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Construction and Effectiveness Test of AI-Enabled Blended Teaching Mode for Pedagogy Courses: A Quasi-Experimental Study Based on the Cultivation of Pre-service Teachers' Teaching Competence

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Abstract: This quasi-experimental study (N=96 pre-service teachers, 18 weeks) examines an AI-enabled blended teaching model for pedagogy courses, comparing it with a traditional blended model. The AI model featured intelligent diagnosis, virtual practicum, and real-time feedback. Results showed significant improvements in instructional design, classroom implementation, and AI literacy ($p<0.001$). AI-generated feedback mediated 55.85% of competence gains, and multimodal learning behavior predicted growth trajectories ($R^2=0.624$). Findings provide a practical paradigm for AI integration in teacher education and empirical evidence for advancing blended learning theory.

Keywords: artificial intelligence, pedagogy courses, blended teaching, teacher education, teaching reform

1. Introduction

The digital transformation of education is a global trend, with recent Chinese policies emphasizing AI-driven innovation in teacher education. Empowering core pedagogy courses with AI is thus an urgent research topic.

Pedagogy courses are a key link in the cultivation of pre-service teachers, whose core task is to help learners transform educational theory into teaching practice competence. However, traditional pedagogy courses are mostly dominated by teachers' lectures, supplemented by case discussions and micro-teaching, which have obvious shortcomings in individualized support, real-time feedback, and accurate evaluation. Although some colleges and universities have tried to introduce online platforms to carry out blended teaching, most of them still remain at the level of formal integration of "online + offline", lacking in-depth interaction and intelligent diagnosis based on learning data. The introduction of AI technology provides the possibility to break through the above bottlenecks (Luckin et al., 2016; Zawacki-Richter et al., 2019). Through technologies such as speech recognition, natural language processing, and affective computing, quantitative analysis and real-time feedback of teaching behaviors can be realized, helping students to practice repeatedly and improve continuously in simulated scenarios (Zawacki-Richter et al., 2019; Luckin et al., 2016).

Taking pedagogy courses as the entry point, this study explores the in-depth integration path of AI technology and blended teaching, aiming to build a set of blended teaching reform models with AI empowerment as the core feature, and promote the digital transformation of teacher education curricula.

While recent international scholarship has increasingly attended to AI's role in education (e.g., Uğraş et al., 2024; Katsampoxaki-Hodgetts et al., 2025; Zacharis & Papadakis, 2025), a significant gap remains regarding the systematic integration of AI throughout the entire teaching cycle within core teacher education courses, particularly within non-Western contexts. This study addresses this gap through a quasi-experimental evaluation of an AI-enabled blended teaching model designed for pedagogy courses.

Centering on the core research objectives, this study proposes the following four research questions with a logical progressive relationship:

RQ1: Can the AI deeply embedded blended teaching mode significantly improve pre-service teachers' instructional design competence, classroom implementation competence, and AI application literacy?

RQ2: Is there a significant difference in the cultivation effect of pre-service teachers' teaching competence between the AI-enabled blended teaching mode and the traditional blended teaching mode?

RQ3: Does the real-time feedback generated by AI have a significant mediating effect in the process

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of improving pre-service teachers' teaching competence?

RQ4: Can the multimodal data of pre-service teachers' AI learning behaviors effectively predict the growth trajectory of their teaching competence?

The integration of technological knowledge, pedagogical knowledge, and subject content knowledge is the core of teachers' professional competence, which is also the core proposition of the Technological Pedagogical Content Knowledge (TPACK) framework. The theoretical significance of this study lies in expanding the connotation of blended teaching theory in the intelligent era, reconstructing the TPACK framework in the AI context, and enriching the data-based application path of formative assessment theory by constructing an AI-driven blended teaching mode. The practical significance lies in solving the practical dilemmas of traditional pedagogy courses, providing a replicable and popularizable practical paradigm for the reform of AI-enabled teacher education courses in normal universities and colleges, and offering practical reference for improving pre-service teachers' teaching competence and digital literacy.

