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Intelligent Assessment Model for Educational Management Decision Support Based on Linguistic Feature Extraction

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ABSTRACT

Background: The expansion of digital campuses, massive open online courses (MOOCs), and blended learning environments has resulted in a substantial increase in unstructured student-generated text, including course evaluations, learning feedback, and online forum discussions. Such information offers an important basis for understanding teaching effectiveness, student satisfaction, and weaknesses in course design. Nevertheless, conventional educational management decision-support systems remain largely dependent on structured questionnaires and single-score assessments, limiting their capacity to represent and quantify the multiple dimensions of sentiment expressed through natural language. Decision-making in complex educational settings also frequently constitutes a multi-attribute decision-making (MCDM) problem because comparisons among teaching alternatives are often characterised by uncertainty, ambiguity, and hesitation. Method: To address these methodological and practical constraints, this study develops a hybrid intelligent evaluation framework integrating natural language processing (NLP) with fuzzy MCDM. The framework is designed to support systematic decision-making in educational management. Attribute-based sentiment analysis (ABSA) is initially employed to analyse linguistic information within student evaluations, identify key teaching attributes, including teaching design and teacher-student interaction, and classify the associated sentiments as positive, neutral, or negative. A mapping mechanism subsequently transforms the extracted sentiment information into spherical fuzzy set (SFS) parameters, enabling uncertainty and neutral sentiment to be represented effectively. Indicator importance is established through an integrated subjective-objective weighting procedure. Subjective weights are derived using the fully consistent method (FUCOM), which reduces the cognitive demands placed on experts during pairwise comparisons while preserving decision consistency. Objective weights are obtained through the information entropy method using the spherical fuzzy scoring function. The alternatives are then comprehensively assessed and ranked through the spherical fuzzy technique based on ideal solution similarity ranking (SF-TOPSIS). Results: Empirical validation was performed using large-scale, authentic student evaluation data covering five core courses at an institution of higher learning. The findings demonstrate that the proposed framework can effectively identify and quantify course performance across four principal attribute dimensions. Application of the

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FUCOM-SF-TOPSIS model revealed substantial variation in overall teaching quality among the evaluated courses, with the best-performing course achieving a closest coefficient (CC) of 0.8532. Sensitivity analysis also demonstrated that the principal decision outcomes remained highly robust despite considerable changes in the coefficients assigned to subjective and objective weights. In comparison with existing MCDM approaches, the proposed method showed notable advantages in representing fuzzy information and controlling consistency deviations. Conclusion: The proposed intelligent evaluation framework provides a systematic mechanism for transforming unstructured linguistic information into a structured mathematical decision-making system. Integrating artificial intelligence with operational research methods extends the interdisciplinary application of these approaches within educational management. The framework also offers methodological support for educational administrators seeking to enhance teaching quality, optimise resource allocation, and develop sustainable educational strategies.

1. Introduction

In the contemporary global education ecosystem, where digital technologies have become deeply embedded in teaching and learning, educational management is experiencing a fundamental transition from experience-driven judgement towards data-driven decision-making [1; 2]. This transformation is evident across both conventional higher education institutions and emerging massive open online courses (MOOCs) platforms, which continuously produce substantial volumes of student feedback. Alongside structured information, such as examination scores and responses to multiple-choice questionnaires, these environments generate extensive unstructured textual data through course forum interactions, anonymous end-of-semester evaluations, and unsolicited comments posted on social media [3; 4]. Such natural language data constitutes a particularly rich source of evidence regarding educational service quality, students' actual levels of satisfaction, and deficiencies that may remain hidden within course design and delivery. The principal challenge, therefore, lies in systematically and accurately extracting meaningful features from these complex textual sources and translating them into quantitative measures that educational managers can directly employ in resource allocation and strategic planning. Consequently, this problem has emerged as an important interdisciplinary research area connecting educational data mining with operational decision-making.

Despite the growing availability of these data, educational quality assessment continues to depend predominantly on structured questionnaires with predefined response scales and simple numerical rating mechanisms, such as five-point scales. The shortcomings of these conventional approaches are becoming increasingly apparent. Fixed-scale measurements, for example, provide limited insight into subtle variations in students' emotional responses towards individual aspects of a course, including the depth of theoretical content, ease of practical application, and responsiveness of post-class question-and-answer sessions. More importantly, reducing evaluation to a single numerical value inadequately represents the fuzziness, uncertainty, and hesitation inherent in human cognition and judgement [5] and [6]. These limitations have stimulated growing interest in natural language processing (NLP) techniques within artificial intelligence (AI), particularly text mining and sentiment analysis, for educational assessment [3], [7] and [8]. In this context, aspect-based sentiment analysis (ABSA) enables algorithms to move beyond overall sentiment classification by identifying the particular course attributes discussed by students and quantifying the distribution of sentiment polarity associated with each attribute. The resulting information can therefore provide educational managers with more granular evidence for decision-making [7], [9; 10].

Once language-based evaluation information has been extracted and quantified, the analytical focus moves beyond textual interpretation towards the simultaneous evaluation of several competing dimensions, transforming the management task into some multi-criteria decision-making (MCDM) problem [11-13]. Educational managers must therefore consider multiple criteria that may conflict with one another when comparing available alternatives [11; 14]. Because such evaluations frequently involve uncertainty and imprecision, fuzzy set theory has been progressively incorporated into MCDM frameworks to provide a more suitable representation of ambiguous decision information [15; 16]. Further developments in fuzzy mathematics subsequently introduced the spherical fuzzy set (SFS), offering an expanded structure for modelling complex uncertainty [17-20]. SFS simultaneously represents positive membership, non-membership, and hesitation, while constraining the sum of their squared values to no more than 1. The resulting enlarged decision space allows ambiguous and hesitant judgements to be expressed with greater flexibility. This characteristic makes SFS particularly suitable for student evaluations containing neutral, uncertain, or conflicting responses and provides greater representational flexibility than conventional intuitive fuzzy sets (IFS) and Pythagorean fuzzy sets (PFS) [21; 22].

Another important element of MCDM modelling is the determination of criterion weights because differences in their relative importance can substantially affect the final decision outcome. Conventional weighting techniques, including the Analytic Hierarchy Process (AHP) and the Worst Method (BWM), may impose considerable demands on experts by requiring numerous pairwise comparisons. An increasing number of comparisons can also amplify the influence of subjective cognitive bias and create inconsistencies within the decision matrix [23; 24]. FUCOM was developed to address these limitations by establishing criterion weights through a more parsimonious comparison structure [25-27]. Instead of requiring exhaustive pairwise judgements, its nonlinear programming formulation determines the weights of n criteria using only $n-1$ comparisons. This substantially reduces the cognitive burden placed on experts while preserving a mechanism for assessing the mathematical consistency and reliability of the resulting weights through the deviation from perfect consistency (DFC) [27], [28].

Against this background, interdisciplinary research spanning operations research, AI, and applied mathematics has increasingly sought to integrate these methodological domains within practical engineering and management decision-making environments [6], [11; 12], [26]. Nevertheless, a methodological gap remains in educational management assessment because text-mining techniques and advanced fuzzy decision-making models are frequently treated as separate analytical processes. To bridge this gap, the present study develops an intelligent educational management decision-support model in which linguistic feature extraction is directly integrated with fuzzy decision analysis. The main contributions of this study are summarized as follows:

1. A mathematical mapping mechanism from unstructured text to spherical fuzzy numbers was established. Large-scale student evaluations are first processed through text mining and ABSA to derive a three-dimensional distribution representing positive, negative, and neutral sentiments. These sentiment distributions are subsequently transformed through mathematical mapping rules into spherical fuzzy numbers (SFNs), thereby converting information embedded in natural language into formally defined decision parameters.
2. A dual-drive hybrid weight calculation model was proposed. Subjective judgements from educational professionals are incorporated through FUCOM, while objective weights are derived using the information entropy method based on the SFS distance index. Integrating these two weighting dimensions produces a comprehensive hybrid weighting system that reduces the systematic bias associated with reliance on a single weighting approach and strengthens the

scientific basis for determining indicator importance.

