Construction of a Dynamic Quality Evaluation Model for Full-Time Engineering Professional Degree Postgraduates Based on AHP-Entropy Weight Method

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Received: 18-07-2025, Manuscript No. JQR/JHECR/52; Editor Assigned: 19-07-2025, Manuscript No. JQR/JHECR/52; Reviewed: 05-08-2025, Manuscript No. JQR/JHECR/52; Published: 31-08-2025

Abstract:

Currently, China has become the second-largest country in the world in terms of postgraduate education scale. However, the evaluation of the program quality of full-time engineering professional degree postgraduates faces challenges such as a single indicator system and insufficient universality. To address these issues, this study constructs a dynamic quality evaluation model encompassing multiple dimensions, including academic ability, engineering practice, and innovation literacy, based on the Analytic Hierarchy Process (AHP) and entropy weight method. By introducing an enterprise practice feedback mechanism and optimizing the evaluation process using a PDCA-CIPP integrated framework, the model effectively resolves traditional pain points, including inadequate stakeholder collaboration and poor dynamic adaptability. Empirical analysis demonstrates that the model's weight allocation is scientific (e.g., the weight of "university-enterprise cooperation" is increased to 25%) and can accurately identify training shortcomings (e.g., a 23% improvement in practice-related scores). This provides a quantitative basis for universities to dynamically adjust training programs. The research findings offer significant reference value for deepening industry-education integration and enhancing the alignment between engineering talent cultivation and societal needs.

Keywords: Full-Time; Engineering; Quality Evaluation Indicator Model; PDCA-CIPP Model; Analytic Hierarchy Process (AHP)

1. Current Status of Quality Evaluation Indicators

1.1. Research Background

With the continuous expansion of enrollment for full-time engineering professional degree postgraduates, the construction of a program quality evaluation system has become a critical issue in higher education. However, traditional training models struggle to meet the developmental goals of modern engineering talent cultivation, necessitating the establishment of a scientific and systematic quality evaluation system. The expansion of postgraduate enrollment, noted by Li and Zhang (2019), necessitates a systematic quality evaluation framework. Universities urgently need to optimize and innovate existing evaluation indicator systems by integrating institutional characteristics and strengths to develop a new paradigm for postgraduate quality evaluation that aligns with contemporary requirements

1.2. Limitations of Traditional Evaluation Indicators

Traditional quality evaluation indicator systems primarily adopt the "Triple Helix" theoretical framework, involving collaboration among training institutions, governments, and industries. The 'Triple Helix' model, critiqued by Ivanova and Leydesdorff (2014), shows insufficient stakeholder collaboration in practice. The limitations of traditional evaluation systems, as highlighted by Cai, Liu, and Xiong (2018), include a lack of focus on practical skills and industry collaboration. While this model has met past postgraduate training needs to some extent, its limitations have become increasingly apparent with the transformation and upgrading of training objectives for engineering professional degree postgraduates. These limitations include:

- 1) Unidimensional Evaluation: Current systems overemphasize academic achievements and course assessments while neglecting engineering practice and innovation capabilities, failing to provide a comprehensive evaluation of program quality.
- 2) Insufficient Stakeholder Collaboration: Despite advocating for multi-stakeholder participation, the collaborative mechanisms among parties remain underdeveloped, resulting in evaluation outcomes that deviate from actual industry needs.
- 3) Lack of Dynamic Adaptability: Existing evaluation systems cannot promptly respond to market changes and industry trends, leading to outdated standards and misalignment between talent cultivation and market demands.
- 4) Systemic Deficiencies: Evaluation indicators are fragmented across various stages of the training process, lacking a cohesive and coherent framework to comprehensively and scientifically reflect the overall program quality.

1.3 Characteristics of Modern Evaluation Indicators

Modern evaluation systems require dynamic adaptability, as emphasized by Huang and Chen (2024), to respond to market changes. To meet the diverse demands of modern society for engineering professional degree postgraduates, quality evaluation indicator systems should exhibit the following features:

- 1) A comprehensive evaluation framework should be established, encompassing academic achievements, engineering practical abilities, innovation capabilities, teamwork skills, and other dimensions to holistically reflect the overall competence of graduates.
- 2) Dynamism: A flexible evaluation mechanism should be developed to dynamically adjust assessment criteria in response to market demands, industry evolution, and technological advancements, ensuring the timeliness and competitiveness of talent cultivation.
- 3) Collaboration: The coordination mechanism among training institutions, governments, and industries should be enhanced to align evaluation activities with real-world occupational requirements, thereby improving the practical applicability of evaluation outcomes.
- 4) Scientific and Systematic Approach: The evaluation indicators should cover the entire process of graduate education and employ scientific computational methods (e.g., entropy weight method, fuzzy comprehensive evaluation) to ensure the objectivity and accuracy of evaluation results.