2. Literature Review and Theoretical Foundation

2.1 Definition of core concepts

Core concepts are defined as follows: Pedagogy Courses are compulsory teacher education courses bridging theory and practice; Blended Teaching refers to the organic integration of online and offline learning; AI-Enabled Teaching in this context involves systematically embedding AI technologies (e.g., machine learning, natural language processing) throughout the teaching cycle to enable intelligent diagnosis, personalized support, and real-time feedback.

2.2 Domestic and international research status

2.2.1 Research on blended teaching

Research on blended teaching has gone through three stages: technology application, model construction, and in-depth integration. The Community of Inquiry framework, which emphasizes the interaction of cognitive presence, social presence, and teaching presence, has laid a core theoretical foundation for blended teaching (Garrison & Vaughan, 2008). Chinese scholars have systematically sorted out the design framework of blended teaching, pointing out that effective blending needs to realize the organic integration of online and offline, rather than formal scene splicing (Feng et al., 2018).

In recent years, international research on blended teaching has further extended to the direction of data-driven personalization. Effective blended teaching needs to break through the formal splicing of online and offline, and build a dynamic adaptation mechanism based on learning data, and the embedding of intelligent technology is the core support to achieve this goal (Boerboom et al., 2024). Meta-analysis confirms that blended teaching without data-driven linkage shows no significant advantage over traditional methods (Jung et al., 2022). However, current blended practices often remain superficial, lacking deep data-driven linkage between online and offline activities and failing to form a complete teaching closed loop.

Although existing studies have constructed a mature framework and practical path for blended teaching, most of them still focus on the scene integration of online and offline, and have not yet explored the implementation mechanism of using AI technology as the core driving element to reconstruct the whole process of blended teaching. In particular, there is a lack of research on the construction of intelligent blended teaching mode adapted to the cultivation of pre-service teachers' competence in teacher education courses, which is the core problem that this study focuses on breaking through.

2.2.2 Research on AI application in education

Research on AI application in education is increasingly abundant. Relevant systematic reviews show that the application of AI in higher education mainly focuses on four core fields: learning analytics, adaptive learning, intelligent tutoring, and evaluation feedback (Zawacki-Richter et al., 2019). Relevant studies point out that AI can identify learners' needs through data analysis and provide personalized learning paths, which is the core support for realizing individualized teaching (Luckin et al., 2016). Chinese scholars have discussed the reform direction of educational technology in the era of artificial intelligence, emphasizing that AI should serve students' deep learning and competence development, which clarifies the core direction for AI education application (He, 2019).

In recent years, international research on the application of AI in teacher education has continued to deepen. Some studies have realized the quantitative tracking and real-time feedback of pre-service teachers' teaching behaviors through multimodal learning analytics technology, verifying the improvement effect of AI technology on pre-service teachers' classroom implementation competence (Kleinknecht et al., 2023). Other studies have systematically sorted out the core paradigm of human-machine collaborative teaching, pointing out that the application of AI in teacher education needs to shift from tool assistance to systematic embedding in the curriculum system, rather than the superposition of single functions (Cheung et al., 2024).

In addition, relevant studies have confirmed that AI-based formative assessment can significantly shorten the feedback cycle of pre-service teachers' teaching practice and improve the pertinence and effectiveness of teaching reflection, which is the core entry point of AI empowering teacher education (Henderson et al., 2025). However, existing research has limitations. Most studies verify AI as an auxiliary tool rather than systematically embedding it into core teacher education courses, and findings derive mainly from Western contexts, lacking localized evidence for China's teacher education system, which is difficult to respond to the core demand of the digital transformation of teacher education in China.

