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A Human-Centered Evaluation of AI-Augmented Educational Intelligence Ecosystems Using a T-Spherical Fuzzy SWARA–COPRAS Decision Framework

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ABSTRACT

The rapid adoption of artificial intelligence (AI) within the higher education sector has transformed the traditional learning system into a multifaceted AI-based educational intelligence system, as required by solid, transparent, and human-centered evaluation systems. Such ecosystems involve the multidimensional elements of pedagogical effectiveness, ethical responsibility, technological reliability, organizational readiness, and learner support, all of which are always uncertain, subjective, and professionally tentative. Conventional evaluation techniques are normally incapable of assessing this type of complexity, and thus, give wrongful evaluations and unreliable evaluation outcomes. To overcome this challenge, the proposed T-spherical fuzzy SWARA-COPRAS (TSF-SWARA-COPRAS) decision framework (the human-based) has been proposed: the criterion importance is determined by Step-wise Weight Assessment Ratio Analysis (SWARA), and it ranks the alternatives by using Complex Proportional Assessment (COPRAS). In the model of uncertain and imprecise expert judgments in membership and non-membership levels as well as hesitation levels, the proposed framework presupposes the application of T-spherical fuzzy sets (TSFSs) in the model, which would strengthen the capacity of the model to maximize the modeling flexibility and the realism of decisions. The integrated framework enables the flexible prioritization of the key dimensions of assessment and open assessment of the options of educational intelligence systems. To prove the effectiveness, strength, and usability of the proposed solution, it is represented with the help of a detailed numerical case study and a comparative analysis. The results demonstrate that the framework is effective in managing uncertainty, enhancing ranking stability, and enabling rational and transparent decision-making, which can be of significant value as a decision support tool to policy-makers, educators, and AI system developers as a way of ensuring responsible AI integration and quality improvement in the long-term in higher education.

Keywords: T-spherical Fuzzy sets, SWARA method, COPRAS method, Artificial intelligence in education, Multi-criteria decision-making, Educational Intelligence Ecosystems

(MSC2020) Codes: 03E72, 90B50, 91B65, 90B50

1 | INTRODUCTION

The accelerated innovation of artificial intelligence (AI) technologies is transforming the higher education industry, as it has become possible to develop smart learning environments that integrate adaptive learning, automated assessment, learning analytics, and personalized student care. The outcome of these processes has been a series of AI-enriched learning intelligence systems where the digital infrastructural, pedagogical, ethical, and organizational preparedness have come together in a measure of shaping the quality of education and the output of the institutional processes [1]. Practically, in the field of educational institutions, such ecosystems may support data-driven institutional planning, make the education process more cost-effective, and establish more efficient institutions, and, in that regard, are the key to sustainable digital transformation [2], [3]. Nonetheless, the performance of these AI-driven educational systems is difficult to evaluate as an effective and mature one, as it is subjective and can be measured in many dimensions [4], [5], [6]. The criteria involved in decision-making here should be weighed, and these may be conflicting and various, such as pedagogical efficiency, ethical clarity, technological stability, implementation cost, and learner-centeredness [7], [8], [9]. Conventional statistical and deterministic methods of evaluation are often not sufficient in such complex environments, as they cannot adequately reflect expert hesitation, fuzzy information, and inaccurate educational data.

This leads to the increased requirements of sophisticated decision-support models that are capable of expressing uncertainty and taking a humanistic approach to evaluation [10]. In response to this requirement, this paper suggests a TSF-SWARA-COPRAS decision model of the human-centered assessment of AI-enhanced educational intelligence ecosystems. This approach is based on the incorporation of the SWARA and COPRAS techniques in a T-spherical fuzzy space [11]. The SWARA method is such that a systematic recognition of the difference in criterion importance in expert preference ranking is made in such a way that pedagogical and ethical priorities are included in a meaningful manner. The COPRAS methodology then follows up with the ranking and the assessment of the educational options based on the proportionate mix of the benefit-oriented and the cost-oriented measures to come up with a transparent and comprehensible evaluation. The T-spherical fuzzy sets are also beneficial to the proposed framework because they imply flexibility of membership, non-membership, and hesitation levels, which are the real variables of human judgment. The capability improves the uncertainty capacity, changes in professional ratings, and increases rating consistency. In general, the suggested framework is a powerful decision-support instrument that could be applied to create informed decisions, elaborate them, and improve performance in AI-based learning settings.

1.1. Problem Statement

The expedited adoption of AI in higher education has resulted in the creation of AI-enhanced education intelligence platforms that can be used to facilitate adaptive learning, automated evaluation, and data-driven academic administration. These systems have potential, but their assessment is still problematic based on uncertainty, subjective expert opinions, and the existence of various, mostly conflicting, pedagogical, ethical, technological, and organizational factors. Current assessment schemes often depend on deterministic or entirely statistical schemes that simply cannot reflect the expert hesitation or trade-off between benefit and cost characteristics in an open and humanistic fashion. In order to address these constraints, this paper suggests a TSF-SWARA-COPRAS decision model that methodically judges AI-enhanced educational intelligence systems by combining criterion-based prioritization of experts with proportional aggregation of benefit and cost variables in an uncertain setting, thus allowing dependable, explainable, and sound performance assessment to support sound decision making in higher learning.

1.2. Literature Review

Fuzzy set theory was first suggested to solve vagueness and imprecision in human thought, especially in complicated decision-making situations where crisp values are not enough [12]. Intuitionistic fuzzy sets were then proposed as extensions of classical fuzzy sets, which include an additional non-membership degree in the range of membership and non-membership, to explicitly describe the hesitation in expert judgments [13]. In order to increase the level of flexibility, Pythagorean fuzzy sets and q-rung orthopair fuzzy sets were created, which can express more uncertainty and inconsistent analysis [14], [15]. Later conceptually, spherical fuzzy and T-spherical fuzzy sets [16] have appeared as new powerful extensions, in which all three membership, non-membership, and hesitation degrees are modeled with relaxed mathematical conditions. These extensions have been successful in comprehending the complexity of human cognition in decision-making issues where there is high uncertainty, information inconsistency, and subjective evaluation [17]. Due to the accelerated use of artificial intelligence in education, scholars have started to employ multi-criteria decision-making techniques to assess smart classrooms, online learning systems, and AI-driven education systems [18]. Technological infrastructure, pedagogical performance, digital competence, ethical leadership, and engagement with learners have been popular criteria measured by approaches based on AHP, TOPSIS, VIKOR, EDAS, MARCOS, and COPRAS. A number of studies have included fuzzy environments to deal with uncertainty in educational data and human ratings, especially with intuitionistic and Pythagorean fuzzy representations. These articles prove the usefulness of the systematic decision-support models in higher education planning and digitalization. Nonetheless, the majority of available research focuses on technical and infrastructural parameters, whereas the anthropocentric component, i.e., professional reluctance, moral transparency, and didactic appropriacy, receives inadequate coverage [19], [20].

