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Research on Monitoring System of Postgraduate Education Quality in Electronic Information Major Based on AHP

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Abstract: In the era of strengthening the country through education, the cultivation of high-level innovative talents is of paramount importance. Graduate education, as a crucial pathway for nurturing high-quality talents, has garnered significant attention regarding its quality. Conducting research on its quality monitoring system is an inevitable requirement to meet the needs of high-quality development and enhance national competitiveness. This study establishes a scientific and reasonable quality monitoring index system, objectively and fairly determines the weights of the indices through algorithms, and elaborates on standardized and feasible quality monitoring standards and procedures. In particular, the combined application of the Analytic Hierarchy Process (AHP) and Fuzzy Comprehensive Evaluation Method further enhances the reliability, accuracy, and objectivity of the comprehensive evaluation within the quality monitoring system for master's degree programs in electronic information engineering.

1. Research Background

The report of the 20th National Congress of the Communist Party of China strategically orchestrates the development of education, science and technology, and talent, explicitly stating the goal of achieving a strong educational nation by 2035. This strategic deployment highlights the fundamental and leading role of education in the comprehensive construction of a socialist modernization country, providing clear direction and theoretical support for the research on the construction of a postgraduate training quality monitoring system [1].

As an essential component in the cultivation of such talents, the scale of professional master's education has rapidly expanded, and its training quality has increasingly become a subject of concern [2].

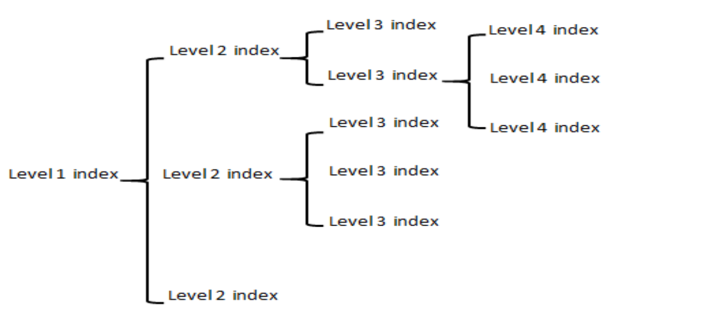
The quality monitoring system can conduct a comprehensive and systematic evaluation of the training process for professional master's students, promptly identify existing problems and deficiencies, and provide targeted improvement measures for the training of master's students in electronic information at our university [3]. Additionally, the quality monitoring system can facilitate communication and comparison among universities, promoting the continuous improvement and development of professional master's education [4].

2. Construction of Monitoring Index System

2.1 Connotation of monitoring index system

The monitoring indicator system is a comprehensive framework, composed of a series of evaluation indicators that reflect the overall aspects of the assessment objectives. It is supplemented by a corresponding indicator weight distribution system, collectively forming a complete evaluation structure [5], as illustrated in Table 1.

Table 1: Monitoring indicator architecture

Index system	Weight coefficient
	ω_1
	ω_2
	...
	ω_n
	$\sum_{i=1}^{n} \omega_i = 1$

The monitoring indicator system is a hierarchical and modularized structure, which is systematically decomposed based on the evaluation objectives. This system comprises multiple sets of indicators, each of which is further subdivided into several subsets [6]. This layered and modularized design possesses significant advantages: when assessing specific aspects of the objectives, one need only select the corresponding module (i.e., subset) to swiftly construct the required indicator system; this approach greatly enhances the targeting and efficiency of the evaluation process [7].

2.2 Monitoring index system construction principles

In constructing the monitoring indicator system, it is essential to balance the number of indicators [8]. Too many can lead to redundancy, compromising accuracy, while too few may result in an incomplete system that fails to fully reflect training quality [9].

Scientific and operational principles require that monitoring indicators precisely capture the essence of training quality, with clear guiding purposes and well-defined conceptual boundaries [10].

Quantitative and qualitative principles emphasize integrating both types of indicators to comprehensively assess training outcomes, adopting a macro-systematic approach [11].

