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An Integrated Fuzzy AHP-TOPSIS Framework for Evaluating AI-Enhanced Competencies of College English Teachers in Blended Learning Environments

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ABSTRACT

In response to the accelerating adoption of generative artificial intelligence, university English education is increasingly being reshaped into an intelligent blended learning environment, consequently raising the competency requirements associated with teachers' use of AI. Drawing upon the Teacher Artificial Intelligence Capability Framework issued by relevant international authorities in 2024, while also accounting for the intercultural communication orientation of university English and the specific instructional conditions of blended learning, this study establishes an assessment framework for teachers' AI capabilities comprising five primary dimensions and fifteen secondary indicators. To address the ambiguity and uncertainty inherent in conventional subjective assessment, a multi-criteria decision analysis approach is incorporated, resulting in a quantitative evaluation framework that combines Fuzzy AHP and Fuzzy TOPSIS. The resulting measurements identify AI teaching methods and AI ethics and safety as the principal dimensions shaping teachers' overall AI competence. In addition, five representative digital profiles of foreign language teachers are evaluated through simulated Fuzzy TOPSIS ranking and proximity coefficient analysis. The results demonstrate that collaborative and integrated teachers achieve the strongest overall performance, particularly when advanced instructional approaches are combined with robust ethical and safety controls. The study therefore offers human resource professionals and academic administrators in higher education a systematic, transparent, and quantitative basis for teacher evaluation and decision-making. At the same time, it highlights a central principle for foreign language teacher development in the intelligent era: technological adoption should remain subordinate to, and guided by, sound pedagogical principles.

1. Introduction

The accelerating advancement of information technology has brought about a major transformation in higher education worldwide, particularly following the emergence of large language models (LLMs) and generative AI applications such as ChatGPT. Within this changing educational landscape, university English occupies an important position as a general education subject that serves both practical and humanistic purposes. However, its teaching practices are

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simultaneously confronted with new possibilities and substantial challenges. For many years, conventional university English instruction has been characterised by structural limitations, including overcrowded classrooms, predominantly teacher-led transmission of knowledge, inadequate opportunities for authentic intercultural language practice, and relatively uniform formative assessment practices [1]. The development of AI systems capable of producing sophisticated multilingual content, performing immediate translation, and facilitating real-time voice-based communication has further intensified this debate. Some scholars have consequently questioned the continued necessity of conventional foreign language education, suggesting that AI-mediated translation technologies can largely overcome linguistic and physical communication barriers and may therefore diminish the perceived strategic importance of language acquisition.

A technologically deterministic interpretation of these developments, however, fails to account for the broader educational role of language learning in shaping human cognition, encouraging intercultural reflection, and developing global competence. A substantial body of academic scholarship instead maintains that, despite the growing importance and versatility of artificial intelligence as an educational resource, AI cannot substitute for learners' active cognitive engagement throughout the language acquisition process. Likewise, it cannot assume the distinctive pedagogical responsibilities performed by teachers, including the provision of cognitive scaffolding, facilitation of affective interaction, mediation of cultural values, and development of critical thinking [2]. In response to these developments, university English education is increasingly being reorganised around an artificial intelligence-enabled blended learning ecosystem. This form of blended learning extends well beyond the physical combination of online and face-to-face instruction. Informed by constructivist learning theory, it seeks to establish an adaptive and interactive learning environment centred on learners through the purposeful integration of intelligent technologies with pedagogical practices.

Within this emerging model, AI-supported blended instruction connects distinct stages of the learning process, including online diagnostic knowledge preparation before class, intensive interaction and knowledge consolidation during classroom activities, and data-informed extension of learning after class [3]. One illustrative development is a blended instructional framework that integrates the BOPPPS (Bridge-In, Objectives, Pre-assessment, Participatory Learning, Post-assessment, Summary) model with the PADD (Presentation, Assimilation, Discussion, Demonstration) model. Empirical findings demonstrate that this systematic alignment between instructional design and technological support can increase classroom participation by 47% and, at the same time, raise teachers' confidence in implementing AI technologies by 45% [4] (Fig.1).

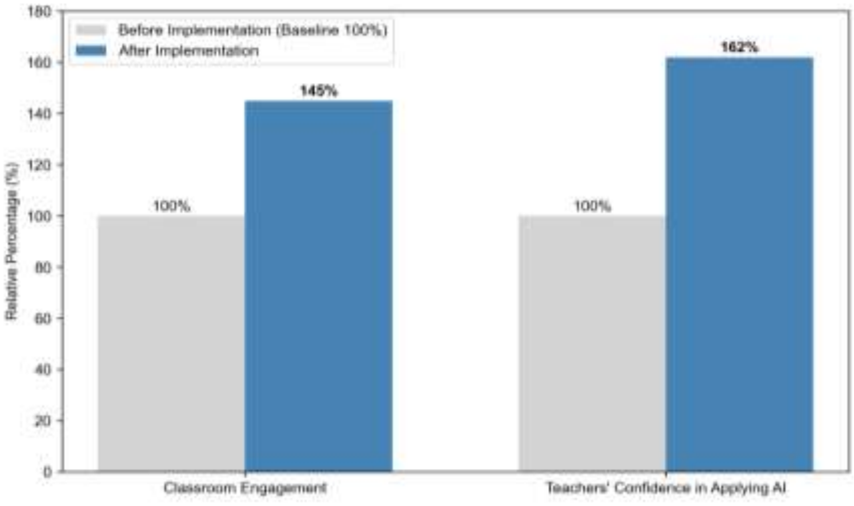

Fig.1: Comparison Chart of the Implementation Effects of BOPPPS and PADD Blended Teaching Mode

The increasing sophistication of AI-mediated educational environments has disrupted the conventional two-way teacher-student instructional relationship, giving rise to a dynamic three-component arrangement involving the teacher, AI, and student, referred to as the Teacher-AI-Student (TAS) system [5]. This reconfiguration of the instructional ecosystem requires educators to reconceive AI as an intelligent collaborator that participates in teaching activities rather than regarding it simply as another classroom instrument. Accordingly, the determinants of educational quality are no longer restricted to teachers' command of the English language and conventional pedagogical expertise. Increasing importance is instead being attached to their AI capabilities (AI Competency) and AI literacy (AI Literacy), which have become essential components of effective teaching in technologically mediated learning environments [6].

The growing importance of these competencies has also created a need for internationally recognised standards defining what teachers should know and be able to do when working with AI. In response, UNESCO published the AI Competency Framework for Teachers in 2024. By connecting educational policy with practical implementation, the framework specifies the knowledge, skills, and values expected of teachers operating within AI-enhanced educational settings. It organises these requirements into five principal areas: human-centred mindset, Ethics of AI, AI foundations and applications, AI pedagogy, and AI for professional learning. Each area is further situated within three progressively advanced stages of professional development, namely acquisition, deepening, and creation [7] (Fig.2).

Fig.2: Radar Chart showing the Distribution of the Five Core Dimensions of the UNESCO Teacher AI Capability Framework

Despite the availability of a broad policy framework at the macro level, higher education management still lacks a rigorous, standardised, and quantitatively grounded mechanism for evaluating the AI capabilities of university English teachers working in blended learning environments. Within universities, teacher appraisal represents an important component of both human resource management and educational quality assurance [8]. The practical difficulty lies in translating broad and abstract AI capability constructs into observable assessment criteria while ensuring fair evaluation across foreign language teachers who differ in age, professional experience, and educational background. This makes teacher capability assessment a complex multi-criteria decision-making (Multi-Criteria Decision Making, MCDM) problem.

Conventional evaluation practices commonly depend on fixed rating scales or student perceptions of teaching performance. Such approaches may be affected by social desirability and other response biases, while also providing limited means of representing the imprecision and cognitive uncertainty that arise when individuals assess multifaceted capabilities [9]. In real-world evaluation settings, decision-makers, including academic administrators and peer reviewers, generally express their judgements through qualitative linguistic terms such as very important, perform well, or poor rather than assigning exact numerical values to complex attributes [10].

