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Optimization of the Reform Path for Higher Education Teaching Evaluation Based on the ELM Algorithm

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Abstract As a solid foundation for gradually establishing and improving the teaching quality assurance system, ensuring the standardized conduct of the teaching process, and enhancing teaching quality, teaching supervision work in higher education institutions plays a crucial role in strengthening the management of teaching processes. To improve the objectivity, scientific rigor, and rationality of teaching quality in higher education institutions, this study first conducted a principal component analysis on 26 factors influencing teaching quality to extract the principal components of these factors. PSO algorithm parameters were set, and the particle swarm optimization algorithm was used to search for the optimal input weights and hidden layer neuron thresholds of the extreme learning machine (ELM) model, thereby proposing an educational quality evaluation model that integrates principal component analysis, particle swarm optimization, and extreme learning machine (PCA-PSO-ELM). Compared to the ELM model, the ELM model optimized by PCA and PSO algorithms has lower error rates and more reliable prediction results. In terms of educational quality grading, the results of the 34 tested datasets fully align with actual outcomes. Finally, based on the fsQCA analysis results, four reform pathways were proposed to enhance higher education quality.

Index Terms principal component analysis, particle swarm optimization algorithm, extreme learning machine, educational quality evaluation model, fsQCA

I. Introduction

Optimizing the reform path of educational evaluation is a critical step in promoting high-quality development of higher education and fulfilling the fundamental task of fostering virtue and cultivating talent [1], [2]. Establishing a long-term mechanism is of great significance for the sustained and in-depth advancement of educational evaluation reform, as it can effectively overcome the shortcomings of traditional evaluation systems, such as the “five sole criteria” (sole reliance on scores, sole reliance on admission rates, sole reliance on diplomas, sole reliance on papers, and sole reliance on titles), and contribute to the scientific, professional, and standardized development of educational evaluation [3]-[6]. This not only concerns the optimization and upgrading of the education system but also has a profound impact on cultivating innovative talents that meet the needs of the new era and enhancing the country's educational competitiveness [7]-[9].

To optimize the reform path of education and teaching evaluation in colleges and universities, we can start from the following aspects: (1) Improve the system of policies and regulations: Construct laws and regulations related to educational evaluation, standardize the behavior of evaluation subjects, effectively protect the legitimate rights and interests of students, teachers, and schools, and make evaluation activities run in an orderly manner on the track of the rule of law [10], [11]. (2) Strengthen organizational leadership and coordinated advancement: Establish a special leading group for educational evaluation reform, whose members include government departments, education experts, school representatives, and other forces, and are responsible for coordinating the reform work [12], [13]. Clarify the division of responsibilities of each member unit, strengthen communication and cooperation between departments, and gather the joint force of reform [14]. (3) Building a professional evaluation team: Strengthen the training of evaluation professionals, set up educational evaluation courses in normal colleges and universities, and cultivate professionals with a solid theoretical foundation and practical ability [15]-[17]. Evaluation training is provided for in-service teachers and educational administrators to improve their evaluation literacy and competence [18]. (4) Promote innovation in evaluation technology: Make full use of modern information technology, such as big data, artificial intelligence, and cloud computing, to provide technical support for educational evaluation [19]-[21]. By building an education big data platform, various data in the learning process of students are collected and analyzed to achieve accurate evaluation of students' development [22], [23].

This paper proposes a PCA-PSO-ELM evaluation model for educational quality in higher education institutions. Based on the actual situation of teaching quality construction in higher education institutions, factors influencing undergraduate teaching quality were summarized, and 26 key influencing factors were identified. A survey questionnaire was designed based on the actual situation of teaching quality construction at a specific higher education institution, and an evaluation indicator system suitable for teaching quality evaluation in higher education institutions was established. Through questionnaire surveys, the 26 factors were categorized into four groups. Principal component analysis was used to extract six principal components to replace the original 26 factors, simplifying the original data while maximizing data utilization. Data from 114 universities obtained through the survey were used to test and train the constructed model, verifying the effectiveness and superiority of the evaluation model. Finally, using fsQCA, based on the six extracted principal components, the study explored the development paths for new high-quality schools. Four reform paths for university education and teaching were proposed: improving course-based teaching, developing distinctive educational characteristics, mobilizing the potential of faculty and students, and addressing organizational issues.

II. Evaluation model for the quality of higher education teaching and learning

II. A. Principal component analysis

Principal component analysis (PCA) uses the idea of dimension reduction to transform high-dimensional variables into a set of linearly independent data through linear transformation. The transformed variables are the principal components [24].

Step 1. Assume that the sample data is:

$$X=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

Then standardize the data:

$$x_{ij}^{*}=(x_{ij}-\overline{x_j})\otimes s_j^{-1} \tag{2}$$

$$\overline{x_j}=\sum_{i=1}^{n} x_j \times n^{-1} \tag{3}$$

$$s_j=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_{ij}-\overline{x_j})^2} \tag{4}$$

In the formula, x_{ij} is the value of the variable in the i th sample. x_j is the sample mean of variable x_j. s_j is the sample standard deviation. x_{ij}^{*} is the standardized value of x_{ij}, forming the standardized data matrix X^{*}.

Step 2. Calculate the correlation coefficient matrix R:

$$R=\frac{X^{*T}X^{*}}{n-1} \tag{5}$$

Solve the characteristic equation $|\lambda E-R|=0$ (where E is the identity matrix) to obtain the eigenvalues $\lambda_i(i=1,2,\cdots,m),\lambda_1\geq\lambda_2\geq\cdots\geq\lambda_n\geq 0$ of the correlation coefficient matrix R. Solve $(\lambda_i E-R)=0$ to obtain the eigenvector $\mu_1\geq\mu_2\geq\cdots\geq\mu_n$ corresponding to λ_i, thereby obtaining the eigenvalues and eigenvectors.