2.2.3 Research on pedagogy course reform

Research on pedagogy course reform mainly focuses on three dimensions: content update, method innovation, and practice strengthening. Relevant studies point out that subject pedagogy courses in normal universities and colleges in China generally face three dilemmas: the separation of theory and practice, weak practical links, and rigid evaluation methods, which are the key bottlenecks restricting the cultivation of pre-service teachers' teaching competence (Wang & Wu, 2023). Some Chinese scholars have tried to introduce models such as micro-teaching, case teaching, and flipped classroom, and have achieved certain results. However, restricted by class hours and resources, students still have limited opportunities for teaching practice.

International research confirms that high-frequency practice with real-time feedback is central to developing teaching competence, yet traditional pedagogy courses constrained by limited hours and resources cannot meet this demand (Rienties et al., 2023). Virtual simulation combined with AI feedback addresses this gap by enabling repeated practice and iterative improvement (Grossman et al., 2024). Existing reforms, however, have yet to establish a comprehensive AI-supported system covering the entire teaching process.

Overall, research on blended teaching is relatively mature, but how to deeply integrate it with AI technology still needs to be explored. Research on AI application in education is increasingly abundant, but there are few special studies on pedagogy courses. The reform of pedagogy courses calls for technology empowerment. Taking pedagogy courses as the entry point, this study explores the in-depth integration path of AI technology and blended teaching, which has clear problem orientation and innovative value.

2.3 Theoretical foundation and mechanism model

2.3.1 Core theoretical foundations

This study is grounded in three established educational frameworks. Constructivist learning theory (Piaget, 1970) posits that knowledge is actively constructed through situated practice and interaction, a process facilitated here by AI-enabled virtual simulations and real-time feedback. The Technological Pedagogical Content Knowledge (TPACK) framework (Mishra & Koehler, 2006) guides the integration of AI technical knowledge with pedagogical strategies and subject content, thereby expanding the scope of pre-service teachers' professional competence. Finally, formative assessment theory (Black & Wiliam, 1998) underscores the role of continuous, data-informed feedback in driving learning gains—a principle operationalized in this study through AI-driven learning analytics. Together, these theories inform the design and evaluation of the AI-enabled blended teaching model.

2.3.2 AI as a feedback agent and co-participant

Extending beyond a tool-centric perspective, this study positions AI in two interrelated roles. First, AI functions as a feedback agent, analyzing multimodal learner data to generate immediate, actionable, and criteria-referenced formative feedback (Henderson et al., 2025; Zacharis & Papadakis, 2025). Second, AI acts as a co-participant, dynamically adapting content and prompting reflection to co-create the learning experience (Cheung et al., 2024). This dual conceptualization grounds the AI-driven mechanism model below, shifting the paradigm from learning from AI to learning with AI.

2.3.3 AI-Driven mechanism model for teaching competence development

Based on constructivist learning theory, the TPACK framework, formative assessment theory, and the conceptualization of AI as a feedback agent and co-participant, this study constructs an AI-driven mechanism model for teaching competence development. Based on multimodal data and with human-machine collaboration as the core, the model forms a closed-loop development path of "perception-analysis-feedback-adjustment-promotion", and clarifies the internal mechanism of AI technology empowering the development of pre-service teachers' teaching competence. It provides a core theoretical framework for the scheme design and practical implementation of this curriculum reform.

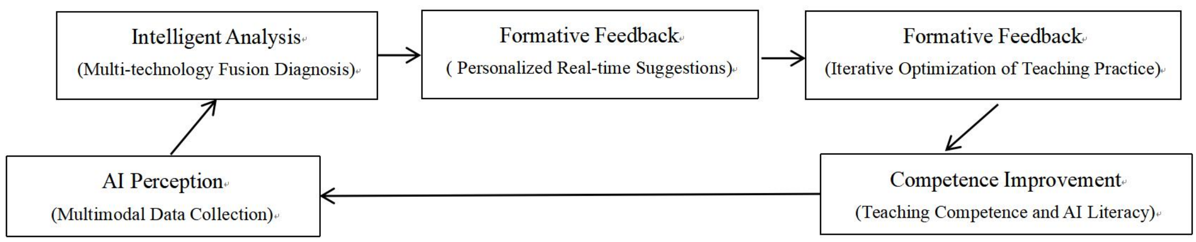

Figure 1 AI-Driven Mechanism Model for Teaching Competence Development

The core operation logic of the model is as follows:

(1) AI perception layer: Collect the whole-process learning data of pre-service teachers through smart classrooms, virtual laboratories, and online learning platforms, including multimodal information such as online learning behavior data, instructional design text data, voice and behavior data of simulated teaching, and teaching reflection text data, to provide full-dimensional data support for subsequent analysis.