Fuzzy-set-based multi-criteria decision analysis provides an effective methodological response to these limitations. In particular, the integrated use of the fuzzy analytic hierarchy process (Fuzzy AHP) and fuzzy technique for order preference by similarity to ideal solution (Fuzzy TOPSIS) has been applied successfully to a range of complex decision problems, including lecturer performance assessment, facility-location selection, supply chain management, and evaluation of online learning system availability [11]. Fuzzy AHP enables qualitative expert judgements to be represented as fuzzy numbers, thereby accommodating uncertainty when determining the relative importance of criteria and supporting more consistent aggregation of judgements within group decision-making processes [12]. Fuzzy TOPSIS subsequently evaluates the overall performance of candidate teachers across the established criteria by determining their respective distances from the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS). This procedure produces comprehensive rankings and closeness coefficients that offer a transparent, reproducible, and comparatively robust basis for decision-making [13].

Against this research background and the identified theoretical gap, the central aim of this research report and academic paper is to develop an AI capability evaluation framework for university English teachers using an integrated Fuzzy AHP-TOPSIS model. The study initially translates UNESCO's overarching competency standards into an assessment index system adapted to the specific context of foreign language blended teaching. It then explicates the mathematical procedures underlying the proposed fuzzy evaluation approach. Finally, scenario-based simulation and systematic quantitative analysis are employed to demonstrate how the model can provide higher education administrators with an objective and evidence-based instrument for teacher assessment and decision support. In doing so, the study establishes a methodological foundation for refining teachers' professional development (TPD) pathways and supporting the strategic implementation of digital transformation within higher education.

2. MATERIALS AND METHODS

This section outlines the methodological structure underpinning the study, covering three principal aspects: the rationale used to develop the evaluation index system, the procedures adopted for obtaining expert judgements, and the systematic mathematical formulation of the integrated Fuzzy AHP-TOPSIS framework.

2.1 Construction and Theoretical Origin of the Evaluation Index System for University English Teachers' AI Competence in a Blended Learning Environment

The development of an evaluation index system with sound content and structural validity constitutes an essential foundation for reliable multi-criteria decision analysis. Rather than selecting indicators arbitrarily, this study developed the proposed system through a systematic process that combined bibliometric evidence with cross-validation against internationally recognised competency standards. UNESCO [7] Framework for Teachers' AI Competencies provides the overarching conceptual structure [7], which is further contextualised through the TPACK perspective on technology-integrated pedagogical content knowledge and the distinctive requirements of university English education, particularly its emphasis on intercultural communication and critical discourse analysis [14]. Following several rounds of expert consultation and indicator refinement conducted through the Delphi method, the study established a hierarchical evaluation structure comprising five first-level indicators representing the principal competency dimensions and fifteen second-level indicators capturing specific manifestations of teachers' capabilities. To clarify the theoretical basis and practical interpretation of this multidimensional framework, Table 1 presents the conceptual sources of the indicators at each level together with their corresponding meanings within the blended university English teaching context.

Table 1

Evaluation Index System for Teachers' AI Competence in the University English Blended Learning Environment

Primary Indicators (Core Dimensions)	Secondary Indicators (Specific Skills)	Theoretical Origin and Explanation of the Connotation of University English Blended Teaching
C1: Human-centered mindset	C1.1 Ensuring teachers' autonomy and students' initiative	Based on the UNESCO framework and digital ethics research. It is required that when introducing AI writing assistants or oral dialogue robots, teachers should ensure that AI acts as an auxiliary framework rather than a dominant force, to prevent the standardization of technology from stifling human educational reasoning, and to guarantee students' autonomy in language output and original thought expression [2].
2-3	C1.2 Promoting educational equity and inclusiveness	Pay attention to the issue of digital divide. Teachers should fairly allocate AI educational resources in blended learning, ensuring that students with different technical backgrounds and different socioeconomic statuses can equally access intelligent assistance tools and creating an inclusive language learning environment [7].
2-3	C1.3 Social Responsibility and Cross-Cultural Sensitivity	Incorporate the attributes of applied linguistics. Guide students to critically examine AI-generated texts, identify cultural hegemony within them, and encourage them to maintain a profound understanding of language diversity, local cultural identity, and global citizenship responsibilities when using machine translation [15].
C2: AI Ethics and Security (Ethics of AI)	C2.1 Data Privacy and Security Protection	Basic Ethical Requirements. Teachers must be familiar with and clearly state in the teaching syllabus the data compliance policies regarding the use of AI tools, ensuring that students' personal privacy and data security are not violated when they register and use third-party generative AI platforms [16].
2-3	C2.2 Algorithm Bias Identification and Mitigation	In response to the inherent training data bias of LLMs, teachers need to have the ability to identify potential gender, racial, ideological, and pragmatic-cultural biases that may be implicit in AI English language materials, and incorporate these biases as materials for critical reading and reflective discussion in the classroom [6].
2-3	C2.3 Promoting Academic Integrity and Responsible Use	Addressing the academic ethics crisis caused by AI homework writing. Teachers can establish transparent and clear boundaries and rules for the use of AI in blended classrooms, adopt process-based evaluation rather than single-result evaluation, and prevent and handle academic misconduct resulting from improper use of AI [17].
C3: AI Fundamentals and Applications (AI foundations & applications)	C3.1 Basic Understanding of AI Technical Principles	Technological Knowledge in TPACK Theory (TK). Teachers need to go beyond the technical black box and understand the underlying concepts of machine learning, natural language processing (NLP), large neural networks, etc., as well as their limitations in language processing (such as the AI illusion phenomenon).
2-3	C3.2 Prompt Engineering for Text Data (Prompt Engineering)	Key operational skills in the era of Generative AI. Teachers can precisely construct and optimize prompts to generate high-quality text data that aligns with specific teaching goals of university English (such as sample essays of specific genres, vocabulary expansion exercises, complex sentence structure analysis cases) [14].
2-3	C3.3 Selection of Tools and Multimodal Integration Capability	Possess the ability to proficiently identify and seamlessly integrate various automated assessment systems, intelligent chatbots (Chatbots), and multimodal visualization tools in MOOC platforms, cloud collaboration spaces, and intelligent tutoring systems.
C4: AI Teaching Method (AI pedagogy)	C4.1 Blended Learning Instructional Design and Closed-loop Reconstruction	Core TPACK Representation. Deeply integrate AI tools into teaching models such as BOPPPS, design a complete closed-loop including pre-class intelligent diagnosis, high-order critical thinking interaction (discussion based on AI-generated content) during class, and post-class adaptive expansion, to achieve the intelligent upgrade of flipped classrooms [4].

Table 1 (continued)
Evaluation Index System for Teachers' AI Competence in the University English Blended Learning Environment

Primary Indicators (Core Dimensions)	Secondary Indicators (Specific Skills)	Theoretical Origin and Explanation of the Connotation of University English Blended Teaching
2-3	C4.2 Intelligent Assistance for Feedback and Framework Construction	Innovative Feedback Mechanism. Beyond the traditional manual grading by teachers, this approach collaborates with AI to provide frequent and immediate grammatical and pragmatic error correction feedback. Teachers can then shift their focus to the construction of higher-level writing scaffolds such as logical structure and depth of arguments, achieving a blended feedback model involving human and machine collaboration [5].
2-3	C4.3 Data-based Personalized Intervention Strategies	Relying on Learning Analytics. By integrating AI to analyze students' online behavior patterns, participation data, and assessment results, personalized and differentiated teaching plans and emotional psychological interventions are implemented for individuals with different learning styles and abilities [18].
C5: AI Facilitating Professional Learning (AI for Professional Learning)	C5.1 Data-driven Teaching Reflection and Self-Efficacy	Teachers can utilize AI to transcribe, summarize, and analyze their own classroom discourse interaction logs, deepening their micro-reflection on teaching behaviors and discourse power, thereby enhancing their self-efficacy and professional identity.
2-3	C5.2 Interdisciplinary Research Collaboration and Academic Innovation	Possess the ability to conduct teaching research using AI literature mining tools and data analysis models (such as qualitative coding assistance), transforming blended classroom practices into rigorous academic outputs for university English education research, and feeding back to improve teaching quality [8].
2-3	C5.3 Lifelong Learning and Adaptability to Intelligent Technologies	In the fast-paced and ever-evolving technological tide, continuously monitor and track the latest AI education (AIEd) policies, trends, and cutting-edge tools worldwide, maintaining a high level of professional acuity, an open mindset, and technological adaptability resilience.