Although significant progress has been made, there are significant limitations to current evaluation systems in AI-enhanced educational systems [21], [22]. Numerous research works are based on fixed or purely objective weighting systems that do not indicate expert priorities and contextual educational demands. Moreover, popular fuzzy extensions are not always able to embody the complicated uncertainty and ambivalence in cases where expert opinions are extremely varied. Other decision models also do not have explicit processes to proportionally balance off benefit and cost criteria, which can decrease interpretability and decision confidence. Furthermore, a few articles specifically take a human-centered view of evaluation and, at the same time, use sophisticated fuzzy representations [23], [24]. These limitations indicate that there is an evident gap in research to come up with adaptable, interpretable, and sound decision-support frameworks to fit in AI-enhanced educational intelligence ecosystems. In order to fill this gap, the current paper suggests a TSF-SWARA-COPRAS decision model to be used in assessing AI-enhanced educational intelligence systems in a human-centered manner. TSFSs allow for modeling the uncertainty, hesitation, and subjective expert judgment in a more positive light. An integrated mix of the SWARA approach enables adaptive and expert-guided ranking of the assessment criteria in such a way that the pedagogical, ethical, and organizational aspects will be properly reflected. In the meantime, the COPRAS method provides an explicit proportional compounding of benefit and cost attributes, which leads to consistent and comprehensible rankings. Through the help of this integrated framework, the proposed strategy will contribute to the existing body of knowledge by providing a powerful, human-focused, practically implemented assessment framework that will help make informed choices and plan strategies in AI-based institutions of higher education. The proposed strategy, with the assistance of this integrated framework, will add to the current knowledge base by offering a strong, human-centered, practically applied assessment framework that will enable informed decision-making and strategic planning in AI-based institutions of higher learning.

1.3. Objectives of the Study

The main aim of the study is to develop and implement the human-centric decision evaluation model, which will contribute to testing AI-based enhanced educational intelligence systems in uncertain and subjective conditions. In that regard, the study includes the TSF-SWARA-COPRAS decision-making strategy that enables a flexible, detailed, and sound evaluation of complex educational systems that have been influenced by artificial intelligence technologies.

In particular, the following objectives of this research are:

- To create a humanistic evaluation model of AI-enhanced educational intelligence systems.

- To make TSFSs useful in analyzing decisions to model uncertainty and expert hesitation.
- To establish the relative significance of evaluation standards using the SWARA approach that relies on expert opinions.
- To prioritize the educational intelligence options under the COPRAS method, bearing in mind the criteria of benefit and cost.

To demonstrate the efficiency and practicability of the proposed framework, the assistance of the numerical case study and the comparative analysis is used.

1.4. Motivation and Contributions of the Study

Artificial intelligence application in the context of learning has dramatically changed the traditional learning systems into an elaborate system with artificial intelligence. Despite the sheer potential of these systems, including personalized learning, adaptive instruction, and intelligent analytics, they are accompanied by the emerging challenges in relation to human-centered design, moral responsibility, uncertainty, and decision complexity. The existing evaluation procedures are more likely to utilize deterministic or classical fuzzy models, whereas they do not capture the inherent ambiguity, subjectivity, and reluctance with which the experts assess such dynamic systems. Moreover, most of the current frameworks of decision-making are centered on technological performance, and little attention is paid to the human values, the quality of pedagogy, and the inclusion of responsible AI. These gaps are meant to arouse the need to have an effective, flexible, and humanistic decision-making model that can be applied within the present learning environments to facilitate strategic evaluation and policy-making. To address these concerns, it is proposed in this paper to have a new TSF-SWARA-COPRAS decision framework applied in considering the AI-enhanced educational intelligence ecosystems in full. The most important conclusions of this paper can be obtained as follows:

1. A humanistic assessment model is proposed, which anatomically incorporates pedagogical, technological, organizational, and ethical aspects, which will provide sustainable and accountable AI-aided educational decision-making.
2. The T-spherical fuzzy sets are also used to better represent uncertainty and vagueness, as well as expert hesitation, which greatly increases the authenticity and sense of trust in the evaluation process.
3. The development of an integrated SWARA-COPRAS methodology is established to get the criteria weights and rank alternatives in a clear, structured, and understandable way.
4. An index system of thorough evaluation is developed to embrace the multidimensional nature of AI-enhanced learning systems.
5. The effectiveness and robustness of the framework described can be explained by the fact that an expanded numerical case study and comparative analysis can confirm that it is superior to the conventional fuzzy decision-making strategies.

In general, the proposed framework provides a feasible decision-support tool that can be used by policymakers, educators, and designers of systems to create such systems and architecture to enable promoting responsible AI use and enhancing educational intelligence ecosystems with an eye toward ongoing development.

1.5. Layout of the study

To make the paper logically structured, it is split into five sections. Section 1 presents the background of the research, its motivation, objectives, and major contributions. Section 2 provides the theoretical basis of T-spherical fuzzy sets and elaborates on the suggested TSF-SWARA-COPRAS decision framework. Section 3 explains how the evaluation index system should be constructed and why it is necessary to design the numerical case study to evaluate AI-augmented educational intelligence ecosystems. Section 4 presents and explains the results of the computations, alternative rankings, comparative analysis, and validation of the robustness. Section 5 summarizes the paper by providing the key findings, practical implications, limitations, and future research directions.

2 I PRELIMINARIES

Definition 1.[16] For any universal set β, a TSFS is of the form

$$Ţ = \{x, ụ(x), ẹ(x), ṿ(x)\ \forall\ x \in \beta\} \tag{1}$$

where $ụ, ẹ, ṿ : \beta \to [0,1]$ represents the membership degree (MD), abstinence degree (AD), and non-membership degree, respectively, provided that for some positive integer

$$ŧ \quad 0 \leq ụ^{ŧ}(x), ẹ^{ŧ}(x), ṿ^{ŧ}(x) \leq 1. \tag{2}$$

We define the refusal degree as follows

$$\mathfrak{r}(x) = \sqrt[ŧ]{1 - \left(ụ^{ŧ}(x), ẹ^{ŧ}(x), ṿ^{ŧ}(x)\right)}. \tag{3}$$

The triplet $(ụ, ẹ, ṿ)$ is known as the T-spherical fuzzy value (TSFV).

Definition 2.[16] Let $Ţ = (ụ, ẹ, ṿ)$ be a TSFS. Then, the score function and accuracy function are defined as

$$Ş(Ţ) = ụ^{ŧ}(x) - ṿ^{ŧ}(x)\ , A(Ţ) = ụ^{ŧ}(x) + ẹ^{ŧ}(x) + ṿ^{ŧ}(x) \tag{4}$$

where $S(Ţ) \in [-1,1]$ and $A(Ţ) \in [0,1]$.

Definition 3. Let $Ţ = (ụ, ẹ, ṿ)$ be a TSFS. Then, the normalized score function and the accuracy function are given by

$$Ş^{*}(Ţ) = \frac{1}{2}(S(Ţ) + 1), A(Ţ) = \frac{1}{2}\left(ụ^{ŧ}(x) + ẹ^{ŧ}(x) + ṿ^{ŧ}(x)\right). \tag{5}$$

Here, $S^{*}(Ţ) \in [0,1]$ and $A(Ţ) \in [0,1]$.

Based on these two rules, for two TSFVs $Ţ_1$ and $Ţ_2$:

- $Ţ_1 > Ţ_2$ if $Ş(Ţ_1) > Ş(Ţ_2)$
- $Ţ_1 < Ţ_2$ if $Ş(Ţ_1) < Ş(Ţ_2)$

If $S(Ţ_1) = S(Ţ_2)$ for two SFVs, then

- $Ţ_1 > Ţ_2$ if $A(Ţ_1) > A(Ţ_2)$
- $Ţ_1 < Ţ_2$ if $A(Ţ_1) < A(Ţ_2)$
- $Ţ_1$ is similar to $Ţ_2$ if $A(Ţ_1) = A(Ţ_2)$

Definition 4.[16] Let $Ţ = (ų, ę, ṽ)$ be a TSFS. Then, the T-spherical fuzzy weighted average (TSFWA) and the T-spherical fuzzy weighted geometric (TSFWG) operators are given by

$$TSFWA(ɣ_1, ɣ_2, \ldots, ɣ_n) = \oplus_{j=1}^{n} \dot{w}ɣ_j = \left(\sqrt[ƭ]{1 - \prod_{k=1}^{l} (1 - ų_K^{ƭ})^{\dot{w}_j}}, \prod_{k=1}^{l} (ę_K)^{\dot{w}_j}, \prod_{k=1}^{l} (ṽ_K)^{\dot{w}_j} \right), \quad (6)$$

$$TSFWG(ɣ_1, ɣ_2, \ldots, ɣ_n) = \oplus_{j=1}^{n} \dot{w}ɣ_j = \left(\prod_{k=1}^{l} (ų_K)^{\dot{w}_j}, \prod_{k=1}^{l} (ę_K)^{\dot{w}_j}, \sqrt[ƭ]{1 - \prod_{k=1}^{l} (1 - ṽ_K^{ƭ})^{\dot{w}_j}} \right). \quad (7)$$

2.1. Proposed Algorithm

The section introduces a new and effective TSF-SWARA-COPRAS model of assessing AI-enhanced educational intelligence ecosystems. The proposed method has a detailed flowchart as shown in Figure 1.

