Comprehensive Evaluation of Teaching Quality in Textile University Courses Based on Fuzzy TOPSIS and Factor Analysis

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ABSTRACT Rapid advances in intelligent textiles, wearable electronics, and electromagnetic-enabled sensing technologies have accelerated the interdisciplinary integration of textile engineering with antenna, propagation, and electronic system education, creating increasing demands for objective and adaptive teaching quality assessment. To address the limitations of conventional evaluation approaches, including indicator redundancy, static weighting, and insufficient representation of curriculum dynamics, this study proposes a comprehensive teaching quality evaluation framework that integrates factor analysis with fuzzy TOPSIS. Factor analysis is employed to reduce dimensionality and identify four latent dimensions—industry–education integration, curriculum update timeliness, resource capacity, and student innovation ability—while their variance contributions are directly incorporated into a data-driven weighting strategy for fuzzy TOPSIS ranking. Experimental validation on 28 textile university courses demonstrates that the proposed model achieves an expert recognition accuracy of 85.7%, a Spearman rank correlation coefficient of 0.74 with student innovation evaluations, and an average ranking consistency of 86.1% under robustness testing with incomplete data. By providing dynamic and interpretable assessment results, the framework supports evidence-based curriculum optimization and resource allocation. The proposed methodology is particularly applicable to interdisciplinary engineering programs that require continuous adaptation to emerging technologies, offering practical reference for quality assurance in textile education and related courses involving wearable electronics and electromagnetic engineering.

INDEX TERMS fuzzy TOPSIS, factor analysis, teaching quality evaluation, interdisciplinary engineering education, wearable electronics

I. INTRODUCTION

THE evaluation of teaching quality in textile universities and colleges is closely linked to evolving educational requirements driven by transformations within the textile industry, characterized by both industry-education integration and rapid technological iterations [1-3]. Course quality is influenced by collaborative projects with real-world enterprises and the practical delivery of training through new technological applications. Furthermore, the technological upgrade cycle in the industry has shortened significantly compared to previous periods, creating an increased need for an evaluation system that can accommodate the dynamic rate of change in course-related educational content and associated metrics [4-6]. Current systems present limitations, including granular indicators that result in redundancy and information overlap due to multicollinearity; numerous measurement points that weaken the core concept of "teaching quality"; and static weighing mechanisms that fail to adapt to course development and changes, leading to delayed or suboptimal evaluation outcomes [7-9]. Additionally, systemic deficiencies hinder the optimal allocation of high-quality teaching resources.

As a fundamental element of higher education, the evaluation system for course teaching quality should prioritize the advancement of course content, the rational allocation of teaching resources, and the effectiveness of student development. However, a comprehensive quality evaluation framework tailored for textile disciplines remains lacking. Textile education is distinguished by its reliance on specialized equipment and resources (e.g., advanced looms, digital printing technology, and material testing platforms), the close alignment of teaching content with industry technical standards, and the high expectations for students' innovative practical skills. While current textile education often incorporates corporate participation and collaborative mechanisms, effective quantification of teaching quality through multi-source evaluation indicators (including enterprise project evaluation, responsiveness to technological updates, equipment utilization efficiency, student innovation achievements, etc.) and dynamic adaptation to the industry's rapid changes remain key bottlenecks impeding system efficiency. Wang Qinghui et al. [10] highlighted the significance of reforming course content and teaching methodologies for collaborative education. Sidian Yao [11] proposed that the integration of sustainable concepts in courses can foster teaching innovation. Mupfumira Isabel Makwara et al. [12] examined challenges in textile teaching and underscored the importance of high-quality teaching resources. In terms of methodology, Akram Muhammad et al. [13] developed a complex spherical fuzzy TOPSIS model to enhance multi-criteria decision-making. Fahmi Aliya [14] utilized triangular fuzzy sets to introduce a novel decision-making approach. Kalita Kanak et al. [15] combined TOPSIS with the Fermat fuzzy method for quality assessment. Mumcu Ahmet's team [16] confirmed the applicability of fuzzy TOPSIS in the textile domain. Bathrinath S [17] employed TOPSIS to analyze industry risks. Chen Qing Qin [18] improved online teaching evaluation accuracy using entropy-weighted TOPSIS. Liu Shulin [19] expanded the evaluation system by applying intuitive fuzzy TOPSIS. Wang Cheng et al. [20] introduced the deviation degree-ideal solution ranking model for university competitiveness assessment. Wu Zhihao et al. [21] employed factor analysis to establish an English teaching index system. Trskan Danijela [22] proposed a general framework for constructing quality indicators. Lu Chen [23] developed an adult education quality evaluation model. Malik Mehreen [24] discussed the impact of teachers' digital competencies on educational quality. Nevertheless, existing research is limited in its application to textile course evaluation: it does not fully reflect the unique course characteristics and teaching objectives of textile disciplines, particularly core dimensions such as rapid technological iteration, deep industry-education integration, and dependence on practical resources. Furthermore, most models involve complex evaluation processes with numerous technical parameters, hindering their widespread adoption within university curricula. Additionally, certain studies emphasize enterprise-side benefit indicators, excessively mapping course effectiveness to industrial performance, and fail to focus directly on core educational indicators such as teaching quality, course design rationality, and student skill development.