3. Expand the application scope of the SF-TOPSIS method in the field of educational management: The spherical fuzzy method based on the similarity sorting of ideal solutions (TOPSIS) is incorporated into the proposed framework to extend its applicability to educational management decisions. This integration provides educational managers with an efficient decision-support mechanism for addressing practical problems involving course plan selection, determination of teaching methods, and teacher evaluation.
4. Conduct empirical tests and sensitivity analysis: The proposed framework is empirically examined using evidence derived from an actual higher education setting. Detailed case analysis and sensitivity testing are employed to assess its effectiveness while providing further insight into the operational and management mechanisms underlying the Quality Assurance System (QS) in universities.

2. Literature Review

2.1 Language Feature Extraction and Aspect-Based Sentiment Analysis

Over the past decade, rapid advances in text mining have established it as an important analytical approach for uncovering meaningful information embedded within unstructured data [22]. The proliferation of online review environments has further expanded its application, with user-generated textual content increasingly utilised to understand demand, evaluate service quality, and anticipate market trends [7], [13]. A similar development is evident in educational management, where course evaluation systems, MOOC discussion forums, and campus-based social networks generate substantial volumes of student feedback that can inform educational assessment and decision-making [3].

Conventional sentiment analysis, however, generally operates at the document or sentence level and therefore provides only a broad classification of whether the expressed opinion is positive or negative. Such an approach offers limited capacity to distinguish the particular objects or attributes towards which different sentiments are directed [10]. Aspect-based sentiment analysis (ABSA) addresses this limitation by identifying individual entities and their associated aspects before determining sentiment polarity separately for each identified component [5], [29]. For instance, in the student comment, “The theoretical derivation of this course is very rigorous, but the equipment for the laboratory class is too old”, two distinct evaluative dimensions can be recognised: theoretical derivation carries positive sentiment, whereas laboratory equipment is evaluated negatively. The usefulness of ABSA has already been investigated across several service-oriented contexts. Existing studies have employed it to extract relevant attributes from automotive reviews [7] and to support the evaluation and ranking of hospital services using sentiments expressed by patients [8-10]. Its integration into educational management decision-making nevertheless remains comparatively limited. In particular, relatively few studies have directly transformed ternary sentiment distributions comprising positive, neutral, and negative evaluations into mathematical decision matrices capable of representing fuzziness and hesitation [6], [10]. Instead, much of the existing literature continues to rely on straightforward linear weighting procedures, which inadequately account for the fuzzy characteristics inherent in natural language expression.

2.2 Fuzzy Multi-Attribute Decision Making and the Evolution of Spherical Fuzzy Sets

Multi-attribute decision-making (MCDM) represents an established area within operations research and has been extensively applied to complex decision problems in supply chain management, sustainability assessment, and policy formulation [12; 13], [14]. Practical decision environments frequently require alternatives to be assessed against competing criteria while simultaneously accommodating uncertainty and ambiguity in human judgement. These characteristics have driven the development of fuzzy MCDM approaches, which provide a more

appropriate basis for representing imprecise information during decision-making [16].

Several extensions of fuzzy mathematics have progressively broadened the representation of uncertainty. The Intuitionistic Fuzzy Set (IFS) introduced membership and non-membership degrees under the restriction that their combined value cannot exceed 1 [15]. This representational space was subsequently extended through the Pythagorean Fuzzy Set (PFS), where the sum of the squared membership and non-membership degrees is constrained to a maximum of 1, thereby providing decision-makers with greater flexibility in expressing their preferences [21]. A further development, the Image Fuzzy Set, incorporated hesitation and abstention by representing positive membership, neutrality, and negative membership simultaneously, while requiring their aggregate value to remain no greater than 1 [18]. Greater flexibility in representing complex uncertainty was achieved with the introduction of Sphere Fuzzy Sets (SFS) in 2019 [17; 20]. Under this formulation, positive membership (μ), non-membership (ν), and hesitation (π) are considered simultaneously, with the sum of their squared values constrained to the interval [0,1] [20], [18; 19]. This three-dimensional representation provides a broader mapping space and exhibits a natural correspondence with the positive, negative, and neutral sentiment distributions obtained from text-based sentiment analysis [19]. Despite substantial theoretical progress in SFS and associated aggregation operators, their integration with textual analytics remains insufficiently developed. In particular, a systematic framework that directly transforms sentiment proportions extracted through natural language processing (NLP) into spherical fuzzy parameters has yet to be adequately established.

2.3 The Fully Consistent Method (FUCOM) and Its Hybrid Evaluation Architecture

Within any MCDM framework, the assignment of criterion weights plays a fundamental role in determining the accuracy and reliability of the final evaluation. Classic subjective weighting methods, like AHP and ANP, require experts to conduct $\frac{n(n-1)}{2}$ pairwise comparisons, which is extensive and prone to consistency test failures due to cognitive limitations [24]. To overcome the limitations associated with conventional weighting procedures, the Fully Consistent Method (FUCOM) was introduced in 2018 [27]. FUCOM is founded on a rigorous mathematical structure in which experts first rank the evaluation criteria according to their importance and subsequently specify the comparative priorities between adjacent criteria. These preference relationships are incorporated into a nonlinear optimisation model subject to transitivity conditions, allowing the optimal weights of n criteria to be determined from only $n-1$ comparisons [25; 28]. The method additionally evaluates the deviation from full consistency (DFC), providing a quantitative means of examining the logical consistency of expert preferences.

Owing to its relatively low cognitive burden and consistency-oriented weighting mechanism, FUCOM has increasingly been incorporated into hybrid decision-making frameworks [12], [14], [26]. Previous applications have combined FUCOM with Z-numbers and MABAC for location-related decision problems [26], while a FUCOM-MARCOS framework has been employed for logistics assessment [1]. Its applicability has also been demonstrated across sustainability, transportation, and evaluation-oriented decision models [12], [26; 27]. Despite parallel advances in text sentiment analysis, SFS, and FUCOM, their combined application within educational management remains insufficiently explored. In particular, an integrated framework that extracts knowledge from natural language, represents ambiguity through spherical fuzzy information, and subsequently supports rigorous management decisions has yet to be systematically established. The present study addresses this theoretical and practical gap by integrating these methodological components within a unified educational decision-support framework.

3. Materials and Methods

This section establishes the theoretical foundations and mathematical formulation of the

proposed intelligent assessment framework. The subsequent subsections describe the transformation of textual information into fuzzy features, the algebraic operations of SFS, the FUCOM optimisation model, and the SF-TOPSIS ranking procedure.

3.1 Mapping Mechanism of Text Sentiment Features to Spherical Fuzzy Sets

In the text mining and sentiment analysis stage, for educational alternatives $A_i (i = 1, 2, \dots, m)$ and evaluation indicators $C_j (j = 1, 2, \dots, n)$, the system extracts feature words and context sentences from student comments using NLP algorithms and ABSA models [3; 4], [13].