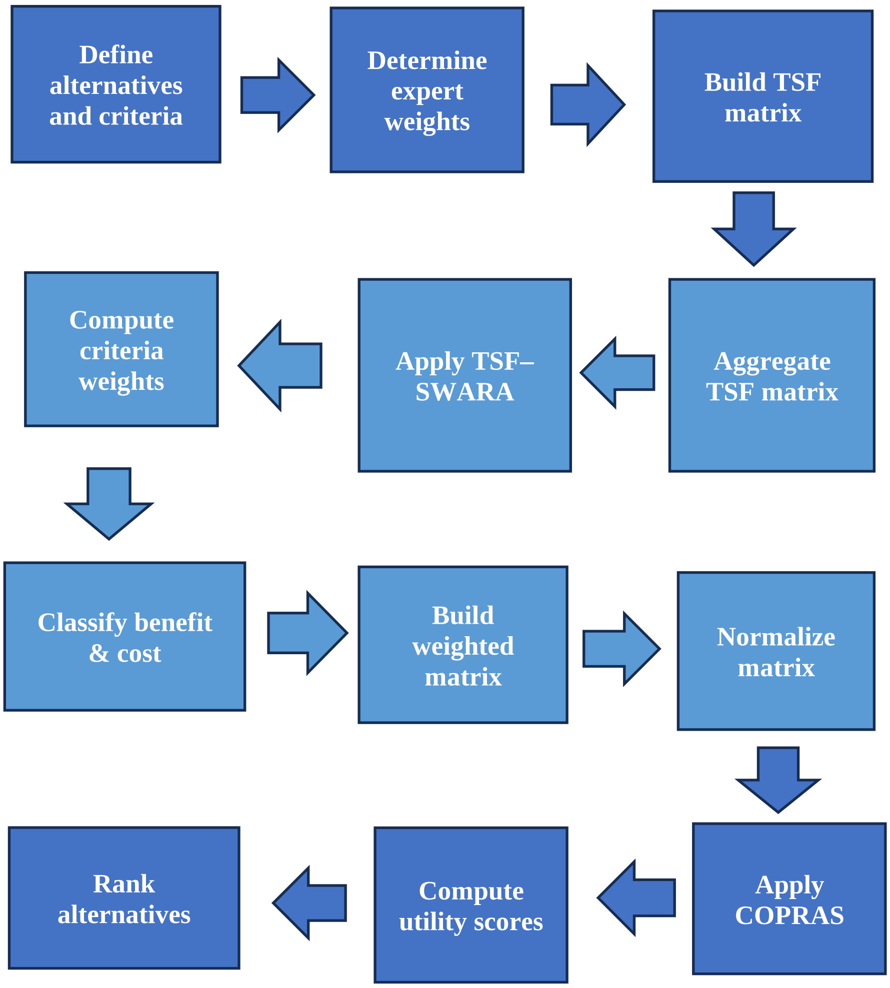

Figure 1. Flowchart of the TSF-SWARA-COPRAS methodology

Step 1. Determination of alternatives and specification of the evaluation criteria

In the multi-criteria decision-making (MCDM) model, the first step is to select the best alternative among a number of m viable alternatives of AI-enhanced educational intelligence $S = \{S_1, S_2, \dots, S_m\}$ based on established n measurement criteria $\check{A} = \{\check{A}_1, \check{A}_2, \dots, \check{A}_n\}$. A panel of decision experts $\hat{E} = \{\hat{E}_1, \hat{E}_2, \dots, \hat{E}_p\}$ is formed to deliver the evaluation of each alternative concerning each criterion. The information provided by the linguistic experts about evaluation is input into the decision matrix $\check{Z} = \{z_{ij}^{(K)}\}$ where $i = 1,2, \dots, m$ and $j = 1,2, \dots, n$. Here, $z_{ij}^{(K)}$ can be described as the linguistic rating of the K^{th} expert in alternative S_i based on the criterion $\check{A}_j$.

Step 2. Identifying the weights of the decision experts

The panel of decision experts is modeled in the context of the assessment of AI-enhanced learning intelligence systems by a weight vector $\ddot{W} = (\ddot{W}_1, \ddot{W}_2, \dots, \ddot{W}_p)^{\mathcal{T}}$.

The weight of each expert is represented in terms of linguistic concepts that are then converted to T-spherical fuzzy values (TSFVs). The importance of the K^{th} expert will be represented by $\hat{E}_K = (\hat{u}_K, \breve{\upsilon}_K, \pi_K)$, where $\hat{u}_K, \breve{\upsilon}_K$ and π_K are the membership, non-membership, and hesitancy degrees, respectively. The K^{th} weight of significance is then determined using the TSF formulation as

$$\ddot{W}_K = \frac{\left(\hat{u}_K^{t} + \pi_K^{t}\left(\frac{\hat{u}_K^{t}}{\hat{u}_K + \breve{\upsilon}_K}\right)\right)}{\sum_K^l \left(\hat{u}_K^{t} + \pi_K^{t}\left(\frac{\hat{u}_K^{t}}{\hat{u}_K^{t} + \breve{\upsilon}_K^{t}}\right)\right)}, K = 1(1)l \tag{8}$$

Step 3. Aggregation of the T-spherical fuzzy decision matrix

In order to obtain coherent assessment results of the AI augmented educational intelligence systems, the TSFWA operator is used to aggregate the individual ratings of the decision experts. In this way, the accumulated decision information is organized in the matrix $R = (\gamma)_{m\times n}$, where

$$\gamma_{kj} = TSFWA\left(\gamma_{kj}^{(1)}, \gamma_{kj}^{(2)}, \dots, \gamma_{kj}^{(p)}\right) = \left(\sqrt[t]{1 - \prod_{k=1}^{l}\left(1 - u_K^{t}\right)^{\dot{w}_j}}, \prod_{k=1}^{l}(\varphi_K)^{\dot{w}_j}, \prod_{k=1}^{l}(\vartheta_K)^{\dot{w}_j}\right) \tag{9}$$

Step 4. Determination of the weights of criteria based on SWARA

The evaluation criteria relative significance is determined using the SWARA approach to AI-augmented educational intelligence ecosystems. These criteria are ranked based on the priority of the experts first and then analyzed sequentially based on comparative values of importance. On the basis of this process, the respective coefficients are computed, and the result is the final normalized criteria weights.

Step 4.1. Derivation of Crisp Scores TSFVs

Based on Definition 3, crisp score $\text{Ş}_{\text{Ҡ}j}$ corresponding to each TSV is calculated using Equation (5). This process converts fuzzy judgments to accurate numerical ratings for further processing.

Step 4.2. Prioritizing Criteria Ordering

The evaluation criteria will be placed in order of priority, from least to most important, to determine the priority of the sequence followed in the SWARA procedure.

Step 4.3. Relative Significance between Adjacent Criteria

To determine the relative significance of the criterion, starting with the second criterion in the ordered list, the relative significance is calculated as the crisp score of the criterion j with the crisp score of the previous criterion $j - 1$.