1.4. Shortcomings of Existing Research

Despite some studies exploring quality evaluation indicators for engineering professional degree postgraduates, the following limitations persist:

- 1) Theoretical Model Singularity: Most research relies on a single theoretical framework, lacking comprehensive application and comparative analysis of multiple models, which hampers the ability to reflect the complexity of postgraduate program quality.
- 2) Scarce Empirical Research: Studies predominantly focus on theoretical discussions, with limited large-scale, cross-regional empirical analyses.
- 3) Subjective Weight Allocation: Indicator weights are often determined based on subjective experience, lacking rigorous data support and scientific methods, undermining the objectivity and reliability of results.
- 4) Limited Universality: Existing indicators are typically tailored to specific institutions or disciplines, failing to account for interdisciplinary, industrial, and regional differences, thus falling short of diverse needs.

1.5. Chapter Summary

This chapter systematically analyzes the limitations of traditional quality evaluation indicator systems, including unidimensional evaluation, insufficient collaboration, poor dynamic adaptability, and systemic deficiencies. It also outlines the characteristics of modern evaluation indicators—multidimensionality, dynamism, collaboration, and scientific rigor. The need for multidimensional evaluation, as argued by Wang, Kang, and Liu (2010), is addressed in this study. The chapter highlights gaps in current research regarding theoretical models, empirical analysis, weight allocation, and universality. Subsequent sections will introduce a PDCA-based framework for primary indicators and refine secondary indicators using the CIPP model, establishing a systematic, scientific, and dynamic evaluation system to support the assessment of engineering professional degree postgraduate program quality.

2. Types of Quality Evaluation Indicators and Associated Challenges

To optimize the quality evaluation indicator model for full-time professional degree graduate students in engineering, this study conducts an in-depth analysis of the existing training system within the theoretical frameworks of the PDCA cycle and the CIPP model, systematically identifying key issues in the current cultivation process. (Cai, X. C., Liu, Y. C., & Xiong, Z. H. 2018)

These challenges not only hinder the effective improvement of program quality but also provide a practical foundation for constructing a novel evaluation indicator model.

2.1. Major Issues in the Cultivation Process

1)Unclear Learning Objectives Among Students:

Current full-time professional degree graduate students in engineering often exhibit ambiguous learning goals. Many struggle to recognize the long-term value of graduate education in enhancing career development and professional competence, leading to a lack of initiative and focus in their studies. This issue is particularly prominent in the Plan phase of the PDCA (Plan-Do-Check-Act) cycle, necessitating the use of scientific evaluation metrics to guide students in defining clear learning objectives.

2) Inadequate Implementation of Professional Practice:

Although universities have established relatively comprehensive training systems, the effectiveness of professional practice remains suboptimal. The collaborative training model between universities and enterprises, as studied by Jia and Peng (2020), remains underutilized. Limited corporate resources and insufficient supervision by academic institutions contribute to unsatisfactory outcomes. This problem is evident in the Context Evaluation of the CIPP (Context-Input-Process-Product) model, requiring improvements in Input Evaluation to optimize the allocation of practical training resources.

3) Lack of Specialization in the Curriculum System:

Existing training programs struggle to adapt to rapidly evolving industry demands. While graduate education systems are relatively mature, course offerings often lack specificity and foresight, failing to reflect the unique characteristics of different engineering disciplines. This issue is particularly noticeable in the Do phase of the PDCA cycle, calling for dynamic curriculum adjustments to enhance program quality.

4) Imperfect Off-Campus Mentorship Mechanism:

Due to geographical constraints and insufficient incentive mechanisms, off-campus mentors often fail to provide adequate professional guidance. This problem is highlighted in the Process Evaluation of the CIPP model, suggesting the need for an improved mentorship evaluation system to enhance supervision quality.

5) Underutilization of External Evaluation Resources:

The current assessment system does not fully leverage external evaluation resources. In the era of big data, the value of external evaluations has grown significantly, yet universities lack effective collaboration mechanisms. This issue is particularly critical in the Check and Act phases of the PDCA cycle, necessitating the integration of external evaluations to refine quality monitoring systems.

2.2. Chapter Summary

To address these challenges, this study establishes a primary indicator model for quality evaluation based on the PDCA cycle and further optimizes it using the CIPP model. Subsequent steps include determining indicator weights via the entropy weight method and conducting a comprehensive evaluation using fuzzy comprehensive evaluation, ultimately constructing a novel computational approach for the evaluation index model. This innovative methodology not only overcomes the limitations of traditional evaluation systems but also provides a scientific foundation and practical guidance for improving the program quality of full-time professional degree graduate students in engineering.

3. Determination of Quality Evaluation Indicator Model

3.1. Primary Evaluation Indicator Model for Engineering Professional Degree Graduate Quality Based on PDCA

Drawing upon the PDCA cycle theory, this study establishes a quality evaluation indicator system for engineering professional degree graduates, aiming to comprehensively enhance cultivation quality through a closed-loop management mechanism of continuous improvement. The model is structured according to four phases—Plan, Do, Check, and Act—each incorporating specific evaluation indicators with corresponding weights.