(2) Intelligent analysis layer: Relying on technologies such as natural language processing, computer vision, and machine learning, conduct in-depth mining of the collected multimodal data, including semantic analysis of instructional design, speech feature analysis of teaching language, behavior recognition of classroom interaction, and in-depth coding of reflection texts, to realize accurate diagnosis of pre-service teachers' learning status and competence level.

(3) Formative feedback layer: Based on the results of intelligent analysis, generate personalized and real-time formative feedback for pre-service teachers, including intelligent push of learning resources before class, real-time prompts of teaching behaviors during class, and after-class ability growth reports and improvement suggestions, replacing the traditional lagging and extensive feedback mode.

(4) Behavior adjustment layer: Based on the feedback report generated by AI, pre-service teachers carry out learning behaviors such as optimization of instructional design, iteration of simulated teaching, and deepening of teaching reflection, and complete the active construction of knowledge and correction of teaching behaviors in the cycle of "virtual teaching trial-feedback improvement".

(5) Competence promotion layer: Through multiple rounds of closed-loop cycles, pre-service teachers' instructional design competence and classroom implementation competence are systematically improved. At the same time, in the process of applying AI tools, they form AI application literacy adapted to the intelligent education era, realizing the all-round development of TPACK ability.

This model fully undertakes the core propositions of the three core theories, realizes the unification of theoretical framework and practical mode, and provides implementable theoretical guidance for the subsequent empirical research.

3. Research Design and Methodology

3.1 Research content

This study restructured the original Pedagogy course into three modules: AI Education Application, Intelligent Instructional Design, and Virtual Teaching Practicum, supported by a dedicated resource library.

The AI-led intelligent blended teaching closed loop embedded AI throughout pre-class diagnosis, in-class real-time analysis, and post-class feedback generation.

In terms of practice link strengthening, relying on the virtual simulation teaching platform, an "AI Teaching Training Center" is built, AI teaching assistant is introduced for real-time feedback, and an "AI Classroom Observation and Feedback System" is established to realize the linkage practice inside and outside the campus.

In terms of evaluation mechanism reform, a four-dimensional comprehensive mechanism of "AI evaluation, peer evaluation, teacher evaluation, and self-reflection" is constructed, and the AI learning analytics dashboard is used to dynamically display students' learning paths and ability growth.

3.2 Research methods

This study adopts the quasi-experimental research method as the core, combined with questionnaire survey method, text analysis method, and semi-structured interview method to carry out systematic research. The specific research design is as follows:

3.2.1 Quasi-Experimental Design

(1) Sample description

This study selected junior students majoring in teacher education from the School of Education of a local university in eastern China as the research subjects. A total of 2 parallel teaching classes with exactly the same training program and teaching teachers were included, with a total of 96 students, including 18 male students and 78 female students.

Cluster random grouping was carried out using a random number table method, with 48 participants in the experimental group and 48 in the control group. To test the baseline homogeneity of the two groups, an independent samples t-test was conducted on the students' previous grades in basic courses of pedagogy and psychology. The results showed no significant difference between the two groups ($t=0.372$, $df=94$, $p=0.711>0.05$), indicating homogeneity between the groups and meeting the grouping requirements of quasi-experimental research (Cohen, Manion, & Morrison, 2018).

The experimental period was one complete semester (18 weeks). The experimental group adopted the AI-enabled blended teaching mode constructed in this study, and the control group adopted the traditional blended teaching mode.