2.2 Data Collection, Expert Group Formation and Definition of Fuzzy Variables

Because assessing AI capabilities among university English teachers spans several interconnected fields, including education, computer science, applied linguistics, and higher education administration, an evaluation based on a single disciplinary perspective may provide only a partial representation of the construct. To address this limitation, the present study follows established practices in rigorous MCDM research [10] and integrates Delphi consultation with focus-group discussions to develop a balanced and representative expert decision matrix. Expert recruitment followed a deliberate combination of competence and professional diversity. A panel of 34 experts with substantial expertise in the relevant domains was established for the evaluation process [19]. The panel comprised senior university English educators, experienced researchers specialising in educational technology (EdTech) and artificial intelligence (AI), as well as senior academic affairs administrators responsible for institutional quality assessment. This multidisciplinary composition enabled the study to incorporate a broad range of professional perspectives, thereby strengthening the external validity of the proposed decision-making model.

Ambiguity is an unavoidable feature of expert judgement in multi-criteria assessment. In practice, experts tend to communicate their evaluations through linguistic expressions, such as indicating that one indicator is more important than another or describing a teacher's performance within a particular dimension as average. Such qualitative judgements contain uncertain boundaries that cannot be represented adequately through conventional crisp numerical values [13]. To account for this inherent uncertainty, the study incorporates fuzzy set theory and applies triangular fuzzy numbers (Triangular Fuzzy Numbers, TFNs) to transform experts' linguistic assessments into quantitative forms suitable for mathematical analysis [13]. Triangular fuzzy numbers are typically defined as $\tilde{A} = (l, m, u)$, where l represents the minimum possible value assessed by the expert (a pessimistic estimate), m represents the most likely value (the consensus point with the highest probability), and u represents the maximum possible value (an optimistic estimate). Their mathematical properties are strictly defined through the membership function $\mu_{\tilde{A}}(x)$ as follows, demonstrating a continuous change process of membership degree from 0 to 1 and back to 0 [13] (Fig.3):

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < l \\ \dfrac{x-l}{m-l}, & l \le x \le m \\ \dfrac{u-x}{u-m}, & m \le x \le u \\ 0, & x > u \end{cases}$$

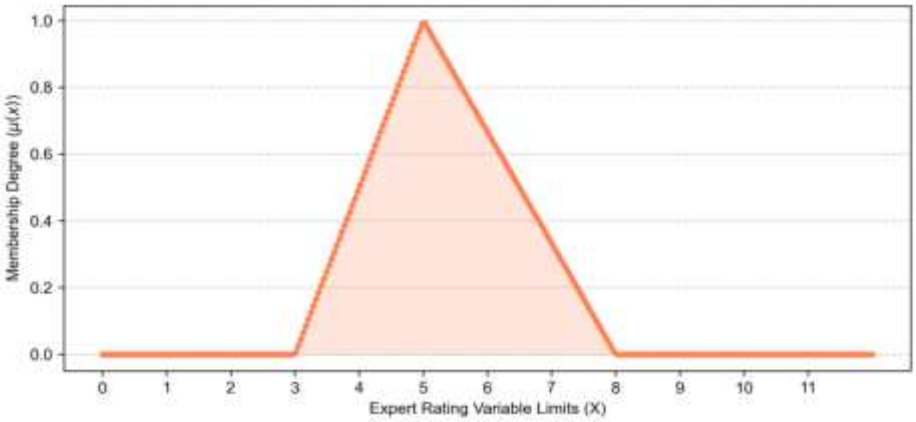

Fig.3: Geometric Distribution Diagram of the Membership Functions of Triangular Fuzzy Numbers (TFNs)

To ensure consistency in expert judgements, the study established a standardised linguistic conversion scale for translating qualitative assessments into fuzzy numerical values. For the pairwise comparison of criteria in Fuzzy AHP, an expanded fuzzy version of Saaty's 1–9 scale was employed. Under this scheme, terms such as equally important were represented by (1,1,1), whereas very important corresponded to (5,7,9). For evaluating the performance of alternative teachers through Fuzzy TOPSIS, linguistic variables based on either a five-point or seven-point scale were applied. For instance, poor were represented by (0,1,3), while excellent was expressed as (7,9,10). This structured linguistic-to-numerical conversion reduces the ambiguity of expert expressions and ensures that qualitative judgements remain within a consistent and mathematically manageable framework.

To promote consistency across expert evaluations, a structured linguistic conversion scheme was established to transform qualitative judgements into fuzzy numerical representations. For pairwise criterion comparisons within Fuzzy AHP, the study adopted a fuzzy extension of Saaty's 1–9 importance scale. Under this scheme, the linguistic expression equally important was assigned the triangular fuzzy number (1,1,1), whereas very important was represented by (5,7,9), with corresponding values defined for the remaining linguistic categories. For assessing the performance of alternative teachers through Fuzzy TOPSIS, either a five-level or seven-level linguistic scale was employed. For example, poor was encoded as (0,1,3), while excellent was assigned (7,9,10). This systematic mapping procedure converts inherently ambiguous linguistic judgements into structured mathematical inputs, thereby restricting interpretive variation to predefined and computationally manageable boundaries.

2.3 Mathematical Derivation of the Fuzzy AHP Weight Determination Model

In this study, Fuzzy Analytic Hierarchy Process (Fuzzy AHP) is applied to establish the relative significance of the dimensions and sub-dimensions within the proposed indicator hierarchy, including both local and global weights. Rather than relying on conventional AHP or earlier fuzzy AHP formulations developed by van Laarhoven and Pedrycz, the study adopts Buckley's Fuzzy Geometric Mean Method. This approach is particularly suitable for the present assessment because its computational procedure yields a unique solution when processing fuzzy algebraic relationships while preserving the structural characteristics of fuzzy numbers. It also provides stable performance when the evaluation contains incomplete observations or multiple expert estimates [12]. The corresponding computational procedure is presented below:

Step 1: Construct the Fuzzy Pairwise Comparison Matrix of the Expert Group

Each expert k ($k = 1,2, \dots, K$) in the expert group K is required to conduct pairwise importance comparisons among the n indicators at the same level. The comparison matrix is obtained using linguistic variables. By integrating the opinions of all experts, an aggregated fuzzy judgment matrix $\widetilde{M} = [\tilde{a}_{ij}]_{n\times n}$ is constructed. Here, the matrix element $\tilde{a}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ represents the comprehensive relative importance of the i-th indicator compared to the j-th indicator. This matrix must strictly satisfy the transitivity axiom, that is: $\tilde{a}_{ji} = \tilde{a}_{ij}^{-1} = (1/u_{ij}, 1/m_{ij}, 1/l_{ij})$, and the diagonal element $\tilde{a}_{ii} = (1,1,1)$ [12].

Step 2: Calculate the Fuzzy Geometric Average of Each Indicator

According to Buckley's algorithm logic, calculate the fuzzy geometric average $\tilde{r}_i$ for each row of the matrix (i.e., for each evaluation indicator). This is equivalent to extracting the overall superiority degree of this indicator across all pairwise comparisons [20].