Step 3. Calculate the variance contribution rate q_j and the cumulative variance contribution rate Q_m:

$$q_j=\frac{\lambda}{\sum_{j=1}^{m}\lambda_j} \tag{6}$$

$$Q_m=\sum_{j=1}^{m}q_j \tag{7}$$

Step 4. Determine the number of principal components based on the cumulative variance contribution rate, and calculate the principal components based on the influence factor component matrix.

II. B.PSO Algorithm

The PSO algorithm is an evolutionary computing technique proposed based on the observation and analysis of bird flocks' hunting and cooperative behavior. The mass and volume of each particle can be ignored. Particles fly through the search space at a certain speed and adjust their spatial positions based on experience.

The basic algorithm principle: in a particle search space with a dimension of n, there is a population containing m particles, where the spatial position of the j particle is $x_j = (x_{j1}, x_{j2}, \cdots, x_{jn})$, and the movement speed of the particles is $v_j = (v_{j1}, v_{j2}, \cdots, v_{jn})$, the optimal position of the particle is $P_j = (P_{j1}, P_{j2}, \cdots, P_{jn})$, the optimal position of the population is $P_g = (P_{g1}, P_{g2}, \cdots, P_{gt})$, the spatial position and movement speed of each particle are constantly changing during the iteration, the formula is:

$$v_{jn}^{i+1} = \omega \cdot v_{jn}^{i} + c_1 \cdot r_1 (P_{jn}^{i} - x_{jn}^{i}) + c_2 \cdot r_2 (P_{jn}^{i} - x_{jn}^{i}) \tag{8}$$

$$x_{ji}^{i} = x_{ji}^{i} + v_{jn}^{i} \tag{9}$$

In the formula: i is the iteration count. ω is the inertia weight factor. c_1, c_2 are learning factors. r_1, r_2 are random numbers in the interval [0, 1]. The PSO algorithm process is shown in Figure 1.

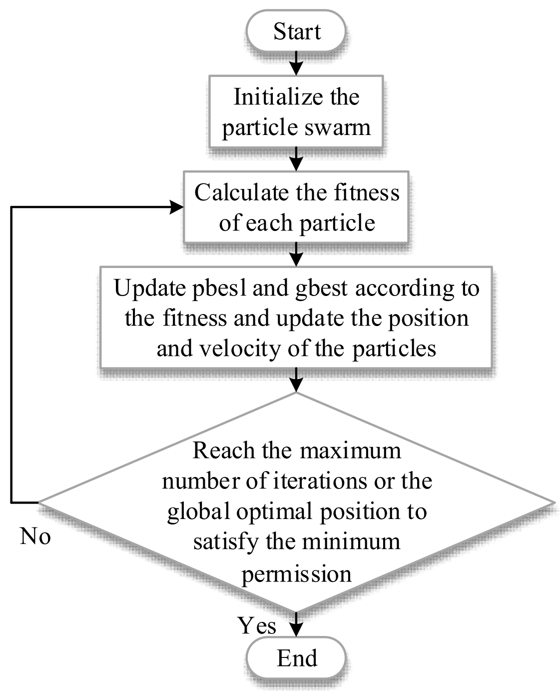

Figure 1: PSO algorithm flow

II. C.PSO-ELM Neural Network Principle

With the development of computer technology, many algorithms have been used to solve practical problems. Traditional classification methods often use BP neural networks, but they converge slowly and the selection of weights and thresholds is highly subjective, which can easily lead to misclassification and has certain limitations. However, compared with BP neural networks, ELM is a feedforward neural network with fast learning speed and strong generalization ability, containing one hidden layer. Its principle is as follows:

Assuming there are n random training samples $(x_i, t_i), x_i = (x_i 1, x_{i2}, \cdots, x_{in})^T, t_i = (t_{i1}, t_{i2}, \cdots, t_{im})^T, x_i \in R^n, t_i \in R^m$, when the ELM has L hidden layer nodes, the output layer function expression is:

$$o_j = \sum_{i=1}^{L} \beta_i g(\omega_i \cdot x_j + b_j), j = 1, \cdots, N \tag{10}$$

When the error in the output result is smallest, it is represented as $\sum_{j=1}^{N}\| o_j - t_j \| = 0$ (o_j is the output result), indicating that the expected learning objective has been achieved. That is:

$$H\beta = T \tag{11}$$

In the formula: H is the hidden layer output matrix. β is the output weight. T is the expected output.

$$H = \begin{bmatrix} g(\omega_1 \cdot x_1 + b_1) & \cdots & g(\omega_1 \cdot x_1 + b_L) \\ \vdots & & \vdots \\ g(\omega_1 \cdot x_N + b_1) & \cdots & g(\omega_L \cdot x_N + b_L) \end{bmatrix}_{N \times L} \tag{12}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_L^T \end{bmatrix}_{L \times m}; T = \begin{bmatrix} T_1^T \\ \vdots \\ T_N^T \end{bmatrix}_{N \times m} \tag{13}$$

$$\overline{\beta} = H^+ \cdot T \tag{14}$$

In equation (12), when the input weights ω_i and biases b_i are randomly determined, the output matrix H is uniquely determined.

The input layer weights and hidden layer biases of the ELM neural network are random and determined by human factors, making them highly subjective. The PSO algorithm improves the ELM neural network by overcoming this drawback and finding the optimal initial parameters [25], [26].

II. D.PCA-PSO-ELM Algorithm Process

The PCA-PSO-ELM prediction model proposed in this paper consists of three stages.

(1) PCA processing stage. PCA is used to reduce the dimensionality of the seven factors affecting earthquake fatalities, eliminating correlations and redundancies between the factors.

(2) Particle swarm optimization phase. The principal component scores calculated by PCA are used as input for the PSO-ELM prediction model. Parameters such as particle velocity and position for the PSO optimization algorithm, as well as model termination conditions, are set, and model training is conducted.