Combine static and dynamic principles to ensure the monitoring system evolves with changes in training objectives, methods, and the educational environment [12]. Static indicators should reflect current realities, while dynamic indicators anticipate future changes [13].

Principles of integrity and independence mandate that the monitoring system ensures internal coherence and comprehensiveness, covering all objectives without omission [14]. The synergistic interaction of indicators collectively fulfills evaluation goals [15].

2.3 Construction of monitoring index system

Upon reviewing literature on monitoring and evaluating master's degree training quality, and considering survey results from questionnaires and the Delphi method, the monitoring indicator system for electronic information training quality has been constructed [16].

In quality monitoring, experts score indicators based on grading standards, forming the evaluation characteristic value matrix. Using the score matrix and a quantitative model, the membership degree matrix is calculated, leading to the level characteristic vector of quantitative evaluation [17].

In qualitative evaluation, monitoring indicators reflect experts' opinions and attitudes toward plan implementation. Opinions are categorized into five levels: excellent, good, fair, average, and poor, while attitudes include agreement, suggestion to modify, and disagreement. Based on expert evaluations, a Boolean matrix of monitoring levels is constructed, and the quality assessment table is developed in line with system requirements.

3. Determination of weight system

Commonly employed methods for determining the weight system encompass the Delphi method, entropy method, fuzzy clustering analysis, and the Analytic Hierarchy Process (AHP) [18].

3.1 Determination method of weight system

It is an evaluation technique that involves pooling the knowledge, wisdom, experience, information, and values of multiple experts to conduct in-depth analysis, assessment, and trade-offs of established evaluation indicators, and to assign corresponding weights. Once the established criteria are met, a preliminary weight vector W^* for the evaluation indicators is obtained. Subsequently, W^* is normalized to determine the final weight vector W^* for each evaluation indicator.

$$\mathrm{W} = \left\{\frac{\mathrm{w}_1^*}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{w}_\mathrm{i}^*}, \frac{\mathrm{w}_2^*}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{w}_\mathrm{i}^*}, \cdots, \frac{\mathrm{w}_\mathrm{n}^*}{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{w}_\mathrm{i}^*}\right\} = \{W_1, W_2, \cdots, W_n\} \tag{1}$$

When indicators exhibit fuzziness, fuzzy clustering analysis classifies them by calculating a fuzzy similarity coefficient, transforming it into a reflexive, symmetric, and transitive equivalence matrix, enabling classification and weight determination. Entropy measures information uncertainty; increased entropy reduces value. The entropy method evaluates weights by calculating information utility coefficients, with higher values indicating greater importance. The Analytic Hierarchy Process (AHP) structures factors hierarchically, measuring relative importance through pairwise comparisons to determine weights, ideal for complex systems. The methods fall into three categories: Delphi and AHP rely on expert judgment, with AHP enhancing rigor mathematically; entropy uses sample information characteristics; and fuzzy clustering classifies indicators based on fuzzy data similarity [19].

3.2 Monitoring system evaluation methods

Mainstream methods for evaluating monitoring systems include Data Envelopment Analysis (DEA), Fuzzy Comprehensive Evaluation (FCE), Grey Relational Analysis (GRA), and the TOPSIS method. DEA uses mathematical programming to compare efficiency among Decision-Making Units (DMUs), requiring more evaluation units than indicators to maintain discriminability. Grey relational assessment quantifies associations among system factors by comparing development trends using geometric relationships of statistical sequences [20]. The TOPSIS method integrates optimal and worst sample values by identifying ideal and negative ideal solutions, ensuring results reflect overall characteristics. Fuzzy comprehensive evaluation addresses fuzzy factors using fuzzy transformation for multi-factor assessments, excelling in handling imprecise information.

