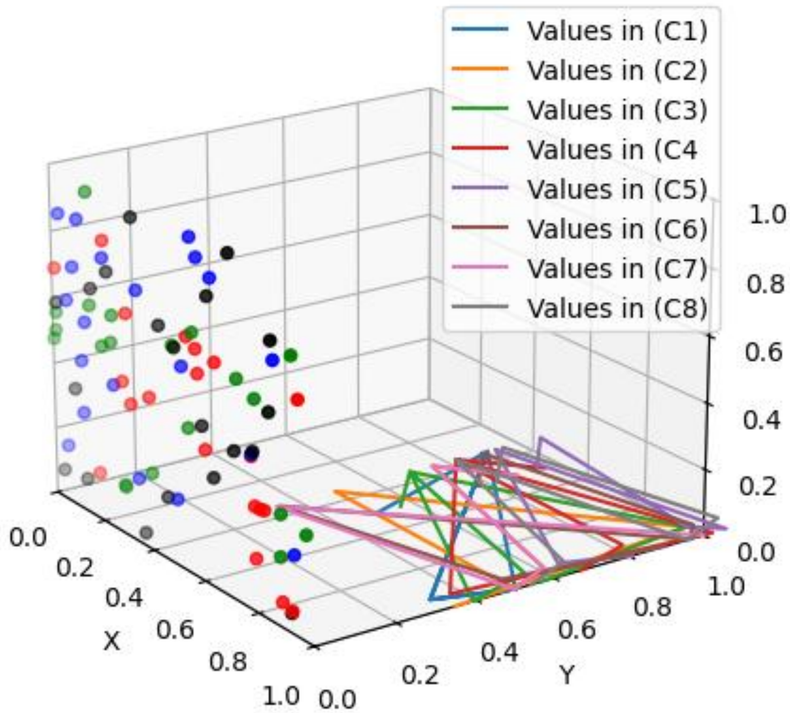

Fig 16. The normalized decision matrix.

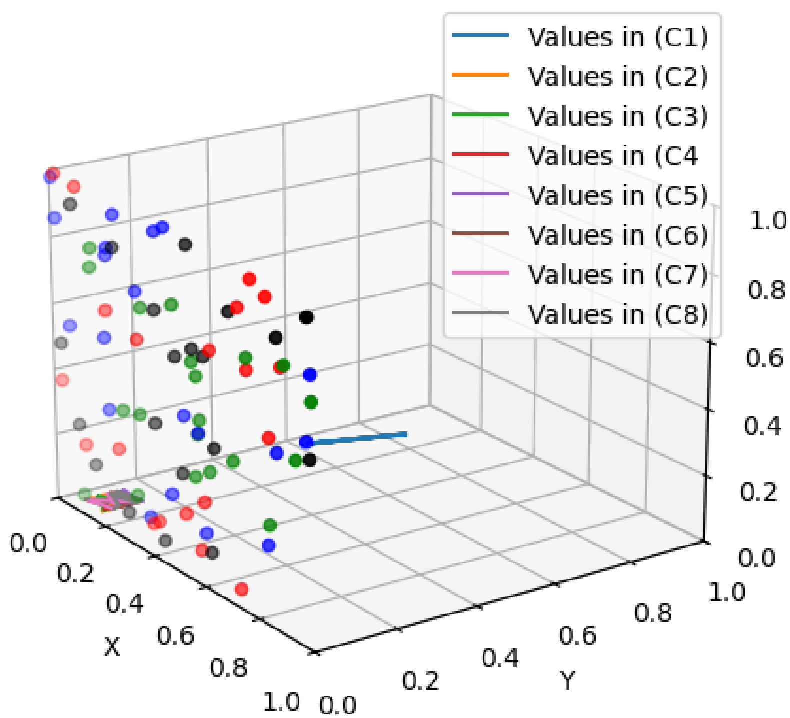

Fig 17. The weighted decision matrix.