To address these challenges, this study centers on the core issue of teaching quality evaluation in the context of textile universities. A comprehensive evaluation model integrating fuzzy TOPSIS and factor analysis is proposed. This model resolves conflicting indicators in textile courses by employing factor analysis to identify core factors closely associated with teaching—namely, effectiveness of industry-education integration, timeliness of course updates, resource capacity, and student innovation. Dimensionality reduction and precise extraction of textile-related dimensions are achieved. The process incorporates the variance-explained principle of factor analysis into the fuzzy TOPSIS weighting framework, replacing static, exogenous weighting methods with an endogenous approach grounded in empirical data. This ensures consistency between dimensionality reduction and multi-criteria evaluation logic, thereby minimizing response lag in course design adaptation inherent in traditional static weighting. The resulting framework is rationally structured, scientifically grounded, and easily implementable, providing direct indications of teaching effectiveness trajectories rather than relying excessively on economic outcomes or technical complexity. The proposed model does not depend on complex dynamic functions or forecasting future industry trends. It focuses on educational objectives in indicator design and results analysis while maintaining flexibility and ease of application within disciplinary practices. The quantitative evaluation data serves as a foundation for curriculum reform, teacher competency enhancement, and student development, thereby improving the scientific rigor and precision of teaching quality measurement.

II. ALGORITHM DESIGN

CONSTRUCTION OF THE TEACHING QUALITY EVALUATION INDEX SYSTEM

Quantitative indicators are normalized using direct techniques as required, with point estimates retained for equipment duration and investment. These indicators are treated as exact values, whereas qualitative indicators (e.g., expert ratings) are modeled as triangular fuzzy numbers to account for uncertainty. Quantitative and qualitative indicators are subsequently integrated into a unified utility function, allowing the evaluation to appropriately incorporate both objective measurements and subjective ratings. Sensitivity analysis is performed to compare the traditional direct TOPSIS approach with the fuzzy TOPSIS method, demonstrating improvements in the handling of subjective indicators through fuzzy modeling without compromising the assessment of objective indicators.

The initial evaluation data matrix is defined as $X = [x_{ij}]_{m\times n}$, where m represents the number of evaluation objects (courses) and n represents the number of evaluation indicators. Quantitative indicators are normalized linearly:

$$r_{ij}=\frac{x_{ij}-\min_i x_{ij}}{\max_i x_{ij}-\min_i x_{ij}}, \text{Among them } i=1,2,\ldots,m; j=1,2,\ldots,n \tag{1}$$

Among them, r_{ij} represents the normalized value of the i-th course on the j-th indicator, ensuring mapping to the $[0,1]$ interval. Qualitative indicators are represented as triangular fuzzy numbers, defined as $\tilde{r}_{ij} = (r_{ij}^L, r_{ij}^M, r_{ij}^U)$, specifying the lower limit, most likely value, and upper limit. The fuzzy decision matrix is constructed as:

$$\tilde{R}=\begin{bmatrix}\tilde{r}_{11} & \tilde{r}_{12} & \cdots & \tilde{r}_{1n}\\ \tilde{r}_{21} & \tilde{r}_{22} & \cdots & \tilde{r}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \tilde{r}_{m1} & \tilde{r}_{m2} & \cdots & \tilde{r}_{mn}\end{bmatrix}, \text{Among them } \tilde{r}_{ij}=(r_{ij}^{L},r_{ij}^{M},r_{ij}^{U}) \quad (2)$$

Among them, r_{ij}^{U} represents the upper limit value of the triangular fuzzy number for the j-th indicator of the i-th evaluation object.

The weight vector generated from factor analysis is $w = (w_1, w_2, \ldots, w_n)$, satisfying:

$$\sum_{j=1}^{n} w_j=1, w_j\geq 0 \quad (3)$$

The weighted fuzzy evaluation matrix is:

$$\tilde{V} = [\tilde{v}_{ij}] = [w_j \times \tilde{r}_{ij}] = \left[w_j \cdot (r_{ij}^{L}, r_{ij}^{M}, r_{ij}^{U})\right] \quad (4)$$

Each fuzzy number is scalar-multiplied by the corresponding weight, preserving the triangular fuzzy number format. To ensure indicator alignment with industry requirements and practical teaching practices, the Delphi method is employed, engaging textile industry experts and senior university faculty in multiple rounds of scoring and feedback on the initially selected indicators. This process results in an evaluation system comprising 36 indicators, structured around the core dimensions: industry-education integration, technological timeliness, resource capacity, and student innovation ability.

The dimension structure of the course teaching quality evaluation is illustrated in Figure 1.

FACTOR ANALYSIS FOR DIMENSIONALITY REDUCTION

The standardized data matrix derived from 36 raw indicators undergoes indicator screening based on correlation analysis and conceptual relevance, yielding a reduced set of 12 input indicators for factor analysis, denoted as $X = [x_{ij}]_{12\times 28}$ (where 12 is the number of selected indicators, and 28 is the number of course samples). This reduction ensures an appropriate sample-to-variable ratio, mitigates overfitting risks, and facilitates stable factor extraction in a high-dimensional space. The Kaiser-Meyer-Olkin (KMO) statistic is defined as:

$$\text{KMO} = \frac{\sum_{j\neq k} r_{jk}^2}{\sum_{j\neq k} r_{jk}^2 + \sum_{j\neq k} q_{jk}^2} \quad (5)$$

Among them, rjk represents the correlation coefficient between indicators j and k, while qjk corresponds to the partial correlation coefficient. The KMO value evaluates the suitability of the correlation matrix for factor analysis.