(2) Experimental variables

Independent variable: Teaching mode, divided into two levels: AI-enabled blended teaching mode (experimental group) and traditional blended teaching mode (control group). The total class hours, core teaching content, teaching teachers, and assessment weight settings of the two groups are completely consistent, with only differences in the teaching implementation mode. The control group followed a conventional blended format comprising pre-class online preview tasks, lecture-based offline sessions with case analysis and micro-teaching, and post-class instructor feedback, without AI-driven diagnosis, virtual training, or real-time analytics.

Dependent variables: Pre-service teachers' teaching competence (including instructional design competence and classroom implementation competence) and AI application literacy.

Control variables: Course content, teaching hours, teaching teachers, and assessment standards were kept consistent to eliminate the interference of irrelevant variables

3.2.2 Semi-Structured interview method

After the course, semi-structured interviews were conducted with 10 students in the experimental group and 2 teaching teachers. The interview outline focused on three dimensions: experience of AI blended teaching, perception of ability improvement, and suggestions for mode optimization. The interview duration was 30-40 minutes per person. After the interview recordings were transcribed, NVivo 12 was used for three-level coding (open coding, axial coding, selective coding) to extract core viewpoints for qualitative analysis.

3.2.3 Text analysis method

Text analysis was conducted on the pre- and post-test instructional design schemes and teaching reflection reports of 48 students in the experimental group. The coding dimensions included the integrity of instructional design (4 secondary indicators), teaching innovation (3 secondary indicators), and reflection depth (3 secondary indicators). Coding consistency test (Kappa value=0.82, $p<0.001$) was used to ensure coding reliability, and the changes in students' competence before and after the experiment were compared and analyzed.

3.2.4 Questionnaire survey method

Through standardized scales, pre- and post-tests were conducted on students in the experimental group and the control group to collect core data such as pre-service teachers' teaching competence, AI application literacy, and AI feedback quality for quantitative analysis.

3.3 Research Instruments

3.3.1 Scale for pre-service teachers' teaching competence assessment

This study adopted the revised Scale for Pre-service Teachers' Subject Teaching Competence as the core assessment instrument. The scale was revised based on the Professional Standards for Middle School Teachers (Trial) issued by the Ministry of Education of China and the mature scale developed by Chinese scholars Wang and Wu (2023).

It is divided into two core dimensions: instructional design competence and classroom implementation competence, with a total of 22 items, including 10 items in the instructional design competence dimension and 12 items in the classroom implementation competence dimension. The scale adopts a 5-point Likert scoring method, with 1=completely inconsistent and 5=completely consistent. The higher the score, the higher the level of the subject's teaching competence.

After reliability and validity tests, the overall Cronbach's α coefficient of the scale is 0.921, the Cronbach's α coefficient of each dimension is greater than 0.850, the KMO value is 0.903, and the significance of Bartlett's test of sphericity is $p<0.001$, indicating good reliability and validity.

3.3.2 AI application literacy scale

The self-compiled Scale for Pre-service Teachers' AI Education Application Literacy was adopted in this study. The scale was designed based on the education industry standard of Teachers' Digital Literacy issued by the Ministry of Education of China, combined with the core scenarios of AI education application.

It is divided into three dimensions: AI application awareness, AI tool application ability, and AI education ethics cognition, with a total of 15 items, including 4 items in the AI application awareness dimension, 6 items in the AI tool application ability dimension, and 5 items in the AI education ethics cognition dimension. The scale adopts a 5-point Likert scoring method, with 1=completely inconsistent and 5=completely consistent. The higher the score, the higher the level of the subject's AI education application literacy.

The initial items were reviewed and revised by 3 professors of educational technology and 2 front-line teacher education course teachers to ensure content validity. After testing, the overall Cronbach's α coefficient of the scale is 0.876, and the Cronbach's α coefficient of each dimension is greater than 0.800, indicating good reliability. The results of exploratory factor analysis show that the KMO value is 0.862, Bartlett's test of sphericity $\chi^2=897.632$, $df=91$, $p<0.001$, which is suitable for factor analysis. Using principal component analysis and maximum variance orthogonal rotation, 3 common factors with eigenvalues greater than 1 were extracted, the factor load of each item is above 0.65, and the cumulative variance explanation rate is 68.72%, which is consistent with the preset dimension structure. The scale has good structural validity, and its reliability and validity meet the requirements of academic research.