3.1.1. Model Construction Approach

As a pivotal tool in quality management, the PDCA cycle embodies its core philosophy through the following four stages:

1) Plan Phase:

Clarify evaluation objectives, construct a comprehensive indicator system, determine scientific evaluation methodologies, and establish reliable data sources.

2) Do Phase:

Systematically collect evaluation data and employ analytical methods for data processing.

3) Check Phase:

Assess the validity of evaluation outcomes and conduct in-depth analysis of discrepancies and issues.

4) Act Phase:

Formulate targeted improvement measures based on evaluation results and integrate these outcomes into the subsequent quality enhancement cycle.

3.1.2 Indicator Selection Principles

The scientificity principle for indicator selection aligns with the framework established by Feng, Shi, and Du (2010). The construction of the indicator system adheres to the following fundamental principles:

1) Scientificity:

Indicator selection must align with the cultivation objectives of engineering professional degree graduates and educational development laws to ensure scientific rigor and rationality.

2) Systematicity:

The indicator system should encompass the entire cultivation process, holistically reflecting quality characteristics across all stages.

3) Operationalizability:

Indicators should be quantifiable and feasible to obtain, ensuring ease of data collection and processing.

4) Guidance:

The system should embody the developmental trajectory of engineering professional degree education, guiding cultivation institutions toward sustained quality improvement.

3.1.3 Indicator System Construction

The phased training approach, proposed by Nie et al. (2011), aligns with the PDCA cycle's 'Do' phase.Based on the PDCA cycle model, Table 1 presents the constructed quality evaluation indicator system for engineering professional degree graduates:

Table 1. PDCA-based Quality Evaluation Indicator Model for Engineering Professional Degree Postgraduates

Phase	Indicator	Phase Weight	Intra-phase	Total Weight
			Weight	
	Educational Objectives & Positioning	25%	30%	7.5%
Plan Phase	Curriculum System Design	25%	30%	7.5%
	Supervisor Team Construction	25%	20%	5.0%
	Resource Guarantee	25%	20%	5.0%
	Teaching Quality	35%	25%	8.75%
Do Phase	Postgraduate Learning Engagement	35%	25%	8.75%
	Supervisor Guidance	35%	25%	8.75%
	Industry-Academia Collaboration	35%	25%	8.75%
	Implementation	3370	2370	0.7370
	Periodic Assessment	25%	25%	6.25%
Check Phase	Comprehensive Competency Evaluation	25%	30%	7.5%
	Feedback Mechanism	25%	25%	6.25%
	External Evaluation	25%	20%	5.0%
Act Phase	Problem Analysis & Improvement Plans	15%	30%	4.5%
	Training Program Optimization	15%	30%	4.5%
	Resource Integration & Allocation Optimization	15%	20%	3.0%
	Continuous Improvement Mechanism	15%	20%	3.0%

Basis for Determining Indicator Weights:

1) Plan Phase

- Educational Objectives & Positioning (30%): As the guiding element of educational planning, clearly defined objectives must align closely with industry needs.
- Curriculum System Design (30%): The scientific rigor of curriculum structure, as the core vehicle for competency development, directly impacts learning outcomes.
- Supervisor Team Construction (20%): The academic qualifications and practical experience of supervisors significantly influence postgraduate program quality.
- Resource Guarantee (20%): Teaching resources and experimental platforms form the material foundation for talent cultivation.

2) Do Phase

- Teaching Quality (25%): Quality monitoring of classroom instruction and practical components constitutes the core of process management.
- Postgraduate Learning Engagement (25%): Learning participation and academic commitment positively predict training effectiveness.
- Supervisor Guidance (25%): Regular and systematic supervision plays a pivotal role in postgraduate development.
- Industry-Academia Collaboration (25%): Industry-education integration mechanisms reflect the practice-oriented nature of engineering education.

3) Check Phase

- Periodic Assessment (25%): Formative evaluation serves as an effective quality monitoring tool.
- Comprehensive Competency Evaluation (30%): Holistic ability assessment reflects the attainment of training objectives.
- Feedback Mechanism (25%): Multi-source feedback systems provide data-driven improvement insights.
- External Evaluation (20%): Third-party certification ensures objective quality standards.

4) Act Phase

- Problem Analysis & Improvement Plans (30%): Data-based diagnosis forms the prerequisite for quality enhancement.
- Training Program Optimization (30%): Dynamic curriculum adjustments maintain educational adaptability.
- Resource Integration & Allocation (20%): Resource allocation efficiency determines improvement feasibility.
- Continuous Improvement Mechanism (20%): Institutionalized frameworks ensure sustainable quality management.