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{a}_{ij}\right)^{1/n} = \left(\left(\prod_{j=1}^{n} l_{ij}\right)^{1/n}, \left(\prod_{j=1}^{n} m_{ij}\right)^{1/n}, \left(\prod_{j=1}^{n} u_{ij}\right)^{1/n}\right)$$

Step 3: Calculate the Fuzzy Relative Weights of Each Indicator

Divide the fuzzy geometric average value $\tilde{r}_i$ of each indicator by the sum of the fuzzy geometric average values of all indicators, and you can obtain the fuzzy weight $\widetilde{w}_i = (lw_i, mw_i, uw_i)$ of indicator i:

$$\widetilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)^{-1}$$

Due to the algebraic operation rules of triangular fuzzy numbers, the above formula can be precisely expanded as:

$$\widetilde{w}_i = \left(\frac{lw_i}{\sum_{k=1}^{n} u\,w_k}, \frac{mw_i}{\sum_{k=1}^{n} m\,w_k}, \frac{uw_i}{\sum_{k=1}^{n} l\,w_k}\right)$$

Step 4: Weight Defuzzification and Normalization

Since the final TOPSIS calculation requires the use of explicit real weights, the fuzzy weights $\widetilde{w}_i$ must be defuzzified. In this study, the widely used and physically meaningful centroid method (Center of Area, CoA) is adopted to calculate the exact weights (Crisp Weight, W_i), and they are normalized to ensure that the sum of all weights is 1 [9]:

$$W_i = \frac{lw_i + mw_i + uw_i}{3}$$

Step 5: Consistency Check

Even after applying the fuzzification process, experts may still encounter logical inconsistencies when conducting numerous comparisons (for example, considering A to be more important than B, B to be more important than C, yet also believing that C is more important than A). To ensure the logical consistency and scientific rigor of the decision-making system, it is necessary to conduct a consistency check on the precise central value matrices of each comparison matrix [21]. Calculate the maximum eigenvalue λ_{max} of the matrix, and then obtain the consistency index (Consistency Index,

CI) and the consistency ratio (Consistency Ratio, CR):

$$CI = \frac{\lambda_{max} - n}{n-1}, \quad CR = \frac{CI}{RI}$$

Among them, RI represents the random consistency index that varies with the matrix order n. If $CR < 0.10$, it can be concluded that the expert judgment matrix has satisfactory consistency and the weight calculation is valid; otherwise, it is necessary to feedback to the experts for re-examination and adjustment of their initial pairwise comparison judgments [21].

2.4 Mathematical Derivation of the Fuzzy TOPSIS Comprehensive Evaluation and Ranking Model

After obtaining the high-quality index weights that have been verified for consistency, the research then proceeds to the stage of evaluating the alternative candidates. In this stage, the Fuzzy TOPSIS model is used to conduct a deep assessment of the comprehensive AI ability of university English teachers. The core philosophical logic of TOPSIS (Approach to Nearest Ideal Solution) is elegant and intuitive: in a multi-dimensional decision space, the optimal alternative solution should simultaneously possess the geometric characteristics of being closest to the ideal optimal state and being farthest from the worst negative ideal state [13].

Step 1: Construct the Expert Aggregated Fuzzy Decision Matrix and Perform Standardization Processing

Suppose there are m university English teachers to be evaluated (i.e., alternative options $A_1, A_2, \dots, A_m$), and n established evaluation indicators (i.e., $C_1, C_2, \dots, C_n$). Through expert evaluation, an initial fuzzy decision matrix $\widetilde{D} = [\tilde{x}_{ij}]_{m\times n}$ is constructed, where $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ reflects the comprehensive rating of the i-th teacher in the j-th capability indicator. In order to eliminate the possible dimensional differences among different evaluation indicators and ensure the consistency of the calculation, the matrix must be standardized. Given that all 15 secondary indicators within this indicator system are of the benefit type (Benefit Criteria, meaning the higher the score a teacher achieves in these capabilities, the more favorable it is for the overall assessment), a linear scale transformation method is adopted for standardization, resulting in the standardized fuzzy matrix $\widetilde{V} = [\tilde{v}_{ij}]_{m\times n}$ [13]:

$$\tilde{v}_{ij} = \left(\frac{l_{ij}}{u_j^+}, \frac{m_{ij}}{u_j^+}, \frac{u_{ij}}{u_j^+}\right), \quad u_j^+ = \max_i\{u_{ij}\}$$

Step 2: Construct the Weighted Standardized Fuzzy Decision Matrix

Multiply each element in the standardized fuzzy decision matrix $\widetilde{V}$ with the corresponding exact weight vector $W = (W_1, W_2, \dots, W_n)$ obtained in the Fuzzy AHP stage and normalized. This process assigns the appropriate strategic weights to the performance of each dimension, resulting in the weighted fuzzy decision matrix $\widetilde{V}'$ [13]:

$$\tilde{v}_{ij}' = \tilde{v}_{ij} \otimes W_j = (l_{ij}W_j, m_{ij}W_j, u_{ij}W_j)$$

Step 3: Determine the Fuzzy Positive Ideal Solution (FPIS) and the Fuzzy Negative Ideal Solution (FNIS)

In the weighted multi-dimensional evaluation space, define the absolute benchmark state. The fuzzy positive ideal solution A^* represents the theoretical optimal combination across all indicators, while the fuzzy negative ideal solution A^- represents the theoretical worst combination [13]:

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \dots, \tilde{v}_n^*)$$
$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-)$$

In the standardized fuzzy evaluation calculation, for simplicity and to ensure the coverage of extreme values, the ideal maximum value $\tilde{v}_j^* = (1,1,1)$ and the ideal minimum value $\tilde{v}_j^- = (0,0,0)$ can be directly defined.

Step 4: Calculate the Euclidean Spatial Distance of Each Alternative Teacher Vector to FPIS and FNIS

To accurately calculate the difference of two triangular fuzzy numbers in the geometric space, this study adopts the vertex method (Vertex Method) to define the fuzzy distance. Given any two triangular fuzzy numbers $\tilde{a} = (l_1, m_1, u_1)$ and $\tilde{b} = (l_2, m_2, u_2)$, the vertex distance measurement formula is [22]:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}\left[(l_1 - l_2)^2 + (m_1 - m_2)^2 + (u_1 - u_2)^2\right]}$$

Based on this formula, the comprehensive performance of the i-th alternative teacher in all n indicators is calculated respectively. The cumulative distance d_i^* to the fuzzy positive ideal solution and the cumulative distance d_i^- to the fuzzy negative ideal solution are obtained [13]:

$$d_i^* = \sum_{j=1}^{n} d\,(\tilde{v}_{ij}^{'}, \tilde{v}_j^*), \quad d_i^- = \sum_{j=1}^{n} d\,(\tilde{v}_{ij}^{'}, \tilde{v}_j^-)$$

Step 5: Calculate the Comprehensive Closeness Coefficient (CC_i) and Generate the Final Ranking

The closeness coefficient CC_i is a relative integration of the distances d_i^* and d_i^-, used to comprehensively measure the final score of the overall quality of the candidate teachers. Its calculation formula is precisely defined as [23]:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*} \quad (i = 1,2, \dots, m)$$

From the structure of the formula, the value range of CC_i is strictly limited within the interval $[0,1]$. When the actual performance of the teacher closely approaches the positive ideal solution and completely deviates from the negative ideal solution (that is, $d_i^* \to 0$), $CC_i \to 1$. Therefore, the larger the value of CC_i, the closer the comprehensive AI application ability and professional quality of this teacher in the blended learning environment are to the theoretically perfect and outstanding state. Ultimately, the evaluation system will directly sort the abilities of the evaluated group of university English teachers based on the descending order of the CC_i values, generating a scientific, transparent and conclusive quantitative ranking of their capabilities.