Step 4.4. Computation of Comparative Coefficient (CC)

The coefficient Ҡ_j of each criterion is determined as:

$$\text{Ҡ}_j = \begin{cases} 1, & j = 1 \\ \text{Ş}_j + 1 & j > 1 \end{cases} \tag{10}$$

where Ş_j depicts the comparative significance value.

Step 4.5. Calculation of Final Weights for Criteria

$$\mathcal{P}_j = \begin{cases} 1, & j = 1 \\ \dfrac{\text{Ҡ}_{j-1}}{\text{Ҡ}_j} & j > 1 \end{cases} \tag{11}$$

The final weight attributed to every criterion is computed as

$$\hat{W}_j = \frac{\mathcal{P}_j}{\sum_j^{n} \mathcal{P}_j} \tag{12}$$

Step 5. Combination of Benefit- and Cost-Type Criteria

The aggregate value of the performance of the alternative ị of benefit-type criteria is derived as:

$$\gamma_{\text{ị}} = \oplus_{j=1}^{l} \ddot{W}_j \text{ɣ}_{\text{ị}j} \quad \text{ị} = 1(1)m \tag{13}$$

To describe cost-oriented criteria, suppose $\nabla = \{l + 1, l + 2, \ldots, n\}$ denote the set of cost criteria. to represent the cost criteria set. The total cost value of the alternative ị will be calculated as

$$\zeta_{\text{ị}} = \oplus_{j=l+1}^{n} \ddot{W}_j \text{ɣ}_{\text{ị}j} \quad \text{ị} = 1(1)m \tag{14}$$

where l represents the number of benefit criteria and n is the total number of criteria.

Step 6. Evaluation of Relative Weight Degree (RWD)

The degree of relative weight $\delta_{\text{ị}}$ of each AI-enhanced learning option is calculated as:

$$\delta_{\text{ị}} = \text{Ş}^*(\gamma_{\text{ị}}) + \frac{min\dot{S}^*(\zeta_{\text{ị}}) \sum_{\text{ị}=1}^{\mathcal{P}} \text{Ş}^*(\zeta_{\text{ị}})}{\text{Ş}^*(\zeta_{\text{ị}}) \sum_{\text{ị}=1}^{\mathcal{P}} \frac{min\text{Ş}^*(\zeta_{\text{ị}})}{\text{Ş}^*(\zeta_{\text{ị}})}}, \ \text{ị} = 1(1)m \tag{15}$$

Here, $\dot{S}^*(\gamma_{\text{ị}})$ *and* $\dot{S}^*(\zeta_{\text{ị}})$ are the values of the benefits and cost elements, respectively.

Equation (15) may also be rewritten as:

$$\delta_{i} = Ş^{*}(\gamma_{i}) + \frac{\sum_{i=1}^{\mathcal{P}} Ş^{*}(\zeta_{i})}{Ş^{*}(\zeta_{i})\sum_{i=1}^{\mathcal{P}}\frac{1}{Ş^{*}(\zeta_{i})}},\ i = 1(1)m \tag{16}$$

Step 7. Calculating Alternative Ranking

The AI-enhanced educational options are ranked based on the calculated degrees of relative weights. The alternative having the highest relative weight is determined as

$$Ş^{*} = \max_{i} \delta_{i} \quad i = 1(1)m \tag{17}$$

The degree of utility of the i^{th} alternatively, denoted by l_{i}, is determined as

$$l_{i} = \frac{\delta_{i}}{\delta max} \times 100\% \ i = 1(1)m \tag{18}$$

where δ_{i} and δ_{max} is the relative weight of the i^{th} alternative and the maximum weight of all alternatives, respectively.

Step 8. Decision Procedure Finalized

2.2. Human-Centered Assessment of AI-Enhanced Educational Ecosystems

The rapid artificial intelligence adoption in the academic field has led to the creation of academically oriented AI-based intelligent learning systems that integrate intelligent learning platforms, adaptive assessment applications, analytics of learning, and AI-guided training of teaching services. These ecosystems will support efficacy in instruction and customization in the student study experience, and enhanced leadership of data-directed institutional choice. Unlike the conventional digital-based classrooms, AI-enhanced learning systems are concerned with the continuous communication between humans and intelligent machines, which is why the human-based assessment is an essential demand of a sustainable educational transformation. Human-centered educational intelligence ecosystems represent the level of transparency, ethical, and pedagogically significant support of the AI technologies to instructors, learners, and administrators. These ecosystems have the ability to consider several related aspects, which include intelligent content delivery, real-time learner analytics, explainable AI decision support, data security, and institutional flexibility. As the utilization of the AI-based systems in the universities becomes increasingly common as a way of supplementing the traditional teaching and management techniques, the overall efficiency and readiness of the corresponding ecosystems turn into a strategic concern.

The institutions are challenged with major problems trying to select or revise AI-enhanced educational intelligence ecosystems, despite their immense potential benefits. At the pedagogical level, the discrepancy in the willingness of the faculty to embrace digital competency and confidence in AI-based recommendations has introduced ambiguity to the results of the assessment. The organizational issues that also contribute to the complexity of the decision-making include the governance policies, adherence to ethics, and long-term maintenance costs. As a student, one should also consider the differences in engagement, accessibility, and digital literacy as well to achieve inclusive and equal learning environments. The problems indicate that the evaluation of AI-enhanced educational intelligence systems, in its turn, constitutes an MCDM problem. These decision makers must be able to deal with qualitative and quantitative criteria at the same time, which are generally expressed through subjective judgments and verbal judgments. The traditional way of assessment is ineffective in uncertainty, indecision, and deviation of professional judgment, and largely in the field of human-centered AI, where perceptions and values play a significant role.

In order to solve these problems, this paper uses a decision framework of TSF-SWARA-COPRAS to conduct a human-based assessment of AI-enhanced educational intelligence systems. The T-spherical fuzzy model can be used to make a more detailed representation of expert judgment by incorporating levels of acceptance, rejection, and indeterminacy, which is closer to human reasoning under uncertainty. The evaluation criteria are weighted using the SWARA method, as it uses the expert prioritization to ascertain the relative importance of evaluation criteria, enabling weighting to be done by human judgment. Then, the COPRAS method is used to prioritize competing ecosystem options by weighting the benefit-oriented characteristics (e.g., pedagogical usefulness and explainability) and cost-oriented characteristics (e.g., complexity of implementation and overhead) together. The suggested model results in a performance index of every AI-enhanced learning intelligence system, as well as allows institutions to compare options in a transparent and understandable way. A combination of human aspects with high-level fuzzy decision intelligence enables the system to make informed strategy decisions based on the balance between technological nucleus and pedagogical importance, moral accountability, and organizational survival. In the end, this case study illustrates that the TSF-SWARA-COPRAS framework is a powerful and structure-oriented decision support system that can be used to determine educational change in higher education that is driven by AI.

2.3. Numerical Example

The suggested T-spherical fuzzy SWARA-COPRAS model is used to aid human-friendly decision-making to choose AI-empowered educational intelligence ecosystems in higher education. To determine the major criteria of the evaluation of the AI-enhanced educational intelligence systems, a systematic analysis was performed according to the policies of AI-in-education, digital learning systems, and consultations of specialists. Based on the result of this analysis, four main dimensions were discovered, i.e., pedagogical intelligence, human-AI interaction and trust, organizational and ethical governance, and economic sustainability, which, in their turn, consist of eleven evaluation criteria, including those listed in Table 1. To compute the assessments, six alternatives of AI-enhanced educational intelligence ecosystems were contemplated, which comprise adaptive learning platforms ($\breve{A}_1$), learning analytics and early-warning systems ($\breve{A}_2$), AI-assisted assessment systems ($\breve{A}_3$), intelligent academic advising systems ($\breve{A}_4$), integrated smart campus intelligence platforms ($\breve{A}_5$), and hybrid AI-supported teaching ecosystems ($\breve{A}_6$), as illustrated in Table 2. These options were considered as opposed to the eleven criteria, which are divided into the four dimensions, with each of the criteria being categorized as either benefit-type or cost-type, as demonstrated by Table 3. Linguistic terms were used to gather expert appraisals, which were modeled by T-spherical fuzzy information, and the process of SWARA was applied to find the weights of criteria, and the COPRAS technique was used to rank alternatives.