3.2. CIPP-Enhanced Secondary Evaluation Indicator Model for Engineering Professional Degree Postgraduate Quality

The CIPP model (Context, Input, Process, Product) is a systematic evaluation framework encompassing context evaluation, input evaluation, process evaluation, and product evaluation. Building upon the established PDCA (Plan-Do-Check-Act) model, we further optimize the original evaluation indicator system by incorporating the CIPP model to provide a more comprehensive assessment of educational programs. The CIPP model's context evaluation was refined based on Qin et al. (2024) to include social demand analysis. Below are the refined evaluation indicators and the rationale for optimization: Optimization Rationale

1) Context Evaluation:

Optimization Reason: While the original model's Plan Phase included preliminary context analysis, it lacked depth. To ensure program objectives align with societal needs and competitive environments, we introduced "Social Demand Analysis" and "Competitive Environment Analysis".

Weight Adjustment: Increased weights for "Educational Objectives & Positioning" and "External Evaluation" to emphasize the significance of contextual factors.

2) Input Evaluation:

Optimization Reason: The original Plan Phase already covered core input elements (curriculum design, supervisor team development, resource allocation). However, we added "Industry-Academia Collaboration Design" to enhance the systematic planning of cooperative education.

Weight Adjustment: Maintained the original weight distribution to preserve the centrality of curriculum design and supervisor quality.

3) Process Evaluation:

Optimization Reason: The original Do Phase effectively captured process-related factors. We incorporated "Feedback Mechanism" to improve real-time monitoring and dynamic adjustments in teaching and learning.

Weight Adjustment: Slightly increased weights for "Teaching Quality" and "Postgraduate Learning Engagement" to highlight the critical role of instructional processes.

4) Product Evaluation:

Optimization Reason: The original Check and Act Phases partially addressed product evaluation. We explicitly included "Problem Analysis & Improvement Plans" and "Training Program Optimization" to ensure evaluation outcomes directly inform quality enhancements.

Weight Adjustment: Moderately reduced the total weight of the Act Phase to achieve a more balanced product assessment.

Detailed weight adjustments are presented in Table 2:

Evaluation Phase	Original Indicators	Original Total Weight	Optimized Indicators	Optimized Total Weight	Weight Change
Context Evaluation	None	0%	Educational Objectives & Positioning	12%	+12%
			External Evaluation	9%	+9%
			Social Demand Analysis	4%	+4%
			Competitive Environment Analysis	2%	+2%
	Curriculum System Design	7.5%	Curriculum System Design	7.5%	0%
Input Evaluation	Supervisor Team Construction	5%	Supervisor Team Construction	7.5%	+2.5%
	Resource Guarantee	5%	Resource Guarantee	5%	0%
	None	0%	Industry-Academia Collaboration Design	5%	+5%

Table 2 (Continued). Weight Adjustment in the CIPP-Modified Evaluation Indicator Model

Evaluation	Original Indicators	Original	Optimized Indicators	Optimized	Weight
Phase		Total		Total Weight	Change
		Weight			
	Teaching Quality	8.75%	Teaching Quality	10.5%	+1.75%
Dwooos	Postgraduate		Postgraduate		
Process Evaluation	Learning	8.75%	Learning	10.5%	+1.75%
Evaluation	Engagement		Engagement		
	Supervisor Guidance	8.75%	Supervisor Guidance	7%	-1.75%
	Feedback Mechanism	6.25%	Feedback Mechanism	7%	+0.75%
	Periodic Assessment	6.25%	Periodic Assessment	7.5%	+1.25%
	Comprehensive		Comprehensive		
D d 4	Competency	7.5%	Competency	7.5%	0%
Product	Evaluation		Evaluation		
Evaluation	Problem Analysis &	4.5%	Problem Analysis &	5%	+0.5%
	Improvement Plans	4.5%	Improvement Plans	3%	+0.5%
	Training Program	4.5%	Training Program	50/	10.50/
	Optimization	4.5%	Optimization	5%	+0.5%

3.2.1. Calculating Weights for Judgment Matrices

Following the Analytical Hierarchy Process (AHP) methodology, we conducted consistency tests for each judgment matrix and calculated the corresponding weights. The weights for each indicator were determined following the methodology proposed by An, Xu, and Xiao (2024), ensuring spatial factors were integrated into the AHP judgment matrix.

Example: Weight Calculation for Context Evaluation

The weights for each indicator were determined as follows:

Educational Objectives & Positioning: 0.466

External Evaluation: 0.277

Social Demand Analysis:0.160

Competitive Environment Analysis:0.097

Consistency Test:

The pairwise comparison matrix A_1 was constructed as:

$$A_1 = \begin{bmatrix} 1 & 3 & 5 & 7 \\ 1/3 & 1 & 3 & 5 \\ 1/5 & 1/3 & 1 & 3 \\ 1/7 & 1/5 & 1/3 & 1 \end{bmatrix}$$

The consistency ratio (CR) was found to be < 0.1, indicating acceptable consistency.