3. Results

This section reports the simulation results obtained by applying the integrated Fuzzy AHP-TOPSIS model to the proposed teacher capability assessment framework. The structured tables and graphical interpretation of the quantitative findings are used to examine the practical applicability of the evaluation index system developed in the preceding section, identify the underlying patterns in expert-derived criterion weights, and illustrate the multidimensional AI capability profiles of different categories of foreign language teachers within the blended learning environment.

3.1 Fuzzy AHP Index Weight Calculation and Value Orientation Analysis

Based on the fuzzy evaluation input data provided by an expert group consisting of educational technology experts, front-line English teachers and managers, after calculation using Buckley's geometric mean method, defuzzification processing with the center-of-gravity method, and strict consistency ratio ($CR < 0.10$) verification, the comprehensive weight distribution covering the five core dimensions (primary indicators) and their sub-dimensions (secondary indicators) was ultimately calculated. The core data of the simulation analysis is shown in the following table. This weighting system reflects the core value considerations of the current higher education community when evaluating the AI literacy of foreign language teachers [8].

Table 2
The Comprehensive Index Weights and Ranking Distribution Calculated by Fuzzy AHP

Primary Indicators (Dimensions)	Global Weight	Secondary Indicators (Specific Capabilities)	Local Weight	Overall Global Weight	Overall Ranking
C4: AI Teaching Method	0.345	C4.1 Blended learning instructional design	0.410	0.1415	1
3-6 (AI Pedagogy)		C4.2 Intelligent Assistance for Feedback and Support	0.355	0.1225	2
3-6		C4.3 Data-based Personalized Intervention	0.235	0.0811	5
C2: AI Ethics and Security	0.228	C2.3 Promoting Academic Integrity and Usage	0.450	0.1026	3
3-6 (Ethics of AI)		C2.2 Identification and Mitigation of Algorithmic Bias	0.320	0.0730	6
3-6		C2.1 Data Privacy and Security Protection	0.230	0.0524	9
C3: AI Foundation and Applications	0.182	C3.2 Corpus Prompt Engineering	0.460	0.0837	4
3-6 (AI Foundations)		Selection and Integration of C3.3 Tools	0.340	0.0619	7
3-6		C3.1 Basic Understanding of AI Technology Principles	0.200	0.0364	12
C1: People-Oriented Thinking	0.135	C1.1 Protecting teachers' autonomy	0.420	0.0567	8
3-6 (Human-Centered)		C1.3 Social Responsibility and Cultural Sensitivity	0.350	0.0473	10
3-6		C1.2 Promoting Educational Equity and Inclusiveness	0.230	0.0311	14
C5: AI Facilitates Professional Learning	0.110	C5.1 Teaching Reflection and Self-Efficacy	0.440	0.0484	11
3-6 (Professional Learning)		C5.2 Interdisciplinary Research and Innovation	0.320	0.0352	13
3-6		C5.3 Lifelong Learning and Technological Adaptability	0.240	0.0264	15

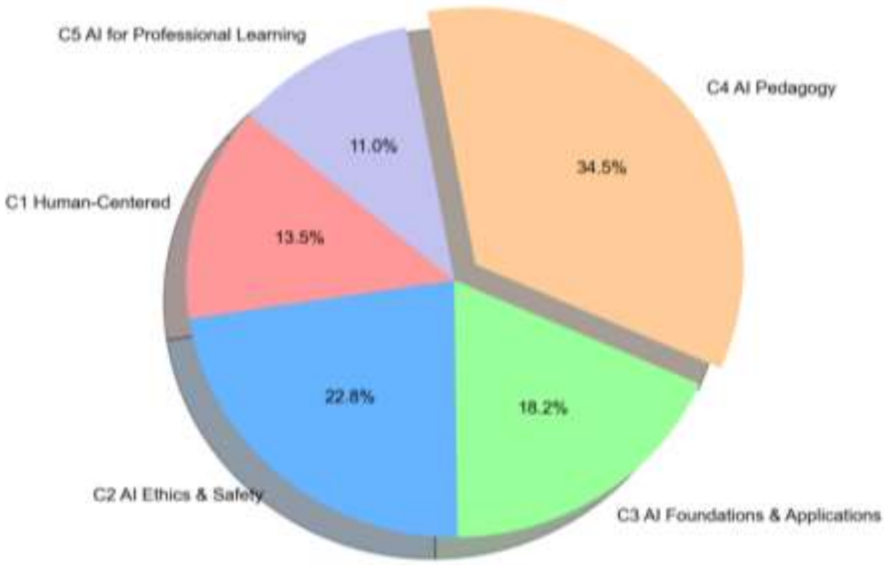

Fig.4: Global Weight Distribution Map of the First-Level Dimension of the AI Capability Assessment Indicators for University English Teachers

The quantitative findings reveal a pronounced hierarchy among the five principal competency dimensions. AI Teaching Method (C4) receives the highest global weight at 0.345, followed by AI Ethics and Security (C2) with a weight of 0.228. AI Basic Knowledge and Application (C3), despite traditionally being viewed as a fundamental component of AI competence, ranks third with a weight of 0.182 (Table 2, Fig.4). This distribution provides an important and somewhat unexpected indication of how teacher AI competence should be understood within advanced university English blended learning environments. Technical familiarity alone, including the ability to operate AI software or understand basic programming principles, does not constitute the primary criterion of high-level teacher competence. Greater importance is instead attached to teachers' capacity to embed emerging technologies within effective language-teaching practices and achieve meaningful AI-TPACK integration. Equally important is their ability to preserve humanistic and ethical standards by preventing academic misconduct and addressing potential linguistic and cultural biases embedded in algorithmic systems during rapid technological development [15].

The ranking of the secondary indicators further reinforces this interpretation. C4.1 (Blended Learning Instruction Design), C4.2 (Intelligent Assisted Feedback and Scaffolding Construction), and C2.3 (Promoting Academic Integrity and Responsible Use) occupy the first three positions, respectively. Their prominence corresponds closely with the principal challenges facing foreign language education under the influence of generative AI. Conventional practices centred on essay assignment and subsequent manual marking are becoming increasingly inadequate. Teachers therefore need to redesign blended learning activities, including human-AI collaborative processes within flipped classrooms, while using AI effectively to deliver iterative, process-oriented, and context-sensitive feedback [5]. At the same time, they must guide students towards responsible and academically appropriate use of AI-generated material when incorporating such content into research writing, presentations, or academic speeches [17] (Fig.5).