(3) ELM network training phase. The initial weights optimized by PSO are substituted into the ELM model for testing, and the results are analyzed. The model processing workflow is shown in Figure 2.

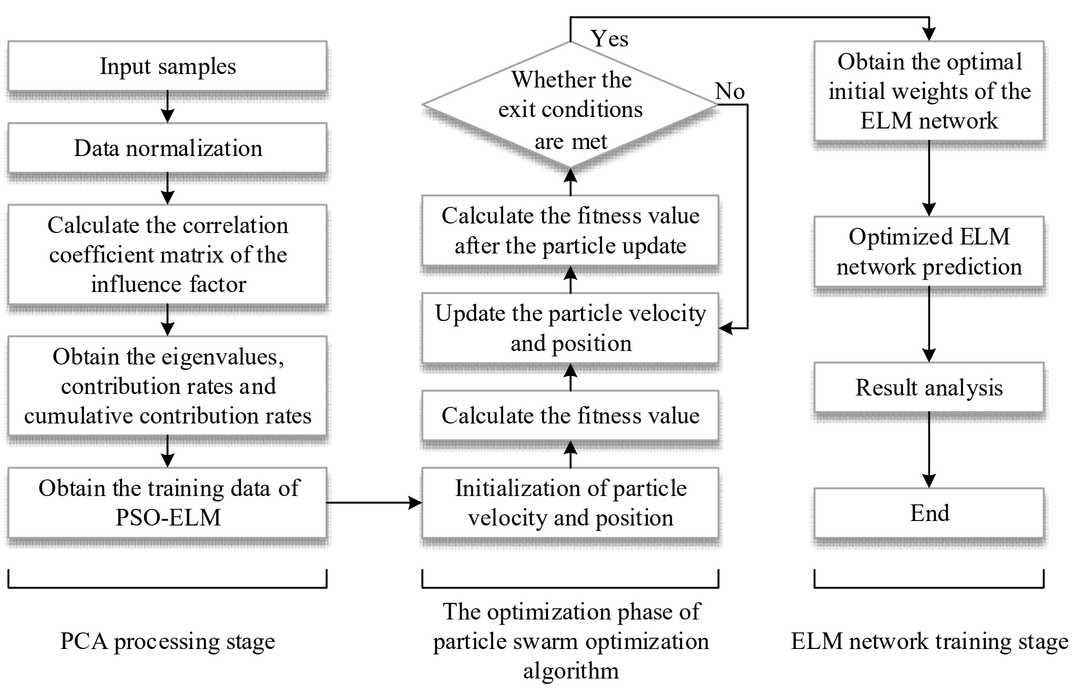

Figure 2: The flow chart of PCA-PSO-ELM mode

III. Educational and teaching quality evaluation index system

III. A. Construction Principles and Methods

In the construction of an evaluation indicator system for the quality of higher education teaching and learning, it is crucial to clearly define four fundamental principles: scientific rigor, systematicity, practicality, and dynamism. These principles ensure that the evaluation system is not only comprehensive and practical but also capable of adapting in a timely manner to changes in educational needs and industry standards.

The scientific nature of the evaluation system requires that the selection and design of indicators be based on rigorous educational theory and empirical evidence. This means that each indicator should have a clear theoretical foundation and empirical basis, accurately reflecting the quality status of vocational education and teaching. Systemicity emphasizes that the indicator system must comprehensively reflect the quality of higher education teaching from multiple dimensions. The indicators should not only assess academic achievements but also evaluate teaching processes, student development, educational resources, and the educational environment. Systematicity ensures that evaluation results comprehensively reflect the multifaceted impacts of educational activities. The operability of the indicator system requires evaluation tools and methods to be easy to implement and effectively used by educational administrators and teachers. Indicators should be specific and clear, facilitating data collection and analysis, making the evaluation process both effective and efficient. The principle of dynamism requires the evaluation system to adapt to changes in educational policies, technology, and market demands. As the vocational field rapidly develops, the evaluation system also needs to be regularly updated to maintain its relevance and effectiveness.

To construct such a multidimensional, scientifically reasonable evaluation system, the Delphi method and the Analytic Hierarchy Process (AHP) can be adopted. The Delphi method defines evaluation indicators by collecting and summarizing expert opinions, which enhances the system's comprehensiveness and professionalism. Through multiple rounds of questionnaire surveys, the Delphi method helps researchers integrate expert consensus to define teaching quality evaluation indicators that meet practical needs.

The Analytic Hierarchy Process (AHP) is used to assign weights to these indicators. By constructing a hierarchical structure model, complex evaluation problems are decomposed into multiple components, each of which is further divided into smaller elements. Through comparative analysis, AHP can help determine the relative importance of different indicators, making the evaluation system more precise and customized. By combining these two methods, the teaching quality evaluation system for vocational education will be more scientific and effective, comprehensively reflecting educational quality and guiding future educational improvements and decision-making.

III. B. Overall framework of the evaluation indicator system

The teaching quality evaluation system is a complex, non-linear system. After conducting in-depth research on frontline teachers, teaching management departments, teaching supervision groups, and student feedback, this paper established a three-level teaching quality evaluation indicator system model. A judgment matrix was then constructed to compare indicators at the same level with each other, determine the weight of each indicator, and finally perform a hierarchical total ranking and consistency test. The resulting teaching quality evaluation indicator system is shown in Table 1.