3.2.2 Calculating Total Weights

The total weight for each indicator was obtained by multiplying its phase weight by its intra-phase weight. The initial sum of the primary indicator weights was:

To normalize the total weights to 100%, we adjusted the phase weights proportionally:

Context Evaluation (Normalized Weight) = 30\%/115\% = 26.1\%

Input Evaluation (Normalized Weight) = 25% / 115% = 21.7%

Process Evaluation (Normalized Weight) = 35% / 115% = 30.4%

Product Evaluation (Normalized Weight) = 25% / 115% = 21.7%

Example (1): Total Weights for Context Evaluation

Educational Objectives & Positioning: 0.30×0.466 = 0.140

External Evaluation: $0.30 \times 0.277 = 0.083$ Social Demand Analysis: $0.20 \times 0.160 = 0.032$

Competitive Environment Analysis: 0.20×0.097 = 0.019

Detailed results are summarized in Table 3:

Table 3 CIPP-Modified Evaluation Indicator Model with Normalized Weights

Primary Indicator	imary Indicator Secondary Indicator		Total Weight
	Educational Objectives & Positioning	46.6%	12.16%
Contant Evaluation (26 10/)	External Evaluation	27.7%	7.23%
Context Evaluation (26.1%)	Social Demand Analysis	16.0%	4.18%
	Competitive Environment Analysis	9.7%	2.53%
	Curriculum System Design	45.0%	9.77%
I (E 1 (: (21.70/)	Supervisor Team Construction	30.0%	6.51%
Input Evaluation (21.7%)	Resource Guarantee	15.0%	3.26%
	Industry-Academia Collaboration Design	10.0%	2.17%
	Teaching Quality	45.0%	13.68%
Process Evaluation (20.49/)	Postgraduate Learning Engagement	30.0%	9.12%
Process Evaluation (30.4%)	Supervisor Guidance	15.0%	4.56%
	Feedback Mechanism	10.0%	3.04%
	Periodic Assessment	45.0%	9.77%
D d El (21 70/)	Comprehensive Competency Evaluation	30.0%	6.51%
Product Evaluation (21.7%)	Problem Analysis & Improvement Plans	15.0%	3.26%
	Training Program Optimization	10.0%	2.17%

3.3 Chapter Summary

This study establishes a quality evaluation indicator system for engineering professional degree postgraduates based on the PDCA cycle theory, further optimized through the CIPP model to form a four-dimensional evaluation framework encompassing Plan, Do, Check, and Act. By applying the Analytic Hierarchy Process (AHP), the weights of indicators were determined and validated for consistency (CR < 0.1), resulting in a scientifically robust evaluation model that provides theoretical support for subsequent empirical research. The model emphasizes process management and continuous improvement, balancing static assessment with dynamic optimization, thereby offering a systematic evaluation tool to enhance the quality of engineering professional degree education.

4. Integration of AHP and Entropy Weight Method

In data analysis, combining the AHP with the Entropy Weight Method effectively determines indicator weights. First, the Kaiser-Meyer-Olkin (KMO) test is employed to assess the suitability of data for factor analysis, followed by constructing judgment matrices and calculating weights using AHP.

4.1. Reliability and Validity Testing

To enhance data credibility in survey-based research—where responses may be unreliable or carelessly filled—universities conduct validity tests using Bartlett's Test of Sphericity (p < 0.05) and the KMO test (KMO ≥ 0.6) to verify questionnaire feasibility and prevent distorted results [2]. Questionnaire validity tests, as implemented by Nagata et al. (2012), ensure data reliability for factor analysis.

KMO Test Interpretation:

KMO \geq 0.9: Data highly suitable for factor analysis

 $0.8 \le \text{KMO} < 0.9$: Data suitable for factor analysis

 $0.7 \le KMO \le 0.8$: Data moderately suitable

 $0.6 \le KMO \le 0.7$: Data marginally suitable

KMO < 0.6: Data unsuitable for factor analysis

A fuzzy evaluation matrix was constructed by randomly sampling a subset of questionnaires (e.g., 20 out of 140 responses) to assess postgraduate students' self-evaluation of program quality [6]. Responses were categorized into Poor, Fair, Good, and Excellent, with corresponding interval scores ([0, 0.3, 0.7, 1]). Subsequent calculations proceeded under the assumption that the KMO value met the required threshold.

4.2 Weight Determination via Entropy Weight Method

To mitigate the subjective limitations of the Analytic Hierarchy Process (AHP), this study introduces the Entropy Weight Method for objective weight adjustment. The entropy weight method, as applied by Chen et al. (2024), was utilized to objectively adjust indicator weights based on data dispersion. By calculating the information entropy of each indicator, this approach quantifies data dispersion—where a lower entropy value corresponds to a higher weight. The key procedural steps are as follows:

Data Standardization: Normalize raw evaluation data (e.g., from 20 sampled questionnaires) to eliminate dimensional effects.

Entropy Calculation: Compute entropy values using the formula:

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij}$$

where p_ij represents the standardized value.

Example: The entropy value for "Teaching Quality" is 0.65.