Using pre-trained classifiers or dictionary-based rules, valid comments for A_i under indicator C_j are classified into positive, negative, and neutral sentiment sets [7], [10]. Let P_{ij} be the frequency of positive evaluations, N_{ij} negative evaluations, and O_{ij} neutral evaluations. The total number of valid sentiment statements T_{ij} satisfies (1):

$$T_{ij} = P_{ij} + N_{ij} + O_{ij} \quad (1)$$

To convert these frequencies into operable parameters for decision-making, this paper utilizes a proportional mapping mechanism to transform them into positive membership degree μ_{ij} , non-membership degree ν_{ij} , and hesitation degree π_{ij} in spherical fuzzy numbers [20], [18; 19] (2)-(4):

$$\mu_{ij} = \frac{P_{ij}}{T_{ij}} \quad (2)$$

$$\nu_{ij} = \frac{N_{ij}}{T_{ij}} \quad (3)$$

$$\pi_{ij} = \frac{O_{ij}}{T_{ij}} \quad (4)$$

Proof of Constraints: The parameters must satisfy the constraint that the sum of their squares is less than or equal to 1. From the mapping definition, $\mu_{ij}, \nu_{ij}, \pi_{ij} \in [0, 1]$, and their linear sum equals 1 (5):

$$\mu_{ij} + \nu_{ij} + \pi_{ij} = 1 \quad (5)$$

For any non-negative real numbers $a, b, c \geq 0$ where $a + b + c = 1$ (6):

$$a^2 + b^2 + c^2 \leq (a + b + c)^2 = 1 \quad (6)$$

Thus (7),

$$\mu_{ij}^2 + \nu_{ij}^2 + \pi_{ij}^2 \leq 1 \quad (7)$$

The proposed mapping mechanism provides a logically consistent means of translating sentiment tendencies expressed in language into the geometric space of SFS, thereby establishing a quantitative basis for subsequent decision-making. The constructed elements are expressed as SFNs $\tilde{S}_{ij} = \langle \mu_{ij}, \nu_{ij}, \pi_{ij} \rangle$ [5; 6], [13], [19].

3.2 Mathematical Definition and Operation Rules of Spherical Fuzzy Sets (SFS)

Definition 1 (Spherical Fuzzy Set): Given a domain X , an SFS $\tilde{A}$ on X is defined as (8):

$$\tilde{A} = \{ \langle x, \mu_{\tilde{A}}(x), \nu_{\tilde{A}}(x), \pi_{\tilde{A}}(x) \rangle | x \in X \} \quad (8)$$

Where $\mu_{\tilde{A}}(x): X \rightarrow [0, 1]$ represents the membership degree of element x , $\nu_{\tilde{A}}(x): X \rightarrow [0, 1]$ the non-membership degree, and $\pi_{\tilde{A}}(x): X \rightarrow [0, 1]$ the hesitation degree. For all $x \in X$, these parameters are constrained by [20] (9):

$$0 \leq \mu_{\tilde{A}}(x)^2 + \nu_{\tilde{A}}(x)^2 + \pi_{\tilde{A}}(x)^2 \leq 1 \quad (9)$$

Specific elements are denoted as SFNs $\tilde{a} = \langle \mu, \nu, \pi \rangle$.

Definition 2 (Algebraic Operations): For two SFNs $\tilde{a}_1 = \langle \mu_1, \nu_1, \pi_1 \rangle$ and $\tilde{a}_2 = \langle \mu_2, \nu_2, \pi_2 \rangle$, and positive real scalar $\lambda > 0$, the basic operation rules based on the extended Einstein and algebraic norms are [17; 18], [21]:

Addition (10):

$$\tilde{a}_1 \oplus \tilde{a}_2 = \left\langle \sqrt{\mu_1^2 + \mu_2^2 - \mu_1^2 \mu_2^2}, \nu_1 \nu_2, \sqrt{(1 - \mu_2^2) \pi_1^2 + (1 - \mu_1^2) \pi_2^2 - \pi_1^2 \pi_2^2} \right\rangle \quad (10)$$

Multiplication (11):

$$\tilde{a}_1 \otimes \tilde{a}_2 = \left\langle \mu_1 \mu_2, \sqrt{\nu_1^2 + \nu_2^2 - \nu_1^2 \nu_2^2}, \sqrt{(1 - \nu_2^2) \pi_1^2 + (1 - \nu_1^2) \pi_2^2 - \pi_1^2 \pi_2^2} \right\rangle \quad (11)$$

Scalar Multiplication (Exponential Weighting) (12):

$$\lambda \tilde{a}_1 = \left\langle \sqrt{1 - (1 - \mu_1^2)^\lambda}, \nu_1^\lambda, \sqrt{(1 - \mu_1^2)^\lambda - (1 - \mu_1^2 - \pi_1^2)^\lambda} \right\rangle \quad (12)$$

Power Operation (13):

$$\tilde{a}_1^\lambda = \left\langle \mu_1^\lambda, \sqrt{1 - (1 - \nu_1^2)^\lambda}, \sqrt{(1 - \nu_1^2)^\lambda - (1 - \nu_1^2 - \pi_1^2)^\lambda} \right\rangle \quad (13)$$

Definition 3 (Score Function and Distance Measure): For MCDM ranking, an SFN $\tilde{a} = \langle \mu, \nu, \pi \rangle$ is defuzzified using the score function $S(\tilde{a})$ [19]:

$$S(\tilde{a}) = \mu^2 - \nu^2$$

where $S(\tilde{a}) \in [-1, 1]$. A higher score indicates a more positive evaluation. An accuracy function $H(\tilde{a}) = \mu^2 + \nu^2 + \pi^2$ is used for secondary sorting when scores tie.

The standardized Euclidean distance between $\tilde{a}_1$ and $\tilde{a}_2$ is [18; 19] (14):

$$D(\tilde{a}_1, \tilde{a}_2) = \sqrt{\frac{1}{2} ((\mu_1^2 - \mu_2^2)^2 + (\nu_1^2 - \nu_2^2)^2 + (\pi_1^2 - \pi_2^2)^2)} \quad (14)$$

3.3 Consistency-Based Method (FUCOM) Model Construction

FUCOM determines consistent indicator weights while minimising the number of required pairwise comparisons [25; 28]. The procedure is implemented through the following steps:

Step 1: Determine the priority of subjective indicators. Experts rank n evaluation indicators $C_j (j = 1, 2, \dots, n)$ in descending order of importance (15):

$$C_{j(1)} > C_{j(2)} > \dots > C_{j(n)} \quad (15)$$

Step 2: Determine comparative priorities of adjacent indicators. The relative importance ratio of indicator $C_{j(k)}$ over its successor $C_{j(k+1)}$ is denoted as $\varphi_{k/(k+1)}$ (16):

$$\varphi_{k/(k+1)} = \frac{\text{Importance of indicator } C_{j(k)}}{\text{Importance of indicator } C_{j(k+1)}} \quad (16)$$

This generates the comparative priority vector $\Phi = (\varphi_{1/2}, \varphi_{2/3}, \dots, \varphi_{(n-1)/n})$ using $n - 1$ comparisons.