Table 1: Education teaching quality evaluation index

Primary indicator	Secondary indicator	Tertiary index
Evaluation of teaching quality in colleges and universities	Teaching quality goals and management responsibilities	X1. Personnel training target audit
		X2. Professional design evaluation
		X3. Undergraduate evaluation
		X4. Functional assessment
		X5. Institutional rationality evaluation
		X6. Quality assurance system evaluation
		X7. The policy system performs monitoring
		X8. Standard rationality evaluation
	Teaching resource management	X9. Staff evaluation
		X10. Teacher's teaching evaluation
		X11. Funding monitoring
		X12. Teaching hardware scientific evaluation

		X13. Professional assessment
		X14. Course assessment
		X15. Textbook evaluation
		X16. Evaluation of research and reform projects
	Teaching process management	X17. The talent training plan reviews
		X18.Supervision and evaluation of xufeng construction
		X19. Evaluation of teaching quality monitoring
		X20. Practice teaching quality evaluation
		X21. Evaluation of teaching management documents
	Student	X22. Source quality evaluation
		X23. Student evaluation
		X24. Graduation degree award review
		X25. Student employment review
		X26. Graduation satisfaction survey

IV. Evaluation of the quality of higher education teaching and learning

IV. A. Determination of model input variables

To compare different methods, this paper also employs principal component analysis (PCA) to evaluate the teaching quality of the school. PCA aims to simplify data while ensuring high data utilization. In this study, the principal components of 26 factors were extracted based on a cumulative contribution rate of 94%. To ensure the reliability of the extraction results, the data from four years were uniformly processed during data extraction, yielding the final principal components and contribution rates (weights). To enable comparison with the analytic hierarchy process, the weighted results of the principal components were scaled vertically to obtain the final evaluation results (ranging from 60 to 100). The data from 2015 to 2018 were still selected as the original data, and the variance results extracted through calculation are shown in Table 2.

Table 2 shows the total variance of the original evaluation indicators explained by each component. Based on the principle that the cumulative contribution rate reaches a certain value (generally between 85% and 95%), this paper extracted six principal components according to the cumulative contribution rate of 94.446%. That is, these six principal components contain 94.446% of the information in the original data, and these principal components can represent the main factors affecting the teaching quality of the university.

Table 2: Explains the total variance

Constituent	Initial eigenvalue			Extract the sum of squares and load		
	Total	Variance/%	Cumulation/%	Total	Variance/%	Cumulation/%
1	9.354	35.977	35.977	9.354	35.977	35.977
2	6.446	24.792	60.769	6.446	24.792	60.769
3	4.532	17.431	78.200	4.532	17.431	78.200
4	2.383	9.165	87.365	2.383	9.165	87.365
5	1.056	4.062	91.427	1.056	4.062	91.427
6	0.785	3.019	94.446	0.785	3.019	94.446
7	0.629	2.419	96.865			
8	0.162	0.623	97.488			
9	0.101	0.388	97.876			
10	0.082	0.315	98.191			
11	0.072	0.277	98.468			
12	0.065	0.250	98.718			
13	0.059	0.227	98.945			
14	0.054	0.208	99.153			
15	0.026	0.100	99.253			
16	0.025	0.096	99.349			
17	0.025	0.096	99.445			
18	0.025	0.096	99.541			
19	0.022	0.085	99.626			

20	0.022	0.085	99.711			
21	0.021	0.081	99.792			
22	0.021	0.081	99.873			
23	0.015	0.058	99.931			
24	0.012	0.046	99.977			
25	0.005	0.019	99.996			
26	0.001	0.004	100.000			

The principal components F1 to F6 are named technical facilities, core concepts, organizational leadership, curriculum and teaching, teacher team, and student development, respectively. Table 3 shows the principal component factor loading matrix, which displays the linear relationship between the original variables and the principal components. It can largely represent the loadings of each principal component on each variable, thus enabling the derivation of the score expressions for these six principal components:

F1 = 0.298X1 + 0.204X2 - 0.272X3 - 0.17X4 + 0.076X5 + 0.053X6 - 0.34X7 - 0.058X8 + 0.283X9 + 0.111X10 - 0.336X11 + 0.769X12 - 0.403X13 - 0.377X14 + 0.505X15 + 0.402X16 + 0.131X17 + 0.115X18 + 0.168X19 + 0.149X20 + 0.117X21 + 0.019X22 + 0.264X23 - 0.184X24 + 0.147X25 + 0.073X26

F2 = 0.844X1 - 0.397X2 - 0.073X3 + 0.088X4 - 0.14X5 + 0.241X6 - 0.099X7 + 0.818X8 + 0.42X9 + 0.054X10 + 0.169X11 - 0.143X12 - 0.219X13 + 0.356X14 - 0.417X15 - 0.425X16 + 0.681X17 - 0.208X18 + 0.234X19 + 0.122X20 + 0.118X21 + 0.28X22 - 0.224X23 - 0.189X24 - 0.17X25 + 0.075X26

F3 = 0.057X1 - 0.401X2 + 0.026X3 + 0.822X4 + 0.781X5 + 0.863X6 + 0.774X7 + 0.356X8 + 0.437X9 + 0.074X10 + 0.649X11 + 0.109X12 - 0.192X13 + 0.152X14 + 0.084X15 - 0.056X16 + 0.02X17 - 0.388X18 + 0.131X19 - 0.149X20 + 0.817X21 - 0.083X22 + 0.09X23 - 0.446X24 - 0.215X25 - 0.146X26

F4 = 0.275X1 + 0.747X2 + 0.827X3 - 0.019X4 + 0.275X5 + 0.315X6 - 0.317X7 + 0.38X8 - 0.059X9 - 0.42X10 + 0.218X11 + 0.333X12 + 0.678X13 + 0.704X14 + 0.705X15 + 0.582X16 + 0.335X17 + 0.148X18 + 0.69X19 + 0.696X20 - 0.107X21 + 0.097X22 - 0.338X23 + 0.079X24 - 0.142X25 - 0.036X26

F5 = -0.155X1 - 0.438X2 - 0.315X3 + 0.424X4 - 0.364X5 - 0.101X6 + 0.434X7 - 0.425X8 + 0.883X9 + 0.893X10 + 0.417X11 - 0.058X12 + 0.319X13 + 0.166X14 + 0.108X15 - 0.432X16 - 0.095X17 + 0.26X18 + 0.179X19 - 0.417X20 + 0.171X21 + 0.005X22 - 0.45X23 + 0.303X24 - 0.178X25 + 0.27X26

F6 = 0.285X1 - 0.224X2 + 0.134X3 + 0.306X4 - 0.017X5 - 0.313X6 - 0.323X7 + 0.05X8 + 0.064X9 - 0.224X10 + 0.222X11 + 0.401X12 + 0.402X13 + 0.009X14 - 0.415X15 - 0.187X16 + 0.424X17 + 0.641X18 - 0.092X19 + 0.119X20 + 0.16X21 + 0.819X22 + 0.864X23 + 0.558X24 + 0.673X25 + 0.731X26

Use these six principal components as input variables for the next step of the PCA-PSO-ELM prediction model.