Table 1. Linguistic terms and corresponding TSFVs for alternative evaluation and criteria weighting

Linguistic Terms (LTs)	Interpretation	T-Spherical Fuzzy Values
Extremely Unsatisfactory (EU)	Very weak performance (VWP)	$(0.20, 0.75, 0.35)$
Very Unsatisfactory (VU)	Highly weak performance (HWP)	$(0.30, 0.65, 0.35)$
Unsatisfactory (U)	Weak performance (WP)	$(0.40, 0.55, 0.30)$
Slightly Unsatisfactory (SU)	Below average (BA)	$(0.45, 0.50, 0.30)$
Moderate (M)	Acceptable performance (AP)	$(0.50, 0.45, 0.30)$
Slightly Satisfactory (SS)	Above average (AA)	$(0.60, 0.35, 0.30)$
Satisfactory (S)	Good performance (GP)	$(0.70, 0.25, 0.25)$
Very Satisfactory (VS)	Very good performance (VGP)	$(0.80, 0.15, 0.20)$
Outstanding (OS)	Excellent performance (EP)	$(0.90, 0.10, 0.15)$

Table 2. Linguistic terms (LTs) for assessing the significance level of decision experts

Ratings	T-Spherical Fuzzy Values
Critically Influential (CI)	$(0.90, 0.10, 0.15)$
Highly Influential (HI)	$(0.80, 0.15, 0.20)$
Strongly Influential (SI)	$(0.70, 0.25, 0.25)$
Moderately Influential (MI)	$(0.60, 0.35, 0.30)$
Weakly Influential (WI)	$(0.45, 0.50, 0.30)$
Minimally Influential (MinI)	$(0.30, 0.65, 0.35)$
Negligibly Influential (NI)	$(0.20, 0.75, 0.35)$

The assessment data were gathered with the help of three specialists who work with AI-enhanced training. According to the literature review and expert consultation, eleven criteria in pedagogical, human-AI, organizational, and economic dimensions were settled, as seen in Table 3.

Table 3. Criteria evaluation for AI-augmented educational intelligence ecosystem selection

Dimensions	Criteria	Criteria Type	Classification	Options
Pedagogical	Teaching effectiveness enhancement $(\breve{A}_1)$	Benefit	Qualitative	(S_1)
	Learning personalization complexity $(\breve{A}_2)$	Cost	Quantitative	
	Assessment accuracy and feedback quality $(\breve{A}_3)$	Benefit	Quantitative	(S_2)
	Cognitive workload imposed by AI systems $(\breve{A}_4)$	Cost	Quantitative	
Human–AI Interaction	User trust and acceptance level $(\breve{A}_5)$	Benefit	Qualitative	(S_3)
	Human–AI collaboration support $(\breve{A}_6)$	Benefit	Qualitative	
Technological	System reliability and scalability $(\breve{A}_7)$	Benefit	Quantitative	(S_4)
	Integration flexibility $(\breve{A}_8)$	Benefit	Quantitative	
Student-Centered	Student engagement facilitation $(\breve{A}_9)$	Benefit	Qualitative	(S_5)
	Accessibility and inclusiveness $(\breve{A}_{10})$	Benefit	Qualitative	
	Learning outcome enhancement $(\breve{A}_{11})$	Benefit	Qualitative	(S_6)

The terms used to express uncertainty in assessing AI-enhanced educational intelligence ecosystems were linguistic words, as they can be converted to vague expert judgments. Tables 2 and 3 give the linguistic scales to support the expert preference evaluation and the alternative evaluation. Expert weights based on these scales were calculated and are given in Table 4. Table 5 displays the individual T-spherical fuzzy scores of the experts, and Table 6 displays the aggregate decision matrix obtained by the use of the corresponding aggregation rule.

Table 4. Expert Weights for AI-Augmented Education Systems

DEs	$\hat{E}_1$	$\hat{E}_2$	$\hat{E}_3$
Linguistic variables	**MI**	**WI**	**SI**
TSFVs	$(0.60, 0.35, 0.30)$	$(0.45, 0.50, 0.30)$	$(0.70, 0.25, 0.25)$
	0.3484	0.2613	0.3902

Table 5. T-spherical fuzzy ratings provided by DMs for evaluating AI-augmented educational intelligence ecosystems

Criterion		S_1	S_2	S_3	S_4	S_5	S_6
$\breve{A}_1$	$\hat{E}_1$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$	$(0.70, 0.25, 0.25)$	$(0.50, 0.45, 0.30)$	$(0.60, 0.35, 0.30)$	$(0.70, 0.25, 0.25)$
	$\hat{E}_2$	$(0.60, 0.35, 0.30)$	$(0.90, 0.10, 0.15)$	$(0.70, 0.25, 0.25)$	$(0.50, 0.45, 0.30)$	$(0.40, 0.55, 0.30)$	$(0.80, 0.15, 0.20)$