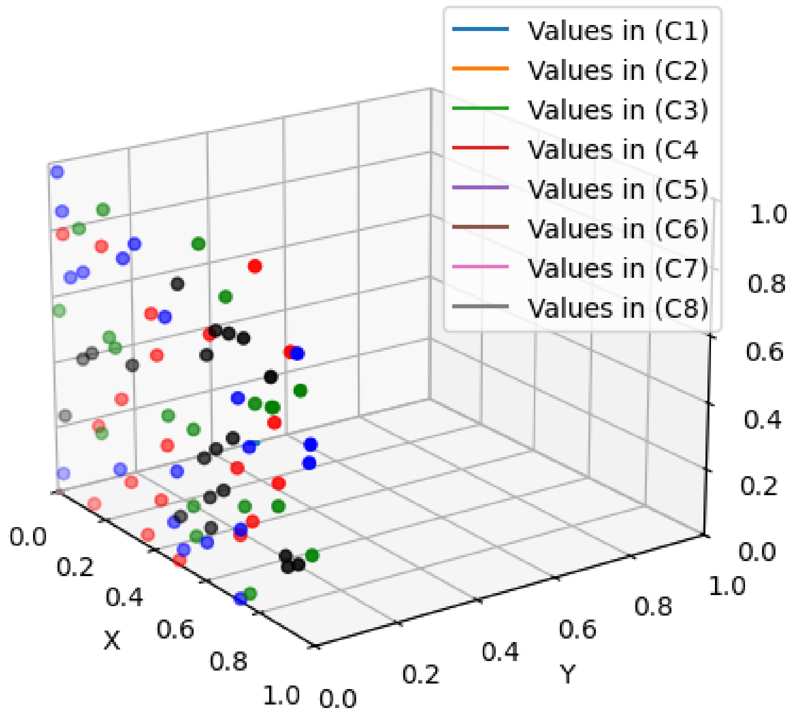

Fig 18. The values of $T(D_j)$.

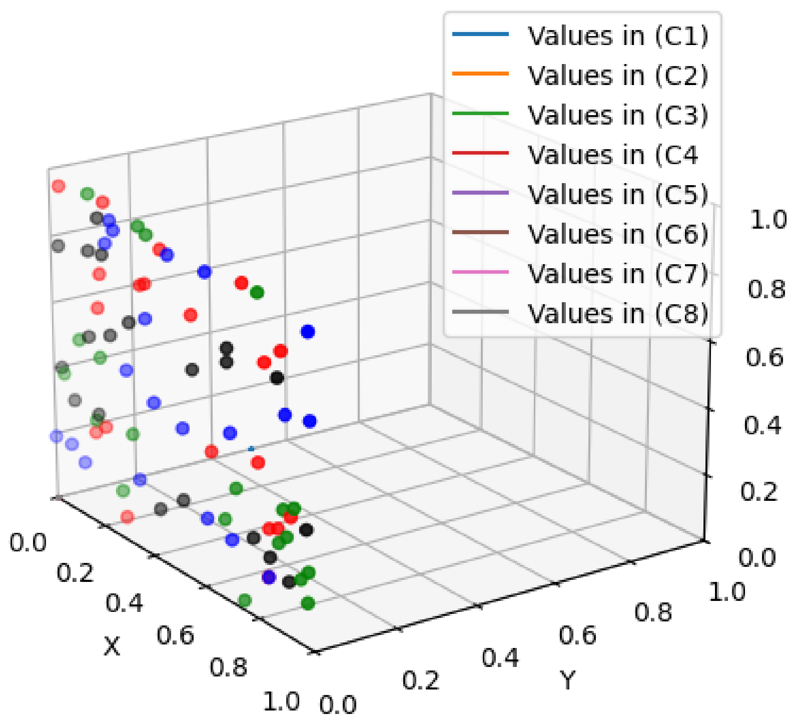

Fig 19. The values of $T(A_j)$.

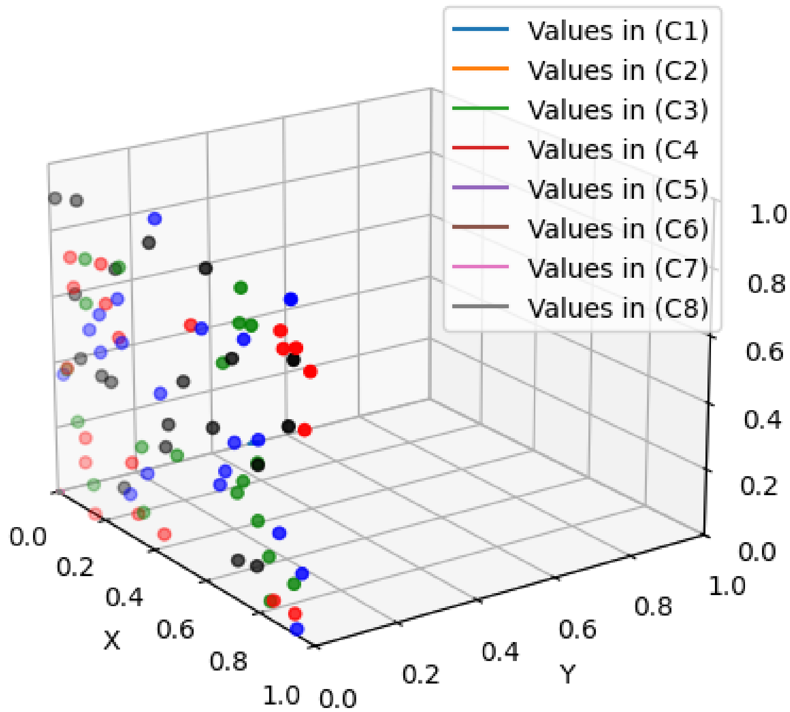

Fig 20. The values of $T(Q_j)$.