Step 3: Define constraints and solve the nonlinear optimization model. The global optimal weight vector $W = (w_1, w_2, \dots, w_n)^T$ must satisfy:

Condition 1 (Proportional Consistency) (17):

$$\frac{w_{j(k)}}{w_{j(k+1)}} = \varphi_{k/(k+1)} \quad (17)$$

Condition 2 (Mathematical Transitivity) (18):

$$\frac{w_{j(k)}}{w_{j(k+2)}} = \varphi_{k/(k+1)} \times \varphi_{(k+1)/(k+2)} \quad (18)$$

To meet these strict conditions, FUCOM minimizes the maximum consistency deviation (χ) via the following model (19):

$$\begin{aligned} & \min \chi \\ & \text{subject to:} \\ & \left| \frac{w_{j(k)}}{w_{j(k+1)}} - \varphi_{k/(k+1)} \right| \leq \chi, \quad \forall k \in \{1, 2, \dots, n-1\} \\ & \left| \frac{w_{j(k)}}{w_{j(k+2)}} - \varphi_{k/(k+1)} \cdot \varphi_{(k+1)/(k+2)} \right| \leq \chi, \quad \forall k \in \{1, 2, \dots, n-2\} \\ & \sum_{j=1}^n w_j = 1 \\ & w_j \geq 0, \quad \forall j \end{aligned} \quad (19)$$

Solving this model yields the subjective optimal weights $w^{sub} = (w_1, w_2, \dots, w_n)^T$ and DFC χ . A value of χ close to 0 indicates high consistency among expert comparisons [27], [25].

4. Implementation Steps of the Proposed Intelligent Evaluation Framework

This study develops a hybrid intelligent evaluation framework, termed Language-SF-FUCOM-TOPSIS, which links sentiment information extracted from fragmented textual data with quantitative decision-making. The framework is implemented through five sequential stages.

4.1 Phase One and Phase Two: Automated Text Collection, Pre-Processing, and Feature Extraction

Phase One: Automated Collection and Pre-Processing

Collecting Data Sources: Student interaction texts relating to specific courses and predefined historical periods are retrieved from internal assessment systems and MOOC platforms using customised web-scraping tools or database interfaces [3; 4].

Cleaning and Pre-Processing: The NLP toolkit processes the original corpus by removing duplicates, splitting long paragraphs into sentences, applying stop word filtering, and extracting noun and adjective groups through part-of-speech (POS) tagging, etc., for feature matching. Preparing the text [22].

4.2 Phase Two: Feature Extraction and Sentiment Polarity Classification (ABSA)

Feature Extraction and Mapping: Construct domain ontology and feature dictionary to reflect educational quality. Pre-process token matching to ontology nodes (for example, education description matches to indicator C_1 , rapid response matches to indicator C_2) [7] and [10].

Emotional Polarity Determination: A pre-trained deep neural network language model (e.g., BERT or RoBERTa) classifies statements into positive, negative, and neutral categories. The system records the frequency of each alternative A_i across these sentiments P_{ij}, N_{ij}, O_{ij} under different indicators C_j [3], [7].

4.3 Phase 3: Construction of the Initial Spherical Fuzzy Matrix and Objective Weighting

Construct the initial SFN decision matrix: Frequencies (P_{ij}, N_{ij}, O_{ij}) are transformed into SFN parameters $\tilde{S}_{ij} = \langle \mu_{ij}, \nu_{ij}, \pi_{ij} \rangle$ via the mapping formula, generating an $m \times n$ initial spherical fuzzy decision matrix $\tilde{X}$ [19].

Objective weight extraction based on information entropy: Using Shannon's information entropy principle [30], SFNs are defuzzified into scores $S_{ij} = \mu_{ij}^2 - \nu_{ij}^2$. Scores are normalized (20):

$$p_{ij} = \frac{S_{ij}}{\sum_{i=1}^m S_{ij}} \quad (20)$$

The information entropy E_j for each indicator C_j is calculated (21):

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^m p_{ij} \ln p_{ij} \quad (21)$$

The information divergence $d_j = 1 - E_j$ is normalized to obtain the objective weight vector w_j^{obj} driven by data distribution (22):

$$w_j^{obj} = \frac{d_j}{\sum_{j=1}^n d_j} \quad (22)$$

4.4 Stage Four: Applying FUCOM and Generating Hybrid Weights

Obtain subjective weights: An expert group (e.g., teaching deans) ranks indicators via consensus. These parameters are input into the FUCOM optimization model to yield the subjective expert weight vector w_j^{sub} [18], [25].

Constructing Comprehensive Mixed Weights: To balance expert preferences and objective data, an allocation coefficient $\lambda \in [0,1]$ (default 0.5) is applied to generate the hybrid weight vector W_j [19] (23):

$$W_j = \lambda \cdot w_j^{sub} + (1 - \lambda) \cdot w_j^{obj} \quad (23)$$

4.6 Phase Five: Education Program Optimization (SF-TOPSIS)

Construct a Weighted Spherical Fuzzy Decision Matrix: Using SFS scalar multiplication, mixed weights W_j are incorporated into the initial matrix [19] (24):

$$\tilde{v}_{ij} = W_j \tilde{s}_{ij} = \left\langle \sqrt{1 - (1 - \mu_{ij}^2)^{W_j}}, v_{ij}^{W_j}, \sqrt{(1 - \mu_{ij}^2)^{W_j} - (1 - \mu_{ij}^2 - \pi_{ij}^2)^{W_j}} \right\rangle \quad (24)$$

Establish Ideal Solution Boundaries: For benefit-oriented evaluation features, the positive ideal solution (SF-PIS, $\tilde{A}^+$) is composed of elements with the highest membership and lowest non-membership/hesitation degrees per column. The negative ideal solution (SF-NIS, $\tilde{A}^-$) comprises the poorest-performing extremes [19] (25)-(26):

$$\tilde{A}^+ = \{\langle \max_i(\mu_{\tilde{v}_{ij}}), \min_i(v_{\tilde{v}_{ij}}), \min_i(\pi_{\tilde{v}_{ij}}) \rangle\} \quad (25)$$

$$\tilde{A}^- = \{\langle \min_i(\mu_{\tilde{v}_{ij}}), \max_i(v_{\tilde{v}_{ij}}), \max_i(\pi_{\tilde{v}_{ij}}) \rangle\} \quad (26)$$

Calculate Spatial Distance: The Euclidean distance from each alternative A_i to the positive (D_i^+) and negative (D_i^-) ideal solutions is calculated.

Proximity (CC) Calculation and Ranking: The proximity coefficient (Closeness Coefficient, CC_i) represents the alternative's proximity to the ideal state (27):

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-} \quad (27)$$

Alternatives are ranked in descending order of $CC_i \in [0,1]$ to output a detailed assessment report for administrative decision-making [19].

5. Case Study: Empirical Application

To evaluate the validity and diagnostic capability of the Language-SF-FUCOM-TOPSIS framework, it was applied to a teaching-quality assessment conducted at a higher education institution. Using student feedback collected across two semesters, the Academic Affairs Office sought to rank five core courses covering general education and professional foundation subjects:

- A_1 : Advanced Math
- A_2 : College Physics
- A_3 : Computer Networks
- A_4 : Database Systems
- A_5 : Software Engineering

Rather than relying solely on conventional pass rates, the department examined textual student feedback obtained from the learning management system (LMS). Based on this information, an expert committee established four dimensions for evaluating teaching quality:

- C_1 (Pedagogical Design): Rationality of course structure, logical theoretical derivation, and multimedia quality.
- C_2 (Interaction): Student participation enthusiasm and response frequency of teachers/assistants in forums.
- C_3 (Practical Value): Experimental course relevance and enhancement of practical skills via projects.
- C_4 (Academic Support): Richness of reference materials and usability of teaching tools.

5.1 Feature Extraction and Matrix Construction

The system extracted all valid text comments for the 5 courses and applied ABSA processing. Natural sentences were classified and polarity-annotated. For example, for Computer Networks (A_3) under Teaching Design (C_1), the algorithm identified 170 relevant sentences: 140 positive, 20 neutral, and 10 negative. Table 1 summarizes the original sentiment frequency for each course.

