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PAPER

Research on Teaching Quality Evaluation of Interactive Mobile AI Smart Classrooms Based on AHP

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ABSTRACT

The interactive mobile artificial intelligence (AI) smart classroom is a new teaching model that deeply integrates mobile terminals, AI, and classroom instruction. However, current teaching quality evaluations face challenges such as high subjectivity and vague indicators. To address these issues, this paper selects five evaluation factors: teaching objectives, interactive teaching processes, AI application, learning experience, and teaching effectiveness. The analytic hierarchy process (AHP) is first utilized to determine the weight of each indicator, followed by the Fuzzy comprehensive evaluation (FCE) method for integrated assessment. This study selects three representative smart teaching courses offered in universities as empirical samples for analysis. The results indicate that Research Methods in Educational Technology scored 86.77, Python Programming scored 86.29, and Design and Development of Smart Courses scored 90.86. Overall, the performance ranges from "Good" to "Excellent." These findings provide a quantitative basis for teachers to optimize instruction and for institutions to improve management levels.

KEYWORDS

analytic hierarchy process (AHP), fuzzy comprehensive evaluation (FCE), interactive mobile technology, smart classroom, teaching quality evaluation

1 INTRODUCTION

Currently, many universities have gradually introduced mobile terminals into the classroom. Teachers deliver knowledge to students via mobile devices using interactive technologies such as artificial intelligence (AI) and smart classroom systems, achieving full-process intelligent learning and providing new pathways for students to acquire knowledge [1]. However, traditional classroom evaluation systems suffer from an excessive proportion of subjective assessment and a lack of scientific quantitative methods. These systems struggle to adapt to the real-time interaction and process-oriented generation characteristics of mobile AI classrooms, resulting in

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lagging feedback mechanisms. Therefore, establishing a scientific evaluation model is crucial for enhancing the quality of smart teaching [2].

The significance of this research lies in two aspects: first, by combining analytic hierarchy process (AHP) and Fuzzy comprehensive evaluation (FCE), it constructs an evaluation model tailored for mobile AI smart classrooms, enriching the theoretical framework of intelligent teaching evaluation. Second, it provides schools and teachers with operational, quantifiable, and feedback-oriented evaluation tools to optimize AI teaching strategies and improve classroom quality [3].

2 CORE CONCEPTS AND THEORETICAL FOUNDATIONS

2.1 Core concepts

Interactive Mobile AI Smart Classroom: A new classroom model that uses mobile devices as carriers and integrates AI technology to support multi-directional interaction between teachers, students, and devices. It enables personalized teaching, process-oriented evaluation, and precise feedback [4].

AHP: A method that decomposes evaluation problems into a goal layer, a criterion layer, and an indicator layer. It calculates the weight of each indicator by constructing pairwise comparison judgment matrices [5].

FCE: A method used to handle fuzziness and uncertainty in evaluations. By constructing a judgment matrix and combining it with weight vectors, it produces scientific evaluation results [6].

2.2 Theoretical foundations

Constructivist Learning Theory: Emphasizes the student's central role and values interaction, collaboration, and meaning construction, providing a basis for the "Interactive" evaluation dimension [7].

Process-Oriented Evaluation Theory: Focuses on data across the entire teaching process, meeting the dynamic evaluation needs of "pre-class, in-class, and post-class" phases in mobile AI classrooms [8].

Human-Machine Collaboration Theory: Defines the boundaries between AI empowerment and teacher leadership, providing support for the design of "AI application and human-machine synergy" indicators [9] [10].

3 ESTABLISHMENT OF AHP INDICATOR WEIGHTS

3.1 AHP formulas

The formulas for the AHP are as follows [11]:

Construct the Judgment Matrix: Perform pairwise comparisons of the indicators to obtain the judgment matrix $A = (a_{ij})_{n \times n}$

Calculate Weights: Compute the eigenvector to determine the weight W for each indicator.

Consistency Check: Calculate the Consistency Index $CI = \dfrac{\lambda max - n}{n - 1}$

Verify the Consistency Ratio $CR = \frac{CI}{RI} < 0.1$

(Where RI is the random index. If $CR < 0.1$, the consistency of the judgment matrix is considered acceptable.)

3.2 Indicator identification

In March 2026, a panel of 10 experts—including educational technology specialists, frontline teachers, and AI educational product developers—was invited to participate in an online conference. The panel reached a consensus on the establishment of the evaluation indicators, as shown in Table 1.

