Application of Quantum Fuzzy Decision-Making in the Cultivation of Humanistic Literacy in College English Courses

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ABSTRACT To address the high subjectivity and inability of traditional models to handle cognitive superposition and psychological interference in multi-source evaluations, this paper proposes a dynamic evaluation model based on quantum fuzzy decision-making for cultivating humanistic literacy in college English courses. An evaluation system comprising three primary and seven secondary indicators is established. Unstructured teaching data is mapped onto a complex Hilbert space using quantum state probability amplitude, effectively capturing evaluators' multiple cognitive superposition characteristics without information loss. Furthermore, quantum coherence and phase angle parameters are introduced to quantify and correct cognitive interference biases stemming from subjective preferences, contextual dependence, and cross-cultural differences. A quantum spherical fuzzy aggregation operator then performs a nonlinear weighted fusion of the heterogeneous data. This process outputs comprehensive results while preserving individual dimensional traits to support precise tiered teaching interventions. Simulation experiments utilizing five hundred real teaching samples demonstrate the significant superiority of this approach over traditional linear methods. The proposed model reduces the average absolute percentage error by over fourteen percent when processing highly conflicting subjective data, maintains strict logical consistency, and exhibits strong robustness against random noise perturbations with minimal information loss. Ultimately, this framework accurately identifies students' individual weaknesses, offering a reliable engineering paradigm to facilitate targeted teaching interventions and improve the overall effectiveness of interdisciplinary educational evaluation.

INDEX TERMS Fuzzy Decision-Making; Quantum Fuzzy Decision-Making; College English; Cognitive Interference; Humanistic Literacy

I. INTRODUCTION

With the deepening of higher education reform, college English courses have shifted from simple language skills training to a comprehensive education stage driven by both "language ability and humanistic literacy" [1-2]. As the core carrier for cultivating students' sentiments, international perspective, and cross-cultural communication skills, the quality of humanistic literacy cultivation in college English courses is directly related to the effectiveness of the fundamental task of moral education in higher education [3-4]. However, a prominent problem of "disconnect between evaluation and cultivation" is prevalent in current college English teaching practice: the cultivation goals of humanistic literacy are difficult to transform into operable teaching guidelines through scientific and quantitative evaluation methods; evaluation results are only used as the basis for final assessment scores and cannot provide precise decision support for process-based teaching intervention and personalized tiered cultivation [5-6]. This contradiction has led to the cultivation of humanistic literacy in college English remaining at the level of "ideological advocacy" for a long time, making it difficult to form a closed-loop cultivation mechanism of "evaluation-diagnosis-intervention-improvement," which seriously restricts the full play of the educational function of the course [7-8].

In response to the current predicament of humanistic literacy cultivation in college English courses, a scientific, objective, and precise evaluation system has become a key bottleneck in breaking through the cultivation chain. Unlike purely humanities courses such as Chinese literature and ideological and political education, the humanities literacy in college English has an implicit characteristic of being deeply integrated with language skills [9-10]. Students' intercultural critical thinking ability, aesthetic taste, and value identification are not presented through independent knowledge assessments, but are embedded in language use processes such as English text interpretation, intercultural dialogue, translation practice, and group projects [11-12]. This particularity makes the evaluation of humanities literacy in college English face more severe challenges than other disciplines: the evaluation objects are highly abstract and have blurred boundaries; the evaluation data comes from multiple heterogeneous channels such as teacher classroom observation, student peer evaluation, online assignments, and final presentations; and the differences in cross-cultural cognition, language proficiency, and subjective preferences of evaluators can easily lead to systematic biases in the evaluation results. More importantly, the traditional evaluation system cannot capture the dynamic development process of students' humanities literacy and is difficult to identify the individualized shortcomings of different students in

different dimensions, so that teaching intervention can only adopt a "one-size-fits-all" extensive model, which cannot meet the needs of differentiated cultivation. To address these issues, scholars have attempted to introduce fuzzy mathematics and multi-criteria decision-making methods into the field of college English humanities literacy evaluation. Among these, the most widely used are the Fuzzy Analytic Hierarchy Process (F-AHP) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [13-14]. Usually, these use triadic fuzzy numbers or Euclidian distances as a method to quantify linguistic behaviors [15-16]. Unfortunately, traditional linear decision-making logic and traditional fuzzy evaluative methods have much limitations in common with one another; both methods map strings of potentially conflictive data (it could be assumed that an evaluator could exhibit a "both yes and no" evaluative pattern) into one rigid, single scalar, where there is no decoupling mechanism to allow for the combining of different attitudes [17-18]. They are both unable to quantify many of the "superposition states" and "psychological interference effects" that result from the cognitive processes of their evaluators [19-20], creating conflicting subjective data evaluations; therefore, at times, traditional forms of evaluation expose the underlying logical contradictions of their methods, produce highly distorted evaluations, and offer low levels of robustness to any type of inherent interference; therefore, the traditional methods are unreliable for making evaluations under extreme objects of conflictive data [21-22]. This paper introduces quantum fuzzy decision-making methods for the development of a dynamic evaluation system devoid of the primary limitations associated with traditional evaluation paradigms that enhance the cultivation of Humanistic Literacy in college English courses. It is recommended that a quantum fuzzy decision-making dynamic evaluation model is utilized for the cultivation of humanistic literacy in college English courses. This research is also developed for the purpose of providing a customized design that correlates to the core constraints of the college English course training objectives, teaching scenarios, and evaluation areas of frustration. Based upon these training requirements, a dynamic evaluation system with three primary indicators and seven secondary indicators, including cognitive/intercultural competence, ethical/aesthetic orientation, and socio-emotional literacy, can be constructed. This system supports automatic adjustment of indicator weights according to different training objectives at the basic, advanced, and extended stages. Second, unstructured language teaching evaluation data is mapped to a complex Hilbert space using quantum state probability amplitude, losslessly representing the multiple cognitive superposition characteristics of evaluators regarding implicit humanistic literacy, thus solving the information loss problem of traditional models. Third, quantum coherence and phase angle parameters are introduced to quantify and correct cognitive interference biases caused by evaluators' intercultural cognitive differences, subjective preferences, and contextual dependence, improving the accuracy of evaluation results. Finally, a quantum spherical

fuzzy aggregation operator is constructed to fully retain the feature values of each dimension while outputting the comprehensive evaluation results, providing teachers with a precise decision-making basis for designing differentiated instruction and specialized tutoring. Based on 500 real samples collected from the process teaching links of college English reading, writing, listening and speaking courses, a simulation experiment is conducted. The results show that the QFD model proposed in this paper is not only significantly better than the traditional model in terms of evaluation accuracy and anti-interference robustness, but also can effectively identify the individualized shortcomings of students' humanistic literacy, guide teachers to carry out targeted teaching interventions, and provide a feasible engineering computing paradigm for the construction of a closed-loop training mechanism of "evaluation-diagnosis-intervention-improvement" in college English courses. It also provides a new methodological reference for similar interdisciplinary education evaluation and teaching applications.