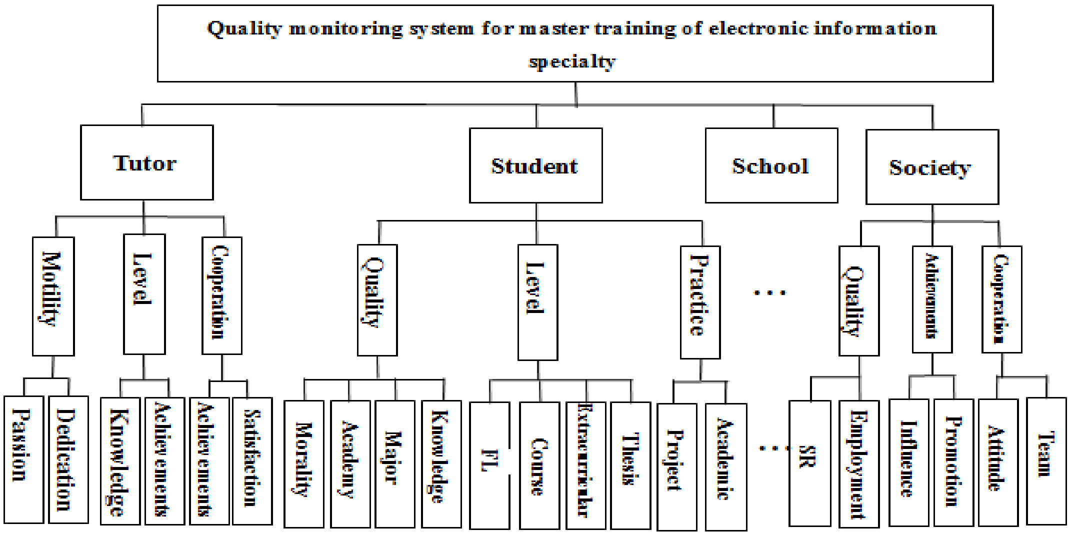
4. Implementation of analytic hierarchy process in training quality monitoring system

4.1 Basic principles of Analytic Hierarchy Process

The Analytic Hierarchy Process (AHP) determines the ranking of factor weights by dividing the elements of complex issues into ordered hierarchies and quantitatively representing the relative importance of each level.

4.2 Establishing the Evaluation Hierarchy Model

As previously discussed, the first-level indicators of the quality monitoring system for master's programs in electronic information include mentors, students, the institution, and society. Each first-level indicator is composed of several second-level indicators, which in turn are composed of several third-level indicators. The hierarchical structure is depicted in Figure 1.



Note: FL means “foreign languages”; SR means “Scientific research”

Figure 1: Hierarchical analysis model of quality monitoring system for master training of electronic information major

4.3 Construct judgment matrix

Firstly, experts in teaching evaluation, instructional supervision, student affairs, academic administration, personnel management, and science and technology management are invited to complete the "Survey on the Importance of Quality Monitoring Indicators for Master's Programs in Electronic Information." Based on their expertise, they rate the significance of each indicator. The importance of these indicators is determined through statistical analysis of the survey data, reflecting varying degrees of importance.

Table 2: Questionnaire on the importance degree of training quality monitoring indicators for electronic information major masters

Secondary index		Degree of importance
Source quality		1 2 3 4 5
Three-level index	1 Ideology and morality	1 2 3 4 5
	2 Academic institution	1 2 3 4 5
	3 Professional background	1 2 3 4 5
	4 Knowledge structure	1 2 3 4 5

Note: In the table 2, the number 1 represents the lowest level of importance, while 5 represents the highest level of importance.

Assuming α and β are the importance scores of any two indicators, the following rules are established to construct the judgment matrix A:

If $0.2<Z_{ij}-Z_{ik}\leq 0.5$, then indicator Z_{ij} is slightly more important than indicator Z_{ik}, and the Saaty scale is set to 3;

If $0.75 <Z_{ij}-Z_{ik}\leq 1.0$, then indicator Z_{ij} is significantly more important than indicator Z_{ik}, and the Saaty scale is set to 5;

If $1.25 <Z_{ij}-Z_{ik}\leq 1.5$, then indicator Z_{ij} is strongly more important than indicator Z_{ik}, and the Saaty scale is set to 7;

If $1.75 <Z_{ij}-Z_{ik}$, then indicator Z_{ij} is extremely more important than indicator Z_{ik}, and the Saaty scale is set to 9;

If the difference falls between two scales, the Saaty scale is set to 2, 4, 6, or 8.