Table 3: Main component factor load matrix

Evaluation index	Constituent					
	1	2	3	4	5	6
X1	0.298	**0.844**	0.057	0.275	-0.155	0.285
X2	0.204	-0.397	-0.401	**0.747**	-0.438	-0.224
X3	-0.272	-0.073	0.026	**0.827**	-0.315	0.134
X4	-0.17	0.088	**0.822**	-0.019	0.424	0.306
X5	0.076	-0.14	**0.781**	0.275	-0.364	-0.017
X6	0.053	0.241	**0.863**	0.315	-0.101	-0.313
X7	-0.34	-0.099	**0.774**	-0.317	0.434	-0.323
X8	-0.058	**0.818**	0.356	0.38	-0.425	0.05
X9	0.283	0.42	0.437	-0.059	**0.883**	0.064
X10	0.111	0.054	0.074	-0.42	**0.893**	-0.224
X11	-0.336	0.169	**0.649**	0.218	0.417	0.222
X12	**0.769**	-0.143	0.109	0.333	-0.058	0.401
X13	-0.403	-0.219	-0.192	**0.678**	0.319	0.402
X14	-0.377	0.356	0.152	**0.704**	0.166	0.009
X15	0.505	-0.417	0.084	**0.705**	0.108	-0.415
X16	0.402	-0.425	-0.056	**0.582**	-0.432	-0.187
X17	0.131	**0.681**	0.02	0.335	-0.095	0.424
X18	0.115	-0.208	-0.388	0.148	0.26	**0.641**
X19	0.168	0.234	0.131	**0.69**	0.179	-0.092

X20	0.149	0.122	-0.149	**0.696**	-0.417	0.119
X21	0.117	0.118	**0.817**	-0.107	0.171	0.16
X22	0.019	0.28	-0.083	0.097	0.005	**0.819**
X23	0.264	-0.224	0.09	-0.338	-0.45	**0.864**
X24	-0.184	-0.189	-0.446	0.079	0.303	**0.558**
X25	0.147	-0.17	-0.215	-0.142	-0.178	**0.673**
X26	0.073	0.075	-0.146	-0.036	0.27	**0.731**

IV. B. Verification of the rationality of model stage division

Data was collected through university surveys combined with quantitative standards for evaluation indicators. The collected data helps to provide detailed support for case studies by understanding the development levels of universities in smart manufacturing across various evaluation indicators. A total of 120 universities in Zhejiang Province were visited and surveyed for this study. Among these, 114 valid data sets were obtained.

University scores were calculated based on predetermined weights. The criteria for determining the educational and teaching levels of universities are shown in Table 4, and the scores for each stage of the evaluation are shown in Table 5. Through the calculation of scores for each stage, it was found that all 114 universities possess the relevant capabilities and development conditions.

Table 4: Education teaching level evaluation standards

Grade	Score
5	[2.5,3]
4	[2,2.5)
3	[1.5,2)
2	[1,1.5)
1	[0.5,1)

Table 5: Points in each stage

University number	Technical facilities	Core idea	Organizational leadership	Course teaching	Faculty	Student development
1	1.54	1.66	1.66	1.85	1.76	1.66
2	1.47	1.69	1.6	1.68	1.78	1.6
3	1.47	1.79	1.63	1.87	1.82	1.63
……	……	……	……	……	……	……
112	1.57	1.65	1.68	1.79	1.9	1.64
113	1.51	1.77	1.65	1.61	1.75	1.42
114	1.56	1.72	1.54	1.64	2.04	1.56

The six indicator data points from the sample data were analyzed. The numerical change curves are shown in Figure 3. It can be seen that the trends across the six stages are largely consistent, and universities with higher-quality faculty generally also have higher levels of technical facilities, core concepts, organizational leadership, course instruction, and student development compared to other universities.

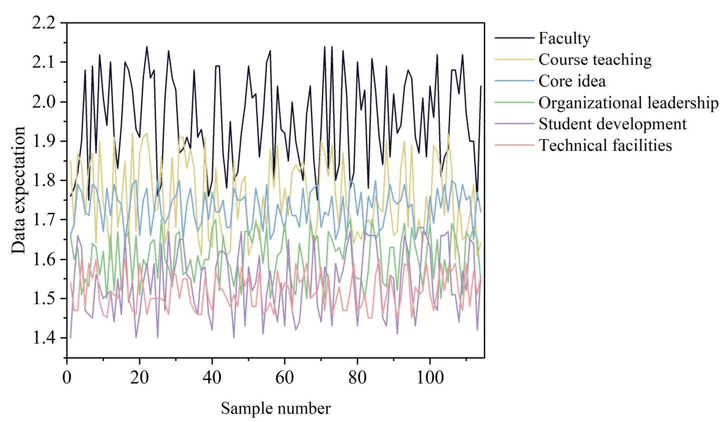

Figure 3: Data expected change curve

Next, a correlation analysis was conducted on the sample data for the six indicators, with the results shown in Table 6. As can be seen from Table 6, the correlation coefficients between the indicators are all greater than 0.5. Table 7 presents the criteria for judging correlation coefficients. Based on this table, it can be concluded that the relationships between the indicators are closely interrelated. Therefore, it is reasonable to adopt a phased approach for evaluating the educational and teaching standards of higher education institutions.