II. QUANTUM FUZZY DECISION-MAKING EVALUATION MODEL AND ITS TEACHING APPLICATION ARCHITECTURE DESIGN

A. DESIGN OF MULTIDIMENSIONAL HUMANISTIC LITERACY EVALUATION INDEX SYSTEM

To address the problem that the concept of humanistic literacy in college English courses is abstract and difficult to quantify directly, this study adopts a hierarchical deconstruction method to decompose the core evaluation goal of humanistic literacy into dimensions and construct a multidimensional evaluation framework consisting of a goal layer, a criterion layer, and an index layer [23-24]. First, through expert surveys and text mining of the teaching syllabus, a comprehensive evaluation set of humanistic literacy is established, represented as:

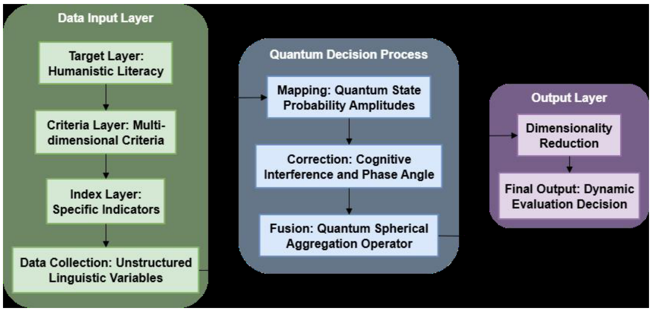

FIGURE 1. Overall architecture topology of the quantum fuzzy evaluation model

$$U = \{u_1, u_2, \ldots, u_n\} \tag{1}$$

U=u1,u2,...,un (1) U represents the set of primary indicators, and ui represents the i-th evaluation criterion (cognitive and intercultural competence, ethical and aesthetic orientation, and socio-emotional literacy). Subsequently, for each primary indicator ui, it is further refined into an observable set of secondary indicators Vi:

$$V_i = \{v_{i1}, v_{i2}, \ldots, v_{im}\} \tag{2}$$

vij represents the j-th secondary observation point belonging to the primary indicator ui. Through this recursive deconstruction, the evaluation pressure is shifted from subjective, emotional cognition to specific indicators with clear teaching behavior orientations, providing a standardized data input for the subsequent precise mapping of quantum state probability amplitudes. After constructing the indicator set, the model defines the logical flow from data collection to decision output by constructing a global topological structure. This structure not only covers the hierarchical relationship of the evaluation indicators but also defines the transmission and evolution path

of quantum state vectors between different levels in the subsequent calculation process. Fig 1 shows the overall architecture topology of the quantum fuzzy evaluation model, clearly presenting the multi-level network topology and hierarchical spatial relationships from the "data input layer" (including the target layer, criterion layer, indicator layer and unstructured linguistic variable collection), through the "quantum decision-making process" (mapping, correction, fusion), to the "output layer" (dimensionality reduction and dynamic evaluation decision).

To adapt to the requirements of the quantum decision model for input data, this section sets a fuzzy language variable set L for the initial collection of evaluation information. The evaluator provides natural language feedback on the performance of the secondary indicator vij within the preset evaluation interval. These unstructured data is used as the ground state input of the quantum superposition state in the subsequent process. The weight allocation of each indicator is preset using the entropy weight method to avoid the bias of manually setting weights. The weight vector of the evaluation system is expressed as:

$$W = \{w_1, w_2, \ldots, w_n\} \tag{3}$$

wi is the objective weight coefficient of the corresponding indicator ui, which satisfies the normalization constraint: $\sum_{i=1}^{n} w_i = 1$. This design ensures that the evaluation system maintains the rigor and objectivity of the underlying mathematics while deconstructing abstract concepts.

B. FUZZY EVALUATION DATA MAPPING BASED ON QUANTUM STATE PROBABILITY AMPLITUDE

To address the problem of quantifying the superposition of evaluators' coexistence of multiple attitudes towards fuzzy humanistic indicators, the indicator evaluation space established in Section 2.1 is placed into a two-dimensional complex Hilbert space H2 for analysis [25-26]. Mutually orthogonal Dirac symbols $|0\rangle$and $|1\rangle$are set as the orthogonal ground states of this space, corresponding to the absolute extremes in the evaluation scale (i.e., "absolute disagreement" and "absolute agreement"), respectively. Within this framework, the evaluator's subjective cognition of a specific secondary indicator vij is no longer forced to converge to a single definite scalar, but is mapped to a superposition distribution state in a complex vector space spanned by the ground states.

Unstructured linguistic fuzzy evaluation data needs to be transformed into definite parameters in the standardized real number domain through semantic distance measurement [27-28]. Let k be the independent evaluator number (k=1,2,...,ki). After fuzzy semantic mapping, the standard measure value zjk∈[0,1] is extracted from the natural language input of the j -th secondary indicator. Using the quantum state probability amplitude conversion mechanism, the measure value is nonlinearly deconstructed into probability amplitude parameters αjk and βjk , which tend towards the $|0\rangle$state and the $|1\rangle$ state, respectively:

$$\alpha_{jk} = \sqrt{1 - z_{jk}} \tag{4}$$

$$\beta_{jk} = \sqrt{z_{jk}} \tag{5}$$

In the formulas, α_{jk} and β_{jk}, as real-valued amplitudes, accurately represent the square root of the probability that the evaluator tends to a certain ground state when cognitive collapse occurs, and strictly obey the probability conservation constraint in mathematical derivation:

$$\alpha_{jk}^2 + \beta_{jk}^2 = 1 \tag{6}$$

Through the linear combination of probability amplitude parameters, the single-dimensional language variable is reconstructed into a quantum state vector $|\psi_{jk}\rangle$ carrying high-dimensional superposition characteristics:

$$|\psi_{jk}\rangle = \alpha_{jk}|0\rangle + \beta_{jk}|1\rangle \tag{7}$$

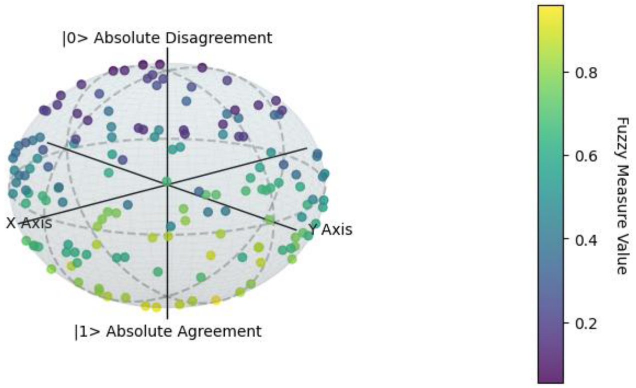

FIGURE 2. Mapping distribution of fuzzy linguistic variables to Bloch spherical quantum states

This vector effectively preserves the boundary ambiguity and selection uncertainty unique to the initial stage of humanistic evaluation.

As shown in Fig 2, after probability amplitude transformation, the original fuzzy linguistic data exhibits a continuous scatter distribution of coordinate points on a three-dimensional Bloch sphere. The north pole corresponds to $|0\rangle$(absolutely disagree); the south pole corresponds to $|1\rangle$(absolutely agree); and other positions on the sphere represent intermediate cognitive states of the evaluator in different superposition states. The color gradient from dark purple to bright yellow reflects the continuous change of fuzzy measure values from 0 to 1, visually

demonstrating the geometrical distribution of the evaluation superposition states in Hilbert space. After completing the feature extraction of the local dimension, the system traverses the global network containing m secondary indicators and K evaluation samples, and aggregates the isolated vectors into a multidimensional initial quantum decision matrix Q:

$$Q = \begin{bmatrix} |\psi_{11}\rangle & |\psi_{12}\rangle & \cdots & |\psi_{1K}\rangle \\ |\psi_{21}\rangle & |\psi_{22}\rangle & \cdots & |\psi_{2K}\rangle \\ \vdots & \vdots & \ddots & \vdots \\ |\psi_{m1}\rangle & |\psi_{m2}\rangle & \cdots & |\psi_{mK}\rangle \end{bmatrix} \tag{8}$$

Matrix Q completes the underlying transformation of unstructured data into computable mathematical parameters, laying the foundation of a structured matrix for subsequent nonlinear interference operations and cognitive bias correction.