The correlation coefficient matrix $R = [r_{jk}]_{12\times 12}$ is constructed, and eigenvalue decomposition is performed:

$$Re_i = \lambda_i e_i, \quad i = 1, 2, \ldots, 12 \quad (6)$$

Among them, λ_i represents the i-th eigenvalue, and e_i indicates the corresponding eigenvector. The KMO measure returns a value of 0.87, and Bartlett's test of sphericity is significant at the 0.001 level, confirming the appropriateness of the data for factor analysis. Principal component analysis is conducted, retaining four factors based on eigenvalues exceeding 1 and the scree plot. These four factors explain 82.3% of the total variance. The rotated factor loading matrix exhibits a clear structure, with all primary loadings above 0.65 and cross-loadings below 0.35, supporting the interpretation of the factors as effectiveness of industry-education integration, timeliness of course updates, resource capacity, and student innovation ability. The rotated factor loading matrix $L = [\lambda_{ji}]$ employs the maximum variance (Varimax) method to optimize the objective function:

$$max \sum_{i=1}^{4} \left[\frac{1}{12}\sum_{j=1}^{12} \lambda_{ji}^4 - \left(\frac{1}{12}\sum_{j=1}^{12} \lambda_{ji}^2\right)^2\right] \quad (7)$$

Among them, λji is the loading of the j -th indicator on the i -th factor. This procedure enhances the simplicity and interpretability of the factor structure.

Finally, the factor score matrix $F = [f_{ik}]_{28\times 4}$ is calculated by combining the rotated loading matrix and the standard deviation of the indicators:

$$f_{ik} = \sum_{j=1}^{12} \frac{\lambda_{ji}(x_{kj}-\bar{x}_j)}{\sigma_j} \quad (8)$$

Among them, f_{ik} is the score of the k-th course on the i-th factor, and $\bar{x}_j$ and σ_j are the mean and standard deviation of the j-th indicator, respectively. The factor analysis dimensionality reduction process is depicted in Figure 2.

CALCULATION OF TEACHING FACTOR SCORES

The factor scores obtained from factor analysis serve as the sole input for subsequent fuzzy TOPSIS evaluation, forming a dimensionality-reduced decision matrix with courses as objects and four major latent variables as dimensions. Each entry in this matrix represents the standardized score of each course across four comprehensive dimensions: effectiveness of industry-education integration, timeliness of course updates, resource capacity, and student innovation ability. The fuzzy TOPSIS process is conducted based on this dimensionality-reduced matrix. The normalized variance contribution rate of each factor determines its weight in the comprehensive ranking, obviating the need for repeated weight allocation at the original indicator level. Triangular fuzzy number conversion is applied solely to factor-level qualitative evaluation values, ensuring consistency between fuzzy processing and weighting logic. Factor scores and their weights, derived from contribution rates, follow a single analytic pathway, where the covariance structure of observed indicators defines both the conceptual dimensions

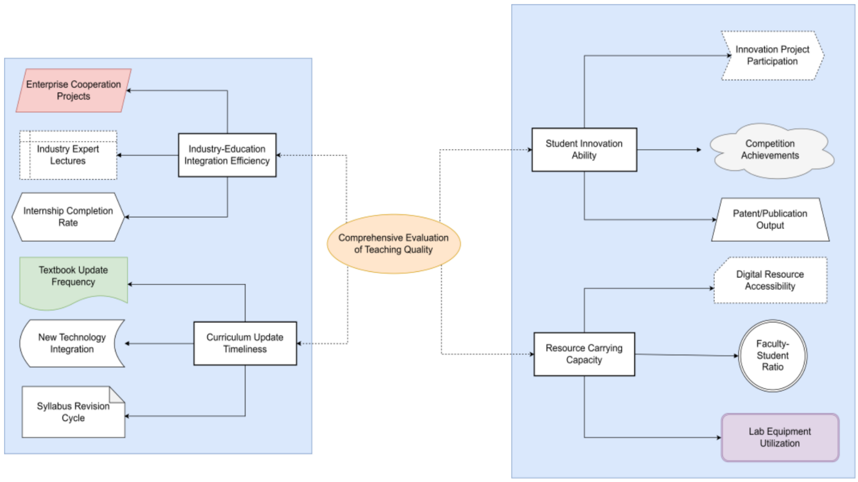

FIGURE 1. Dimensional structure diagram of course teaching quality evaluation

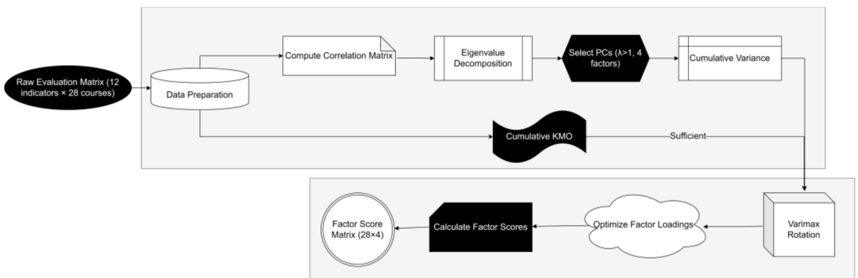

FIGURE 2. Flow chart of the factor analysis dimensionality reduction process

and operational influence relevant to ranking in the next stage, maintaining methodological coherence throughout.