Table 6: Correlation analysis results

Index	Technical facilities	Core idea	Organizational leadership	Course teaching	Faculty	Student development
Technical facilities	1					
Core idea	0.691**	1				
Organizational leadership	0.638**	0.72**	1			
Course teaching	0.711**	0.747**	0.657**	1		
Faculty	0.646**	0.607**	0.748**	0.582**	1	
Student development	0.597**	0.652**	0.555**	0.631**	0.658**	1

Note: ** indicates significant correlation at the 0.01 level.

Table 7: Correlation coefficient judgment criteria

Correlation coefficient	Judging result
≥0.7	Very close
0.4~0.7	Close relationship
0.2~0.4	Relations
≤0.2	Weak relationship

IV. C. Verification of the superiority of the model in university evaluation

To further validate the superiority of the PCA-PSO-ELM model in evaluating the quality of higher education teaching and learning, the comprehensive score was calculated again using a weighted sum method, with the evaluation results shown in Table 8. Additionally, the teaching quality standard evaluation model was used to assess the 114 surveyed universities, referencing the current standard model grading criteria and the corresponding teaching quality evaluation methods of this model. A quantitative assessment was also conducted on the 114 universities, with the final results shown in Table 9. An analysis of the evaluation results from the two models is presented in Figure 4, which shows the data change curves. As shown in Figure 4, the evaluation results using the current standard model struggle to distinguish the gaps between universities and assess their developmental levels. However, the evaluation model established in this paper can clearly differentiate the developmental levels of different universities. Therefore, the validation results demonstrate the superiority and applicability of this model in evaluating the quality of higher education teaching and learning.

Table 8: Expected Output Values of sample data

University number	Comprehensive score	University number	Comprehensive score	University number	Comprehensive score
1	1.77	……	……	108	1.5
2	2.01	……	……	109	2.05
3	2.24	103	2.06	110	1.53
4	2.38	104	2.04	111	1.8
5	1.85	105	1.55	112	1.86
6	2.42	106	2.25	113	2.37
……	……	107	2.15	114	2.32

Table 9: Evaluation Results of the standard model

University number	Comprehensive score	University number	Comprehensive score	University number	Comprehensive score
1	0.93	……	……	108	0.96
2	0.99	……	……	109	0.95
3	0.91	103	0.85	110	1.01
4	0.87	104	0.98	111	0.95
5	1.01	105	0.92	112	1.03

6	1.05	106	1.04	113	0.93
……	……	107	0.85	114	1.01

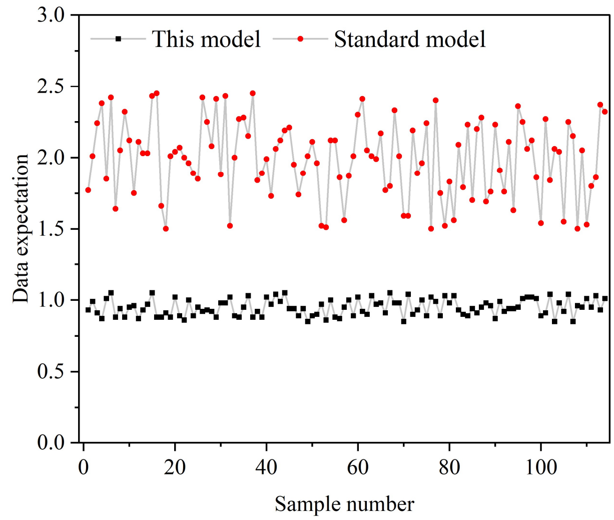

Figure 4: Comparison of model results

IV. D. PCA-PSO-ELM Model Training and Testing

IV. D. 1) Training of the PCA-PSO-ELM model

This paper collected 114 valid data points, using the first 80 as training data samples and the remaining 34 as test data samples.

The MATLAB 2020b trial version was used as the platform for training and simulating the PCA-PSO-ELM model. The training data was input into the PCA-PSO-ELM program for training, and the PSO optimization iteration results are shown in Figure 5. As can be seen from Figure 5, after 50 iterations, the error value tends to level off.

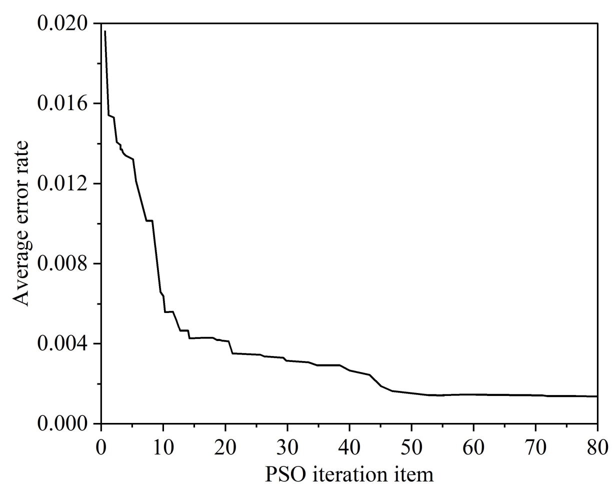

Figure 5: PSO optimization iteration diagram

IV. D. 2) PCA-PSO-ELM model testing

The 34 sets of test data were input into the pre-trained PCA-PSO-ELM model for simulation. The simulation results are shown in Figure 6. As can be seen from Figure 6, the optimized ELM algorithm achieves higher accuracy and lower error compared to the pre-optimized prediction results. Furthermore, the optimized regression coefficient R^2 is very close to 1 compared to the original model, indicating that the evaluation performance of the PCA-PSO-ELM model is excellent. Table 10 shows the comparison results of the relative errors between the model output values and the actual values for the test set samples. It can be concluded that the PCA-PSO-ELM evaluation model has a small error, and the classification results are fully consistent, which also demonstrates that this algorithm has a certain degree of accuracy and feasibility in the evaluation of higher education teaching quality.