C. COGNITIVE INTERFERENCE CORRECTION BASED ON COHERENCE AND PHASE ANGLE

To eliminate the nonlinear psychological biases generated by evaluators when processing highly ambiguous humanistic indicators, this study uses a phase angle matrix to perform interference correction on the initial quantum state vector matrix. First, the phase angle parameter is used to quantify the degree of cognitive entanglement between indicators. For any two evaluation dimensions u and v, their correlation is characterized by the phase angle θuv, which is used to capture the cognitive overlap and contextual dependence generated by evaluators between different criteria:

$$\cos\theta_{uv} = \frac{\mathrm{Re}\langle\psi_u|\psi_v\rangle}{\sqrt{\langle\psi_u|\psi_u\rangle\langle\psi_v|\psi_v\rangle}} \tag{9}$$

θ_{uv} represents the cognitive phase angle between indicator u and indicator v; $|\psi\rangle$ is the indicator quantum superposition state vector defined in Section 2.2; $\langle\psi|$ is the conjugate transpose of this vector; Re represents the real part of the complex term. Second, the interference correction term is derived based on quantum coherence theory. A coherence coefficient I_{uv} is constructed to quantify the cross-influence strength between different evaluation dimensions, and then the probability bias caused by subjective preference is corrected:

$$I_{uv} = 2\alpha_u\alpha_v\cos\theta_{uv} \tag{10}$$

I_{uv} is the quantum coherence interference term between the u-th and v-th dimensions; α_u and α_v are real probability amplitudes after index mapping.

As shown in Fig 3, the matrix of calculated coherence coefficients between all indicators of humanities literacy shows visually representationally the complex cognitive interference network of multiple indicators of humanities literacy. A number of pairs of indicators exhibit moderate positive synergistic effects (e.g., with a coherence coefficient of 0.88, evaluators have a very consistent cognitive perception of "cross-cultural critical thinking ability" and "global awareness"). Likewise, evaluators possess high confidence in their cognitive evaluation of the "value identification" and "moral reasoning" dimensions of this system (0.82). On the other hand, there are dark blue areas in the matrix that represent cognitive conflict or trade-off. Evaluators have moderate negative cognitive co-influences (e.g., coherence coefficients of -0.54 between "cross-cultural critical thinking ability" and "social responsibility" and -0.55 between "aesthetic taste" and "social responsibility"). This indicates that evaluators may be experiencing cognitive marginalization or attritional psychological processes when evaluating distinct dimensions of literacy. The full range of non-linear coupling states exists on the matrix as indicated by the color gradient; the gradient ranges from dark red (strong positive interference) to dark blue (strong negative interference). Finally, interference terms are injected into the initial evaluation matrix to achieve nonlinear correction of the evaluation results. The elements qjk in the corrected quantum probability distribution matrix Qare calculated as follows:

$$\widetilde{q}_{jk} = p_{jk} + \xi\sum_{v\neq j} I_{jv} \tag{11}$$

$\widetilde{q}_{jk}$ is the elements of the corrected quantum probability distribution; p_{jk} is the initial probability observations

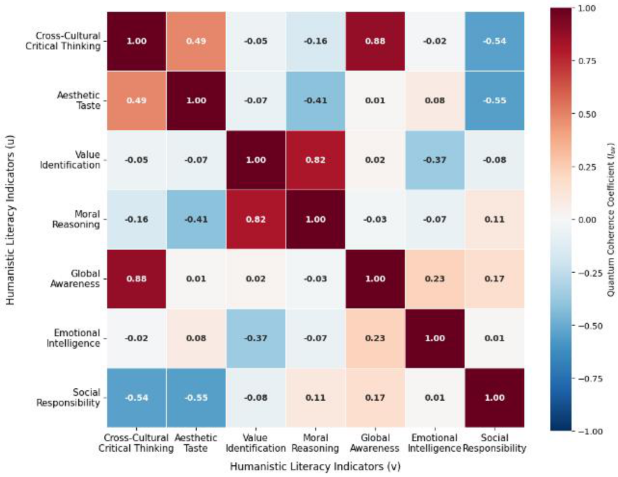

FIGURE 3. Heatmap of quantum phase angle distribution under cognitive interference effect

corresponding to the quantum states; ξ is the cognitive interference adjustment factor, used to balance the correction strength of environmental dependence on the evaluation results. Through the above steps, the model completes the transformation from a complex domain vector to a probability matrix containing interference features, effectively overcoming the logical distortion problem of traditional models when dealing with evaluation conflicts.

D. NONLINEAR FUSION USING QUANTUM SPHERICAL FUZZY AGGREGATION OPERATOR

Following the interference correction probability distribution matrix $\widetilde{Q} = [\widetilde{q}_{jk}]_{m\times K}$ output in Section 2.3, this section aims to construct a nonlinear dimensionality reduction mapping mechanism from high-dimensional quantum state features to one-dimensional decision scalars. To address the issues of feature homogenization and information annihilation that easily arise when processing multi-source heterogeneous data using traditional linear weighted summation, a quantum spherical fuzzy aggregation operator is introduced to achieve accurate decision fusion under complex cognitive states [29-30]. To balance the extreme biases that may be induced by differences in index dimensions during the evaluation process and to further enhance the model's ability to suppress abnormal disturbance signals, a weight penalty factor γ is introduced to nonlinearly modulate the initial objective weights w_j preset by the entropy weight method in Section 2.1. This process strengthens the dominance of high significance indicators through exponential mapping, while attenuating the weight ratio of low discriminative indicators, generating a modified nonlinear weight vector $\widetilde{w}_j$:

$$\widetilde{w}_j = \frac{w_j^{\gamma}}{\sum_{j=1}^{m} w_j^{\gamma}} \tag{12}$$

γ is the weight penalty adjustment factor, and satisfies the constraint $\gamma > 1$; m is the total dimension of the secondary evaluation indicators. The modified weights strictly follow the normalization constraint $\sum_{j=1}^{m} \widetilde{w}_j = 1$. Based on the weight allocation reconstruction, a quantum spherical fuzzy weighted aggregation operator is designed based on the quantum state collapse characteristics and nonlinear evolution logic [31-32]. This operator uses a logarithmic and exponential composite mapping structure to compress the multidimensional feature information in the high-maintenance positive quantum state matrix layer by layer, and finally collapses it into a single comprehensive evaluation value with order value significance. For the k-th evaluation sample, its nonlinear aggregation operation formula is defined as follows:

$$S_r = \left[1 - \exp\left(-\eta \sum_{j=1}^{m} \widetilde{w}_j \ln\left(1 - \widetilde{q}_{jk}^{2}\right)\right)\right]^{1/2} \tag{13}$$

In the formula: Sr is the comprehensive evaluation scalar value generated after the r -th sample is fused by the quantum spherical fuzzy operator; qjk is the quantum probability distribution element output in Section 2.3, containing cognitive interference correction features; η is the global aggregation sensitivity coefficient, used to finely control the response threshold of the fusion operator to fluctuations in the underlying indicators. Mathematically replacing linear arithmetic superposition with a logarithmic multiplication structure by using this aggregation process works to prevent information dilution during the dimensionality reduction of large amounts of high-dimensional complex cognitive data. Whenever one single indicator exhibits polarization characteristics, the nonlinear mechanism of damping which is embedded within the operation provides that indicator with an adequate weight in the final output decision,

preventing it from being masked by the mean effect of many other inconsequential dimensional indicators. Finally, standardization and/or normalization processing followed by descending sort order done on the entire sample's comprehensive evaluation index Sr produces a dynamic scoring sequence of college-level English humanities based upon their outcomes. This nonlinear aggregation architecture maps the superpositioned state in the complex domain into an equivalent decision value in the real domain while also providing the basis for independent probability distributions to exist for each input feature so that the features can subsequently be used to form teaching and training strategies.