	$\hat{E}_3$	(0.80, 0.15, 0.20)	(0.70, 0.25, 0.25)	(0.60, 0.35, 0.30)	(0.40, 0.55, 0.30)	(0.40, 0.55, 0.30)	(0.50, 0.45, 0.30)
$\breve{A}_2$	$\hat{E}_1$	(0.40, 0.55, 0.30)	(0.60, 0.35, 0.30)	(0.50, 0.45, 0.30)	(0.70, 0.25, 0.25)	(0.40, 0.55, 0.30)	(0.60, 0.35, 0.30)
	$\hat{E}_2$	(0.30, 0.65, 0.35)	(0.50, 0.45, 0.30)	(0.40, 0.55, 0.30)	(0.60, 0.35, 0.30)	(0.30, 0.65, 0.35)	(0.50, 0.45, 0.30)
	$\hat{E}_3$	(0.40, 0.55, 0.30)	(0.50, 0.45, 0.30)	(0.60, 0.35, 0.30)	(0.80, 0.15, 0.20)	(0.50, 0.45, 0.30)	(0.70, 0.25, 0.25)
$\breve{A}_3$	$\hat{E}_1$	(0.60, 0.35, 0.30)	(0.80, 0.15, 0.20)	(0.70, 0.25, 0.25)	(0.80, 0.15, 0.20)	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)
	$\hat{E}_2$	(0.50, 0.45, 0.30)	(0.70, 0.25, 0.25)	(0.80, 0.15, 0.20)	(0.90, 0.10, 0.15)	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)
	$\hat{E}_3$	(0.60, 0.35, 0.30)	(0.80, 0.15, 0.20)	(0.70, 0.25, 0.25)	(0.90, 0.10, 0.15)	(0.50, 0.45, 0.30)	(0.80, 0.15, 0.20)
$\breve{A}_4$	$\hat{E}_1$	(0.50, 0.45, 0.30)	(0.60, 0.35, 0.30)	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)	(0.60, 0.35, 0.30)	(0.60, 0.35, 0.30)
	$\hat{E}_2$	(0.40, 0.55, 0.30)	(0.50, 0.45, 0.30)	(0.50, 0.45, 0.30)	(0.60, 0.35, 0.30)	(0.50, 0.45, 0.30)	(0.70, 0.25, 0.25)
	$\hat{E}_3$	(0.50, 0.45, 0.30)	(0.60, 0.35, 0.30)	(0.50, 0.45, 0.30)	(0.70, 0.25, 0.25)	(0.50, 0.45, 0.30)	(0.60, 0.35, 0.30)
$\breve{A}_5$	$\hat{E}_1$	(0.70, 0.25, 0.25)	(0.60, 0.35, 0.30)	(0.80, 0.15, 0.20)	(0.90, 0.10, 0.15)	(0.70, 0.25, 0.25)	(0.80, 0.15, 0.20)
	$\hat{E}_2$	(0.60, 0.35, 0.30)	(0.50, 0.45, 0.30)	(0.70, 0.25, 0.25)	(0.80, 0.15, 0.20)	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)
	$\hat{E}_3$	(0.80, 0.15, 0.20)	(0.60, 0.35, 0.30)	(0.80, 0.15, 0.20)	(0.90, 0.10, 0.15)	(0.70, 0.25, 0.25)	(0.90, 0.10, 0.15)
$\breve{A}_6$	$\hat{E}_1$	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)	(0.70, 0.25, 0.25)	(0.80, 0.15, 0.20)	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)
	$\hat{E}_2$	(0.50, 0.45, 0.30)	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)	(0.70, 0.25, 0.25)	(0.50, 0.45, 0.30)	(0.60, 0.35, 0.30)
	$\hat{E}_3$	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)	(0.80, 0.15, 0.20)	(0.90, 0.10, 0.15)	(0.60, 0.35, 0.30)	(0.80, 0.15, 0.20)
$\breve{A}_7$	$\hat{E}_1$	(0.70, 0.25, 0.25)	(0.80, 0.15, 0.20)	(0.70, 0.25, 0.25)	(0.90, 0.10, 0.15)	(0.70, 0.25, 0.25)	(0.80, 0.15, 0.20)
	$\hat{E}_2$	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)	(0.60, 0.35, 0.30)	(0.80, 0.15, 0.20)	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)
	$\hat{E}_3$	(0.80, 0.15, 0.20)	(0.80, 0.15, 0.20)	(0.70, 0.25, 0.25)	(0.90, 0.10, 0.15)	(0.70, 0.25, 0.25)	(0.90, 0.10, 0.15)
$\breve{A}_8$	$\hat{E}_1$	(0.50, 0.45, 0.30)	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)	(0.80, 0.15, 0.20)	(0.60, 0.35, 0.30)	(0.70, 0.25, 0.25)

	$\hat{E}_2$	$(0.40, 0.55, 0.30)$	$(0.60, 0.35, 0.30)$	$(0.60, 0.35, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.50, 0.45, 0.30)$	$(0.60, 0.35, 0.30)$
	$\hat{E}_3$	$(0.50, 0.45, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$	$(0.60, 0.35, 0.30)$	$(0.80, 0.15, 0.20)$
$\breve{A}_{\mathbf{9}}$	$\hat{E}_1$	$(0.70, 0.25, 0.25)$	$(0.60, 0.35, 0.30)$	$(0.80, 0.15, 0.20)$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$	$(0.90, 0.10, 0.15)$
	$\hat{E}_2$	$(0.60, 0.35, 0.30)$	$(0.50, 0.45, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.60, 0.35, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$
	$\hat{E}_3$	$(0.80, 0.15, 0.20)$	$(0.60, 0.35, 0.30)$	$(0.80, 0.15, 0.20)$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$	$(0.90, 0.10, 0.15)$
$\breve{A}_{\mathbf{10}}$	$\hat{E}_1$	$(0.60, 0.35, 0.30)$	$(0.50, 0.45, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.60, 0.35, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$
	$\hat{E}_2$	$(0.50, 0.45, 0.30)$	$(0.40, 0.55, 0.30)$	$(0.60, 0.35, 0.30)$	$(0.50, 0.45, 0.30)$	$(0.60, 0.35, 0.30)$	$(0.70, 0.25, 0.25)$
	$\hat{E}_3$	$(0.60, 0.35, 0.30)$	$(0.50, 0.45, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.60, 0.35, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$
$\breve{A}_{\mathbf{11}}$	$\hat{E}_1$	$(0.70, 0.25, 0.25)$	$(0.60, 0.35, 0.30)$	$(0.80, 0.15, 0.20)$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$	$(0.90, 0.10, 0.15)$
	$\hat{E}_2$	$(0.60, 0.35, 0.30)$	$(0.50, 0.45, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.60, 0.35, 0.30)$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$
	$\hat{E}_3$	$(0.80, 0.15, 0.20)$	$(0.60, 0.35, 0.30)$	$(0.80, 0.15, 0.20)$	$(0.70, 0.25, 0.25)$	$(0.80, 0.15, 0.20)$	$(0.90, 0.10, 0.15)$

The SWARA process, the component of expert judgment, is predominant in deciding on the importance of criteria. All the experts assess and prioritize the criteria according to experience and knowledge, which are summarized in Table 7. Final weights are then computed by the prioritized ordering of criteria, and the results are stated in Table 8.

$$W = (0.0999,0.0988,0.0958,0.0950,0.0933,0.0886,0.08829,0.08780.0857,0.0840,0.0829)$$

By employing (13)-(18), the values of $\gamma_{ị}, \dot{S}^*(\gamma_{ị}), \dot{S}^*(\zeta_{ị}), \gamma_{ị}$ and $l_{ị}$ of each AI-enhanced educational intelligence ecosystem alternative $(ị = 1(1)5)$ were calculated based on the evaluation criteria $Ł_j (j = 1(1)11)$, as shown in Table 9.

Table 6. Aggregated Decision Matrix for Evaluating AI-Augmented Educational Intelligence Ecosystems

	$\boldsymbol{S}_1$	$\boldsymbol{S}_2$	$\boldsymbol{S}_3$	$\boldsymbol{S}_4$	$\boldsymbol{S}_5$	$\boldsymbol{S}_6$
$\breve{A}_{\mathbf{1}}$	$(0.7289, 0.2236, 0.2403)$	$(0.8045, 0.1647, 0.2024)$	$(0.6644, 0.2851, 0.2684)$	$(0.4631, 0.4867, 0.3000)$	$(0.4791, 0.4699, 0.3000)$	$(0.6706, 0.2752, 0.2532)$
$\breve{A}_{\mathbf{2}}$	$(0.3753, 0.5745, 0.3123)$	$(0.5374, 0.4123, 0.3000)$	$(0.5193, 0.4299, 0.3000)$	$(0.7239, 0.2236, 0.2403)$	$(0.4182, 0.5313, 0.3123)$	$(0.6210, 0.3278, 0.2794)$