Table 1. Evaluation indicators

Primary Indicators	Secondary Indicators	Indicator Description
B1 Teaching Objectives & Content	C11 Goal Alignment	Objectives align with curriculum standards and student profiles; compatible with AI teaching scenarios.
	C12 Content Accuracy	Knowledge is accurate and logically rigorous without errors.
	C13 Content Timeliness	Integration of cutting-edge knowledge and AI case studies; timely updates.
	C14 Content Personalization	AI-driven delivery of layered content tailored to varying learning levels.
B2 Interactive Teaching Process	C21 Teacher-Student Interaction Frequency	Real-time frequency of questioning, Q&A, and discussions.
	C22 Peer Interaction Quality	Effectiveness of group collaboration, peer assessment, and inquiry-based learning.
	C23 Human-Machine Interaction Fluency	Experience of interaction between students, AI tutors, and mobile terminals.
	C24 Instructional Pacing Control	Dynamic adjustment of teaching progress based on AI-generated student data.
	C25 Diversity of Interaction Modes	Variety of formats such as mobile quizzes, live AI interactive sessions, etc.
B3 AI Application & Support	C31 Technical Stability	Seamless operation of mobile terminals and AI platforms without lag or disconnection.
	C32 AI Functional Suitability	Utility of functions like intelligent Q&A, learning analytics, and resource recommendation.
	C33 Data Collection Comprehensiveness	Collection of multi-modal data including learning behaviors, interactions, and grades.
	C34 Depth of Tech Integration	Deep integration of AI into the instructional workflow rather than superficial application.
	C35 Privacy & Security	Encryption of student data; compliance with educational data standards.
B4 Student Experience & Engagement	C41 Classroom Participation	Rate of active speaking, answering questions, and inquiry participation.
	C42 Learning Interest	Student interest and concentration levels in the mobile AI classroom.
	C43 Autonomous Learning Ability	Ability to learn independently using mobile terminals and AI tools.
	C44 Collaborative Learning Outcomes	Quality of group task completion and contribution to collaboration.
B5 Teaching Effectiveness & Feedback	C51 Knowledge Mastery	Improvement in knowledge point tests and homework accuracy.
	C52 Competency Development	Growth in critical thinking, innovation, and information literacy.
	C53 Feedback Timeliness	Real-time feedback from teachers to improve learning and instructional strategies.

3.3 Indicator weights

Primary indicator weights. Using the Saaty 9-point scale, the 10 experts performed pairwise comparisons of indicators at the same level to construct a judgment matrix. The judgment matrix for the primary indicators is shown in Table 2.

Table 2. Judgment matrix of primary indicators

Primary Indicators	B1	B2	B3	B4	B5
B1	1	1/5	1/4	1/6	1/7
B2	5	1	3	1/3	1/5
B3	4	1/3	1	1/4	1/6
B4	6	3	4	1	1/3
B5	7	5	6	3	1

The calculated weights for the primary indicators are presented in Table 3.

Table 3. Weights of primary indicators

Primary Indicators	Weight	Interpretation
B1	3.6%	A foundational but traditional indicator; assigned the lowest weight in AI-driven scenarios.
B2	13.7%	An essential process dimension, as AI significantly enhances interaction.
B3	7.7%	Technology serves as a prerequisite but is not the ultimate goal.
B4	25.3%	High weight reflecting the core value of AI-powered personalization.
B5	49.6%	The most important result-oriented dimension, representing the final output and feedback loop.

Consistency Check Results:
Maximum Eigenvalue $\lambda\, max = 5.367$
Consistency Index $CI = 0.0918$
Random Index $RI = 1.12$
Consistency Ratio $CR = 0.082 < 0.1$
The judgment matrix passed the consistency check, indicating that the weight distribution is scientific and valid.

B1 secondary indicator weights. The judgment matrix for the secondary indicators of B1 is presented in Table 4.

Table 4. Judgment matrix of B1 secondary indicators

Secondary Indicators of B1	C11	C12	C13	C14
C11	1	3	5	1/3
C12	1/3	1	2	1/5
C13	1/5	1/2	1	1/7
C14	3	5	7	1

The calculated weights for the B1 secondary indicators are shown in Table 5.

Table 5. Weights of B1 secondary indicators

Secondary Indicators of B1	Weight	Interpretation
C11	26.3%	If objectives do not align with AI scenarios, the technology becomes merely performative.
C12	12.2%	While a baseline requirement, it carries relatively less weight in innovation-oriented evaluations.
C13	5.7%	Important, but plays only a supporting role within the teaching objectives.
C14	55.8%	The "soul" of the AI classroom lies in data-driven layered delivery, the most critical variable distinguishing it from traditional classrooms.

B2 secondary indicator weights. The judgment matrix for the secondary indicators of B2 is presented in Table 6.