E. MAPPING MECHANISM FROM MODEL OUTPUT TO TEACHING AND TRAINING STRATEGIES

The final output of the quantum fuzzy decision-making model is not a single comprehensive evaluation score, but a structured diagnostic report containing "comprehensive literacy level + sub-dimensional features". This section constructs a standardized mapping mechanism from the model's quantitative output to actionable teaching strategies, realizing the automatic transformation from "evaluation results $\rightarrow$problem diagnosis $\rightarrow$training program". Based on

the training objectives and teaching practice of humanistic literacy in college English courses, the standardized comprehensive evaluation scalar Sr∈0,1 output from Section 2.4 is divided into four levels with clear teaching meanings. Each level corresponds to a different overall training strategy:
① Sr∈[0.85,1.00]: Excellent, possessing solid cross-cultural critical thinking skills, able to independently conduct in-depth text interpretation and cross-cultural dialogue, with correct values and elegant aesthetic taste. It provides extended learning resources, encourages participation in international exchange programs and academic competitions, and guides them to become role models of humanistic literacy in the class.
② Sr∈ [0.70,0.85); Good, with basic intercultural communication skills, understanding differences between cultures, possessing some humanistic appreciation ability, and having positive and healthy values. It strengthens specialized skills training, supplements and improve weak areas, and encourages participation in classroom presentations and group discussions.
③ Sr∈[0.55,0.70); Moderate. Intercultural cognition is relatively superficial; humanistic appreciation ability needs improvement, can abide by basic moral norms, but lacks proactive thinking. It strengthens basic humanistic knowledge input, increases classroom interaction frequency, and uses task-driven teaching to guide participation in humanistic practices.
④ Sr∈[0.00,0.55); Needing improvement, lacking basic intercultural awareness, having low interest in humanistic content, and having ambiguous values. It adopts a one-on-one tutoring model, starting with interest cultivation, and gradually integrates humanistic literacy education in conjunction with language skills training.

Based on the comprehensive grading, and using the scores of the seven secondary indicators output by the model, a one-to-one mapping rule base for "dimensional weaknesses - teaching activities" is constructed to automatically generate personalized training paths. The rule base adopts an "IF-THEN" conditional judgment structure, as shown in the following example:

IF Cross-cultural Critical Thinking Score < 0.6 THEN: Recommended teaching activities include "Chinese-Western Cultural Comparison Debate" and "English Current Affairs Commentary Writing," with one English editorial reading and commentary assignment per week.

IF Aesthetic Appreciation Score < 0.6 THEN: Recommended addition of teaching content such as "Analysis of Classic Excerpts from British and American Literature" and "English Poetry Recitation," along with organizing film appreciation groups and book sharing sessions.

IF Social Responsibility Score < 0.6 THEN: Recommended design of "Global Issues Group Projects," such as English research and presentations on topics like climate change and public health, to cultivate students' global citizenship awareness.

IF Emotional Intelligence Score < 0.6 THEN: Recommended use of role-playing, scenario simulation, and other teaching methods to increase the proportion of group cooperative learning and improve students' communication and collaboration skills.

At the same time, the "rule base" supports dynamic changes for each of the three learning settings (basic, intermediate, and advanced) of college English education based on the objectives in each of the three stages of college English education. For example, the basic level is focused on developing students' intercultural awareness and their ability to appreciate the aesthetics of different cultures, while the advanced level is focused on developing students' critical thinking abilities and helping them gain a global perspective as well as develop an understanding of their own outlook and that of others.

IV. SIMULATION EXPERIMENTS AND TEACHING APPLICATION VERIFICATION

A. EXPERIMENTAL ENVIRONMENT AND CONSTRUCTION OF COLLEGE ENGLISH CLASSROOM SAMPLE DATASET

To test how useful a quantum fuzzy decision-making model (QFD) is when making decisions in complex cognitive environments, a simulation dataset is created that contains 500 teaching evaluation records for university-level English classes [33-34]. The evaluation subjects come from two different types of data acquisition mechanisms: 1) Teachers observing and evaluating student performance; 2) Students within student groups interacting and providing evaluations about one another. Therefore, the evaluators' own subjective fuzzy tendencies are retained during the collecting of their evaluative information (since they all provide their evaluation). All of the data are collected via one common uniform collection method - using a natural language scale to describe how they evaluated each teacher (e.g., by saying something like "very good," "average," or "poor").

To fix the issues of completeness and subjective evaluations being based on noise, a strict preprocessing pipeline is followed to prepare the data before creating a final spatial matrix. When the data is missing randomly because of objective reasons, K-Nearest Neighbors (KNN) is used as the multiple imputation method to keep the structure of the original dataset's covariance characteristics. Besides, outliers created from subjective or arbitrary rating or emotional bias ratings use DBSCAN for identification and removal [35-36]. This filtering of "dirty" data that doesn't have cognitive reference can ensure convergence and stability for the next step of mapping the quantum state. Tensor operations in a high-dimensional complex domain as well as interference matrix dimensionality reduction impose a significant burden on computability. Therefore, simulation studies must be conducted utilizing a specific high-performance computing architecture. The physical hardware utilized consists of an Intel Core i9 processor, 64 GB of high-frequency RAM, and an NVIDIA RTX 4090 Graphics Processing Unit (GPU) providing acceleration for massive scale tensor operations. The programming environment is implemented with the Python 3.10 programming language, using core mathematical computing libraries (NumPy and SciPy) to develop efficient mathematical computations for converting probability amplitudes of a quantum state, extracting phase angle measurements, and aggregating spherical fuzzy operators. Preprocessed multiple-source evaluation samples can be normalized and encapsulated based on logical rules following the collection process. All observational dimensions have defined hierarchical affiliations and mathematical attributes, as well as defined fuzzy semantic reference boundary limits for all observational dimensions with regards to association of data elements generated; therefore, a uniform defined underlying architecture of all data generated for use in the computational algorithm with respect to parallel input to the algorithm can be created. The quantitative mapping rules and variable attribute definitions for the indicator system quantifications are shown in Table 1.

This data dictionary establishes the basic limitations that guide transitioning from natural language variable mappings to the quantum computer space, thus guaranteeing that any given input tensor meets the mathematical requirements needed for complex projection into Hilbert space in order for dimensional alignment, boundary normalization, and semantic parsing to occur. The standardized, encapsulated data structure is capable of directly interfacing with the probability amplitude transformation module (see Section 2.2) and provides a consistent, traceable input stream for high-dimensional interference matrix computations performed in parallel.

B. BASELINE MODEL CONFIGURATION AND EVALUATION INDEX SETTING

To systematically assess the performance limits of the quantum fuzzy decision-making model (QFD) while working with subjective evaluation results, this work compares the Fuzzy Analytic Hierarchy Process (F-AHP) and TOPSIS models as baseline models. The F-AHP uses triangular fuzzy numbers as an initial quantification of linguistic inputs and the eigenvector method to determine local weights for the various input factors, while TOPSIS calculates the relative proximity of an evaluation object to each of the two ideal solutions using Euclidean distances. Both methods use standard linear logic and serve a control function for the purpose of demonstrating the algorithmic advantages of using the proposed model to eliminate cognitive bias and assess the superposition characteristics of results. The specific configurations of the experimental baseline model and hyperparameters are shown in Table 2.