Set 5 results described such as:

Normalize the decision matrix using eq.(1) as shown in Fig 21.

Compute the weighted decision matrix using eq. (2) as shown in Fig 22.

Compute the distance values from ideal solutions using eqs. (3,4, and 5).

Determine the distance to positive and cost criteria using eqs. (6, 7, and 8) as shown in Figs 23,24, and 25.

Determine the final distance using eq. (9).

Order the alternatives.

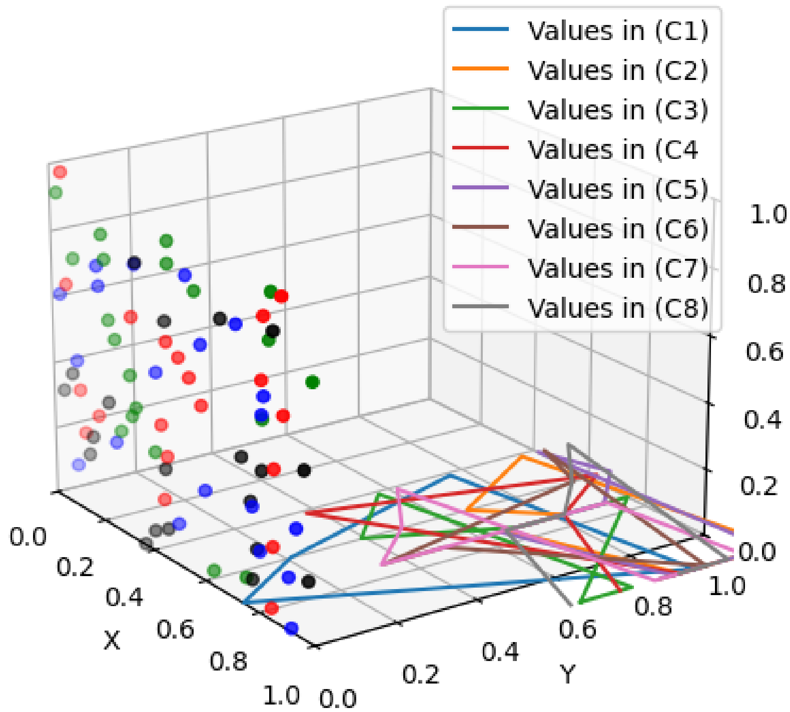

Fig 21. The normalized decision matrix.

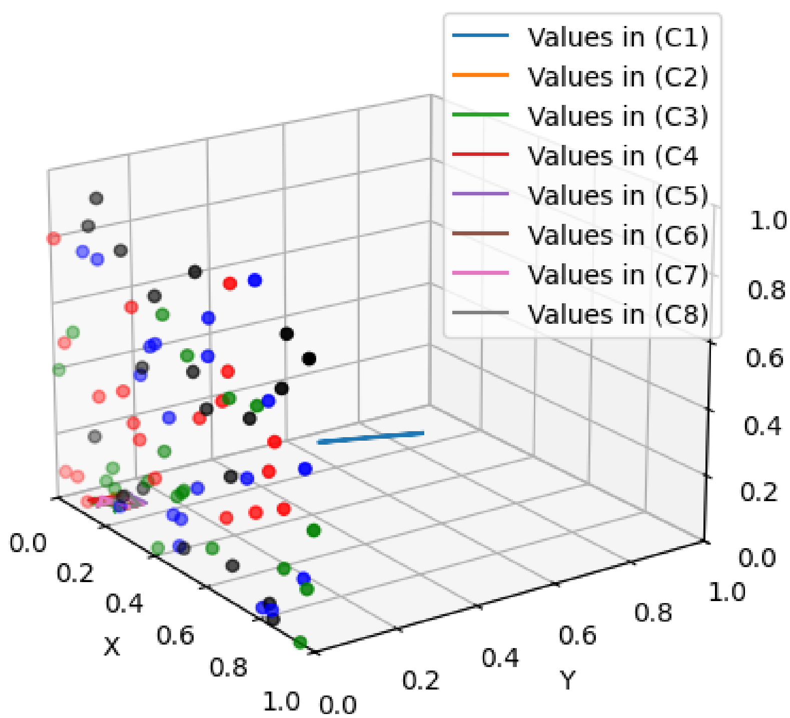

Fig 22. The weighted decision matrix.