Table 1

Original Frequency Statistics of Student Sentiment Texts Extracted by NLP Models

Alternative courses	C1 (Teaching Design)	C2 (Teacher-Student Interaction)	C3 (Practical Value)	C4 (Academic Support)
A1 (Advanced Mathematics)	(120, 30, 10)	(80, 50, 20)	(60, 40, 30)	(110, 25, 15)
A2 (University Physics)	(90, 40, 20)	(100, 30, 10)	(70, 50, 10)	(85, 45, 20)
A3 (Computer Network)	(140, 20, 10)	(110, 40, 10)	(130, 25, 15)	(120, 30, 10)
A4 (Database System)	(100, 50, 20)	(90, 45, 25)	(110, 30, 20)	(95, 40, 15)
A5 (Software Engineering)	(130, 30, 15)	(120, 25, 15)	(140, 20, 10)	(130, 30, 10)

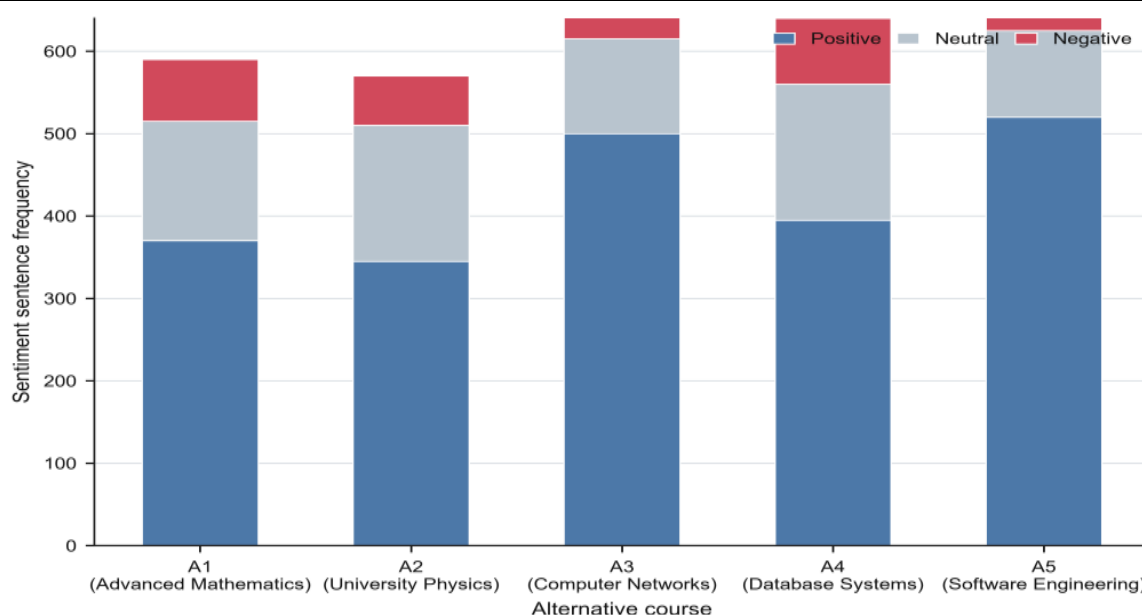


Fig.1: Stacked Chart Showing the Overall Sentiment Polarity Distribution of Each Alternative Course

Using the proposed mapping mechanism, the discrete frequency distributions were converted into SFNs. For instance, for A_1 under C_1 : total frequency $T_{11} = 160$. Positive membership $\mu_{11} = 120/160 = 0.7500$; hesitation $\pi_{11} = 30/160 = 0.1875$; non-membership $\nu_{11} = 10/160 = 0.0625$, yielding SFN $\langle 0.7500, 0.0625, 0.1875 \rangle$. The resulting initial decision matrix is presented in Table 2.

Table 2

Initial Spherical Fuzzy (SFN) Evaluation Decision Matrix

Course	C1 (Teaching Design)	C2 (Teacher-Student Interaction)	C3 (Practical Value)	C4 (Academic Support)
A1	$\langle 0.7500, 0.0625, 0.1875 \rangle$	$\langle 0.5333, 0.1333, 0.3333 \rangle$	$\langle 0.4615, 0.2308, 0.3077 \rangle$	$\langle 0.7333, 0.1000, 0.1667 \rangle$
A2	$\langle 0.6000, 0.1333, 0.2667 \rangle$	$\langle 0.7143, 0.0714, 0.2143 \rangle$	$\langle 0.5385, 0.0769, 0.3846 \rangle$	$\langle 0.5667, 0.1333, 0.3000 \rangle$
A3	$\langle 0.8235, 0.0588, 0.1176 \rangle$	$\langle 0.6875, 0.0625, 0.2500 \rangle$	$\langle 0.7647, 0.0882, 0.1471 \rangle$	$\langle 0.7500, 0.0625, 0.1875 \rangle$
A4	$\langle 0.5882, 0.1176, 0.2941 \rangle$	$\langle 0.5625, 0.1562, 0.2812 \rangle$	$\langle 0.6875, 0.1250, 0.1875 \rangle$	$\langle 0.6333, 0.1000, 0.2667 \rangle$
A5	$\langle 0.7429, 0.0857, 0.1714 \rangle$	$\langle 0.7500, 0.0938, 0.1562 \rangle$	$\langle 0.8235, 0.0588, 0.1176 \rangle$	$\langle 0.7647, 0.0588, 0.1765 \rangle$

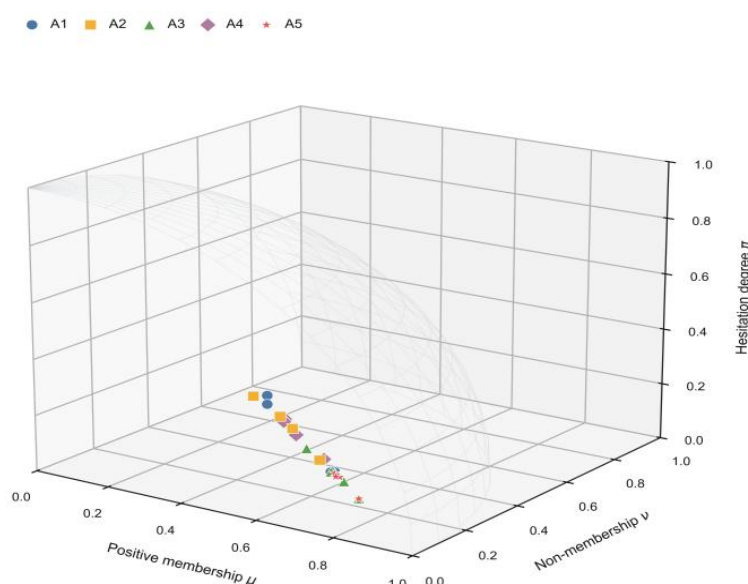


Fig.2: Three-Dimensional Mapping Distribution of Language Feature Spherical Fuzzy Number (SFN)

The system calculated precise scores $S(\tilde{a}) = \mu^2 - \nu^2$ and derived objective information entropy weights: $w^{obj} = (0.1802, 0.1932, 0.4961, 0.1305)^T$. The findings indicate that practical value (C3) exhibited the greatest variation in students' emotional feedback, receiving a weight of 0.4961 and emerging as a key factor differentiating student satisfaction (Fig. 2).

5.2 Generation of Hybrid Weights

To incorporate expert judgement into the weighting process, FUCOM was subsequently applied. The expert panel arranged the indicators in descending order of strategic importance (28):

$$C_1 > C_2 > C_3 > C_4 \quad (28)$$

Comparative priorities were assessed: Instructional design was evaluated as 1.2 times more important than teacher-student interaction ($\varphi_{1/2} = 1.2$); interaction 1.3 times over practical value ($\varphi_{2/3} = 1.3$); and practical value 1.15 times over academic support ($\varphi_{3/4} = 1.15$).