Table 6. Judgment matrix of B2 secondary indicators

Secondary Indicators of B2	C21	C22	C23	C24	C25
C21	1	3	1/2	2	5
C22	1/3	1	1/4	1/2	3
C23	2	4	1	3	7
C24	1/2	2	1/3	1	4
C25	1/5	1/3	1/7	1/4	1

The calculated weights for the B2 secondary indicators are shown in Table 7.

Table 7. Weights of B2 secondary indicators

Secondary Indicators of B2	Weight	Interpretation
C21	25.7%	While AI is supportive, real-time questioning and discussion between teachers and students remain the core of teaching quality.
C22	11.7%	Although group collaboration is important in AI environments, it is constrained by terminal usage, making its weight slightly lower than teacher-student interaction.
C23	43.1%	In mobile AI classrooms, any lag in interaction between students and AI tutors or terminals renders all instructional designs ineffective.
C24	15%	Dynamic adjustment of progress based on AI learning data reflects the deep application of technology.
C25	4.5%	The richness of formats like live streaming is considered an "icing on the cake" and should not carry excessive weight.

Maximum Eigenvalue $\lambda\,max = 5.14$

Consistency Ratio $CR = 0.031 < 0.1$

The judgment matrix passed the consistency check, indicating that the weight distribution is scientific and valid.

B3 secondary indicator weights. The judgment matrix for the secondary indicators of B3 is presented in Table 8.

Table 8. Judgment matrix of B3 secondary indicators

Secondary Indicators of B3	C31	C32	C33	C34	C35
C31	1	3	5	1/7	2
C32	1/3	1	2	1/9	1/2
C33	1/5	1/2	1	1/9	1/3
C34	7	9	9	1	5
C35	1/2	2	3	1/5	1

The calculated weights for the B3 secondary indicators are shown in Table 9.

Table 9. Weights of B3 secondary indicators

Secondary Indicators of B3	Weight	Interpretation
C31	16.7%	Technical stability is the fundamental prerequisite; without it, all other functions are non-negotiable.
C32	6.5%	While important, functional suitability depends largely on the quality of the other indicators.
C33	4.1%	Comprehensive data collection is the necessary condition for AI intelligence.
C34	61.4%	The depth of integration determines whether AI truly empowers teaching; therefore, it carries the highest weight.
C35	11.3%	Privacy and security represent a "red line" bottom requirement; any breach renders the entire system unusable.

Maximum Eigenvalue $\lambda\, max = 5.136$

Consistency Ratio $CR = 0.03 < 0.1$

The judgment matrix passed the consistency check, indicating that the weight distribution is scientific and valid.

B4 secondary indicator weights. The judgment matrix for the secondary indicators of B4 is presented in Table 10.

Table 10. Judgment matrix of B4 secondary indicators

Secondary Indicators of B4	C41	C42	C43	C44
C41	1	3	5	7
C42	1/3	1	2	4
C43	1/5	1/2	1	3
C44	1/7	1/4	1/3	1

The calculated weights for the B4 secondary indicators are shown in Table 11.

Table 11. Weights of B4 secondary indicators

Secondary Indicators of B4	Weight	Interpretation
C41	57.7%	Classroom participation is the most direct and observable experience indicator; thus, it carries the highest weight.
C42	23%	Learning interest serves as the prerequisite and emotional foundation for sustained engagement.
C43	13.3%	Autonomous learning ability reflects the long-term value of AI empowerment.
C44	6%	While important, collaborative outcomes are more influenced by students' own collaboration literacy; the impact of AI is relatively weaker here, resulting in the lowest weight.

Maximum Eigenvalue $\lambda\, max = 4.067$

Consistency Ratio $CR = 0.025 < 0.1$

The judgment matrix passed the consistency check, indicating that the weight distribution is scientific and valid.

B5 secondary indicator weights. The judgment matrix for the secondary indicators of B5 is presented in Table 12.

Table 12. Judgment matrix of B5 secondary indicators

Secondary Indicators of B5	C51	C52	C53
C51	1	1/3	1/5
C52	3	1	1/2
C53	5	2	1

The calculated weights for the B5 secondary indicators are shown in Table 13.

Table 13. Weights of B5 secondary indicators

Secondary Indicators of B5	Weight	Interpretation
C51	11%	While important, knowledge mastery is a foundational level that traditional teaching can also achieve effectively; AI's incremental impact is relatively limited, resulting in the lowest weight.
C52	30.9%	Competency development represents the long-term core objective pursued by AI-enhanced instruction.
C53	58.1%	Timely feedback is the most distinctive core advantage of AI classrooms for directly improving learning efficiency; thus, it carries the highest weight.