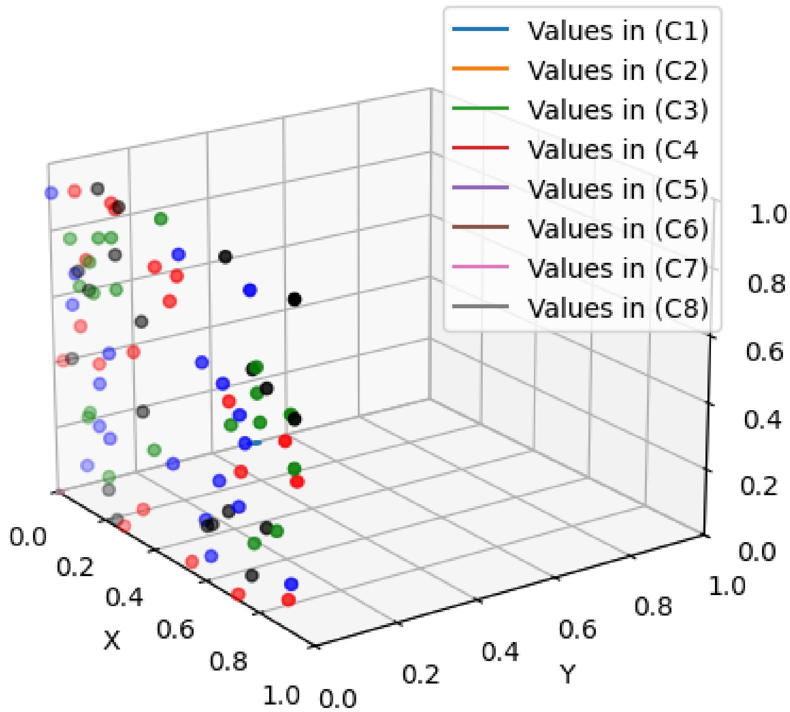

Fig 23. The values of $T(D_j)$.

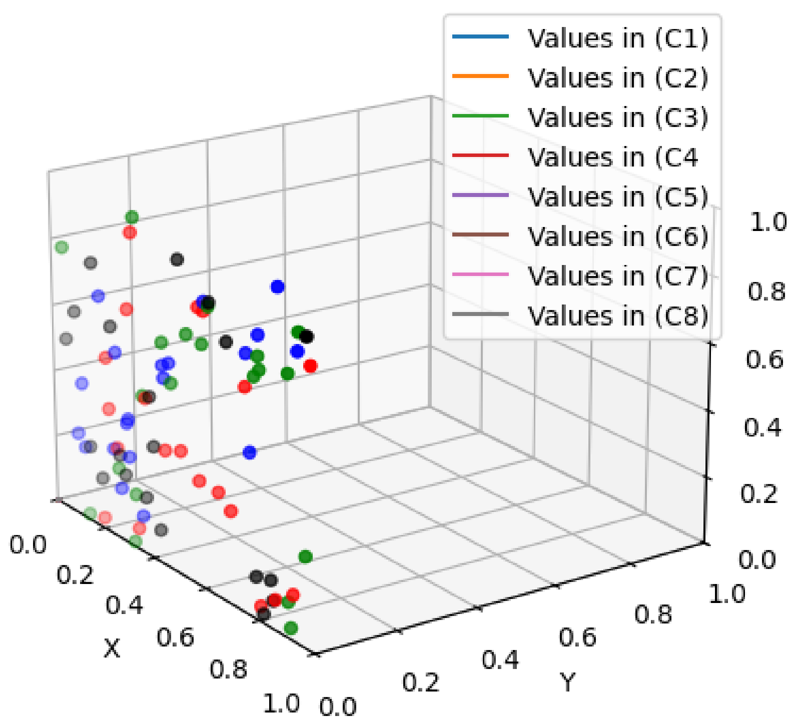

Fig 24. The values of $T(A_j)$.