Initially, the 28×12 original indicator data is standardized to zero mean and unit variance, thereby eliminating dimensional effects. The loading matrix $F_{12\times4}$ and the diagonal indicator variance matrix $D_{12\times12}$ are extracted and rotated to obtain the score coefficient matrix:

$$F_{12\times4} = D^{-1} \times L \tag{9}$$

Among them, D^{-1} is the diagonal matrix comprising the inverse of each indicator's variance. The standardized matrix $Z_{28\times12}$ is then multiplied by the coefficient matrix $F_{12\times4}$ to yield the factor score matrix:

$$S_{28\times4} = Z_{28\times12} \times F_{12\times4} \tag{10}$$

The score of the i-th course on the k-th factor is:

$$S_{ik} = \sum_{j=1}^{12} Z_{ij} \times F_{jk} \tag{11}$$

The score matrix S directly reflects the comprehensive performance of the four dimensions: effectiveness of industry-education integration, timeliness of course updates, resource capacity, and student innovation ability.

Fuzzy TOPSIS utilizes the normalized variance contribution rates of extracted factors as weights in the evaluation. The weighting scheme is directly determined by the underlying data structure. When new teaching data is incorporated in subsequent evaluations, the factor structure and corresponding contribution rates are recalculated, updating weights to reflect the current assessment of course development. Calculations are validated using MATLAB matrix operations or the Python NumPy library, with cross-validation against SPSS outputs. Outliers are identified, and matrix S is inserted into the fuzzy TOPSIS ranking module for efficient, dimensionally reduced ranking. This process also reduces indicator redundancy through load weight mapping, enhancing model stability, computational efficiency, and reliability.

FUZZY PROCESSING OF INDICATORS

For quantitative indicators, the normalization formula distinguishes between positive and reverse indicators:

$$x'_{ij} = \begin{cases} \dfrac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}}, & \text{If the } j \text{ indicator is a positive indicator} \\[2ex] \dfrac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}}, & \text{If the } j \text{ indicator is a reverse indicator} \end{cases} \quad i=1,2,\ldots,28; j=1,2,\ldots,12 \tag{12}$$

Among them, x_{ij} is the original score of the i-th course on the j-th indicator; $x_j^{\min}$ and $x_j^{\max}$ are the minimum and maximum values for the j-th indicator, respectively; $x'_{ij} \in [0, 1]$ denotes the normalized indicator value.

After normalization, x'_{ij} is transformed into a triangular fuzzy number representation:

$$\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij}) = (m_{ij} - \delta_j, m_{ij}, m_{ij} + \delta_j) \quad (13)$$

The parameter δ_j reflects the uncertainty margin associated with the j-th indicator, representing the degree of variation in survey precision. It is derived from the standard deviation of expert ratings for qualitative indicators and the coefficient of variation for quantitative indicators, ensuring that the fuzzy width is grounded in empirical values and symmetric with respect to data dispersion.

For qualitative indicators, expert assignment based on a Likert five-level scale defines the fuzzy number interval as:

$$\tilde{x}_{ij} \in \begin{cases} [0.1, 0.3], & \text{Level 1,} \\ [0.3, 0.5], & \text{Level 2,} \\ [0.5, 0.7], & \text{Level 3,} \\ [0.7, 0.9], & \text{Level 4,} \\ [0.9, 1.0], & \text{Level 5.} \end{cases} \quad (14)$$

The expert consensus value adjusts the fuzzy number median m_{ij}, ensuring consistency of expert opinions and constructing a fuzzy decision matrix: $\tilde{X} = [\tilde{x}_{ij}]_{28\times 12}$. This matrix serves as input for subsequent fuzzy TOPSIS comprehensive evaluation, unifying fuzzy expressions and comparisons across different indicators. The course fuzzy scoring interval and corresponding level divisions are presented in Table 1.

CONSTRUCTION OF THE FUZZY TOPSIS RANKING MODEL

Each fuzzy indicator in the fuzzy decision matrix is weighted to reflect the intrinsic importance of the evaluation dimensions. The weighted fuzzy decision matrix is denoted as $\tilde{V} = [\tilde{v}_{ij}]_{m\times n}$, where $\tilde{v}_{ij} = (l_{ij}, m_{ij}, u_{ij})$ is the triangular fuzzy number for the i-th course on the j-th indicator after weighting l_{ij}, m_{ij}, and u_{ij} represent the lower bound, most likely value, and upper bound, respectively, and w_j as the weight of the j-th indicator, satisfying $\sum_{j=1}^{n} w_j = 1$. The fuzzy positive ideal solution is expressed as $A^{+} = (l_j^+, m_j^+, u_j^+)$, with $l_j^+ = \max_i l_{ij}$, $m_j^+ = \max_i m_{ij}$, and $u_j^+ = \max_i u_{ij}$. The fuzzy negative ideal solution is expressed as $A^{-} = (l_j^-, m_j^-, u_j^-)$, with $l_j^- = \min_i l_{ij}$, $m_j^- = \min_i m_{ij}$, and $u_j^- = \min_i u_{ij}$.

Then, the fuzzy positive ideal solution $\tilde{A}^+ = (l^+, m^+, u^+)$ and the negative ideal solution $\tilde{A}^- = (l^-, m^-, u^-)$ are constructed, and the maximum upper limit and minimum lower limit of each column of fuzzy numbers are taken, respectively. The fuzzy Euclidean distance formula is used:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}\left[(l_a - l_b)^2 + (m_a - m_b)^2 + (u_a - u_b)^2\right]} \quad (15)$$

The distances D_i^+ and D_i^- between each course and the ideal solution are calculated, and the closeness coefficient is computed as follows:

$$C_i = D_i^- / (D_i^+ + D_i^-) \quad (16)$$

This coefficient serves as the basis for ranking overall teaching quality of each course, integrating multi-source heterogeneous information to enhance ranking discrimination and stability. For instance, a course such as "Intelligent Textile Design" may achieve high closeness to the fuzzy positive ideal solution due to outstanding scores in "Industry-education integration effectiveness" and "Student innovation ability," resulting in a top ranking.