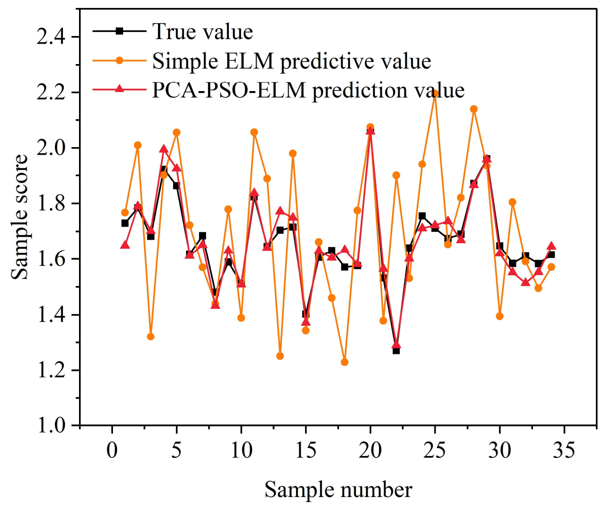

Figure 6: Algorithm simulation results

Table 10: Relative error

Test set	True value	Grade	Optimize model evaluation	Grade	Relative error	YES/NO
1	1.729	3	1.649	3	0.04627	YES
2	1.784	3	1.79	3	-0.00336	YES
3	1.682	3	1.701	3	-0.0113	YES
4	1.923	3	1.994	3	-0.03692	YES
5	1.863	3	1.925	3	-0.03328	YES
6	1.618	3	1.611	3	0.004326	YES
7	1.684	3	1.651	3	0.019596	YES
8	1.481	2	1.432	2	0.033086	YES
9	1.589	3	1.63	3	-0.0258	YES
10	1.511	3	1.509	3	0.001324	YES
11	1.823	3	1.836	3	-0.00713	YES
12	1.645	3	1.641	3	0.002432	YES
13	1.704	3	1.771	3	-0.03932	YES
14	1.715	3	1.749	3	-0.01983	YES
15	1.403	2	1.372	2	0.022096	YES
16	1.606	3	1.629	3	-0.01432	YES
17	1.631	3	1.605	3	0.015941	YES
18	1.571	3	1.633	3	-0.03947	YES
19	1.576	3	1.582	3	-0.00381	YES
20	2.064	4	2.059	4	0.002422	YES
21	1.532	3	1.565	3	-0.02154	YES
22	1.271	2	1.29	2	-0.01495	YES
23	1.64	3	1.601	3	0.02378	YES
24	1.755	3	1.711	3	0.025071	YES
25	1.711	3	1.722	3	-0.00643	YES
26	1.674	3	1.736	3	-0.03704	YES
27	1.69	3	1.668	3	0.013018	YES
28	1.871	3	1.865	3	0.003207	YES
29	1.961	3	1.959	3	0.00102	YES
30	1.648	3	1.62	3	0.01699	YES
31	1.584	3	1.552	3	0.020202	YES

32	1.611	3	1.514	3	0.060211	YES
33	1.583	3	1.553	3	0.018951	YES
34	1.616	3	1.645	3	-0.01795	YES

V. Configuration analysis of key factors in building new high-quality schools

V. A. Necessary Condition Analysis

Before conducting factor configuration analysis, it is necessary to perform a necessity analysis on the conditional variables to determine the explanatory effect of individual factors on the teaching quality of higher education institutions. This is reflected in the conditional variables as whether they are necessary conditions for the outcome variables. When the consistency of the conditional variables exceeds 0.9 and the coverage rate exceeds 0.5, the conditional variable is considered a necessary condition. The necessity analysis of single conditional variables is shown in Table 11. Regardless of whether the educational and teaching quality of higher education institutions is high or low, the consistency levels of the six conditional variables are all below 0.9, indicating that the explanatory power of individual conditional variables on higher education institutions is insufficient. This suggests that the quality of higher education institutions is not the result of a single factor but rather the result of multiple factors interacting. Therefore, it is necessary to analyze the configuration of each variable.

Table 11: Necessity analysis of single element variables

Variable	Factual analysis		Counterfact analysis	
	Consistency	Coverage	Consistency	Coverage
Technical facilities	0.382	0.783	0.475	0.430
~ Technical facilities	0.741	0.700	0.815	0.360
Core idea	0.555	0.746	0.543	0.351
~ Core idea	0.546	0.696	0.650	0.410
Organizational leadership	0.572	0.877	0.349	0.285
~ Organizational leadership	0.585	0.670	0.858	0.460
Course teaching	0.728	0.826	0.596	0.310
~ Course teaching	0.401	0.647	0.689	0.564
Faculty	0.825	0.904	0.584	0.329
~ Faculty	0.443	0.639	0.833	0.633
Student development	0.710	0.830	0.647	0.383
~ Student development	0.514	0.753	0.746	0.510