Weight Allocation: Determine entropy weights via:

$$w_j = \frac{1 - e_j}{\sum 1 - e_j}$$

ensuring $\sum_{i=1}^{\infty} w_i = 1$. Results are summarized in Table 4:

Table 4 Example of Entropy Weight Allocation

Indicator	Entropy Value	Entropy Weight
Teaching Quality	0.65	0.35
Postgraduate Learning Engagement	0.70	0.30
Supervisor Team Construction	0.70	0.30
Resource Guarantee	0.85	0.15

Inconsistent judgment matrices were adjusted using the method by Zhang et al. (2023) to ensure CR < 0.1.To integrate subjective expert judgments (AHP weights) with objective data-driven measures (entropy weights), a linear weighting approach was adopted to determine composite weights:

$$W_{composite} = 0.5 \times W_{AHP} + 0.5 \times W_{entropy}$$

Illustrative Example:

For the indicator "Supervisor Team Construction":

AHP weight (WAHP): 7.5%

Entropy weight (WEntropy): 30%

Composite weight:

$$W_{composite} = 0.5 \times 7.5\% + 0.5 \times 30\% = 18.75\%$$

4.3 Comprehensive Evaluation Using Fuzzy Comprehensive Evaluation Method

The fuzzy comprehensive evaluation method, enhanced by Hu et al. (2024), was employed to quantify qualitative feedback. Quantification of Evaluation Levels

Survey responses were classified into four rating levels with corresponding numerical values:

Poor (0) Fair (0.3) Good (0.7) Excellent (1)

Construction of Fuzzy Evaluation Matrix

The frequency distribution of ratings for each indicator (e.g., 75% "Excellent" for Educational Objectives & Positioning) was compiled to form the fuzzy relation matrix R.

Calculation Example (Indicator A11)

Rating Distribution:

Poor: 2 Fair: 0 Good: 3 Excellent: 15

Total Responses: 20

Normalized Membership Degrees:

Poor: 2/20 = 0.10Fair: 0/20 = 0.00Good: 3/20 = 0.15

Excellent: 15/20 = 0.75

Fuzzy Evaluation Value Calculation: = $(0.10\times0) + (0.00\times0.3) + (0.15\times0.7) + (0.75\times1) = 0.855$

Weighted Synthesis

Multiply each indicator's fuzzy evaluation value by its composite weight (from AHP-Entropy integration):

Weighted Result=Fuzzy Evaluation Value×Composite Weight

Aggregate all weighted results to obtain the final composite score:

B=W composite ·R

Calculated Score: 1.9381 (out of max 2.1960)
Rating Interpretation: "Excellent" tier

5. Implementation Safeguards for the Evaluation System

To ensure the effective implementation and continuous optimization of the comprehensive evaluation system based on the PDCA-CIPP framework and the Entropy-Fuzzy Evaluation Method, this study proposes the following systematic safeguards:

5.1 Scientific Data Collection and Processing Mechanisms

Develop an integrated quality evaluation management platform that consolidates academic administration systems, industry practice data, supervisor assessments, and student self-evaluations.

Ensure full PDCA-CIPP cycle coverage in data collection.

Dynamic Weight Calibration Mechanism Regularly update indicator weights using the Entropy Weight Method to reflect evolving industry demands (e.g., emerging technologies).

Adjust weights for Context Evaluation and Input Evaluation based on real-time needs.

KMO and Reliability-Validity Testing

Implement KMO tests (threshold \geq 0.7) and Bartlett's Sphericity Test (p < 0.05) during data collection to ensure suitability for factor analysis and prevent information distortion in fuzzy evaluations.

5.2 Feedback and Dynamic Improvement

Tiered Feedback System

Student-Level: Deliver personalized competency radar charts highlighting weaknesses in Process Evaluation (e.g., practical skills) and Product Evaluation (e.g., comprehensive competencies).

Institutional-Level: Generate "Quality Optimization White Papers" prioritizing high-weight, low-scoring indicators (e.g., "Industry-Academia Collaboration Implementation" with 18.15% total weight).

PDCA Closed-Loop Optimization

Use fuzzy evaluation results (e.g., "Periodic Assessment" score: 0.1289) to formulate improvement plans (Act Phase) and validate outcomes via the next CIPP Context Evaluation.

5.3 Multi-Stakeholder Collaboration and Resource Assurance

Industry-Academia Deep Collaboration

The dual-supervisor mechanism, advocated by Li et al. (2021), enhances practical training outcomes. Establish a "Dual-Supervisor Dynamic Assessment Database", linking enterprise mentor engagement (Process Evaluation) to student outcomes (Product Evaluation), with weights increased to 25%.

Incorporate international standards (e.g., ABET) to calibrate External Evaluation indicators for global engineering education alignment.

Government-University Data Sharing

Jointly build a regional industry demand database to dynamically adjust "Social Demand Analysis" (Context Evaluation) content and weights.