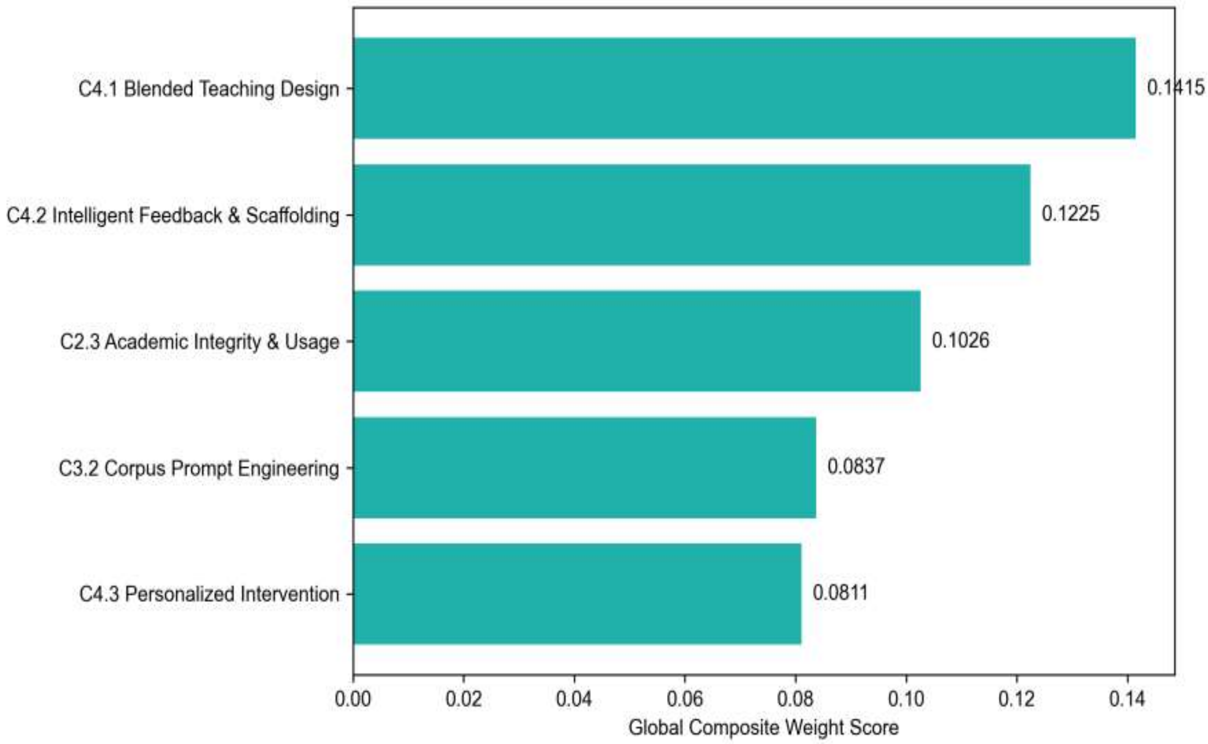

Fig.5: Comparison of the Comprehensive Weights of the Top Five Secondary Capability Indicators

3.2 Fuzzy TOPSIS Ranking of Teacher Candidates' Competencies and Clustering of Digital Profiles

In order to comprehensively verify the resolution, sensitivity of the evaluation model and its practical value in the real scenario of university personnel assessment, this study refined and constructed five representative digital profiles of college English teachers (alternative options A1 to A5) and used the Fuzzy TOPSIS matrix operation to obtain the comprehensive closeness coefficients (CC_i) of these five groups.

- A1 (Technology-Oriented Type): Usually a newly hired digital native. They are well-versed in various large language models, intelligent tutoring plugins, and multimodal generation tools (performing exceptionally well in the C3 dimension). However, their teaching skills are relatively weak. They often delegate too much authority to AI in the classroom, which can easily lead to students developing a tool dependence in language output, weakening the depth of cross-cultural emotional communication [1].
- A2 (Experience-Oriented Type): Experienced traditional backbone staff. They have a profound foundation in teaching methods and emphasize real cross-cultural communication and emotional resonance between people in the classroom (outstanding in C1 and some C4 dimensions). Although they have a vague understanding of the underlying AI logic and are slightly clumsy in technical practicality, they have strict control over academic ethics and language authenticity [2].
- A3 (TAS Collaborative Integration Type): The ideal pioneer of educational reform. They can seamlessly integrate the BOPPPS blended model with AI intelligent diagnosis, possess strong AI ethical reflection awareness and corpus prompter engineering capabilities, and are skilled in designing highly challenging high-level human-machine collaboration + critical reflection foreign language tasks (performing excellently in all high-weight dimensions).
- A4 (Conservative Resistance Type): Has a strong sense of vigilance or even resistance towards disruptive technologies. In classroom practice, they still adhere to the one-way vocabulary and grammar translation teaching mode with chalk and PPT, and only passively adopt the school-mandated basic online testing system during the final assessment (completely lagging).
- A5 (Research-Oriented Type): Focuses mainly on academic publications. They frequently and proficiently apply AI-assisted data mining and qualitative coding analysis in their personal research fields (outstanding in C5 dimension), but due to a lack of teaching enthusiasm or time investment, they have not been able to convert these advanced digital technologies into teaching productivity for the blended classrooms of undergraduate students [18].

Using the spatial distance formula based on the vertex method, the evaluation sequencing results output by the computer simulation are as shown in the following table 3, Fig.6:

Table 3

Ranking of alternative teachers' capabilities and closeness coefficient (CC_i)

Alternative Teacher Profile	d^*	d^-	CC_i	Overall Model Ranking	Development Rating Ranks
A3 (TAS Collaborative Integration Type)	0.2154	0.8427	0.7964	1	Outstanding (Deep Integration State)
A2 (Experience-Oriented Type)	0.4328	0.5891	0.5765	2	Good (Cognitive Deepening and Reconstruction)
A1 (Technology-Oriented Type)	0.4982	0.5146	0.5081	3	Qualified (Shallow Tool Application)
A5 (Research-oriented Type)	0.6120	0.4285	0.4118	4	Needs Improvement (Cognitive Transformation Imbalance)
A4 (Conservative Resistance Type)	0.8553	0.1764	0.1710	5	Warning (Core Skills Missing)

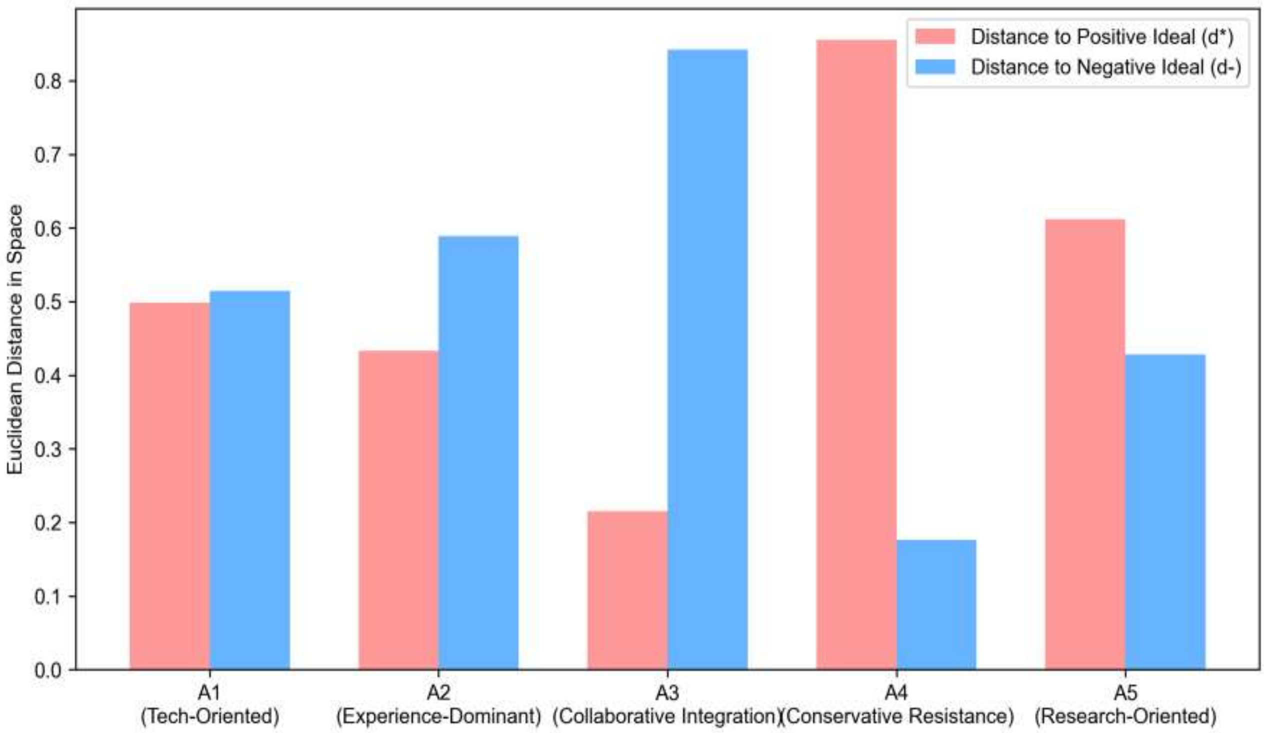

Fig.6: Comparison of Cumulative Distances between 5 Types of Candidate Teacher Profiles and the Positive and Negative Ideal Solutions

The results of the clustering and sorting analysis revealed a profound educational evaluation philosophy. Without a doubt, the A3 integrated teacher, representing the ideal development direction, led the way with a closeness coefficient (CC_i) of 0.7964, which was significantly higher. In terms of distance measurement, it exhibited a high alignment with its fuzzy positive ideal solution [13].