V. B. Factor Configuration Analysis

Given the number of cases, this study set the frequency threshold before truth table analysis to 1 and the consistency threshold to 0.8. The truth table was constructed and adjusted using fsQCA 4.1 software, followed by standardization analysis to obtain complex solutions, simplified solutions, and intermediate solutions for the conditional variable configurations. Considering the advantages and disadvantages of the simplified and complex solutions, this study followed previous practices, using the intermediate solution as the primary focus and the simplified solution as a supplement for configuration analysis. The conditional variables present in both solutions are core conditions, those present only in the intermediate solution are marginal conditions, and the remaining conditions are not considered. Based on this, five scenarios can be identified: core conditions present, core conditions absent, marginal conditions present, marginal conditions absent, and conditions having no impact on the results. The results are shown in Table 12. Both the consistency of individual solutions and the overall solution is high, indicating a high level of reliability. The coverage rate of the overall solution is 0.799, meaning that the four configurations can explain 79.9% of the new high-quality university construction cases, thereby effectively explaining the characteristics of the effectiveness of new high-quality university construction. The construction of new high-quality universities presents seven different solutions. By comparing the commonalities and differences among the configurations, this study categorizes the seven solutions into four pathways for the construction of new high-quality universities: improving course teaching (I), developing educational characteristics (II), mobilizing the potential of teachers and students (III), and correcting organizational issues (IV). Configuration 1 belongs to the Improving Curriculum and Teaching Type, Configuration 2 belongs to the Cultivating Educational Characteristics Type, Configurations 3 and 4 belong to the Mobilizing Faculty and Student Potential Type, and Configurations 5, 6, and 7 belong to the Addressing Organizational Issues Type.

Table 12: Key factors of new high quality universities

Conditional variable	Ⅰ	Ⅱ	Ⅲ		Ⅳ		
	Configuration 1	Configuration 2	Configuration 3	Configuration 4	Configuration 5	Configuration 6	Configuration 7
Technical facilities	⊗	⊗					⊗
Core idea		●	•			⊗	
Organizational leadership					●	●	●
Course teaching	●			•	⊗		
Faculty			●	●	•	•	
Student development		●	●	●	⊗	⊗	•
Original coverage	0.594	0.349	0.392	0.488	0.199	0.225	0.371
Unique coverage	0.094	0.013	0.018	0.017	0.031	0.007	0.019
Consistency	0.845	0.898	0.947	0.910	0.965	0.961	0.929
Overall coverage	0.799						
Overall consistency	0.862						

Note: ● indicates that the core condition exists. ⊗ indicates that the core condition is missing. ● indicates that the peripheral condition exists. ⊗ indicates that the peripheral condition is missing. A blank space indicates that the condition has no effect on the result.

Improving course teaching refers to the process by which universities enhance the quality of course instruction without significant changes to their physical infrastructure. This is achieved by reorganizing the curriculum, exploring new teaching models and learning methods, and strengthening evaluation and guidance of student learning outcomes. There are numerous typical examples of this approach, involving both newly established and established universities. Newly established universities often have better hardware facilities and more dynamic faculty. By developing a curriculum system with regional characteristics or leveraging the advantages of the main campus to innovate teaching models, they can quickly become new high-quality universities.

Building a distinctive educational profile refers to the process by which universities, without significant changes to their physical infrastructure, clarify their geographical characteristics, refine their educational philosophy, and establish a shared vision among faculty and students. This approach aims to highlight the university's unique educational characteristics, foster a shared sense of value among faculty and students, and through the implementation of a holistic educational approach, further emphasize the university's distinctive educational profile. Typical universities that adopt this approach often have a solid educational foundation but still face challenges in promoting students' all-round development. They are under pressure to reform their educational methods and pursue higher-quality education, and the formation of unique characteristics often requires external catalysts.

Mobilizing the potential of faculty and students refers to focusing on human factors. On the input side, this involves enhancing teachers' professional capital, reforming educational and teaching practices through improved welfare benefits, or restructuring the teacher workforce through recruitment and exit mechanisms to elevate human resource standards. On the output side, it involves enriching the five-education activities and forming a collaborative effort between schools, families, and communities to nurture students' diverse intelligences and enhance educational outcomes. Meanwhile, the enhancement of teachers' professional capital may be accompanied by changes in the university's educational philosophy and vision, and the implementation of five-education activities may be accompanied by reforms in curriculum and teaching. Therefore, while universities are mobilizing the potential of faculty and students, they often also undergo changes in core concepts and curriculum and teaching. Universities that have adopted this development path are mostly those that were previously weak institutions with unstable teaching staff and insufficient vitality. Such universities urgently need to boost the confidence of faculty and students, stimulate expectations for the university's future development, and thereby stabilize student enrollment and faculty, entering a virtuous cycle of development.

The organizational issue correction type refers to universities that, in the absence of significant changes in hardware conditions, core concepts, or even curriculum and teaching, leverage leadership by example and party building to improve work systems and optimize workflows, thereby rationalizing organizational structures and moving toward high-quality development. This development path often involves adjustments to the faculty, as teachers, being key members of the university, the outcomes of organizational issue corrections ultimately manifest in faculty development. Universities adopting this development path can be divided into two categories: one category consists of universities that have fallen into a development bottleneck for various reasons, and these universities often return to the path of development through institutional reforms after undergoing group management or the appointment of new presidents. The other category consists of ordinary universities in regions with many prestigious universities that are exploring breakthroughs for survival and development, and these universities have further enhanced their educational quality and influence after undergoing organizational restructuring.

VI. Conclusion

This paper proposes a higher education teaching quality evaluation model based on PCA-PSO-ELM, which can be applied to the actual evaluation of teaching supervision working groups.

(1) This paper uses the Delphi method to collect and summarize expert opinions to define evaluation indicators. From the perspectives of teaching quality objectives and management responsibilities, teaching resource management, teaching process management, and students, 26 evaluation indicators were selected. Through principal component analysis for dimensionality reduction, six principal components were selected: technical facilities, core concepts, organizational leadership, course instruction, faculty team, and student development.

(2) Based on the model training and testing data, the error converges to a stable state after 50 iterations. Compared to the pre-optimized LEM evaluation model, this model achieves higher evaluation accuracy.

(3) Using fsQCA analysis, it was found that a single factor is insufficient to drive school reform. Further analysis of factor configurations identified four typical pathways for building high-quality schools: improving curriculum and instruction, developing educational characteristics, mobilizing the potential of teachers and students, and addressing organizational issues.

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