Maximum Eigenvalue $\lambda\, max = 3.004$

Consistency Ratio $CR = 0.003 < 0.1$

The judgment matrix passed the consistency check, indicating that the weight distribution is scientific and valid.

3.4 Composite weights

After calculation, the composite weights of the primary and secondary indicators are presented in Table 14.

Table 14. Composite weights of all indicators

Primary Indicators	Secondary Indicators	Indicator Name	Primary Weight	Secondary Weight	Composite Weight
B1	C11	C11 Goal Alignment	3.60%	26.30%	0.95%
	C12	C12 Content Accuracy		12.20%	0.44%
	C13	C13 Content Timeliness		5.70%	0.21%
	C14	C14 Content Personalization		55.80%	2.01%
B2	C21	C21 Teacher-Student Interaction Frequency	13.70%	25.70%	3.52%
	C22	C22 Peer Interaction Quality		11.70%	1.60%
	C23	C23 Human-Machine Interaction Fluency		43.10%	5.90%
	C24	C24 Instructional Pacing Control		15.00%	2.06%
	C25	C25 Diversity of Interaction Modes		4.50%	0.62%
B3	C31	C31 Technical Stability	7.70%	16.70%	1.29%
	C32	C32 AI Functional Suitability		6.50%	0.50%
	C33	C33 Data Collection Comprehensiveness		4.10%	0.32%
	C34	C34 Depth of Tech Integration		61.40%	4.73%
	C35	C35 Privacy & Security		11.30%	0.87%
B4	C41	C41 Classroom Participation	25.30%	57.70%	14.60%
	C42	C42 Learning Interest		23.00%	5.82%
	C43	C43 Autonomous Learning Ability		13.30%	3.36%
	C44	C44 Collaborative Learning Outcomes		6.00%	1.52%
B5	C51	C51 Knowledge Mastery	49.60%	11.00%	5.46%
	C52	C52 Competency Development		30.90%	15.33%
	C53	C53 Feedback Timeliness		58.10%	28.82%

4 FCE MODEL

4.1 FCE formulas

A 5-level fuzzy evaluation set is established: V = {Excellent, Good, Moderate, Poor, Very Poor}. These levels are assigned the numerical values V = {100, 80, 60, 40, 20}.

First, the membership matrix R is determined. Then, combined with the weight vector W, the comprehensive evaluation vector B is calculated as: B = W * R. The final score is calculated using the weighted average of the evaluation set:

$$B = (w_1, w_2, \dots, w_n) \cdot \begin{bmatrix} r_{11} & \cdots & r_{14} \\ \vdots & \ddots & \vdots \\ r_{n1} & \cdots & r_{n4} \end{bmatrix} \tag{1}$$

The final quality grade is determined according to the Principle of Maximum Membership Degree [12].

4.2 Research subjects

Three mobile AI smart classroom courses commonly offered in universities were selected as empirical samples:

Research Methods in Educational Technology
Python Programming
Design and Development of Smart Courses

4.3 Data collection

An online expert review was conducted. Twenty participants (including teachers and students) were invited to evaluate the three courses via "Questionnaire Star" (Wenjuanxing) between March 25 and March 31, 2026.

4.4 Questionnaire design

The questionnaire utilized a Likert scale to score the primary indicators across five scales, ranging from "Excellent" to "Very Poor."

4.5 Scoring results

The expert scoring results for the three courses are presented in Tables 15–17.

Table 15. Scoring results for research methods in educational technology

Primary Indicators	V1	V2	V3	V4	V5
B1 Teaching Objectives & Content	14	5	1		
B2 Interactive Teaching Process	10	7	2	1	
B3 AI Application & Support	10	5	4	1	
B4 Student Experience & Engagement	11	7	2		
B5 Teaching Effectiveness & Feedback	9	8	3		

The Membership Matrix R:

$$R = \begin{pmatrix} 0.70 & 0.25 & 0.05 & 0.00 & 0.00 \\ 0.50 & 0.35 & 0.10 & 0.05 & 0.00 \\ 0.50 & 0.25 & 0.20 & 0.05 & 0.00 \\ 0.55 & 0.35 & 0.10 & 0.00 & 0.00 \\ 0.45 & 0.40 & 0.15 & 0.00 & 0.00 \end{pmatrix} \tag{2}$$

The Overall Evaluation Vector B = (0.49455, 0.36315, 0.13060, 0.01070, 0.00000)
The final evaluation score F = VBT, is 86.77