$\breve{A}_3$	(0.5760, 0.3738, 0.3000)	(0.3738, 0.1714, 0.2120)	(0.7302, 0.2188, 0.2358)	(0.8727, 0.1152, 0.1658)	(0.5636, 0.3861, 0.3000)	(0.7439, 0.2048, 0.2292)
$\breve{A}_4$	(0.4756, 0.4742, 0.3000)	(0.5760, 0.3738, 0.3000)	(0.5374, 0.4123, 0.3000)	(0.6766, 0.2730, 0.2622)	(0.5374, 0.4123, 0.3000)	(0.6290, 0.3205, 0.2860)
$\breve{A}_5$	(0.7239, 0.2236, 0.2403)	(0.5760, 0.3738, 0.3000)	(0.7776, 0.1714, 0.2120)	(0.8801, 0.1112, 0.1617)	(0.5374, 0.2730, 0.2622)	(0.8303, 0.1463, 0.1895)
$\breve{A}_6$	(0.5760, 0.3738, 0.3000)	(0.6766, 0.2730, 0.2622)	(0.7439, 0.2048, 0.2292)	(0.8303, 0.1463, 0.1895)	(0.5760, 0.3738, 0.3000)	(0.7239, 0.2236, 0.2403)
$\breve{A}_7$	(0.7239, 0.2236, 0.2403)	(0.7776, 0.1714, 0.2120)	(0.6766, 0.2730, 0.2622)	(0.8801, 0.1112, 0.1617)	(0.6766, 0.2730, 0.2622)	(0.8303, 0.1463, 0.1895)
$\breve{A}_8$	(0.4756, 0.4742, 0.3000)	(0.6425, 0.3069, 0.2794)	(0.6766, 0.2730, 0.2622)	(0.7776, 0.1714, 0.2120)	(0.5760, 0.3738, 0.3000)	(0.7239, 0.2236, 0.2403)
$\breve{A}_9$	(0.7239, 0.2236, 0.2403)	(0.5760, 0.3738, 0.3000)	(0.7776, 0.1714, 0.2120)	(0.6766, 0.2730, 0.2622)	(0.7776, 0.1714, 0.2120)	(0.8801, 0.1112, 0.1617)
$\breve{A}_{10}$	(0.5760, 0.3738, 0.3000)	(0.4756, 0.4742, 0.3000)	(0.6766, 0.2730, 0.2622)	(0.5760, 0.3738, 0.3000)	(0.6766, 0.2730, 0.2622)	(0.7776, 0.1714, 0.2120)
$\breve{A}_{11}$	(0.7239, 0.2236, 0.2403)	(0.5760, 0.3738, 0.3000)	(0.7776, 0.1714, 0.2120)	(0.6766, 0.2730, 0.2622)	(0.7776, 0.1714, 0.2120)	(0.8801, 0.1112, 0.1617)

Table 7. Linguistic Criteria Weights for AI-Augmented Educational Intelligence Ecosystems

LTs	$\hat{E}_1$	$\hat{E}_2$	$\hat{E}_3$	**Aggregated TSFVs**	**Crisp Values**
$\breve{A}_1$	GP	VGP	GP	(0.7302, 0.2188, 0.2358)	0.6881
$\breve{A}_2$	AP	AP	AA	(0.5417, 0.4080, 0.3000)	0.5660
$\breve{A}_3$	GP	GP	AA	(0.6644, 0.2851, 0.2684)	0.6369
$\breve{A}_4$	AP	BA	AA	(0.5301, 0.4194, 0.3000)	0.5610
$\breve{A}_5$	AA	GP	VGP	(0.7169, 0.2303, 0.2442)	0.6769
$\breve{A}_6$	GP	AA	AA	(0.6382, 0.3113, 0.2815)	0.6188
$\breve{A}_7$	HWP	WP	HWP	(0.3276, 0.6222, 0.3362)	0.4986
$\breve{A}_8$	AA	AP	BA	(0.5199, 0.4296, 0.3000)	0.5568
$\breve{A}_9$	BA	WP	HWP	(0.3818, 0.5679, 0.3186)	0.5117
$\breve{A}_{10}$	GP	AA	GP	(0.6766, 0.2730, 0.2622)	0.6458
$\breve{A}_{11}$	AP	BA	WP	(0.4496, 0.5002, 0.3000)	0.5319

Table 8. Evaluation of AI-Augmented Educational Intelligence Ecosystems Using the TSF-SWARA–COPRAS Framework

Criteria	**Crisp Values**	**Comparative Significance of Criteria Values** ($\dot{S}_j$)	**Coefficient** (K_j)	**Recalculated weight** ($\mathcal{P}_j$)	**Criteria Weight** ($\hat{W}_j$)
$\breve{A}_1$	0.6881	–	1.0000	1.0000	0.0999
$\breve{A}_5$	0.6769	0.0111	1.0111	0.9890	0.0988
$\breve{A}_{10}$	0.6458	0.0311	1.0311	0.9592	0.0958
$\breve{A}_3$	0.6369	0.0089	1.0089	0.9507	0.0950
$\breve{A}_6$	0.6188	0.0182	1.0182	0.9337	0.0933
$\breve{A}_2$	0.5660	0.0528	1.0528	0.8869	0.0886
$\breve{A}_4$	0.5610	0.0050	1.0050	0.8825	0.0882
$\breve{A}_8$	0.5568	0.0042	1.0042	0.8788	0.0878
$\breve{A}_{11}$	0.5319	0.0248	1.0248	0.8575	0.0857
$\breve{A}_9$	0.5117	0.0203	1.0203	0.8405	0.0840
$\breve{A}_7$	0.4986	0.0131	1.0131	0.8296	0.0829

Table 9. Evaluation of AI-Augmented Educational Intelligence Ecosystems Using the TSF-SWARA–COPRAS Framework

	γ_i	$S^*(\gamma_i)$	ζ_i	$S^*(\zeta_i)$	$\varkappa_i$	η_i
S_1	$(0.5865, 0.3602, 0.3358)$	0.6253	$(0.0939, 0.8914, 0.8111)$	0.1414	0.8173	93%
S_2	$(0.5592, 0.3487, 0.3294)$	0.6149	$(0.1341, 0.8476, 0.8083)$	0.1629	0.7815	89%
S_3	$(0.6555, 0.2900, 0.3074)$	0.6740	$(0.1244, 0.8582, 0.8083)$	0.1581	0.8457	96%
S_4	$(0.7037, 0.2653, 0.2846)$	0.7095	$(0.1923, 0.7810, 0.7832)$	0.2045	0.8422	95%
S_5	$(0.5650, 0.3663, 0.3370)$	0.6140	$(0.1095, 0.8743, 0.8111)$	0.1492	0.7959	90%
S_6	$(0.7276, 0.2364, 0.2737)$	0.7270	$(0.1592, 0.8194, 0.7998)$	0.1797	0.8780	100%

The alternatives of the AI-augmented educational intelligence ecosystem are ranked as per their relative utility value as reported in Table 9. The ranking order is $S_6 > S_3 > S_4 > S_1 > S_5 > S_2$, which means that S_6 achieves the largest preference score and is thus determined as the most appropriate alternative of the available choices that have been evaluated.

3 | RESULTS AND DISCUSSION

Table 9 presents the assessment results of the suggested TSF-SWARA-COPRAS model of evaluating AI-enhanced educational intelligence environments in higher education. Table 9 shows the aggregated benefit values γ_i their respective score value $S^*(\gamma_i)$, the aggregated cost values ζ_i with their scores $\dot{S}^*(\zeta_i)$, the relative utility indices $\varkappa_i$ and normalized performance levels η_i in terms of percentages. The combination of these indicators offers a complete picture of the performance of each AI-enhanced ecosystem due to the balance of pedagogical advantages, human-centered value, organizational viability, and cost-effectiveness. According to the utility figures in Table 9, the ranking order of the alternatives will be $S_6 > S_3 > S_4 > S_1 > S_5 > S_2$. The most appropriate AI-augmented educational intelligence ecosystem is S_6 as it has the highest level of performance (100%) and is therefore identified as the most suitable AI-augmented educational intelligence ecosystem. The alternatives S_3 and S_4 alternatives have a high-performance level of 96% and 95%, respectively, so they are effective with balanced benefit-cost features. The other alternatives demonstrate relatively lower performance, which represents a gap in one or more dimensions, including the integration of the system, human-AI interaction, or operational efficiency. In general, the findings validate the assumptions that the TSF-SWARA-COPRAS framework offers a sound and human-centered decision support system with the ability to assess AI-based educational ecosystems in uncertain conditions. The performance comparison of the alternatives is given in Figure 2.