3.3.3 AI feedback quality scale

The revised AI feedback quality scale was adopted, which was revised based on the mature scale developed by Cheung et al. (2024). It has a total of 8 items and adopts a 5-point Likert scoring method, with 1=completely inconsistent and 5=completely consistent. The higher the score, the higher the quality of AI feedback perceived by the subject. After testing, the overall Cronbach's α coefficient of the scale is 0.842, with good reliability, which is suitable for the mediating effect test in this study.

3.3.4 AI learning platform behavior data collection

The whole-process learning behavior data of pre-service teachers were collected through the course AI learning platform. The core variables were defined as follows: learning engagement (online learning duration, task completion rate, forum interaction times), AI tool use frequency, simulated teaching times, and feedback iteration times. All variables were standardized for subsequent data analysis.

3.3.5 Technical specifications and limitations of the AI system

The AI-enabled platform integrated automatic speech recognition (ASR), natural language processing (NLP) based on a BERT architecture, and facial action unit analysis via OpenFace 2.0 to capture multimodal teaching behaviors. Detailed technical specifications and known limitations regarding dialect accuracy, semantic nuance, and affective inference are provided in the Appendix. These limitations should be considered when interpreting the effects of AI-generated feedback.

3.4 Data analysis methods

This study used SPSS 26.0 and AMOS 24.0 for data analysis. Paired and independent samples t-tests were used for within- and between-group comparisons. Analysis of Covariance (ANCOVA) with pre-test scores as covariates was conducted to verify the main effect of teaching mode. Pearson correlations examined relationships among core variables. Mediating effects of AI-generated feedback were tested using hierarchical regression and Bootstrap methods (PROCESS macro, Model 4). Multiple linear regression assessed the predictive effect of multimodal learning behavior data on teaching competence growth.

4. Reform Scheme of AI-Enabled Pedagogy Course

4.1 Reconstruction of the three-dimensional curriculum system

The total class hours of the reformed pedagogy course are 48 class hours, which are divided into three learning forms: 16 class hours of theoretical teaching, 16 class hours of online independent learning, and 16 class hours of virtual training. The 48-hour course was restructured into three integrated modules—AI Education Application (8h), Intelligent Instructional Design (16h), and Virtual Teaching Practicum (24h)—each blending theoretical teaching, online independent learning, and AI-supported virtual simulation. The AI Education Application module introduces AI concepts, tools (e.g., ChatGPT, iFlytek Spark), and ethical considerations through case analysis and hands-on experience. The Intelligent Instructional Design module guides students in using AI to formulate objectives, generate resources, and design assessments. The Virtual Teaching Practicum module requires students to complete at least three simulated teaching sessions with AI-generated feedback reports, supported by a curated resource library of cases, templates, and micro-lecture videos.

4.2 Intelligent blended teaching closed loop

This study innovatively constructs an AI-led intelligent blended teaching closed loop of "pre-class intelligent diagnosis - in-class training and interaction - after-class feedback iteration". The complete framework is shown in Figure 2.