Table 16. Scoring results for Python programming

Primary Indicators	V1	V2	V3	V4	V5
B1 Teaching Objectives & Content	12	5	3		
B2 Interactive Teaching Process	10	8	1	1	
B3 AI Application & Support	10	4	4	1	1
B4 Student Experience & Engagement	12	6	2		
B5 Teaching Effectiveness & Feedback	10	6	3	1	

The Membership Matrix R:

$$R = \begin{pmatrix} 0.60 & 0.25 & 0.15 & 0.00 & 0.00 \\ 0.50 & 0.40 & 0.05 & 0.05 & 0.00 \\ 0.50 & 0.20 & 0.20 & 0.05 & 0.05 \\ 0.60 & 0.30 & 0.10 & 0.00 & 0.00 \\ 0.50 & 0.30 & 0.15 & 0.05 & 0.00 \end{pmatrix} \tag{3}$$

The overall evaluation vector B = (0.52840, 0.30390, 0.12735, 0.03550, 0.00385)
The final evaluation score F = 86.29.

Table 17. Scoring results for design and development of smart courses

Primary Indicators	V1	V2	V3	V4	V5
B1 Teaching Objectives & Content	15	3	2		
B2 Interactive Teaching Process	12	8			
B3 AI Application & Support	15	4	1		
B4 Student Experience & Engagement	14	5	1		
B5 Teaching Effectiveness & Feedback	9	11			

The Membership Matri R:

$$R = \begin{pmatrix} 0.75 & 0.15 & 0.10 & 0.00 & 0.00 \\ 0.60 & 0.40 & 0.00 & 0.00 & 0.00 \\ 0.75 & 0.20 & 0.05 & 0.00 & 0.00 \\ 0.70 & 0.25 & 0.05 & 0.00 & 0.00 \\ 0.45 & 0.55 & 0.00 & 0.00 & 0.00 \end{pmatrix} \tag{4}$$

The Overall Evaluation Vector B = (0.56725, 0.41165, 0.02010, 0.0000, 0.0000)
The final evaluation score F = 90.86.

5 CONCLUSION AND DISCUSSION

5.1 Conclusion

Based on the research findings, the following conclusions are drawn: Research Methods in Educational Technology: 86.77 (High-end of "Good," approaching "Excellent"). Python Programming: 86.29 (High-end of "Good"). Design and Development of Smart Courses: 90.86 (Excellent). The overall fuzzy comprehensive evaluation result for the three courses is above Good and approaching Excellent, with an average score of 87.97.

Key Trends observed: Grade Distribution: The average membership degree for the "Excellent" grade (V1) is approximately 53.01%, representing the highest proportion. The "Good" grade (V2) averages 35.96%, while the combined membership for "Moderate" and below (V3–V5) is only 10.93% (with "Moderate" at 9.27% and "Poor/Very Poor" being negligible). This indicates high student approval and strong overall performance.

Course Ranking: The ranking is Design and Development of Smart Courses > Research Methods in Educational Technology > Python Programming. The core gaps are concentrated in Teaching Effectiveness & Feedback (B5) and Student Experience & Engagement (B4):

The highest score for Design and Development of Smart Courses is due to the high alignment between its course attributes and the evaluation system, as it is a core curriculum for smart education. Its B5 and B4 dimensions were particularly outstanding.

The second-highest score for Research Methods in Educational Technology shows a balanced integration of theory and AI, though it lacked slightly in detail, resulting in a 4.09-point gap behind the top course in the B5 dimension.

The lowest score for Python programming reveals shortcomings in technical adaptation and interaction quality. The main points were lost in AI Application & Support (B3) and the Interactive Teaching Process (B2).

5.2 Discussion

While this study successfully constructed an evaluation model for interactive mobile AI smart classrooms using AHP and FCE, several limitations remain:

Limited Sample Size and Representativeness: The study only sampled three courses from a single university with 20 evaluators. The focus on educational technology and computer science limits the generalizability across different disciplines, institution types, and geographic regions.

Subjectivity in Data Collection: Although FCE mitigates fuzziness, the data relies heavily on expert questionnaires. The lack of real-time, objective classroom data means subjective judgment still plays a significant role.

Short Evaluation Window: The five-day survey period lacks long-term tracking and cannot reflect how courses improve dynamically over time.

Model Depth: The FCE was conducted primarily at the primary indicator level. Future research should implement full hierarchical FCE for secondary indicators and introduce dynamic weight adjustment mechanisms or comparative methods (e.g., Entropy Weight Method, TOPSIS, or machine learning models) to enhance robustness [13].

External Validity and Application: While the indicators were expert-validated, they have not undergone large-scale teacher training or system-platform integration. The practical landing of the feedback loop in school management requires further verification.

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