Suppose 20 experts score the importance of the third-level indicators under the second-level indicator of student source quality. The total and average scores are presented in Table 3.

Table 3: Total and average scores of the four three-level indicators

Score Index	Ideology and morality	Academic institution	Professional background	Knowledge structure
Total value	91	94	95	92
Average score	4.45	4.65	4.75	4.65

According to the importance score, the judgment matrix is constructed as follows:

$$A=\begin{bmatrix} 1 & 1/2 & 1/2 & 1/2 \\ 1 & 1 & 2 & 2 \\ 2 & 1/2 & 1 & 2 \\ 2 & 1/2 & 1/2 & 1 \end{bmatrix} \tag{2}$$

The judgment matrix (denoted as $A=(a_{ij})_{n\times n}$) obtained by calculating the weight of each index at three levels on the upper index and consistency test by the root method is as follows:

$$\bar{W}_1 = \sqrt[n]{\prod_{j=1}^{n} a_{1j}} = \sqrt[4]{1 \times 1/2 \times 1/2 \times 1/2} = 0.5946$$

$$\bar{W}_2 = \sqrt[n]{\prod_{j=1}^{n} a_{2j}} = \sqrt[4]{2 \times 1 \times 2 \times 2} = 1.6818$$

$$\bar{W}_3 = \sqrt[n]{\prod_{j=1}^{n} a_{3j}} = \sqrt[4]{2 \times 1/2 \times 1 \times 2} = 1.1892$$

$$\bar{W}_4 = \sqrt[n]{\prod_{j=1}^{n} a_{4j}} = \sqrt[4]{2 \times 1/2 \times 1/2 \times 1} = 0.8409$$

$$W_1 = \bar{W}_1/\sum \bar{W}_t = 0.5946/4.3319 = 0.1372$$

$$W_2 = \bar{W}_2/\sum \bar{W}_t = 1.6818/4.3319 = 0.3882$$

$$W_3 = \bar{W}_3/\sum \bar{W}_t = 1.1892/4.3319 = 0.2745$$

$$W_4 = \bar{W}_4/\sum \bar{W}_t = 0.8409/4.3319 = 0.1941$$

That is, the weight of the third-level indicator set to the second-level indicator is:

$$\mathrm{W} = (W_1, W_2, W_3, W_4)^T = (0.1372, 0.3882, 0.2745, 0.1941)^T \tag{3}$$

The following is the calculation of the maximum eigenvalue of the judgment matrix to test the compatibility of the matrix:

$$AW = \begin{bmatrix} 1 & 1/2 & 1/2 & 1/2 \\ 2 & 1 & 2 & 2 \\ 2 & 1/2 & 1 & 2 \\ 2 & 1/2 & 1/2 & 1 \end{bmatrix} \begin{bmatrix} 0.1372 \\ 0.3882 \\ 0.2745 \\ 0.1941 \end{bmatrix} = \begin{bmatrix} 0.5656 \\ 1.5998 \\ 1.1312 \\ 0.7999 \end{bmatrix} \tag{4}$$

$$\lambda_{max} = \sum_{i=1}^{n} \frac{(AW)_i}{nW_t} = \frac{0.5656}{4\times0.1372} + \frac{1.5998}{4\times0.3882} + \frac{1.1321}{4\times0.2745} + \frac{0.7999}{4\times0.1941} = 4.1222 \tag{5}$$

$$\mathrm{CI} = \frac{\lambda_{max}-n}{n-1} = \frac{4.1222-4}{4-1} = 0.0407 \tag{6}$$

CR= $\frac{CI}{RI} = \frac{0.0407}{0.90} = 0.0452 < 0.1$, the matrix is satisfactory compatibility.