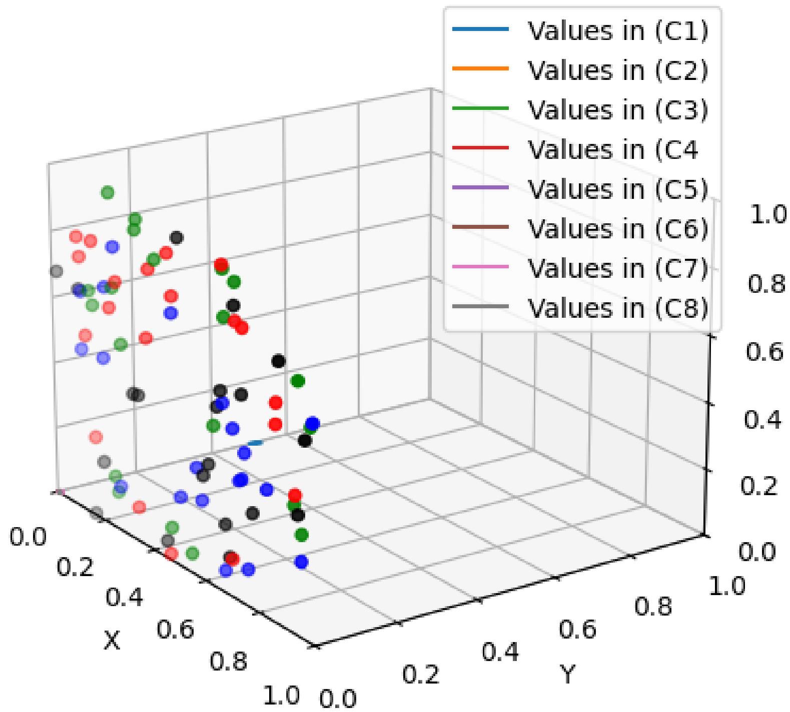

Fig 25. The values of $T(Q_j)$.

Set 6 results described such as:

Normalize the decision matrix using eq.(1) as shown in Fig 26.

Compute the weighted decision matrix using eq. (2) as shown in Fig 27.

Compute the distance values from ideal solutions using eqs. (3,4, and 5).

Determine the distance to positive and cost criteria using eqs. (6, 7, and 8) as shown in Figs 28,29, and 30.

Determine the final distance using eq. (9).

Order the alternatives.

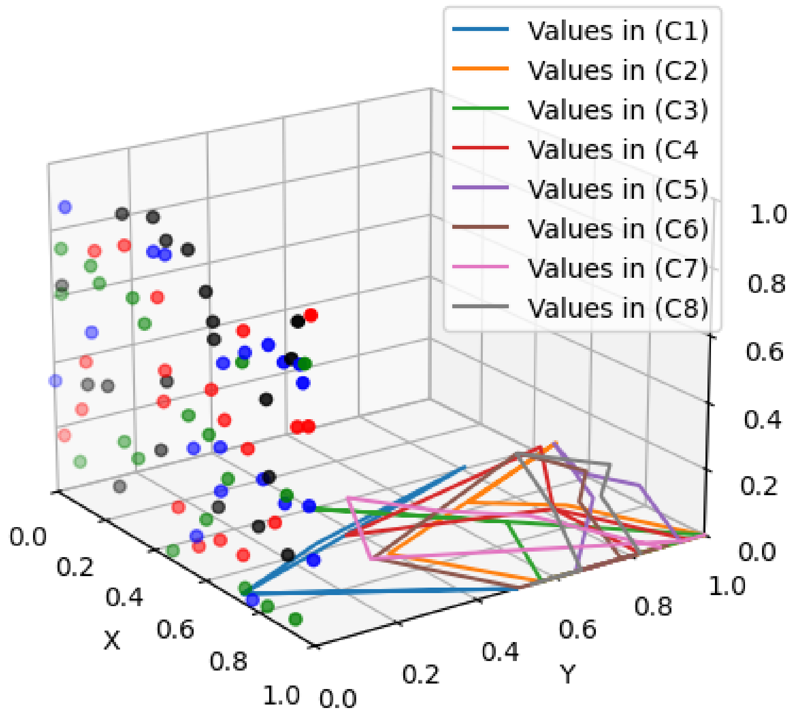

Fig 26. The normalized decision matrix.