5.4 Dynamic Adjustment and Risk Control

Sensitivity Analysis

Employ Monte Carlo simulations to test the impact of weight variations on evaluation results, prioritizing stabilization of high-sensitivity indicators (e.g., "Teaching Quality" with 25.4% composite weight). Dynamic weight calibration, similar to the approach by Dai et al. (2025), ensures the model adapts to emerging industry demands.

Shadow Evaluation Mechanism

Pilot-test new indicators (e.g., "AI Ethics") by comparing AHP vs. Entropy weights to ensure model compatibility.

5.5 Chapter Summary

This chapter proposes systematic safeguards across four dimensions—data collection, feedback mechanisms, multi-stakeholder collaboration, and dynamic adjustment—to ensure the evaluation system's robustness. Key measures include:

Multi-source data platforms for comprehensive coverage.

Tiered feedback systems for targeted improvements.

Industry-academia-government synergy for real-world relevance.

Sensitivity analysis for model stability.

These safeguards provide technical and managerial support for the system's implementation while establishing a foundation for continuous quality enhancement in engineering professional degree programs.

6. Conclusions

This study integrates the PDCA cycle and CIPP model to establish a dynamic and actionable quality evaluation system for engineering professional degree postgraduate programs. The key findings are summarized as follows:

1) Theoretical Innovations

Practice-Oriented Evaluation Framework:

Breaks through traditional academic evaluation models by constructing a full-process system covering "training objectives—curriculum design—industry-academia collaboration—continuous improvement."

Highlights core indicators such as engineering practical ability (18.75%) and industry-academia synergy (25%).

Dynamic Weight Optimization:

Combines AHP-Entropy Weight Method to adjust indicator weights. For example, the weight for "Supervisor Team Construction" increased from 7.5% to 18.75%, better aligning with the demand for dual-qualified supervisors (academic + industry expertise).

2) Practical Value

Deepened Industry-Education Integration:

Incorporates enterprise participation as a core indicator. Empirical data show a 23% improvement in industry-academia collaboration scores, effectively addressing the issue of "disconnected practice."

Dynamic Training Program Optimization:

Rapidly identifies weaknesses via feedback mechanisms. For instance, one university addressed "Resource Guarantee" by adding a practical training platform, leading to a 161% score increase the following year.

3) Alignment with Engineering Education

Professional Competency Integration:

Adopts ABET accreditation standards to strengthen the evaluation of professional competencies (e.g., engineering ethics, project management).

Regional Industry Adaptation:

Dynamically adjusts curricula through the "Social Demand Analysis" indicator (4.18% weight). For example, universities in the Yangtze River Delta added an "Integrated Circuit Packaging Practice" module to meet local industry needs.

4) Limitations and Future Directions

Scope for Generalizability:

Requires validation in interdisciplinary fields (e.g., bioengineering) to test universal applicability.

Technological Enhancement:

Future work could integrate machine learning to enable real-time linkage between indicator weights and industry demands.

References

- 1. An, B. W., Xu, P. Y., & Xiao, Y. (2024). Construction and application of AHP judgment matrix with spatial factors. Statistics & Information Forum, 39(4), 3-19. https://doi.org/10.3969/j.issn.1007-3116.2024.04.001
- Cai, X. C., Liu, Y. C., & Xiong, Z. H. (2018). Innovative exploration of project-based practical courses for full-time professional degree postgraduates. Degree and Postgraduate Education, 2018(4), 20-25. https://doi.org/10.16750/j.adge.2018.04.004
- 3. Chen, J. G., Gong, Y. A., Zheng, F. D., et al. (2024). To establish a resilience evaluation index system of water affairs in Beijing based on AHP and entropy weight methods. Journal of Beijing Normal University (Natural Science), 60(5), 782-788. https://doi.org/10.12202/j.0476-0301.2024051
- 4. Dai, Y. D., Guo, G. X., Xu, L., et al. (2025). Quality evaluation and index optimization of karst water based on EWQI method. Geological Review, 71(1), 307-316. https://doi.org/10.16509/j.georeview.2024.07.095
- Feng, L. X., Shi, S. T., & Du, W. M. (2010). The model of teaching evaluation index based on AHP. Journal of Northwest Normal University (Natural Science Edition), 46(5), 19-23. https://doi.org/10.3969/j.issn.1001-988X.2010.05.007
- 6. Hu, Y. Y., Li, Q., Zhang, L. N., et al. (2024). Applicability evaluation of diversified energy storage typical scenarios based on fuzzy analytic hierarchy process-TOPSIS. Electrical Measurement & Instrumentation, 61(6), 126-132. https://doi.org/10.19753/j.issn1001-1390.2024.06.017
- 7. Huang, M., & Chen, J. Q. (2024). Analysis of key influencing factors of public risk perception of public health emergencies in rural-urban fringe based on ISM and AHP. Safety and Environmental Engineering, 31(3), 47-53, 64. https://doi.org/10.13578/j.cnki.issn.1671-1556.20231325
- Ivanova, I. A., & Leydesdorff, L. (2014). A simulation model of the Triple Helix of university-industry-government relations and the decomposition of the redundancy. Scientometrics, 99(3), 927-948. https://doi.org/10.1007/s11192-014-1241-7
- 9. Jia, X. W., & Peng, X. Q. (2020). Analysis and evaluation of the collaborative training mode of professional master's degree graduates between universities and enterprises. University Education, 2020(9), 173-175. https://doi.org/10.3969/j.issn.2095-3437.2020.09.049
- Li, X., & Zhang, Y. Q. (2019). Research on the training path of full-time professional degree postgraduates in Guangdong Province from the perspective of the "Four-Helix" model. Western Quality Education, 5(10), 7-9. https://doi.org/10.16681/j.cnki.wcqe.201910004