As shown in Table 2, the QFD model employs entropy-weighted nonlinear modulation in its weighting mechanism, enhancing the dominance of highly significant indicators through a penalty factor γ . In handling fuzzy variables, it utilizes the quantum probability amplitude mapping zjk→(αjk,βjk) to preserve superposition characteristics, distinguishing it from the triangular fuzzy number defuzzification of F-AHP. Regarding similarity measurement, QFD introduces the Hilbert space inner product and phase angle θuv to capture cognitive entanglement, while the baseline model relies solely on Euclidean distance. Furthermore, QFD's unique interferometry correction module quantifies cross-influence through the coherence coefficient Iuv and employs the quantum spherical fuzzy operator Sr for nonlinear aggregation. Key hyperparameters are set as γ=1.5, ξ=0.3, and η=1.0. In terms of computational complexity, the QFD model is mainly limited by the matrix coherence calculation and aggregation steps, with a complexity of O(m2K+mKlogK). To quantify the absolute accuracy differences between models in the prediction and calculation processes, the mean absolute percentage error is selected as the first core evaluation indicator. This metric measures the deviation between the model's output score and the baseline score formed after multiple rounds of expert calibration, intuitively reflecting the algorithm's error convergence capability when processing highly conflicting and ambiguous data. Its mathematical definition is as follows:

$$\mathrm{MAPE} = \frac{1}{N}\sum_{n=1}^{N}\left|\frac{O_n - E_n}{O_n}\right| \times 100\% \tag{14}$$

In the formula: N is the total number of evaluation samples participating in the calculation; On is the objective benchmark observation value of the n th sample after multiple rounds of consensus calibration by the Delphi method expert group; En is the comprehensive score estimate of the corresponding sample calculated by the evaluation model. To address the logical conflict problem that is prone to occur in multi-source subjective evaluation, the Consistency Ratio (CR) is introduced to test the internal logical consistency of the judgment matrix. By monitoring the fluctuation of CR under high-conflict data input, the ability of the model to maintain matrix stability through intervention correction is determined. Its calculation formula is constructed as follows:

$$CR = \frac{\frac{\Lambda_{\max} - D}{D-1}}{IR} \tag{15}$$

In the formula: Λmax is the largest eigenvalue of the evaluation decision matrix generated by the algorithm; D is the dimension constant of the decision matrix; IR is the average random consistency index of the same order matrix (preset value provided by the standard lookup table). In order to assess an algorithm's robustness to noise and other external interference such as erroneous random judgments and very high levels of emotional scoring, the Spearman Rank Correlation Coefficient is employed to compare output sequence data before and after adding noise. It provides a measure of the degree of similarity between standard evaluations' rankings and the rankings of evaluations with injected random noise added. It also quantifies the degree to which the system retains information fidelity in regards

TABLE 1. Data dictionary of multidimensional evaluation indicators for college English humanities literacy

First-Level Indicator	Second-Level Indicator	Variable Type	Value Range	Fuzzy Semantic Definition
Cognitive and Cross-Cultural Competence	Cross-Cultural Critical Thinking	Continuous (Fuzzy-Quantum Mapped)	[0.00, 1.00]	Linguistic scales converted to normalized measure z_{jk} for probability amplitude extraction $(\alpha_{jk}, \beta_{jk})$.
	Global Awareness	Continuous (Fuzzy-Quantum Mapped)	[0.00, 1.00]	Maps subjective assessments of international perspective to initial quantum superposition states.
Ethical and Aesthetic Orientation	Value Identification	Continuous (Fuzzy-Quantum Mapped)	[0.00, 1.00]	Evaluates alignment with core humanistic values; inputs transformed into basis state probabilities.
	Moral Reasoning	Continuous (Fuzzy-Quantum Mapped)	[0.00, 1.00]	Quantifies ethical judgment complexity; serves as input for coherence coefficient I_{uv} calculation.
	Aesthetic Taste	Continuous (Fuzzy-Quantum Mapped)	[0.00, 1.00]	Captures literary and artistic appreciation; mapped to phase angle parameters θ_{uv} for interference correction.
Social-Emotional Literacy	Emotional Intelligence	Continuous (Fuzzy-Quantum Mapped)	[0.00, 1.00]	Measures self-awareness and interpersonal regulation; fuzzy semantics normalized to mitigate subjective bias.
	Social Responsibility	Continuous (Fuzzy-Quantum Mapped)	[0.00, 1.00]	Assesses civic engagement awareness; final aggregated score S_r derived via spherical fuzzy operator.

TABLE 2. Experimental baseline model and hyperparameter configurations

Parameter Category	QFD (Proposed)	F-AHP (Baseline)	TOPSIS (Baseline)
Weight Mechanism	Entropy-based nonlinear modulation: $\widetilde{w}_j = w_j^\gamma / \sum_j w_j^\gamma$	Eigenvector method with triangular fuzzy numbers	Entropy weight or subjective assignment
Fuzzy Variable Handling	Quantum probability amplitude mapping: $z_{jk} \to (\alpha_{jk}, \beta_{jk})$	Triangular fuzzy number defuzzification	Linguistic term to crisp value conversion
Distance/Similarity Metric	Hilbert space inner product with phase angle: $\cos\theta_{uv} = \frac{\mathrm{Re}\langle\psi_u\|\psi_v\rangle}{\sqrt{\langle\psi_u\|\psi_u\rangle\langle\psi_v\|\psi_v\rangle}}$	Euclidean distance on defuzzified scalars	Standard Euclidean distance to ideal solutions
Interference Correction	Quantum coherence coefficient: $I_{uv} = 2\alpha_u\alpha_v\cos\theta_{uv}$	Not applicable	Not applicable
Aggregation Operator	Quantum spherical fuzzy operator: $S_r = \left[1 - \exp\left(-\eta\sum_{j=1}^m \widetilde{w}_j\right)\right]$	Weighted arithmetic mean of fuzzy scores	Weighted normalized distance to positive/negative ideal
Key Hyperparameters	$\gamma = 1.5$, $\xi = 0.3$, $\eta = 1.0$	Fuzzy scale: $[1/9, 9]$; consistency threshold: $C_R < 0.10$	Ideal solution definition: max/min per criterion
Computational Complexity	$O(m^2K + mK\log K)$ (matrix coherence + aggregation)	$O(m^3)$ (eigen-decomposition of pairwise matrix)	$O(mK)$ (linear distance computation)

Note: All models are implemented under identical preprocessing pipelines (KNN imputation + DBSCAN outlier removal) to ensure fair comparison. The hyperparameters for QFD are optimized via grid search on a held-out validation subset (20% of total samples) and remain fixed during main experiments. Complexity notation: m = number of secondary indicators; K = number of evaluation samples.

to susceptibility to external disturbance using the following formula:

$$R_S = 1 - \frac{6\sum_{n=1}^{N}\Delta_n^2}{N(N^2-1)} \tag{16}$$

In the formula: RS is the Spearman rank correlation coefficient, with a value range constrained between -1,1 ; Δn is the difference in rank between the n th evaluation object in the noise-free standard output sequence and the noisy output sequence.

C. SIMULATION OF TEACHING APPLICATION SCENARIOS AND VALIDATION OF EFFECTIVENESS

To verify the effectiveness of the model output in transforming into teaching and training strategies, this section designs a simulation experiment of teaching application scenarios to examine the consistency between the personalized training suggestions generated by the model and the teaching judgments of experienced teachers. Fifty representative student evaluation data are randomly selected from 500 experimental samples and input into the QFD model and submitted to three university English teachers with more than 10 years of teaching experience. The model

automatically outputs the comprehensive literacy level and personalized training suggestions, while the teachers independently provide diagnostic reports with the same content based on their own teaching experience. The teaching application value of the model is verified by calculating the consistency between the two in terms of the overall grade determination and the training recommendations.

As shown in Fig 4, the QFD model and experienced teachers achieve 92% consistency in determining the comprehensive competence level, 88% consistency in identifying core weaknesses, and 84% consistency in matching personalized training suggestions. This indicates that the diagnostic results output by the model are highly consistent with the judgments of teaching experts, providing reliable decision support for frontline teachers.