However, the most thought-provoking result emerged in the second round: The overall score of A2 (Experience-oriented Type) teachers (0.5765) unexpectedly surpassed that of A1 (Technology-oriented Type) teachers (0.5081), who were seemingly of higher technical proficiency. The fundamental reason for this reversed ranking lies in the weighting mechanism of Fuzzy AHP. Although the original evaluation of A2 teachers in AI Principles and Operations (C3) was relatively low, due to the expert group assigning absolute leading weight scores to Teaching Design (C4), Ethical Control (C2), and Defending Students' Initiative (C1), A2 teachers gained a significant compensatory advantage in the calculation of these key weighted distances. This simulation result, with precise mathematical logic, intuitively proves that the evaluation model constructed in this study successfully corrected the widespread technological supremacy tendency and technical anxiety prevailing in the current education field, and resolutely defended the commanding position of the pedagogical essence (Pedagogical Essence) in the technological tide [2]. As for A4 conservative teachers, their CC_i is only 0.1710, which has fallen into the serious warning range of professional elimination, highlighting the marginalization predicament that will inevitably be faced when refusing to embrace AI in the era of blended learning (Fig.7).

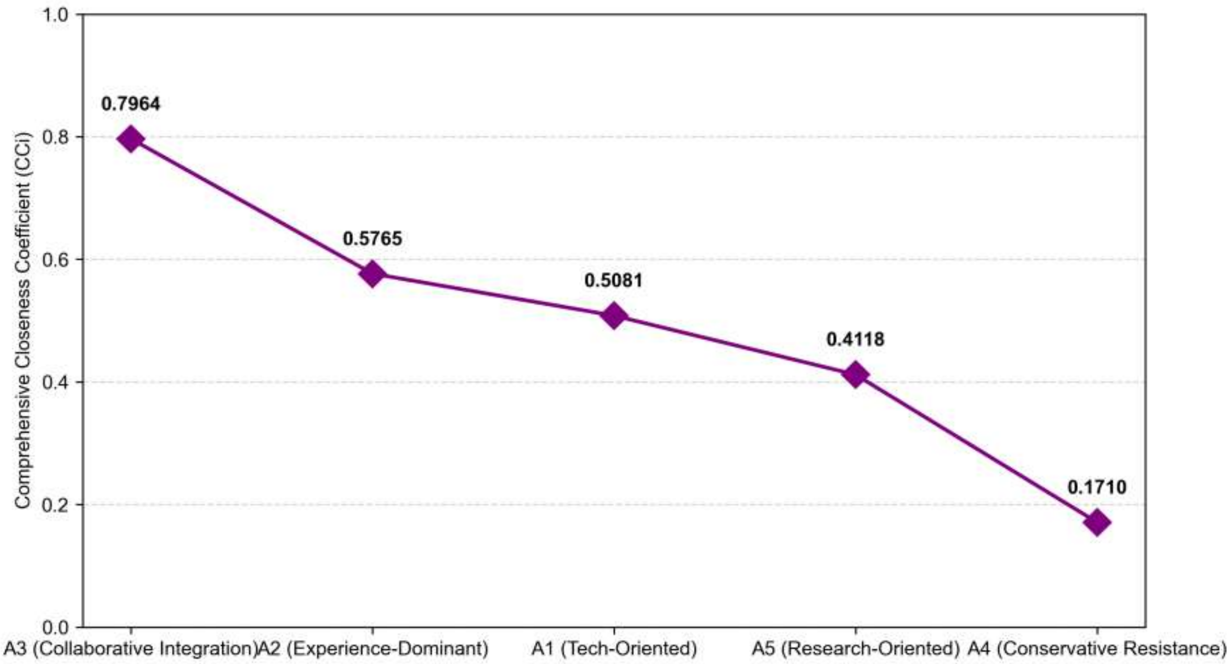

Fig.7: Final assessment ranking of the comprehensive closeness coefficient (CCi) of the alternative teacher profiles

4. Discussion

The Fuzzy AHP-TOPSIS hybrid framework developed in this study extends beyond its function as a mathematical instrument for addressing teacher evaluation challenges in university human resource management. It also provides a conceptual lens through which the changing priorities of foreign language education can be understood as generative artificial intelligence becomes increasingly embedded in teaching and learning. By examining the distribution of criterion weights and the ranking patterns generated by the model, this section interprets the findings from three complementary perspectives: the transformation of pedagogical thinking, the evolution of the educational ecosystem, and the methodological contribution of the proposed approach.

4.1 Deep Educational Insights Behind the Evaluation Results: Returning from Technological Rationalism Mania to Teaching Ontological Reflection

A fundamental implication emerging from the analysis is that AI literacy, or AI capability, in higher education should not be conceptualised merely as context-independent digital proficiency. Earlier research on educational digitalisation frequently drew upon the Technology Acceptance Model (TAM), concentrating primarily on users' perceived usefulness and perceived ease of use when adopting new technologies. While such perspectives remain relevant to technology adoption, they provide only a limited account of the competencies required for meaningful AI integration in teaching. The weighting structure generated by the present model, particularly the importance assigned to people-oriented thinking (C1) and AI teaching methods (C4), suggests that the nature of teacher AI competence is changing as access to advanced AI systems becomes increasingly straightforward. The emergence of large language models has substantially reduced the technical barriers associated with human-AI interaction, as natural-language prompting can often replace sophisticated programming interfaces. Consequently, technical operation itself is becoming less of a differentiating factor. Greater significance is instead attached to teachers' capacity to rethink and reconstruct pedagogical processes, recognise the risks of technological alienation, and critically examine the ethical implications of AI-mediated education.

This shift is particularly significant in university English, where communication, cultural interpretation, and meaning construction are central to disciplinary practice. AI applications such as ChatGPT and other language-oriented intelligent agents can readily undertake a variety of classroom functions, including conversational practice, large-scale content generation, grammatical support, and preliminary assessment [17]. Nevertheless, when teachers rely on such systems primarily as ready-made instructional tools, for example, by using AI-generated lesson plans, automatically produced reading comprehension questions, or standardised essay corrections without substantial pedagogical adaptation, technology may undermine rather than strengthen personalised learning. Such practices can also restrict opportunities for intercultural reflection, meaning negotiation, and productive cognitive challenge among learners [14].

The stronger-performing teacher profiles identified by the assessment framework, particularly the A3 (Expert Type) profile, demonstrate a different approach. Their distinguishing characteristic is not simply proficiency in operating AI systems but the ability to employ AI as a medium for reflection, inquiry, and critical engagement through sophisticated AI-TPACK integration. For example, an effective teacher could deliberately ask an AI system to generate arguments containing recognisable Anglo-American cultural assumptions within a controversial intercultural topic. Students could then critically examine the generated discourse, identify implicit cultural and pragmatic biases, and question the forms of algorithmic cultural dominance embedded within the response. Such activities correspond to the higher-weight competencies represented by C2.2 and C1.3. Through this process, learners develop advanced English critical-reading abilities while simultaneously examining discourse legitimacy and maintaining their identities as second-language learners within culturally diverse communicative contexts [15]. Accordingly, the central implication of the proposed assessment framework is a movement beyond technology-centred rationality towards a renewed emphasis on humanistic educational values. The meaningful measure of teacher AI capability lies not in how extensively technology is used, but in how effectively it is placed within a purposeful pedagogical, intercultural, and ethical framework.