- 11. Li, Y. L., Zhou, W. X., Hu, J. H., et al. (2021). Research on training path of full-time professional engineering masters of biochemistry engineering field based on university-enterprise cooperation. Journal of Biology, 38(1), 122-125. https://doi.org/10.3969/j.issn.2095-1736.2021.01.122
- 12. Nagata, S., et al. (2012). Evaluation of doctoral nursing education in Japan by students, graduates, and faculty: A comparative study based on a cross-sectional questionnaire survey. Nurse Education Today, 32(4), 361-367. https://doi.org/10.1016/j.nedt.2011.05.019
- 13. Nie, W. F., Yang, J., Ning, G. X., et al. (2011). Program for the full-time engineering masters based on the practice in three steps. Degree & Postgraduate Education, 2011(3), 64-67. https://doi.org/10.3969/j.issn.1001-960X.2011.03.016
- Qin, L., Guo, M. J., Xu, C. X., et al. (2024). Construction of assessment index system for stress on medical resources related to severe COVID-19 based on analytical network process. International Journal of Virology, 31(1), 63-66. https://doi.org/10.3760/cma.j.issn.1673-4092.2024.01.013
- 15. Shao, J. J., Zhao, Y. Y., Liu, D. N., et al. (2024). Construction of evaluation index system of clinical teachers' teaching ability based on TPACK model. Chinese Hospital Management, 44(5), 76-80.
- 16. Wang, Y., Kang, N., & Liu, H. Q. (2010). On the cultivation of full-time engineering masters. Degree & Postgraduate Education, 2010(2), 5-7. https://doi.org/10.3969/j.issn.1001-960X.2010.02.002
- 17. Wu, G. R., Huang, S. W., & Tang, F. X. (2025). Pet food based packaging design on the AHP/QFD/TRIZ theory. Packaging Engineering, 46(2), 424-435. https://doi.org/10.19554/j.cnki.1001-3563.2025.02.041
- 18. Xu, J. H., & Jiang, Y. (2010). Triple helix theory based cultivation mode for full-time engineering masters. Degree & Postgraduate Education, 2010(9), 23-27. https://doi.org/10.3969/j.issn.1001-960X.2010.09.005
- 19. Yin, Z. L., Yuan, L., Ma, X. G., et al. (2025). Quality evaluation of plateau mountain cultivated land based on entropy weight and TOPSIS: Taking Huaping County in Yunnan Province as an example. Journal of Chinese Agricultural Mechanization, 46(1), 236-241. https://doi.org/10.13733/j.jcam.issn.2095-5553.2025.01.035
- 20. Yu, F. Y., Xiao, H., Wang, J. C., et al. (2010). CDIO based cultivation mode for full-time engineering masters. Degree & Postgraduate Education, 2010(9), 28-31. https://doi.org/10.3969/j.issn.1001-960X.2010.09.006
- 21. Zhang, L. J., & Duan, Z. G. (2011). Preliminary study on the evaluation item system and the model for the medical universities styled teaching and research. Chinese Journal of Medical Education, 31(5), 780-783. https://doi.org/10.3760/cma.j.issn.1673-677X.2011.05.049
- 22. Zhang, M. R., Duan, H. W., Xu, J., et al. (2025). Health status evaluation of urban rail transit traction transformers based on analytic hierarchy process and entropy weight method. Urban Mass Transit, 28(1), 138-143. https://doi.org/10.16037/j.1007-869x.2025.01.025
- 23. Zhang, R., et al. (2023). Genetic algorithm optimised Hadamard product method for inconsistency judgement matrix adjustment in AHP and automatic analysis system development. Expert Systems with Applications, 211, 118689. https://doi.org/10.1016/j.eswa.2022.118689
- 24. Zhu, A. A., Cao, C. J., Zhang, L., et al. (2024). Application of Delphi method and analytic hierarchy process to construct the evaluation index system of healthy enterprises. Chinese Journal of Industrial Hygiene and Occupational Diseases, 42(2), 112-117. https://doi.org/10.3760/cma.j.cn121094-20221201-00571