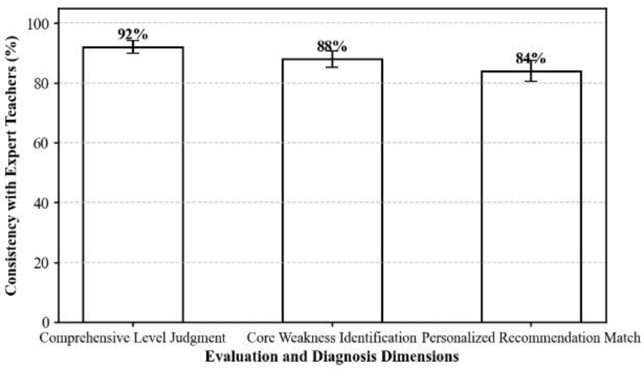

FIGURE 4. Comparison of consistency in teaching applications

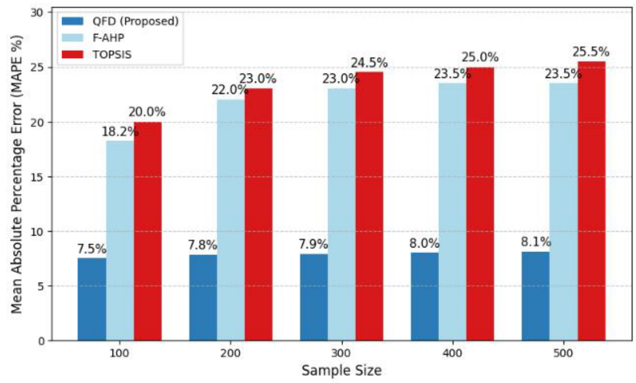

FIGURE 5. Comparison of absolute percentage errors of various models under different sample sizes

IV. EXPERIMENTAL RESULTS

A. COMPARISON OF MODEL PREDICTION ERROR AND CALCULATION ACCURACY

To verify the accuracy advantage of the quantum fuzzy decision-making model in handling highly conflicting subjective data, a quantitative analysis is conducted based on the mean absolute percentage error measure index set in Section 3.2. 500 preprocessed real teaching samples are divided into five test groups (100, 200, 300, 400, and 500) in increasing order of size. These groups are then imported into the QFD model, the traditional fuzzy hierarchical analysis method, and the approximation ideal solution ranking method for parallel simulation calculations. The deviation between the estimated comprehensive score En from the system-level hierarchical controlled calculation output and the expert calibration benchmark On is used to quantify the error convergence limit of different algorithm architectures. Simulation results reveal that traditional linear baseline models exhibit a significant error amplification effect when faced with datasets containing complex semantics and evaluation discrepancies. Global data slicing shows that the overall average MAPE (Mean Absolute Percentage Error) of the F-AHP and TOPSIS models stagnates at 22.04% and 23.6%, respectively. In contrast, the global average MAPE of the QFD model significantly decreases to 7.86%, and its absolute prediction error is reduced by 14.18% compared to the better-performing

control group baseline model. The error distribution under different sample sizes is shown in Fig 5.

Through lateral tracking of multi-scale sample groups, the nonlinear mapping relationship between prediction accuracy and data scale further highlights the differences in algorithms. As shown in the data histogram distribution in Fig 5, as the sample base involved in the calculation expands, the dimension of cognitive bias among groups extends exponentially. Under this high conflict load, the MAPE curve of the F-AHP model deteriorates from 18.2% with a sample size of 100 and eventually oscillates in the range of 23.5%, while the TOPSIS model also shows a synchronous upward trend, reaching a peak of 25.5%. The error divergence due to these errors exposes the dimensionality curse, or trap, related to the use of traditional continuous measures in Euclidean space and the impact on the measurement of high-dimensional heterogeneous features. However, unlike the error from a QFD model, where the nonlinear high-order quantum coherence way of tuning provides an extremely high-level of rigid constraint on the error curve for the entire testing period, with MAPE ranges consistently within an extremely narrow band between 7.5% to 8.1%. This set of dynamic comparative data demonstrates conclusively that the quantum probability framework method of evaluation of the decision engine has computational high-fidelity that far exceeds the traditional methods by eliminating high-order subjective noise and allowing for complex multidimensional fitting.

B. LOGICAL CONSISTENCY TEST UNDER HIGH-CONFLICT EVALUATION DATA

High-conflict evaluation data streams are created by adding fake adversarial examples to prove that evaluating systems are sound even under extremely inconsistent contexts. To do this, for each secondary indicator with relevance from a known dataset, it is mandatory to wrongfully enter fuzzy natural language variables of the opposite polarity into the evaluation system to simulate how an evaluator would experience cognitive dissonance and an inability to make subjective decisions based upon their clear intended outcome when performing an evaluation under complex conditions. Subsequently, decision tensors containing different conflict gradients are synchronously imported into each comparative model, and the dynamic evolution trajectory of the consistency ratio CR is tracked in real time based on the mathematical measure defined in Section 3.2. This experiment only selects the Fuzzy Analytic Hierarchy Process (F-AHP) as

the comparative baseline and did not include the Approximation to Ideal Solution Ranking Method (TOPSIS). The fundamental reason is that the applicability of the consistency ratio (CR) indicator is incompatible with the underlying logic of the TOPSIS model. Simulation monitoring sequences show that, with the nonlinear increase

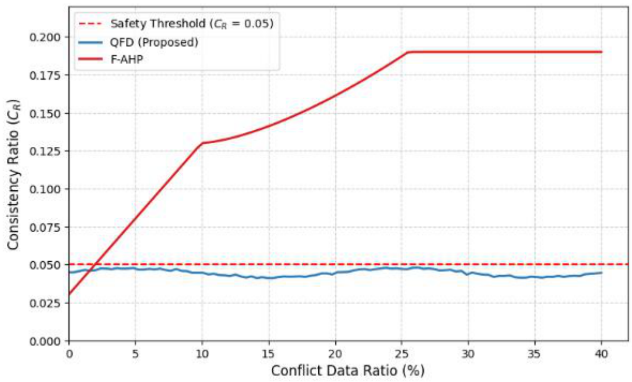

FIGURE 6. Dynamic fluctuation curve of model consistency ratio under multi-source subjective evaluation data input

in the intensity of logical paradoxes among local indicators, the traditional linear evaluation paradigm exhibits significant systemic logical collapse characteristics. Fig 6 illustrates the dynamic fluctuations in the model consistency ratio under different proportions of conflicting data.

As shown in the curve distribution in Fig 6, when the proportion of conflicting samples has not yet reached 5%, the global CR of the F-AHP model has rapidly exceeded the conventional tolerance limit of 0.05 and continues to rise with the increase of adversarial intensity. When the conflict node reaches 10%, the index has deteriorated to around 0.13, and finally diverged to a high plateau region of 0.19 at the 25% conflict ratio. A root cause of algorithm failures stems from using classical hierarchical analysis methods based on independently defined axiomatic assumptions, lacking any means to decouple them, such that multiple opinions can exist together in a single decision-making process. This creates illogical contradictions and errors in outputs from decision chains when subjectively exclusive preferences are mandated to be in linear superposition within low-dimension Euclidean space. The QFD model that is developed from quantum probability measures has much greater logical anchoring and self-tuning than does other models (using the same degrees of extreme perturbation). The logs of the matrix operations have indicated that when a high-conflict evaluation instruction is captured by the system, the quantum coherence correction module at the bottom of the algorithmic layers is impulsively activated. Besides, the extraction of the phase angle parameters between the eigenstates in the complex Hilbert space enables the system to accurately locate and quantify the anomalous entanglement interference effect that exists between the indices' at the off-diagonal location. After the initial probability distribution matrix has been compensated with the coherence coefficient, the irrational bias terms that exist (due to emotional fluctuations and contextual dependence) are completely removed. The final parallel measurement results corroborate that regardless of how much the intensity of the contradiction increases at the input,

the QFD model produces a CR curve output that is rigidly bound within the 0.041 to 0.049 range - which is under the 0.05 safety threshold baseline. This body of dynamic comparative data successfully negates the problems associated with consistency collapse that can exist within the mathematical logic factor of complex subjective evaluation, thus validating the integral role of the intervention correction mechanism in establishing the topological stability of the high-dimensional decision matrix.