5. Realization of fuzzy comprehensive evaluation in training quality monitoring system

5.1 Basic principles of fuzzy comprehensive evaluation

The Fuzzy Comprehensive Evaluation (FCE) method is a technique that employs the principles of fuzzy mathematics to derive evaluation results by constructing a fuzzy mathematical evaluation model [21]. The core of its effective application lies in accurately defining the domain of fuzzy evaluation and properly constructing the fuzzy evaluation matrix.

5.1.1 Determination of the Evaluation Factor Set

Select evaluation factors for the subject of evaluation, which is to determine the evaluation indicator system. The evaluation indicator system consists of a group of specifically combined assessment indicators that are interrelated. The evaluation factor set is denoted by U:

$$U = \{u_{11}, u_{12}, \cdots, u_{k1}\} \tag{7}$$

Where the $U_1 = \{i = 1,2, \cdots, n\}$ represents the primary factor, in the primary factor contains a number of secondary factors:

$$U_1 = \{u_{11}, u_{12}, \cdots, u_{k1}\}$$
$$U_2 = \{u_{21}, u_{22}, \cdots, u_{k2}\};$$
$$\cdots \quad \cdots \quad \cdots$$
$$U_n = \{u_{n1}, u_{n2}, \cdots, u_{kn}\} \tag{8}$$

5.1.2 Determine the set of comments

Select the appropriate comment set and conduct the object evaluation. The comment set is represented by V:$V = \{v_1, v_2, \cdots, v_n\}$.

5.1.3 Determine the weight of evaluation factors

Determine the influence degree of each factor on the evaluation object, and quantify it to form A weight set, represented by A:$A = \{a_1, a_2, \cdots, a_n\}$,The weight sets of the three factors respectively are:$A_1, A_2, \cdots, A_n$,which means :

$$A_1 = \{a_{11}, a_{12}, \cdots, a_{k1}\};$$
$$A_2 = \{a_{21}, a_{22}, \cdots, a_{k2}\};$$
$$\cdots \quad \cdots \quad \cdots$$
$$A_n = \{a_{n1}, a_{n2}, \cdots, a_{kn}\}. \tag{9}$$

The weights in the above weight sets are calculated using the analytic hierarchy process introduced in the previous section.

5.1.4 Establish fuzzy matrix and comprehensive evaluation multi-level model

① Single factor evaluation

If it is a single factor evaluation, then there is a fuzzy mapping from U to V, which means f: u→v. Mapping f determines a fuzzy relationship.

$$u_i \to f(u_i) = (r_{i1}, r_{i2}, \cdots, r_{im}) \in F(V) \tag{10}$$

$$R_f(u_i, v_n) = f(u_i)(v_i) = r_{ij} \tag{11}$$

It can therefore be represented by the fuzzy matrix R:

$$R = \begin{Bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ r_{n2} & r_{n2} & \cdots & r_{nm} \end{Bmatrix} \tag{12}$$

Thus (U, V, R) forms A synthetic evaluation model in which a given a is a fuzzy subset of V.

② Multi-level evaluation model

If the factor set is a two-level model, the transformation starts from the lower level, and U_1 is set as a subset of factor U of the first layer. Firstly, the factors in U_1 are evaluated as single factors, such as the weight distribution of factors in A_1(i=1,2,⋯,n), and the comprehensive evaluation matrix of U_n is R_i(i=1,2,⋯,n), then the judgment result of U_1 is $B_i = A_i R_i$.

The total judgment matrix is R, and the comprehensive judgment result is B:

$$R = \begin{Bmatrix} B_1 \\ B_2 \\ \vdots \\ B_n \end{Bmatrix}, B = AR \begin{Bmatrix} A_1 & R_1 \\ A_2 & R_2 \\ \vdots & \vdots \\ A_n & R_n \end{Bmatrix} \tag{13}$$

According to the above principles, four-level and five-level models can be constructed.