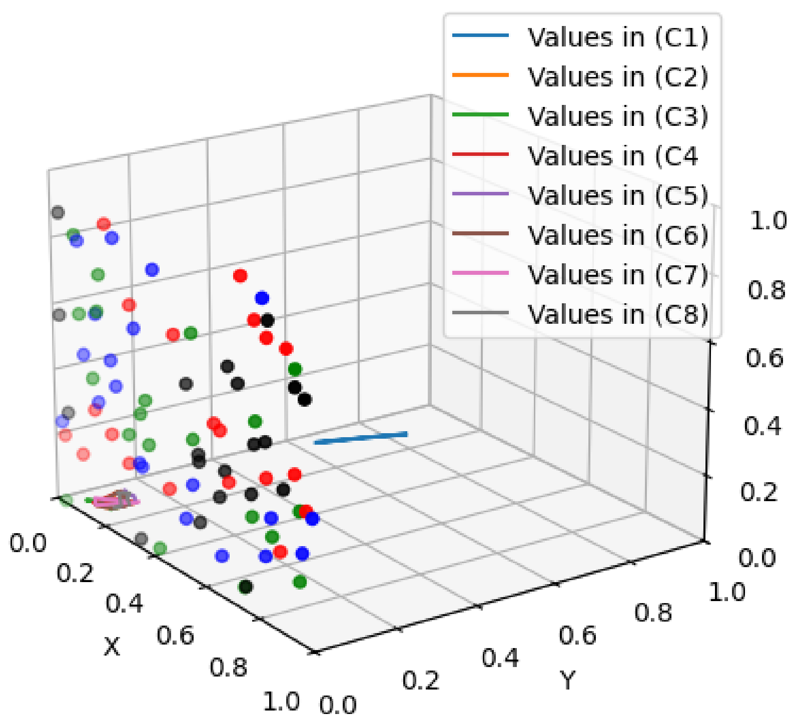

Fig 27. The weighted decision matrix.

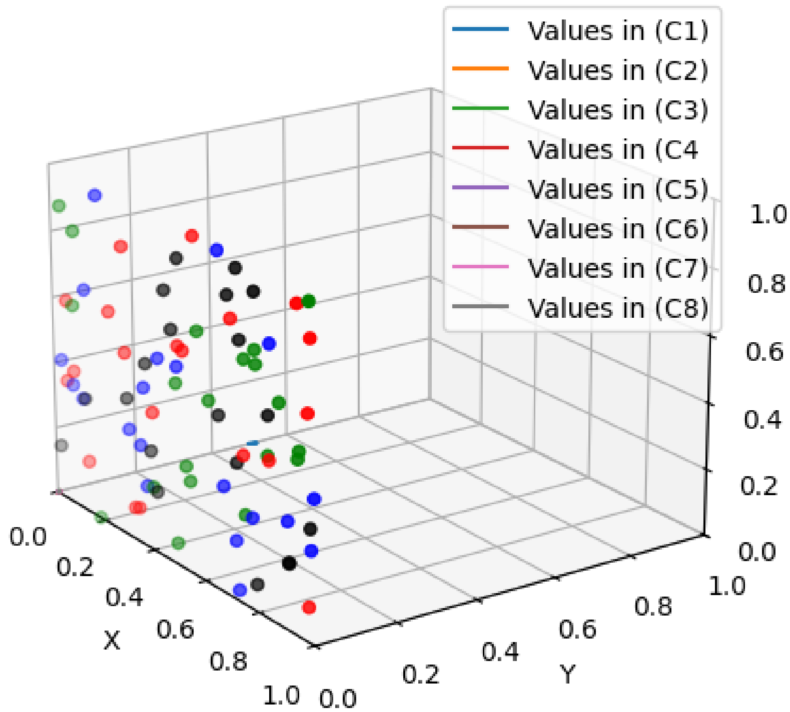

Fig 28. The values of $T(D_j)$.