Inputting these parameters into the FUCOM optimization model yielded consistent results, with a maximum consistency deviation (DFC) $\chi = 0.000$. The subjective weight matrix was: $w^{sub} =$

$(0.3300, 0.2750, 0.2115, 0.1835)^T$.

Applying a fusion coefficient $\lambda = 0.5$, the final comprehensive mixed weight vector W_{hybrid} was calculated:

$$W_1 = 0.5 \times 0.3300 + 0.5 \times 0.1802 = 0.2551$$

$$W_2 = 0.5 \times 0.2750 + 0.5 \times 0.1932 = 0.2341$$

$$W_3 = 0.5 \times 0.2115 + 0.5 \times 0.4961 = 0.3538$$

$$W_4 = 0.5 \times 0.1835 + 0.5 \times 0.1305 = 0.1570$$

Resulting in $W_{hybrid} = (0.2551, 0.2341, 0.3538, 0.1570)^T$ [19] (Figs 3, 4).

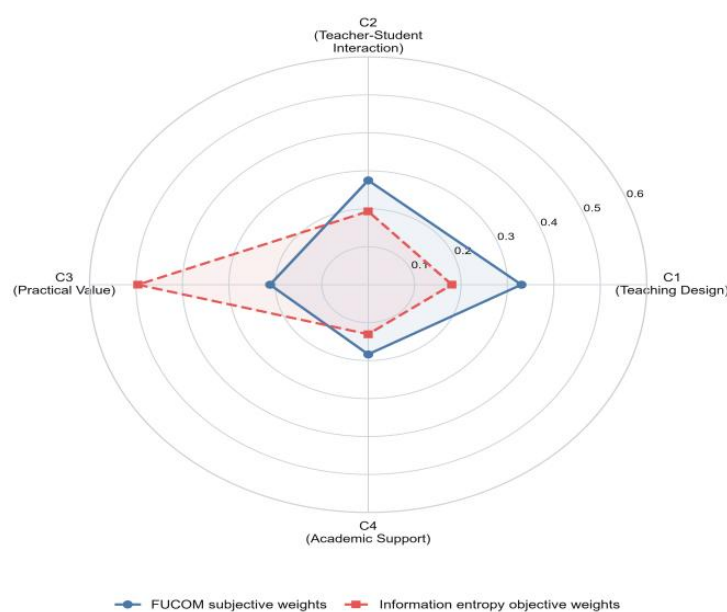


Fig.3: Comparison Radar Chart of Subjective and Objective Weight Distribution of Indicators

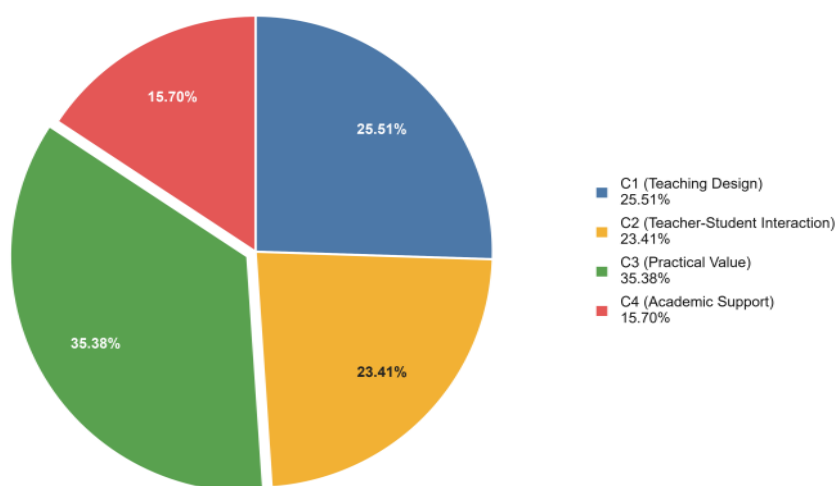


Fig.4: Pie Chart Showing the Final Mixed Comprehensive Weight Distribution of Each Evaluation Index

5.3 Selection of SF-TOPSIS Scheme

The hybrid weights were incorporated into the initial SFN decision matrix using the SFS scalar multiplication operation. The resulting weighted decision matrix is presented in Table 3.

Table 3

Weighted Spherical Fuzzy Decision Matrix

Course	C1 (0.2551)	C2 (0.2341)	C3 (0.3538)	C4 (0.1570)
A1	$\langle 0.4360, 0.4930, 0.1309 \rangle$	$\langle 0.2745, 0.6239, 0.1892 \rangle$	$\langle 0.2850, 0.5952, 0.2018 \rangle$	$\langle 0.3378, 0.6967, 0.0926 \rangle$
A2	$\langle 0.3280, 0.5981, 0.1625 \rangle$	$\langle 0.3923, 0.5391, 0.1388 \rangle$	$\langle 0.3378, 0.4035, 0.2651 \rangle$	$\langle 0.2429, 0.7288, 0.1441 \rangle$
A3	$\langle 0.5011, 0.4854, 0.0913 \rangle$	$\langle 0.3730, 0.5225, 0.1583 \rangle$	$\langle 0.5170, 0.4235, 0.1172 \rangle$	$\langle 0.3489, 0.6471, 0.1071 \rangle$
A4	$\langle 0.3204, 0.5792, 0.1786 \rangle$	$\langle 0.2919, 0.6475, 0.1611 \rangle$	$\langle 0.4501, 0.4791, 0.1387 \rangle$	$\langle 0.2781, 0.6967, 0.1347 \rangle$
A5	$\langle 0.4303, 0.5343, 0.1182 \rangle$	$\langle 0.4195, 0.5746, 0.1049 \rangle$	$\langle 0.5748, 0.3669, 0.1016 \rangle$	$\langle 0.3590, 0.6409, 0.1030 \rangle$

Positive ideal solutions (SF-PIS, $\tilde{A}^+$) and negative ideal solutions (SF-NIS, $\tilde{A}^-$) were extracted based on highest and lowest performance metrics across dimensions:

Extracted SF-PIS: C_1 : $\langle 0.5011, 0.4854, 0.0913 \rangle$ C_2 : $\langle 0.4195, 0.5225, 0.1049 \rangle$ C_3 : $\langle 0.5748, 0.3669, 0.1016 \rangle$ C_4 : $\langle 0.3590, 0.6409, 0.0926 \rangle$

Extracted SF-NIS: C_1 : $\langle 0.3204, 0.5981, 0.1786 \rangle$ C_2 : $\langle 0.2745, 0.6475, 0.1892 \rangle$ C_3 : $\langle 0.2850, 0.5952, 0.2651 \rangle$ C_4 : $\langle 0.2429, 0.7288, 0.1441 \rangle$

Distances D_i^+ and D_i^- were calculated using the standardized Euclidean distance measure, leading to the proximity coefficient (CC) and final ranking (Table 4).