The model supports regular updates of factor analysis results and weights based on new data, dynamically adapting to the evaluation needs arising from the rapid evolution of textile technology and teaching reforms. This approach effectively alleviates the lag inherent in traditional static weighting methods. The fuzzy TOPSIS ranking process is depicted in Figure 3.

III. EXPERIMENTATION AND VALIDATION

DATA SOURCE AND PROCESSING

This study collects data on 36 raw indicators encompassing instructional design, course content, faculty structure, student feedback, and resource allocation. The data, spanning three academic years, is sourced from the educational administration system, corporate collaboration project archives, laboratory usage logs, and annual teaching evaluation reports. All data are uniformly coded, reviewed, and archived by the Teaching Quality Management Office to ensure consistency and standardization.

Data is obtained from the teaching quality evaluation system of 28 core courses at a textile university, covering all major professional directions. The indicator system reflects common features such as industry-education collaboration, technological iteration, resource support, and innovation training. The constructed model relies on the internal data structure to extract core dimensions and generate dynamic weights, making the logic applicable to textile colleges with similar teaching structures. The dataset includes general teaching indicators and textile-specific metrics, such as records of corporate collaboration projects, teaching content pertaining to textile technology, standards and equipment updates, laboratory usage logs, equipment efficiency, and student innovation outputs, patents, and competition results.

Both quantitative and qualitative indicators are processed using the Expectation Maximization (EM) algorithm to address missing values. Standardization and normalization ensure data consistency and comparability. The resulting standardized data matrix is used for subsequent factor analysis and fuzzy TOPSIS procedures, supporting model accuracy and stability. The basic statistical characteristics of the course data sample are presented in Table 2.

TABLE 1. Course fuzzy scoring interval and corresponding level division

Course Indicator	Fuzzy Score Range (Triangular Number)	Level
Course 1 Indicator 1	[0.1, 0.3]	Level 1
Course 1 Indicator 2	[0.3, 0.5]	Level 2
Course 1 Indicator 3	[0.5, 0.7]	Level 3
Course 2 Indicator 1	[0.7, 0.9]	Level 4
Course 2 Indicator 2	[0.9, 1.0]	Level 5
Course 2 Indicator 3	[0.3, 0.5]	Level 2
Course 3 Indicator 1	[0.5, 0.7]	Level 3
Course 3 Indicator 2	[0.1, 0.3]	Level 1
Course 3 Indicator 3	[0.7, 0.9]	Level 4
Course 4 Indicator 1	[0.3, 0.5]	Level 2
Course 4 Indicator 2	[0.5, 0.7]	Level 3
Course 4 Indicator 3	[0.9, 1.0]	Level 5

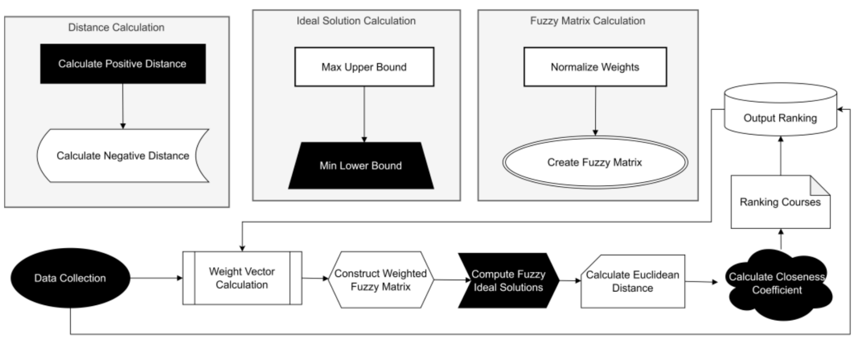

FIGURE 3. Fuzzy TOPSIS ranking process diagram

TABLE 2. Basic Statistical Characteristics of Course Data Samples

Indicator	Mean	Std. Dev.	Min	Max
Teaching Design	0.85	0.05	0.76	0.92
Course Content	0.83	0.06	0.74	0.91
Faculty Composition	0.79	0.07	0.72	0.87
Student Feedback	0.81	0.06	0.75	0.86
Teaching Resource Allocation	0.84	0.05	0.76	0.90

Table 2 summarizes the basic statistical characteristics of the course data sample, including mean, standard deviation, minimum, and maximum values for several teaching quality evaluation indicators. The mean for teaching design is 0.85, indicating high-quality design across most courses. The mean for course content is 0.83, slightly lower than that for teaching design, reflecting consistent course content quality. The mean for faculty composition is 0.79, approximately 4% lower than other indicators, with greater variability, potentially influenced by instructor qualifications and experience. The means for student feedback and teaching resource allocation are 0.81 and 0.84, respectively, suggesting generally high student satisfaction and resource allocation. All indicators show low variability, with resource allocation having a standard deviation of 0.05, indicating reliable and consistent scoring, likely due to uniform resource management across courses.