4.2 Reengineering of the Teacher-AI-Student (TAS) Collaborative Paradigm in the Context of Blended Learning Ecosystem

The hierarchical structure of the proposed assessment indicators, together with its underlying theoretical rationale, provides further insight into the ongoing transformation of university English blended learning. Conventional blended learning has often been implemented primarily by combining face-to-face instruction with digital delivery, with online resources serving largely as extensions of classroom materials. The integration of generative AI, however, changes this arrangement at a structural level by altering the relationships and functional roles of the principal elements within the teaching process [5].

First TAS collaborative model is reshaping the distribution of cognitive effort across activities conducted inside and outside the classroom. Existing research and recent scholarship suggest that, when blended learning is guided by teachers with strong AI literacy, AI-supported ITS and adaptive assessment technologies can efficiently assume many repetitive instructional activities associated with the lower levels of Bloom’s Taxonomy, particularly remembering and understanding. These activities may include repeated vocabulary practice, automated identification of basic grammatical errors, and preliminary analysis and correction of certain pronunciation problems [3]. By transferring such routine cognitive and instructional work to AI-supported systems, teachers can devote greater attention during face-to-face or synchronous online sessions to higher-order learning activities. These may involve interpreting complex intercultural pragmatic situations, producing multimodal language outputs, and developing coherent reasoning structures for advanced academic writing. This reallocation of responsibilities establishes a complementary relationship in which AI handles repetitive instructional operations while teachers concentrate on emotional engagement, contextual interpretation, and deeper meaning construction. Such an arrangement may also help alleviate the considerable workload and professional exhaustion frequently associated with large-class foreign language teaching.

Second, data privacy and the prevention of excessive dependence on AI have emerged as essential safeguards within the blended learning ecosystem. The substantial weighting assigned to AI ethics and security in the proposed framework reflects broader international concerns regarding the uncontrolled adoption of generative language technologies [7]. Large language models are trained on extensive textual datasets that may contain cultural assumptions, normative positions, and linguistic patterns. In foreign language education, insufficient teacher awareness of these limitations could allow uncritically generated content to circulate throughout blended classrooms, potentially reinforcing linguistic standardisation and algorithmically mediated forms of cultural representation. The proposed indicator framework therefore encourages teachers to move beyond their conventional role as knowledge transmitters and assume additional responsibilities as guides for meaning negotiation and guardians of academic integrity. This includes establishing clear, transparent, and academically appropriate boundaries for AI-assisted writing and other forms of generative AI use. Such responsibilities are particularly important for protecting academic integrity, learner autonomy, and the cultural diversity of the educational environment [6].

4.3 Methodological Superiority and Validity Robustness Argumentation of the Evaluation Framework

From the broader perspective of decision science and psychometrics, conventional self-report questionnaires for assessing teachers' digital literacy, particularly those based on single-dimensional Likert scales, contain several inherent limitations. Such instruments are vulnerable to social desirability bias and may produce ceiling effects that reduce their ability to distinguish between respondents with different competency levels [8]. The problem becomes more pronounced when the assessment concerns multifaceted constructs in which ethical considerations, technological proficiency, and pedagogical judgement interact. Human reasoning in such complex evaluation contexts is rarely strictly linear or precisely bounded; instead, it commonly involves ambiguity, uncertainty, and overlapping judgements [9].

The value of the Fuzzy AHP-TOPSIS hybrid MCDM framework adopted in this study therefore extends beyond its mathematical capacity to represent imprecise linguistic judgements. It also establishes a more resilient analytical basis for educational decision-making by allowing uncertainty within expert assessments to be explicitly incorporated into the evaluation process [11]. Using triangular fuzzy numbers (TFNs), the model captures the plausible lower and upper boundaries surrounding expert judgements rather than forcing evaluators to provide artificially precise numerical scores. This approach accommodates variation in individual perspectives and subjective assessments while enabling their systematic aggregation at the group decision-making (Group Decision Making) level. Consequently, the framework can reduce the influence of individual judgemental deviations and provide a more stable basis for comparative evaluation and managerial decision-making [10].

Not only that, the underlying logic of the closeness coefficient (CC_i) embedded in the Fuzzy TOPSIS algorithm presents a highly philosophical evaluation mechanism. It is not satisfied with merely examining how many outstanding strengths a candidate teacher possesses (that is, calculating the closeness degree d^* to the positive ideal solution), but also rigorously examines whether it has effectively avoided how many systematic fatal risks (that is, calculating the deviation degree d^- from the negative ideal solution). In real educational management, this means that if a teacher is proficient in AI software operation (C3), but has no ethical boundary awareness and allows students to use AI for academic fraud (poor on C2), then due to the small distance between the teacher and the fuzzy negative ideal solution (d^-), the final CC_i score will be severely penalized by the system through strict mathematical calculations, thereby significantly lowering the overall ranking. This strict two-way balancing and pulling evaluation mechanism makes the evaluation results not only three-dimensional and objective, but also highly consistent with the long-term safety bottom-line principle of prioritizing the prevention of systemic risks in the construction of high-level education talent teams.

Of course, rigorous academic discussions must address the limitations and challenges faced by this research plan. The construction of the triangular fuzzy matrix and the normalization inverse operation of multi-level matrices have high computational complexity (Computational Complexity), which makes it difficult to directly integrate them into the existing and outdated digital personnel management information systems (HRIS) of ordinary universities in terms of interface development [8]. At the same time, as general artificial intelligence (AGI, Artificial General Intelligence) approaches a breakthrough singularity, the internal weight coefficients of the current set of indicators may undergo drastic shifts within a relatively short period of time. This requires that future management practices must establish a flexible and agile mechanism for dynamic adjustment of indicator weights and re-evaluation by experts [18].

5. Conclusion

Amid the digital transformation of education and the growing integration of AI into teaching, a rigorous and adaptable framework for evaluating university teachers' AI capabilities is increasingly necessary. This study proposes an integrated Fuzzy AHP-TOPSIS model to profile and quantitatively assess university English teachers in blended learning environments. The principal conclusions are as follows:

Localised and Context-Specific Evaluation Model: The study adapts the 2024 Teacher AI Capability Framework to university English blended learning by integrating the BOPPPS, PADD, and TPACK frameworks with cross-cultural communication objectives. This produces a context-specific evaluation system comprising five primary and fifteen secondary dimensions.

Quantitative Precision and Methodological Robustness: Fuzzy set theory addresses uncertainty in educational evaluation. Buckley's geometric mean method is used in Fuzzy AHP to derive consensus-based weights, while Fuzzy TOPSIS calculates teachers' closeness coefficient (CC_i) to the ideal profile. The combined MCDM framework therefore connects subjective expert judgement with systematic quantitative analysis.

Pedagogy as the Basis for Technology Adoption: The weighting and simulation results indicate that teacher AI competence should not be equated with programming proficiency. Its core lies in integrating AI with effective pedagogy and foreign language content. Teachers remain essential for emotional support, intercultural critical thinking, learner agency, and ethical AI governance, demonstrating the continuing importance of human-centred teaching in AI-enhanced education.

Implications for Higher Education Practice: Universities should treat TPD as continuous Lifelong Learning rather than simple software training. AI-TPACK workshops should connect experienced educators with technologically skilled younger teachers through peer teaching and reflective practice. Institutions should also establish cross-departmental AI governance, ethical-use guidelines, and compulsory AI literacy and critical-evaluation training. The proposed framework can further support promotion, performance assessment, personalised training, and differentiated incentives according to teachers' AI competency levels.

Future Research: Further longitudinal studies across representative universities should compare the Fuzzy AHP-TOPSIS closeness coefficient (CC_i) with objective outcomes, including CET-4/CET-6 performance, academic writing quality, and changes in students' critical-thinking abilities. Such evidence would enable rigorous testing of the model's predictive validity and long-term stability and strengthen the scientific basis for digital, ethical, and human-AI collaborative foreign language education.

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