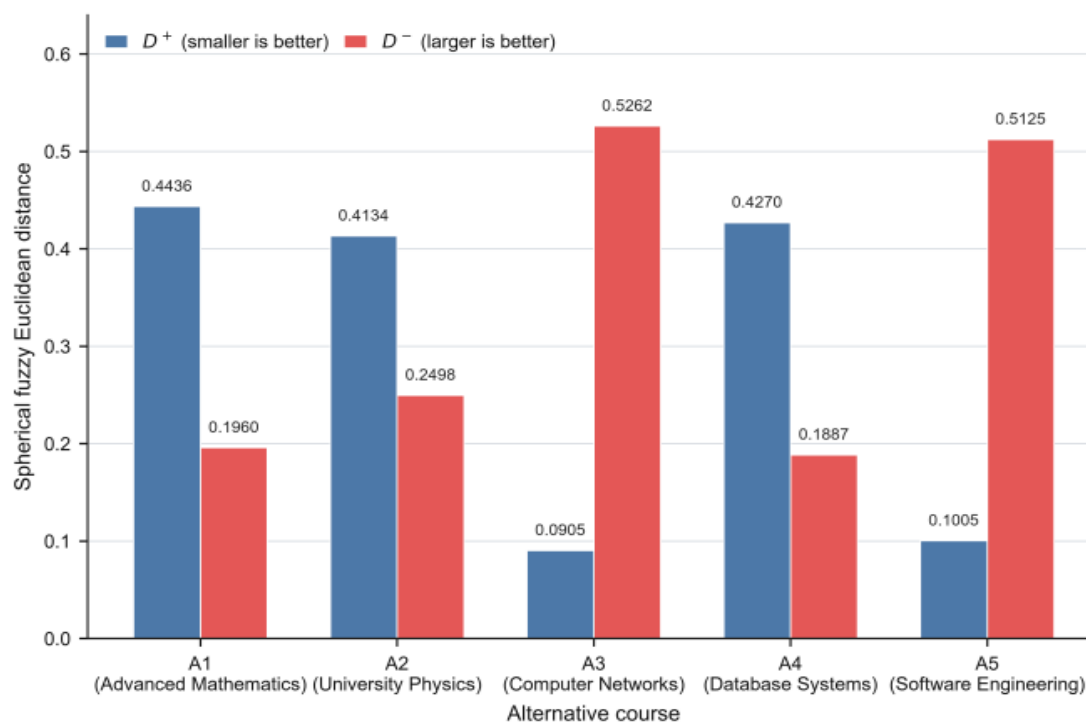


Fig.5: Comparison Chart of the Distance Distribution of Each Alternative Course to the Positive and Negative Ideal Solutions

Table 4

SF-TOPSIS Distance Parameters, Proximity Coefficient and Ranking

Alternative courses	D_i^+	D_i^-	Proximity CC_i	Ranking
A1 (Advanced Mathematics)	0.4436	0.1960	0.3064	4
A2 (University Physics)	0.4134	0.2498	0.3767	3
A3 (Computer Network)	0.0905	0.5262	0.8532	1
A4 (Database System)	0.4270	0.1887	0.3064	5
A5 (Software Engineering)	0.1005	0.5125	0.8361	2

Note: A1 and A4 have equal CC; ranked by larger D^- . This minor difference does not affect the overall conclusions.

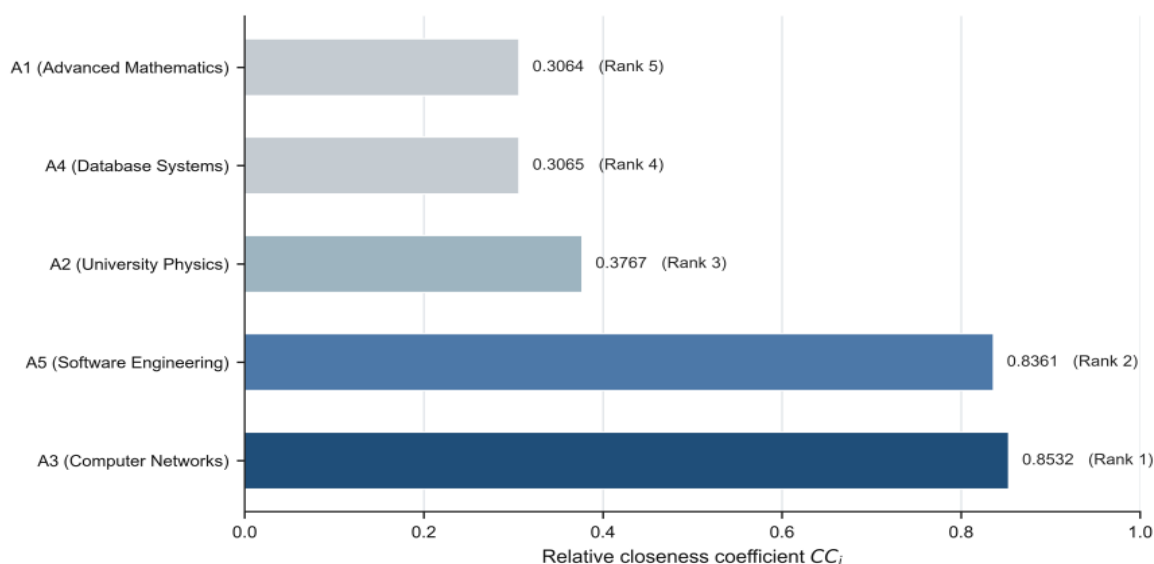


Fig.6: The Final Comprehensive Relative Proximity (CC) Ranking of Each Alternative Course

6. Results and Discussion

This section examines the computational findings, evaluates the robustness of the proposed framework through sensitivity analysis, and compares its performance with existing MCDM methods (Figs. 5 and 6).

6.1 Analysis of Core Model Results

The final ranking derived from language feature extraction and SFS dimensional reduction is A3 (Computer Network) $\rightarrow$ A5 (Software Engineering) $\rightarrow$ A2 (University Physics) $\rightarrow$ A4 (Database System) $\approx$ A1 (Advanced Mathematics). Among the evaluated courses, A3 achieved the highest closeness coefficient ($CC = 0.8532$). Examination of the underlying data shows particularly strong performance for Educational Design (C1), which received the highest subjective weight of 0.3300, with 140 of the 170 feedback responses classified as positive. A5 followed closely ($CC = 0.8361$) and recorded the strongest positive evaluation for Practicality (C3). These findings suggest that engineering-oriented courses incorporating practical and project-based learning are associated with higher levels of student satisfaction. The importance of this dimension is further reflected by its relatively high objective weight of 0.4961. By comparison, A1 and A4 obtained considerably lower CC values of 0.3064 and 0.3065, respectively. The ABSA-based diagnostic results for A1 revealed a marked concentration of negative and neutral feedback within Teacher-Student Interaction (C2) and Practical Value (C3). Rather than reducing these evaluations to an overall numerical score, the integrated NLP framework enables specific sources of dissatisfaction, such as limited interaction or insufficiently evident practical application, to be identified at the attribute level. This diagnostic capability provides more detailed decision-relevant information than conventional aggregate scoring approaches.

6.2 Sensitivity Analysis of Model Decision Robustness

The robustness of the proposed framework was examined through sensitivity analysis by varying the weight allocation coefficient λ across the full range from 0.0 to 1.0. This procedure evaluates the extent to which changes in the relative contributions of subjective and objective weighting affect the final course rankings. Under extreme scenario 1 ($\lambda = 1.0$, purely subjective), objective information entropy is completely excluded, leaving the evaluation dependent solely on the expert-derived

FUCOM weights. A3 retains the highest ranking because of its stronger performance in teaching design, thereby increasing its relative advantage over A5. A slight improvement is also observed in the ranking of A1. Conversely, extreme scenario 2 ($\lambda = 0.0$, purely objective) removes the influence of expert judgement and determines the weights exclusively from objective information. As Practical Value (C3) exhibits the greatest variation, its weight increases to approximately 50%. Consequently, the substantial proportion of positive feedback received by A5 for practical features enables it to surpass A3 under this weighting condition. The changes in course rankings across the five sensitivity-analysis nodes are presented in Table 5.