IDENTIFICATION RATE OF TEACHING ADVANCEMENT

The threshold for advanced courses is established through a Delphi-based expert consensus, involving fifteen experts (eight senior academics and seven industry leaders) selected for their professional standing, experience, and domain contributions. Over three iterative rounds, participants evaluate proposed performance criteria, including teaching innovation, industry integration, resource efficiency, and student achievement. Aggregated feedback is redistributed for refinement, and consensus is achieved when the dispersion of threshold assessments converges within a predetermined range, yielding a statistically robust and collaboratively endorsed criterion.

Figure 4 presents the fuzzy TOPSIS closeness rankings for 28 textile courses, with course ID on the horizontal axis and closeness coefficient on the vertical axis. Course 1 achieves the highest closeness (0.887), followed by Course 2 (0.858) and Course 3 (0.851), with scores declining to Course 28 (0.500). Courses 1 through 6, all with closeness above the advanced course threshold, are classified as advanced courses. Courses 7 through 28, with closeness below or near the threshold, are classified as standard courses. The top 20% (courses 1-6) are highlighted, with closeness scores exceeding 0.788. Recognition accuracy (85.7%) and coverage (83.3%) reflect the alignment between model identification and expert annotation, with accuracy representing the proportion of correct identifications and coverage denoting the effective identification of courses by the model.

DEVIATION OF FACULTY STRUCTURE REASONABLENESS SCORES

Standardized scores for each course on the resource capacity factor are extracted to assess overall teaching resource support. Since factor scores generated through principal component extraction and rotation are standardized to a mean of zero and a standard deviation of one, further Z-score transformation is unnecessary. Cohort mean deviations are analyzed using standardized factor scores to identify courses with exceptionally high or low resource endowment. A threshold of ± 1.5 highlights courses with extreme values, which are further evaluated in terms of underlying indicator profiles, focusing on imbalances in human, material, and digital resources. The causes of deviations are traced by examining auxiliary data, such as course hours and faculty professional title ratios.

This approach enables precise identification of structural imbalances in human resource allocation, providing a quantitative basis for subsequent teaching organization and faculty optimization, thus enhancing the scientific and targeted allocation of teaching resources. The balance of resource allocation across courses is assessed using standardized scores on the resource capacity factor, with deviation patterns illustrated in Figure 5 .

Figure 5 illustrates the rationality deviation analysis of faculty structure across 28 textile courses, with Z-score on the horizontal axis and course name on the vertical axis. Courses are categorized as severely imbalanced, slightly imbalanced, or otherwise based on Z-score values. A Z-score below -1.5 indicates a severely insufficient faculty structure, marked as severely insufficient; for example, Textile Chemistry and Nonwovens exhibit severe shortages. Conversely, courses such as Textile Biotechnology and Quality Control, with positive Z-scores, have an excess of faculty and are marked as severely redundant.

DISCRIMINATIVE ABILITY TO IMPROVE STUDENT INNOVATION

Scores corresponding to the "Student Innovation Ability" factor from factor analysis are combined with fuzzy TOPSIS ranking results to generate course innovation rankings. Simultaneously, subjective ratings of each course's innovation-promoting effect are collected from student survey questionnaires. Mean student perceptions are calculated using a five-point Likert scale, forming a student-based ranking of courses. The Spearman rank correlation coefficient is calculated to assess consistency between model-derived innovation rankings and subjective student rankings, with significance evaluated at the 95% confidence level to confirm reliability. The Spearman coefficient quantifies the monotonic relationship between two ranking sequences, allowing for appropriate evaluation of ordinal consistency without assuming linear association. Courses with consistency levels below 0.6 are further analyzed through teacher feedback and course content evaluation to identify causes of rank discrepancies.

To validate the model's capacity to capture student innovation outcomes, factor-derived rankings are compared with aggregated student subjective ratings using rank consistency analysis, as visualized in Figure 6.

Figure 6 provides a visual comparison of model rankings and student subjective ratings, with scatter plots predominantly near the diagonal, indicating minimal differences between model evaluations and student perceptions for most courses. For instance, the course ranked sixth by the model corresponds to the fifth student ranking, and the course ranked seventh by the model corresponds to the eighth student ranking.

However, notable outliers exist: the course ranked 24th by the model is ranked eighth by students, while the course ranked fifth by the model is rated 22nd by students. These outliers reveal individual course evaluation discrepancies, but the overall trend supports the statistical conclusion of a Spearman rank correlation coefficient of 0.74, signifying high consistency between model rankings and student perceptions. Since both model output and student assessments are expressed as ordinal ranks, Spearman rank correlation is appropriately employed, as opposed to Cohen's Kappa, which is intended for categorical agreement. This methodological choice ensures congruence with the data type and maintains methodological rigor.

ERROR RATE OF TEACHING RESOURCE ADAPTABILITY

The course proximity ranking calculated by the model serves as a proxy for overall teaching quality. Resource configuration intensity data for 28 courses within the teaching resource dimension, including class hours, experimental equipment investment, and platform support, is analyzed. After normalizing resource data, a resource configuration intensity ranking is established.