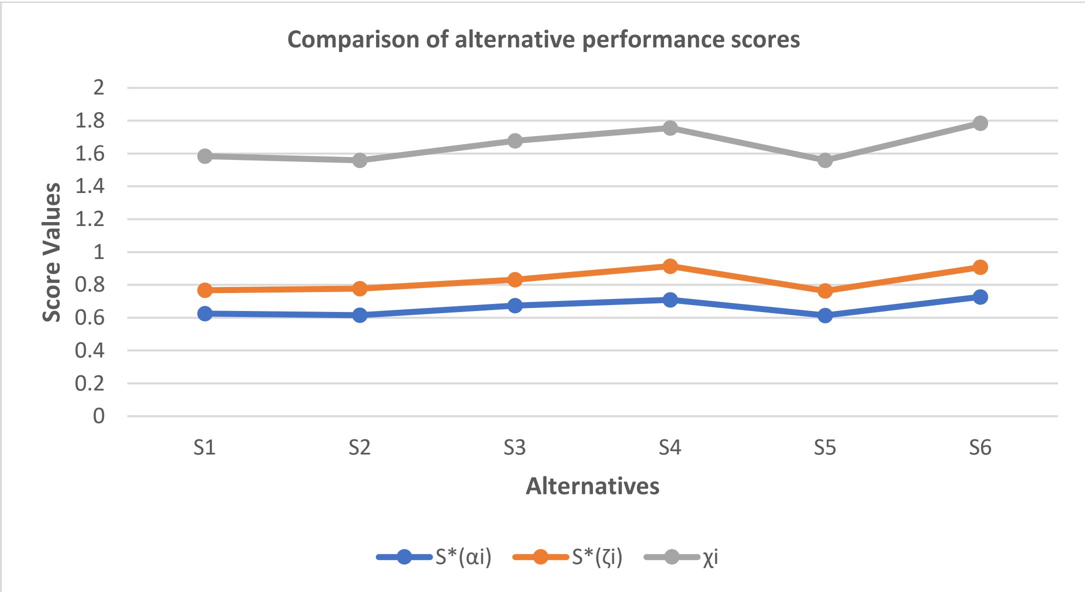

Figure 2. Performance comparison of AI-augmented educational intelligence ecosystems

4 | COMPARATIVE ANALYSIS

To compare the effectiveness of the proposed T-Spherical Fuzzy SWARA-COPRAS (TSF-SWARA-COPRAS) framework with popular methods of the decision-making process, such as VIKOR [25], TOPSIS [26], MEREC [27], EDAS [28], and PROMETHEE [29], a structured comparative analysis is conducted. The comparison is based on methodological features that are key to the assessment of AI-enhanced educational intelligence systems, with human-centered judgment, uncertainty, and dynamic learning environments at the center stage. The relative outcomes are as shown in Table 10. In contrast to conventional decision models, the suggested framework combines T-spherical fuzzy information with subjective expert priority and utility-based ranking by virtue of which it is able to account for multidimensional uncertainty, hesitation, and expert diversity that is bound to occur in educational AI ecosystems. Methods such as TOPSIS and MEREC are very sensitive to crisp normalization or to the spread of the statistical processes and, therefore, they are unable to reflect the subtle human perception. In the same manner, VIKOR and PROMETHEE are premised on compromise procedures, but can degenerate into highly unstable and inaccurate expert judgments. The TSF-SWARA-COPRAS framework demonstrates enhanced ranking stability and interpretability since it possesses a dynamic weighting and distinguishes the benefit- and cost-driven educational standards. This is particularly helpful in AI-driven learning projects, in which the pedagogical, ethical, and learner engagement benefits, as well as the implementation cost, must strike an appropriate balance simultaneously. Moreover, the framework proves to be more computationally efficient with the use of complex, large-scale educational data, and this aspect is suitable in the case of institutional decision-making in real-life situations.

Table 10. Comparative study of MCDM methods for AI-augmented educational ecosystem evaluation

Features	TSF-SWARA–COPRAS	VIKOR	TOPSIS	MEREC	EDAS	PROMETHEE
Handling uncertainty	✓	✗	✗	✗	✗	✗
Advanced aggregation	✓	✗	✗	✗	✓	✓
Dynamic weighting	✓	✓	✗	✓	✓	✓
Compromise-based solution	✓	✓	✗	✗	✓	✓
Ranking stability	✓	✓	✓	✓	✗	✓
Computational efficiency	✓	✗	✓	✗	✓	✗
Applicability in AI-driven education	✓	✗	✗	✗	✗	✗

The TSF-SWARA-COPRAS model is more stable and interprets the ranking due to the dynamic weighting system and the distinct separation of the benefit-oriented and cost-oriented educational standards. This feature is particularly helpful in the example of AI-mediated learning, where the pedagogical benefits, the transparency of ethical issues, interaction between the student, and the affordability of the implementation of the solution have to be balanced. Moreover, the model is also more computationally efficient when it comes to the processing of complex and large-scale learning data, which is why it can be applied to real-world decision situations in an institution.

Table 11. Comparative analysis of existing MCDM-based research in AI-augmented learning settings

Authors	Methodology	Limitations	Remarks
Anbarkhan [30]	Fuzzy TOPSIS-based evaluation model	Limited capability to represent expert hesitation and multidimensional uncertainty	TSF-SWARA–COPRAS explicitly incorporates hesitation degrees through T-spherical fuzzy information, leading to more reliable evaluations
Torkayesh et al.[31]	Entropy-weighted EDAS approach	Purely objective weighting neglects human-centered educational preferences	The proposed framework integrates expert-driven prioritization to reflect pedagogical and ethical considerations
Akram and Bibi [29]	PROMETHEE-based decision model	Ranking results are sensitive to preference thresholds and lack robustness	TSF-SWARA–COPRAS improves ranking stability via benefit–cost utility analysis
Mahamad et al. [32]	Hybrid fuzzy statistical decision model	Limited adaptability to dynamic AI-supported learning environments	Dynamic weighting in TSF-SWARA–COPRAS enables flexible adjustment to evolving educational requirements

As shown in Table 11, the majority of decision-making models that are applied to tackle AI-enhanced educational systems are constrained by uncertainty and do not offer an appropriate inclusion of human judgment, or cannot offer consistent ranking performance. The suggested framework of the TSF-SWARA-COPRAS manages to address such issues, yet by combining advanced fuzzy representation with prioritization of weighting assigned by the professionals and prioritization based on utility as well. This has been incorporated in order to offer more strength, transparency, and usability in the assessment of complex AI-based educational intelligence systems.

4.1. Limitations of the Study

The suggested TSF-SWARA-COPRAS decision model is based on the judgments of experts, which are necessary to preserve the pedagogical factor, ethical issues, and institutional preparedness in the learning scenarios of AI enhancement. The procedures that are involved in calculating uncertainty and adaptive weighting can, however, be computationally intensive with more criteria, alternatives, or experts involved, and larger-scale applications might be necessary. The current assessment system is based on a pre-established system of assessment dimensions, which limits its applicability. The structure ought to be expanded into additional educational environments as well as AI ecosystems to make it stronger. Other than that, the criteria selection as well as the weighting can also influence the final ranking, which is why there ought to be more efficient consensus-building systems, reducing the disparity between the expert opinions. Even though the T-spherical fuzzy information introductions enhance the explanation of hesitation and ambiguity, the model is still overly susceptible to parameter manipulations, linguistic scales, and aggregation decisions. A slight change in these elements can cause discrepancies in comparative results, particularly in situations where substitutes are nearly equal. Therefore, its intensive validation and sensitivity analysis should be done to have a reliable application of advanced fuzzy operators. Lastly, the current research assumes AI-optimized learning conditions in the case of a fixed decision-making situation. It fails to consider changes in time, like the accelerated AI, the changing behavior of the learners, and changes in educational policy. The system of the future might include dynamic modeling and data-driven analytics to increase the scalability and help make real-time decisions in complex and changing learning ecosystems.

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