Table 5

Course Evaluation Rankings under Different Preference Coefficients λ

Course	$\lambda = 0.0$ (Purely Objective)	$\lambda = 0.2$	$\lambda = 0.5$ (Benchmark)	$\lambda = 0.8$	$\lambda = 1.0$ (Purely Subjective)
A1	4	4	4	4	4
A2	3	3	3	3	3
A3	2	1	1	1	1
A4	5	5	5	5	5
A5	1	2	2	2	2

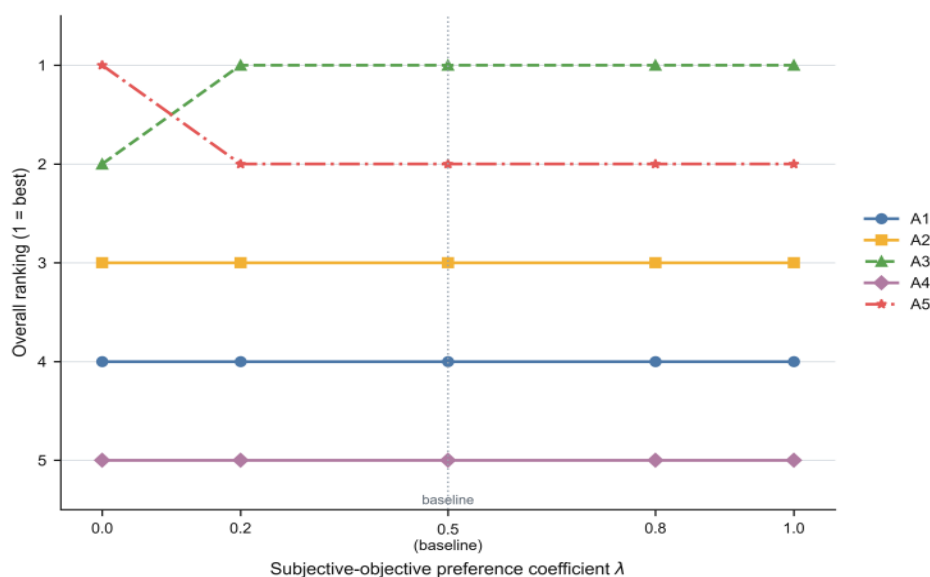


Fig.7: The Line Graph Showing the Sensitivity Changes Under Different Subjective and Objective Preference Coefficients

The results presented in Table 5 and Figure 7 demonstrate that substantial variations in the weighting parameters do not materially alter the underlying hierarchical structure of the spherical fuzzy decision system. A3 and A5 consistently remain the two highest-ranked courses across the examined scenarios, indicating that the framework produces robust evaluation outcomes while retaining sufficient flexibility to accommodate different managerial priorities and strategic preferences.

6.3 Comparative Analysis with Existing Models

For comparative evaluation, the proposed FUCOM-SF-TOPSIS framework was examined against AHP-Fuzzy-TOPSIS, Spherical Fuzzy WASPAS, and the Fuzzy MARCOS model. Regarding cognitive load, conventional AHP requires at least six pairwise comparisons when four indicators are considered. As the number of comparisons increases, maintaining judgement consistency becomes

more demanding, potentially resulting in an unacceptable consistency ratio ($CR > 0.1$) and greater cognitive burden for decision-makers. In contrast, FUCOM requires only three comparisons for the same four indicators. This reduction simplifies the weighting procedure while allowing the deviation from full consistency (DFC) to remain within an optimal range close to zero.

Regarding the processing of fuzzy information, the spherical fuzzy formulation provides an additional dimension, π , for explicitly representing hesitation or neutrality. This feature is particularly relevant to student text mining because evaluations frequently contain neutral expressions, such as “This course is quite average.” Conventional fuzzy TOPSIS approaches based on triangular or intuitionistic fuzzy representations may classify such information within more restrictive categories or fail to represent its neutrality explicitly. The spherical fuzzy formulation instead preserves neutral information through the π dimension, thereby reducing information loss during subsequent dimensional reduction and decision analysis. Regarding discriminatory capability, SF-TOPSIS differs from the weighted aggregated sum product assessment (WASPAS) and measurement of alternatives and ranking according to compromise solution (MARCOS) models by relying on geometric distances from ideal solutions. Within educational assessment, evaluating how far an alternative lies from the negative ideal solution provides diagnostically useful information regarding its relative distance from an undesirable educational condition. This distance-based representation can therefore support the identification of specific areas requiring targeted quality assurance improvements.

6.4 Insights for Educational Decision-Making

The proposed model offers practical support for educational institutions seeking to transition towards data-driven management. First, the framework enables continuous and automated monitoring of teaching and learning processes. By applying the ABSA engine to textual information generated within the LMS, educational administrators can track students’ learning experiences throughout the semester rather than relying exclusively on retrospective evaluations. For instance, limited student interaction in courses such as A1 could be identified before the graduation examination, allowing appropriate interventions to be introduced at an earlier stage.

Second, integrating subjective and objective evaluation provides a more balanced basis for educational management. The framework incorporates the strategic teaching priorities identified by educators while simultaneously accounting for evidence derived from students’ actual learning experiences. Consequently, managerial decisions are informed by both professional judgement and data-driven feedback rather than being dominated by either perspective alone. Furthermore, the framework facilitates more targeted resource allocation. Highly rated courses can be identified as exemplary practices and considered for appropriate recognition and rewards, whereas lower-rated courses can be examined at the individual attribute level to determine the specific sources of weaker performance. For example, a low score for C2 may indicate insufficient teacher–student interaction. Instead of relying primarily on punitive administrative measures, managers can use such diagnostic information to direct appropriate support towards identified deficiencies, including increasing student counselling provision or introducing technologies that promote greater interaction.

7. CONCLUSIONS

The rapid advancement of big data and artificial intelligence has created new opportunities to integrate NLP with MCDM, contributing to a broader transition from conventional management practices towards intelligent, data-driven decision-making. Within educational assessment, this study

addresses three interrelated challenges: extracting meaningful information from unstructured textual data, quantitatively representing sentiment and uncertainty, and limiting the influence of subjective cognitive bias on evaluation outcomes. Accordingly, an intelligent decision-support framework based on natural language feature extraction was developed to establish a systematic connection between student-generated textual information and quantitative educational decision-making. Methodologically, the proposed framework integrates ABSA-based processing of unstructured text, transformation of extracted sentiment information into the SFS domain, hybrid weighting through FUCOM and information entropy, and comprehensive alternative ranking using SF-TOPSIS. Through this integrated architecture, the system addresses important limitations of conventional decision models by retaining ambiguous and uncertain information while reducing inconsistencies associated with expert-based weighting. The empirical findings demonstrate that the framework can differentiate among course quality levels and, more importantly, diagnose the specific educational dimensions contributing to weaker performance. Despite these contributions, several limitations provide opportunities for further investigation. The current text-extraction component relies primarily on standard dictionaries, which may restrict its ability to interpret linguistically complex expressions. Future research could therefore incorporate more advanced pre-trained language models, including transformer-based LLMs, to improve the interpretation of metaphors, context-dependent expressions, and informal online language. In addition, the essentially static characteristics of the FUCOM weighting stage could be extended by integrating reinforcement learning and the MDP. Such developments could support an adaptive, time-aware spherical fuzzy MCDM framework capable of dynamically updating its parameters and correcting decisions as new information becomes available. Extending the framework in this direction may further strengthen its applicability across large-scale academic and educational management platforms.

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