An absolute normalized discrepancy index is defined to measure misalignment between resource allocation and teaching quality, directly linked to the subsequent mathematical formulation. The index employs a squared rank deviation structure, ensuring consistency with theoretical boundary conditions in equation (17) and reflecting relative deviation between rankings under complete discordance. Both numerator and denominator in equation (17) represent sums of squared differences, with the index indicating the ratio of actual sum of squared deviations between quality and resource rankings to the maximum possible sum under complete discordance. Normalization confines the output to [0, 1], where a value of 0 indicates perfect alignment and a value near 1 signifies complete discordance. The index incorporates both the magnitude and distribution of rank differences, providing a straightforward measure of alloca-

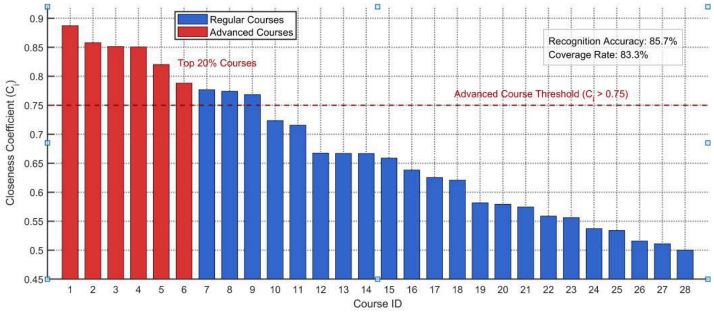

FIGURE 4. Fuzzy TOPSIS closeness ranking of different courses

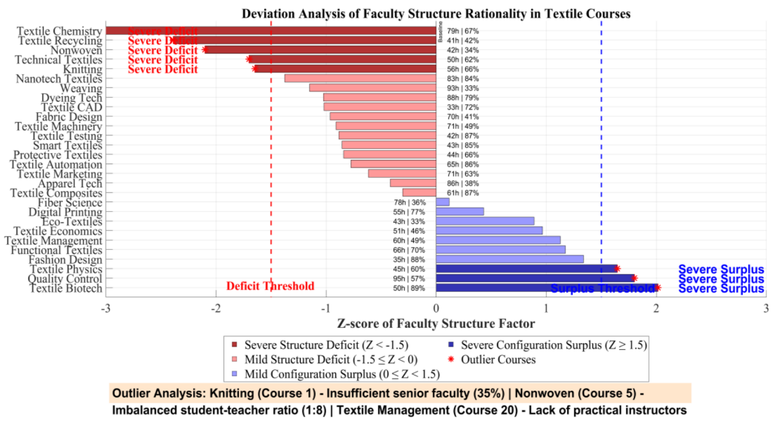

FIGURE 5. Analysis of rationality deviation in faculty structure for textile majors

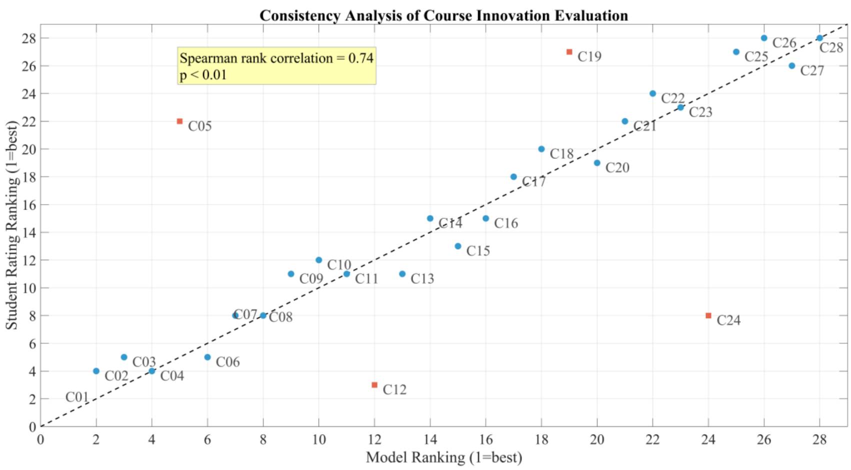

FIGURE 6. Consistency analysis of course innovation evaluation

tion misalignment without relying on monotonic association assumptions inherent in rank correlation coefficients.

$$E = \frac{\sum_{i=1}^{n}(R_i^Q - R_i^R)^2}{\sum_{i=1}^{n}(R_i^Q - R_i^{R*})^2} \tag{17}$$

In this formulation, R_i^{R*} denotes the rank position under complete discordance, corresponding to the reverse order of resource ranking. The denominator captures the maximum possible squared deviation, ensuring the error rate index is normalized to [0, 1]. High error rate values prompt further analysis of resource configuration bias to support decision-making and optimize allocation strategies. The Spearman rank correlation coefficient between teaching quality ranking and resource allocation intensity ranking is 0.41, indicating a limited positive correlation and confirming mismatches in resource allocation and output performance. Specific distribution differences are illustrated in Figure 7.

Figure 7 presents a comparative analysis of teaching

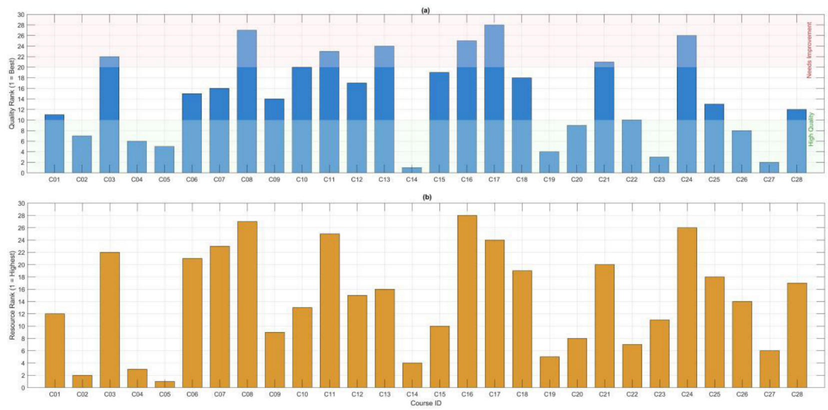

FIGURE 7. Comparative analysis of teaching resource adaptability: Sub-Figure (a): Course teaching quality ranking; Sub-Figure (b): Teaching resource allocation ranking