5.2 Application of the Fuzzy Comprehensive Evaluation Model

Taking the secondary indicator "Student Source Quality" in the quality monitoring system for electronic information professional master's programs as an example, this section elaborates on the application process of the Fuzzy Comprehensive Evaluation method within the monitoring system.

5.2.1 Determination of the Evaluation Factor Set

In the quality monitoring system for electronic information professional master's programs, the secondary indicator "Student Source Quality" is subdivided into four evaluation elements: Moral Character, Educational Institution, Professional Background, and Knowledge Structure.

5.2.2 Determination of the Comment Set

The comment set V is adopted based on the evaluation content, which is V = {A, B, C}.

5.2.3 Determination of the Weights of Evaluation Factors

The weights calculated using the Analytic Hierarchy Process (AHP) as described in the previous section are utilized, with the results as follows:

$$A = \{0.1372,\ 0.3882, 0.2745, 0.1941\} \tag{14}$$

5.2.4 Establish fuzzy evaluation matrix R

It is assumed that there are 20 experts to evaluate the quality monitoring system for the training of master's degree students in electronic information specialty. Each expert evaluates 4 evaluation indicators of student quality according to the standard, and the results are shown in Table 4.

Table 4: Expert evaluation results

Estimate / Index	A	B	C
Ideology and morality	10	8	2
Academic institution	8	6	4
Professional background	6	12	8
Knowledge structure	12	6	0

The evaluation fuzzy matrix is determined by the data in Table 4.

$$R = \begin{Bmatrix} 0.5 & 0.4 & 0.1 \\ 0.4 & 0.3 & 0.2 \\ 0.3 & 0.6 & 0.4 \\ 0.6 & 0.3 & 0 \end{Bmatrix} \tag{15}$$

5.2.5 Fuzzy comprehensive evaluation B

$$B = AR = (0.1372, 0.3882, 0.2745, 0.1941)\begin{Bmatrix} 0.5 & 0.4 & 0.1 \\ 0.4 & 0.3 & 0.2 \\ 0.3 & 0.6 & 0.4 \\ 0.6 & 0.3 & 0 \end{Bmatrix}$$

$$=(0.4227, 0.3943, 0.2011) \tag{16}$$

According to the principle of maximum membership, the quality monitoring system for the training of master's degree in electronic information majors is evaluated as A level in the quality of students.

5.2.6 Set the grading matrix C

In order to obtain an accurate comprehensive evaluation result, let the grade score matrix be C = (95, 85, 75). According to the principle of maximum membership degree, the comprehensive evaluation score W corresponds to the comprehensive evaluation score for the "Student Source Quality" aspect of the electronic information professional master's degree training quality monitoring system:

$$W = BC = (0.4227, 0.3943, 0.2011)(95, 85, 75) = 88.7545 \text{ (points)} \tag{17}$$

6. Conclusion

The Analytic Hierarchy Process (AHP) ensures the rationality of monitoring indicator weights by leveraging expert knowledge and precise mathematical techniques, minimizing subjectivity and validating weights through consistency tests. This enhances the reliability and objectivity of fuzzy comprehensive evaluation. In studying the quality monitoring system for electronic information professional master's programs, we integrated qualitative and quantitative analyses, using scientific methods to transform qualitative issues into quantitative data and then back into qualitative evaluations. This approach mitigates subjectivity and randomness, achieving a seamless blend of qualitative and quantitative analysis.

Both AHP and fuzzy comprehensive evaluation excel in handling imprecise information, simulating human judgment, and bridging qualitative and quantitative gaps. AHP quantifies subjective judgments, determining factor weights through systematic decomposition and synthesis, while fuzzy evaluation provides robust comprehensive judgment. Combined, they enhance the scientific rigor of monitoring processes.

The results from AHP and fuzzy evaluation are applicable for both overall and specific assessments of training sites. Analyzing indicator weights identifies key areas for improving quality, with higher-weighted indicators guiding efforts to enhance teaching, research, and practical outcomes. Quantitative analysis reveals differences in indicator impacts, identifies weaknesses, and, combined with other methods, offers targeted measures for comprehensive quality improvement.

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