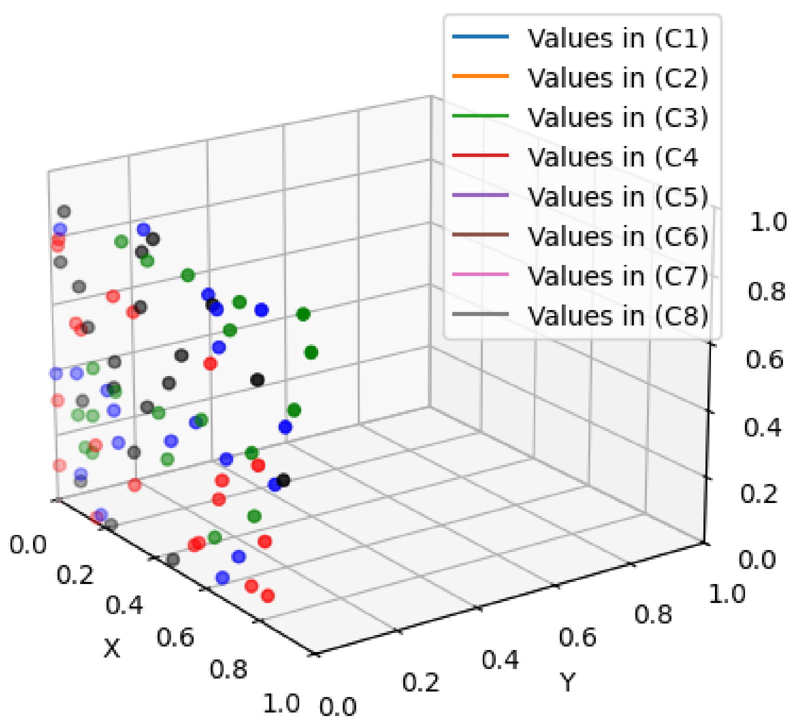

Fig 29. The values of $T(A_j)$.

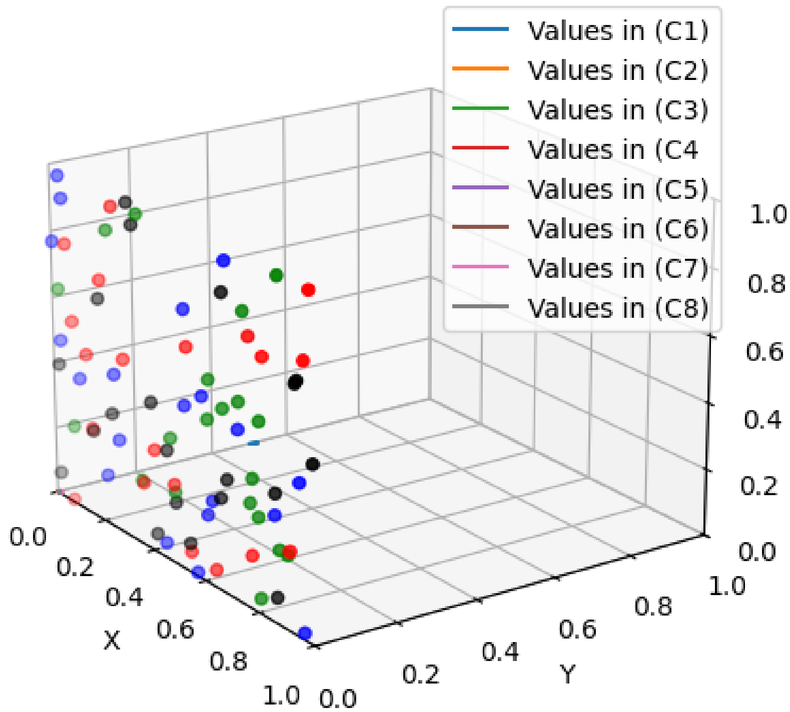

Fig 30. The values of $T(Q_j)$.

We obtain the final ranks of alternatives in each set such as:

Set 1

- Highest Performer: A6 (Rank 1 - lowest), A7 (2 - better).
- Mid Performers: A4 (3), A5 (4), A3 (5).
- Lower Performers: A1 (6), A2 (7 - highest).
- A2 is the strongest (Rank 7); A6 is the weakest.

Set 2

- Highest Performer: A6 (1), A7 (2).
- Mid Performers: A1 (3), A4 (4), A5 (5).
- Lower Performers: A3 (6), A2 (7).
- A2 again is the strongest performer; A6 struggles.

Set 3

- Highest Performer: A6 (1), A7 (2).
- Mid Performers: A5 (3), A1 (4), A4 (5).
- Lower Performers: A2 (6), A3 (7).
- A3 is the best (Rank 7); A6 is the weakest.

Set 4

- Highest Performer: A7 (1), A6 (2).
- Mid Performers: A3 (3), A5 (4), A4 (5).
- Lower Performers: A1 (6), A2 (7).
- A2 shows the highest performance (7); A7 is at the lowest (1).

Set 5

- Highest Performer: A6 (1), A7 (2).
- Mid Performers: A3 (3), A1 (4).
- Lower Performers: A2 (5), A4 (6), A5 (7).
- A5 shows the best result (7); A6 is the lowest.

Set 6

- Highest Performer: A6 (1), A7 (2).
- Mid Performers: A1 (3), A5 (4), A3 (5).
- Lower Performers: A2 (6), A4 (7).
- A4 is the best performer (7); A6 the worst (1).