resource adaptability. The horizontal axis represents 28 textile courses, and the vertical axis shows rankings (1 is best, 28 is worst). In Sub-Figure (a), courses are ranked by comprehensive teaching quality (e.g., C14 ranks 1st, C17 ranks 28th). Sub-Figure (b) displays resource allocation rankings (e.g., C02 ranks 2nd, C07 ranks 23rd). Perfectly matched courses, such as C03, C08, and C24, hold identical ranks in both quality and resource allocation. In contrast, mismatched courses like C15 (quality rank 19, resource rank 10) and C23 (quality rank 3, resource rank 11) reveal substantial discrepancies between resource allocation and teaching quality.

MODEL ROBUSTNESS INDICATORS

Model stability in the presence of missing indicators is assessed by randomly eliminating 20% of secondary evaluation indicator data, without altering sample size. Factor analysis and fuzzy TOPSIS ranking are re-executed, simulating scenarios with missing textile-related data, particularly indicators associated with industry-education integration. This procedure is repeated 50 times, producing 50 sets of perturbed course rankings.

Robustness analysis employs two metrics: ranking consistency rate (proportion of courses with unchanged ranking compared to the original) and standard deviation fluctuation of closeness scores. Average consistency rates and 95% confidence intervals are calculated to statistically confirm model ranking stability. Under repeated perturbations, the model's ranking consistency and score stability are tracked across 50 iterations, with robustness trends depicted in Figure 8.

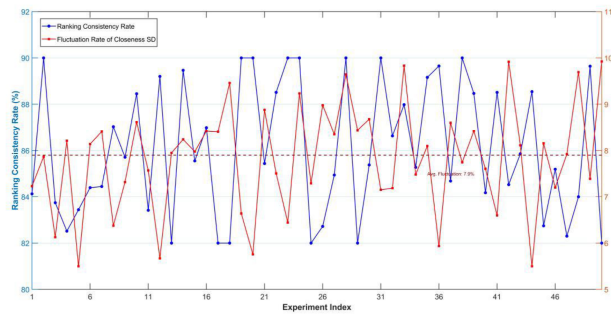

FIGURE 8. Model robustness verification: stability trends across 50 random indicator removal experiments

Figure 8 displays the trend of model robustness over 50 random indicator removal experiments. The horizontal axis denotes experiment number; the left vertical axis represents ranking consistency rate; the right vertical axis shows standard deviation fluctuation of closeness. Consistency rates average 86.1%, ranging from 82% to 90%. Standard deviation shifts average 7.9%, with a range of 5.5% to 9.92%. These results confirm the model's ranking structure remains highly consistent despite indicator omissions, validating robustness.

COMPARISON WITH TRADITIONAL STATIC WEIGHT MODELS

To evaluate the dynamic adaptability and assessment accuracy of the proposed model, a comparative experiment is conducted against two classic static-weight models. Data from 28 textile classes is used, with equal-weighted TOPSIS and entropy-weighted TOPSIS serving as benchmarks. Comparison metrics include recognition accuracy, identification coverage, rank correlation coefficient, and resource adaptation error rate, as summarized in Table 3.

TABLE 3. Comparison Results Between the Proposed Method and Traditional Static Weight Models

Method	Recognition Accuracy (%)	Identification Coverage (%)	Spearman Rank Correlation	Resource Adaptation Error Rate (%)
Proposed Method	85.7	83.3	0.82	13.2
Equal-weighted TOPSIS	71.4	—	0.68	21.5
Entropy-weighted TOPSIS	75.0	—	0.71	19.8

As indicated in Table 3, the proposed method outperforms static models in both recognition accuracy and resource allocation matching. Compared with expert annotations, the proposed model significantly enhances recognition accuracy and reduces resource adaptation error. Rank correlation analysis reveals notable differences between static and dynamic methods, confirming the effectiveness of factor analysis dimensionality reduction and dynamic weight allocation in improving evaluation accuracy and consistency.

IV. CONCLUSIONS

This paper presents a comprehensive evaluation model for teaching quality in textile university courses, integrating fuzzy TOPSIS and factor analysis to address indicator conflicts and static weight lag. Empirical analysis of 28 courses validates the model's effectiveness: it achieves 85.7% accuracy, with coverage of expert-designated advanced courses at 83.3%. The Spearman rank correlation coefficient between student innovation factor scores and subjective student evaluations is 0.74. Robustness tests indicate that, even with random deletion of 20% of metric data, the average consistency between ranking results and the original ranking is 86.1%. The model enhances the responsiveness of evaluation outcomes to dynamic course development, provides a scientific foundation for teaching quality diagnosis and resource allocation optimization, and offers practical guidance for improving teaching quality in textile education.

AUTHOR CONTRIBUTIONS

Conceptualization – Xuehao Hou and Xiaowei Wu; methodology – Xuehao Hou and Xiaowei Wu; formal analysis – Xuehao Hou and Xiaowei Wu; investigation – Xuehao Hou; resources – Xuehao Hou; writing – Xuehao Hou and Xiaowei Wu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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