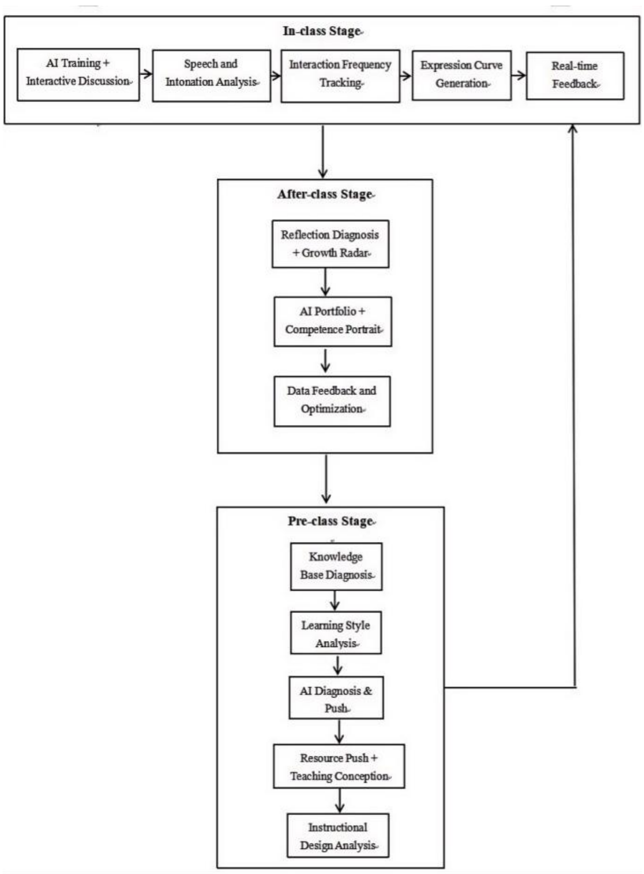

Figure 2 Framework of the "Intelligent Blended Teaching Closed Loop" for AI-Enabled Pedagogy Course

As illustrated in Figure 2, the closed loop integrates AI-driven pre-class diagnosis, in-class real-time feedback during virtual practicum, and post-class portfolio generation, enabling data-informed adaptive teaching and continuous competency tracking.

4.3 Strengthening of practical links

The AI-powered virtual training center enables high-frequency simulated teaching with real-time, context-sensitive prompts, addressing the practicum constraints of traditional courses. AI-assisted analysis extends to field internships, providing performance maps that complement mentor feedback and form a continuous "practice-feedback-improvement" cycle.

4.4 Multiple intelligent evaluation system

Table 1 outlines the five-dimension process evaluation indicator system, detailing data sources and weightings for each component of formative assessment.

Table 1 Process Evaluation Indicator System for AI-Enabled Pedagogy Course

Dimension	Indicators	Data Source	Weight
Learning Engagement	Learning duration, task completion rate, discussion participation times	Platform log	15%
Instructional Design Competence	Clarity of teaching objectives, innovation of activity design	AI semantic analysis	25%
Classroom Implementation Competence	Appropriateness of speech speed, quality of questions, interaction frequency	AI speech and behavior analysis	30%
Reflection Ability	Depth of reflection text, feasibility of improvement plan	AI text analysis	15%
AI Application Literacy	Frequency of AI tool use, innovative application cases	Work analysis	15%

The four-dimensional comprehensive evaluation mechanism adopts a combination of AI evaluation (30%), peer evaluation (20%), teacher evaluation (30%), and self-reflection (20%). The AI system generates quantitative scores and qualitative comments based on preset algorithms, peers score according to the evaluation scale, teachers conduct comprehensive assessment combined with AI reports and classroom observation, and students write reflection reports to explain learning gains and improvement directions.

In terms of visualization of evaluation results, the AI learning analytics dashboard dynamically displays students' learning paths, competence growth radar charts, and weak links. Teachers can view the overall progress of the class in real time, and the system automatically generates teaching optimization suggestions, such as "80% of students in this week have low scores in the questioning strategy dimension, and it is recommended to carry out special training". Students can view their personal portfolios at any time to clarify the direction of improvement.

5. Research Results

Based on the quasi-experimental design, this study obtained the following research results through scale assessment, platform data collection and text analysis, which respond to the research questions raised above one by one, and provide empirical basis for the verification of the theoretical framework.

First, the prerequisite hypothesis test was carried out on all scale data. The results of Shapiro-Wilk normality test showed that the data of each dimension conformed to the normal distribution ($p>0.05$). Levene's test of homogeneity of variance showed that the variance of the two groups of data was homogeneous ($p>0.05$), which met the prerequisites for parametric tests (t-test, analysis of covariance, regression analysis).