4. Conclusions

The evaluation of college teaching competition strategies might be revolutionized by artificial intelligence. AI may overcome many of the long-standing drawbacks of conventional approaches by introducing objectivity, scalability, and data-driven insights into the review process. However, ethical issues, system openness, and the complementing function of human assessors must all be carefully considered. AI-driven assessment tools will probably play a key role in initiatives to foster excellent instruction and encourage academic achievement as education develops in tandem with technology. We use the IndetermSoft Set to solve the indeterminacy in the criteria values. This study has eight criteria and seven alternatives. The COBRA method is used to rank the alternatives.

Acknowledgment

This work was supported by the key project of Anhui Vocational and Adult Education Society "Research on Improving Classroom Teaching Quality of Higher Vocational Education Based on OBE" (Azcj2022042); Chuzhou Vocational and Technical College teaching research key project "Yangtze River Delta integration background of public English difficulties and solutions" (skz-2022-04);）; Chuzhou Vocational and Technical Institute (YJP-2019-03); In 2023, Anhuizhou Quality Engineering Program - Curriculum Ideological and Political Model Curriculum Innovation and Entrepreneurship Education, project number: 2023-kcsz-063; Key Project of Anhui Vocational and Adult Education Society: High-quality Construction of Municipal Industry-Education Consortium (AZCJ2024207); Action Research on the Precise Service of Colleges and Universities to Improve the Quality of Preschool Education and Care in Rural Kindergartens under the Rural Revitalization Strategy, a Project of Humanities and Social Sciences in Anhui Province (Project Number: SK2021A0912) and Research on the Implementation Framework and Path of Artificial Intelligence Enlightenment Education in Kindergartens, a Project of Information Technology in Hefei City (2024-HJG24102).

References

[1] U. Yadav and U. Shrawankar, “Artificial Intelligence Across Industries: A Comprehensive Review With a Focus on Education,” *AI Appl. Strateg. Teach. Educ.*, pp. 275–320, 2025.

[2] M. Halagatti, S. Gadag, S. Mahantshetti, C. V Hiremath, D. Tharkude, and V. Banakar, “Artificial intelligence: the new tool of disruption in educational performance assessment,” in *Smart analytics, artificial intelligence and sustainable performance management in a global digitalised economy*, Emerald Publishing Limited, 2023, pp. 261–287.

[3] F. Pedro, M. Subosa, A. Rivas, and P. Valverde, “Artificial intelligence in education: Challenges and opportunities for sustainable development,” 2019.

[4] A. W. S. A. B. U. EID *et al.*, “Artificial Intelligence in Education Predicting College Plans of High School Students,” *J. Intell. Syst. Appl. Data Sci.*, vol. 2, no. 1, 2024.

[5] V. Kuleto *et al.*, “Exploring opportunities and challenges of artificial intelligence and machine learning in higher education institutions,” *Sustainability*, vol. 13, no. 18, p. 10424, 2021.

[6] R. Bucea-Manea-Țoniş *et al.*, “Artificial intelligence potential in higher education institutions enhanced learning environment in Romania and Serbia,” *Sustainability*, vol. 14, no. 10, p. 5842, 2022.

[7] P. Williams, “AI, analytics and a new assessment model for universities,” *Educ. Sci.*, vol. 13, no. 10, p. 1040, 2023.

[8] H.-T. Chang and C.-Y. Lin, “Applying Competition-Based Learning to Stimulate Students’ Practical and Competitive AI Ability in a Machine Learning Curriculum,” *IEEE Trans. Educ.*, 2024.

[9] J. Carpio Cañada, T. d J. Mateo Sanguino, J. J. Merelo Guervós, and V. M. Rivas Santos, "Open classroom: enhancing student achievement on artificial intelligence through an international online competition," *J. Comput. Assist. Learn.*, vol. 31, no. 1, pp. 14–31, 2015.

[10] B. Li, Y. Fei, and H. Liu, "An artificial intelligence based model for evaluation of college students' ability and characteristics through teaching evaluation," *J. Intell. Fuzzy Syst.*, vol. 40, no. 2, pp. 3397–3407, 2021.

[11] 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.

[12] F. Smarandache, *New types of soft sets "hypersoft set, indetermsoft set, indetermhypersoft set, and treesoft set": an improved version*. Infinite Study, 2023.

[13] F. Smarandache, *Introduction to the IndetermSoft Set and IndetermHyperSoft Set*, vol. 1. Infinite Study, 2022.

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

[15] F. Smarandache, "Foundation of the SuperHyperSoft Set and the Fuzzy Extension SuperHyperSoft Set: A New Vision," *Neutrosophic Syst. with Appl.*, vol. 11, pp. 48–51, 2023.

Received: Nov. 7, 2024. Accepted: April 30, 2025