C. ROBUSTNESS OF ALGORITHMS UNDER RANDOM NOISE PERTURBATION

An experiment is designed to test if the error for which fault tolerant capacity exists in the evaluation system could result from random human error, or extreme external disturbance or interference, using a Monte Carlo simulation with the standard teaching sample dataset outlined in Section 3.1. As an example of the detailed experimental methodology and execution path, perturbation constants from a uniform distribution are randomly mixed in increments of five percent to twenty percent into the underlying fuzzy semantic measure values of the evaluation data tensor, during the input process stage of the fuzzy semantic measures. These perturbations cause the polarity of the original natural language evaluations to be forced into the opposite or totally different evaluation polarity as a result of the subjective human error experiences of the assessors during real teaching evaluations caused by subjective fatigue, emotional changes, and perfunctory attitudes. After noise contamination, heterogeneous matrices carrying conflicting data at different proportions are synchronously and in parallel input into the QFD, F-AHP, and TOPSIS evaluation networks for dimensionality reduction and fusion. The system calls the Spearman rank correlation coefficient defined in Section 3.2 to rigorously calculate the topological similarity between the output evaluation sequences of each algorithm under different noise levels and the standard benchmark sequence under an absolutely noise-free environment. This measurement link focuses on verifying the nonlinear suppression and absorption effectiveness of the weight penalty factor and aggregation coefficient in the quantum spherical fuzzy aggregation operator constructed in Section 2.4 when dealing with local extreme outliers. The degradation trajectory of the algorithm's anti-interference performance under different noise injection ratios is shown in Fig 7.

The data distribution illustrated in Fig 7 indicates that standard linear models are extremely susceptible to minor changes in their data and experience drastic changes in rank correlation coefficients (shown by the curves for F-AHP and TOPSIS models) once the added level of noise in the system reaches 10% at a node. As an example, F-AHP's and TOPSIS rank correlation coefficients drop sharply to 0.785 and 0.721, respectively, after noise is added and perturbations have been applied. Adding additional noise, causing a 20% perturbation (the highest extreme), causes the baseline model to totally collapse and rank correlation coefficients for F-AHP and TOPSIS to fall to 0.675 and 0.598, respectively,

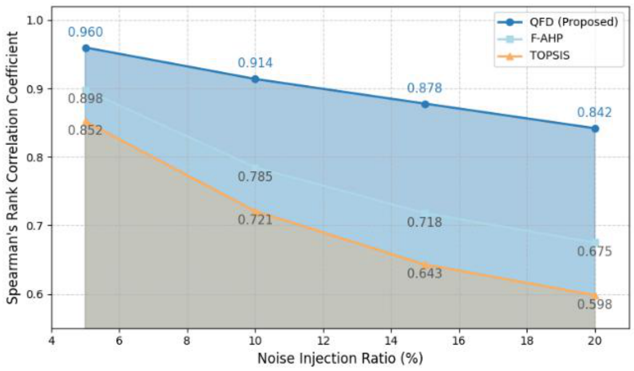

FIGURE 7. Spearman rank correlation coefficient decay trend of various evaluation algorithms under different noise ratios

significantly distorting and logically reversing the global rank ordering for evaluation. This extreme degradation of robustness is due to the classical nature of the underlying measure (Euclidean space) having no nonlinear damping mechanism for local abnormal extreme values, such that as a result of applying a weight summation when there are single-point-input-noise sources result in potentially infinite amplification of that input-noise value contaminating the entire global decision-making process. The QFD model based upon quantum probability architecture exhibits superior rigidity against interference in comparison to the original model under the same environmental stepped noise level. The operational log tracking reveals that, for a 5% low-noise ambient noise level, the model has an initial stability at a baseline value of 0.960, with a value of 0.914 still remaining stable even with a high level of 10% high-frequency random noise interference. Furthermore, as the amount of load increases to the extreme high end of the destructive range (up to 20% and greater), the Spearman Rank Correlation Coefficient for the output data stream remains above a safety threshold of 0.842. This provides conclusive evidence of the extreme strength of the system's robustness and fidelity of information in rapidly changing dynamic evaluation environments.

D. ABLATION EXPERIMENT OF COGNITIVE INTERFERENCE CORRECTION MODULE

To verify the core role of coherence and phase angle parameters in eliminating evaluator subjective bias, a module ablation experiment is performed on the aforementioned quantum fuzzy decision-making framework. By forcibly blocking the interference correction feedback link constructed in Section 2.3 in the algorithm backbone, a degraded stripping model (QFD-NoInt) without quantum interference effects is generated. The specific mathematical operation is as follows: the interference adjustment factor is forcibly set to zero, causing the underlying data entering the nonlinear fusion stage to degenerate from the corrected state to the initial probability observation value:

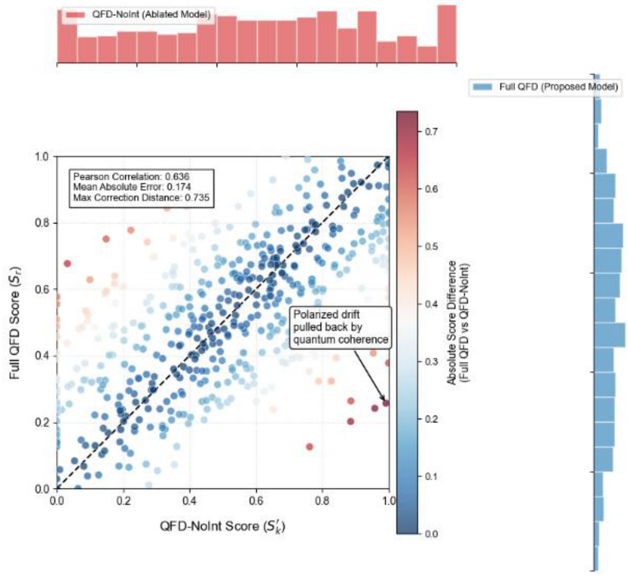

FIGURE 8. Scatter plot comparing the overall evaluation score distribution before and after introducing the coherence parameter

$$\widehat{q}_{jk} = p_{jk} \tag{17}$$

In the formula: $\widehat{q}_{jk}$ is the uncorrected quantum probability input element of the k-th evaluation sample in the j-th dimension after module ablation; p_{jk} is the initial observation state basis after completely stripping cognitive coherent interference features. Subsequently, the tensors of all 500 standard teaching samples are synchronously injected into the complete QFD model and the QFD-NoInt degraded model for parallel dimensionality reduction operations. In the ablation computation chain, the uncorrected tensor $\widehat{q}_{jk}$ is directly pushed into the quantum spherical fuzzy aggregation operator constructed in Section 2.4, forcibly outputting a degraded comprehensive evaluation scalar without filtering out subjective biases. Furthermore, in Formula 13, S_k' replaces the position of S_r, and S_k' is the final evaluation score of the k-th sample output by the degraded model without phase angle tuning intervention. After the data solution is completed, the S_r output by the complete model and the S_k' output by the ablation model are paired and projected into a two-dimensional Cartesian coordinate system. The comparison of the comprehensive evaluation score distribution before and after introducing the coherence parameter is shown in Fig 8.

As shown in the scatter matrix of Fig 8, the evaluation score S_k' output by the ablation model (QFD-NoInt) exhibits a high-variance divergent distribution characteristic under the constraint of the lack of an interference correction mechanism. A large number of sample points carrying complex subjective emotions or contextual dependence deviate from the diagonal baseline $y = x$, forming a significant polarization drift phenomenon. The color gradient mapping on the right further reveals the Euclidean distance distribution between the scatter points and the uncorrected baseline; the dark red area concentratedly represents the severe distortion and logical breakage of the uncorrected model under extreme conflicting data input. In contrast, the output score S_r of the complete QFD model shows an excellent centripetal correction trajectory. The quantum coherence module at the algorithm's underlying level accurately captures the contextual coupling and cognitive entanglement between indicators through the phase angle parameter, generating nonlinear interference compensation

feedback. This feedback mechanism forcibly pulls the abnormal scores that originally exhibited polarization drift back into the objective expectation domain, achieving efficient convergence of the scatter point clustering. The difference in coordinate mapping before and after this set of data stripping confirms, from a geometric topological perspective, the rigid solution capability of the quantum coherence module in filtering systematic cognitive errors and maintaining the objective consistency of evaluation results.

E. INFORMATION RETENTION RATE DURING DIMENSIONALITY REDUCTION AND FUSION

To accurately measure the retention degree of underlying features of multi-source heterogeneous evaluation data after dimensionality reduction and fusion, an information retention rate measurement model is constructed based on the von Neumann entropy mechanism in quantum information theory. Without interfering with the topological structure of the original evaluation tensor, the system extracts the structured basis of the high-dimensional quantum probability distribution before dimensionality reduction and the inverse mapping distribution of the single scalar after dimensionality reduction. By quantifying the divergence difference between the two, the information attenuation caused by the nonlinear operator is directly calculated. The specific calculation logic is as follows: for the full simulation dataset, the entropy difference of the evaluation feature matrix before and after nonlinear weighted aggregation is compared one by one to derive the global average information loss rate parameter:

$$\Phi_{\text{loss}} = \frac{1}{N} \sum_{n=1}^{N} \left(1 - \frac{H_A^{(n)}}{H_Q^{(n)}} \right) \times 100\% \tag{18}$$

In the formula: Φ_{loss} is the global average information loss rate during the collapse of the multidimensional system into a one-dimensional decision space; N is the total size of the evaluation samples involved in the calculation; $H_Q^{(n)}$ is the initial structural entropy of the high-dimensional quantum state interference matrix of the nth sample before it is fused by the quantum spherical fuzzy operator; $H_A^{(n)}$ is the retained structural entropy of the single comprehensive evaluation scalar output by the nth sample after inverse mapping of the equivalent probability distribution. Fig 9 shows the comparison of the spherical probability distribution before

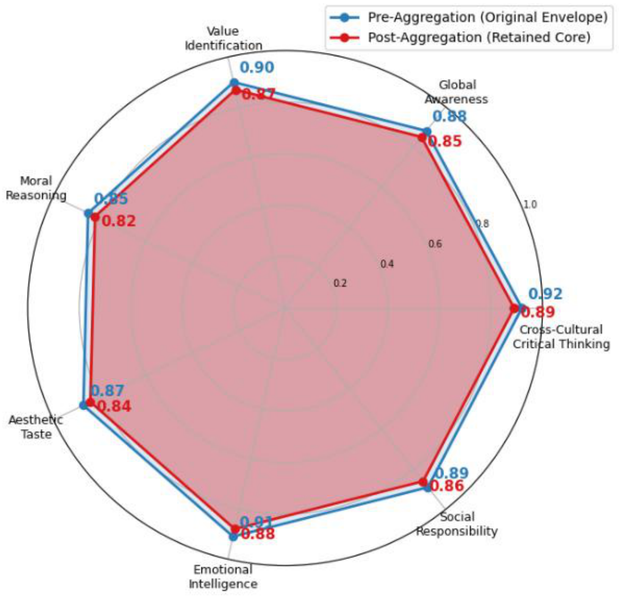

FIGURE 9. Radar chart of spherical probability distribution before and after nonlinear aggregation of multidimensional humanities literacy evaluation results

and after nonlinear aggregation of the multidimensional humanities literacy evaluation results.

As shown in Fig 9, the blue outer polygonal outline represents the original information envelope of the high-dimensional quantum state matrix before aggregation, and the red inner shaded area represents the core feature clusters retained after dimensionality reduction aggregation. Although the evaluation dimensions undergo extreme compression from complex Hilbert space to real number scalars, the two envelope curves show extremely high geometric overlap along the axes of the seven humanities literacy indicators. The feature retention values across all dimensions are closely aligned; for example, cross-cultural critical thinking ability is retained to 0.89, and emotional intelligence to 0.88. The overall profile shows only a slight inward contraction, without the feature distortion or dimensional collapse common in classic linear models. Topological calculations of all 500 samples confirm that using the quantum spherical fuzzy aggregation operator for data integration effectively resists the feature homogenization trap prevalent in traditional linear weighting methods. In classic linear superposition logic, extreme features in local dimensions are easily forcibly averaged by the mediocre performance of other dimensions, leading to the erasure of key underlying humanistic features. However, the results of this model reveal that the global information loss rate Φloss is strictly controlled at an extremely low level of 3.38%. This computational performance is directly attributed to the log-exponential mapping network within the operator. This network tightly locks multidimensional heterogeneous features within the envelope boundary of a complex unit sphere, achieving dimensionality reduction from high-dimensional data to a uniquely sortable scalar limit while maximizing the preservation of the nonlinear correlation and topological integrity of the underlying original humanistic features. Conclusions and Outlook

V. CONCLUSION

A. CONCLUSIONS

This study addresses the high subjectivity and ambiguity in the evaluation of humanities literacy in college English courses, as well as the practical dilemma that traditional evaluation systems cannot support personalized cultivation. It proposes a quantum fuzzy decision-making dynamic evaluation model for cultivating humanities literacy in college English courses. First, a dedicated multi-dimensional evaluation index system is constructed. Then, techniques such as quantum state probability amplitude mapping, cognitive interference correction, and quantum spherical fuzzy aggregation are used to accurately process complex subjective evaluation data. Finally, a standardized mapping mechanism from model output to teaching and cultivation strategies is constructed, establishing a closed-loop cultivation link of "evaluation-diagnosis-intervention-improvement." The evaluation accuracy, logical consistency, and robustness to interference of the model used in this study have been shown through the simulation experiments and teaching application simulations conducted using over 500 actual teaching samples to be better than that of traditional models. In addition, the model allows for accurate identification of students' specific areas of literacy deficiency as a tool for providing reliable support to teachers in making teaching decisions. The model is an assessment application providing a usable engineering computational model for assessing and personally developing humanities literacy skills in college English courses, thus providing a new methodological reference for future interdisciplinary educational evaluation studies.

B. IMPLICATIONS FOR THE APPLICATION OF HUMANITIES EDUCATION IN COLLEGE ENGLISH TEACHING

There are three major implications of the results from this research study for the practice of developing humanities literacy in English college teaching: A dynamic process-oriented assessment system is established: Rather than using traditional summative assessments, the evaluation of students' humanities literacy is accumulated into a process throughout the entire duration of the course. Continuous collection and analysis of multi-source data, such as grades, surveys, and individual learning outcomes, allows for the ongoing identification and monitoring of progress and development in literacy, thus giving way to the timely adjustment of instructional methods. A tiered and individualized instructional model is developed using the results of the evaluation process, to assess student differences and provide differentiated instructional materials to support students at all literacy levels, thus eliminating the "one-size-fits-all" approach to instruction and assessment. The integration of the evaluation process and the instructional process can be promoted; the evaluation, as a part of the instructional process, promotes the development of students' humanities literacy by creating an atmosphere in which students learn and develop through assessment.

C. LIMITATIONS AND FUTURE DIRECTIONS

This research still has some limitations. The first limitation is that the experimental sample is drawn from only one university; future research should broaden the sample to confirm the model across other types of universities and regions to help establish its generalizability to educational institutions. Second, the mapping rules used to develop training strategies are previously determined by expert opinion and therefore could be improved in future research by using machine learning techniques to provide automated optimization and updates based on large data sets of instructional materials. Third, an online platform for evaluating teaching according to this guideline should be developed to seamlessly interface with current university systems, thereby providing comprehensive technical assistance for developing humanities literacy in university English classes.

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