5.1 Correlation analysis of core variables

Pearson correlation analysis was conducted on core variables such as teaching mode, AI feedback quality, learning engagement, AI tool use frequency, and teaching competence improvement.

Teaching mode was positively correlated with teaching competence improvement ($r=0.623$) and AI literacy ($r=0.715$, both $p<0.001$). AI feedback quality correlated with competence improvement ($r=0.687$, $p<0.001$). Learning engagement, AI tool use frequency, simulated teaching frequency, and feedback iterations all showed positive correlations with competence improvement ($r=0.421$–0.612, all $p<0.001$). This result is highly consistent with the core proposition of formative assessment theory, and lays a foundation for subsequent regression analysis and mediating effect test.

5.2 Intra-Group difference test of teaching competence and AI application literacy of pre-service teachers in the two groups before and after the experiment

Paired samples t-test was used to analyze the difference in competence scores between the experimental group and the control group before and after the experiment. The results are shown in Table 2

Table 2 Intra-Group Difference Test of Competence Scores of the Two Groups Before and After the Experiment (M±SD)

Dimension	Group	Pre-test	Post-test	t-value	p-value	Cohen's d
Instructional Design Competence	Experimental Group	3.12±0.58	4.21±0.47	-12.345	<0.001***	2.06
	Control Group	3.09±0.61	3.47±0.55	-3.872	<0.001***	0.73
Classroom Implementation Competence	Experimental Group	2.98±0.63	4.15±0.52	-11.876	<0.001***	1.98
	Control Group	3.01±0.59	3.38±0.58	-3.521	0.001**	0.65
AI Application Literacy	Experimental Group	2.56±0.72	4.08±0.56	-13.259	<0.001***	2.34
	Control Group	2.53±0.69	2.76±0.64	-1.987	0.053	0.37

Both groups improved, but the experimental group showed significantly larger gains with large effect sizes (Cohen's $d > 0.8$) across all dimensions, validating the constructivist learning logic of the AI-enabled model. The control group showed only medium effects ($d < 0.8$) in two dimensions and no significant change in AI literacy.

5.3 Inter-Group difference test of competence scores of the two groups after the experiment

To eliminate the influence of the pre-test baseline, Analysis of Covariance (ANCOVA) was used, with the pre-test score of each dimension as the covariate, the post-test score as the dependent variable, and the teaching mode as the fixed factor, to analyze the inter-group difference between the two groups. The results are shown in Table 3.

Table 3 ANCOVA Results of Competence Scores of the Two Groups After the Experiment

Dependent Variable	Group	Corrected Mean	Standard Deviation	F-value	p-value	η^2
Instructional Design Competence	Experimental Group	4.20	0.06	89.342	<0.001***	0.487
	Control Group	3.48	0.06	-	-	-
Classroom Implementation Competence	Experimental Group	4.14	0.07	78.653	<0.001***	0.456
	Control Group	3.39	0.07	-	-	-
AI Application Literacy	Experimental Group	4.07	0.06	124.578	<0.001***	0.571
	Control Group	2.77	0.06	-	-	-

The results show that after controlling the pre-test baseline scores, the corrected mean scores of the experimental group in the three dimensions of instructional design competence, classroom implementation competence, and AI application literacy are significantly higher than those of the control group, and all η^2 values are greater than 0.14, reaching a high effect level. It indicates that the AI-enabled blended teaching mode has a significantly better effect on the cultivation of pre-service teachers' competence than the traditional blended teaching mode, which directly responds to research questions RQ1 and RQ2, and provides empirical support for the reconstruction of the TPACK framework in the AI context.

5.4 Qualitative research results (interview + text analysis)

Interviews indicated that 80% of experimental group students valued AI virtual training for practice opportunities, and 70% noted enhanced design innovation. Both instructors confirmed reduced feedback workload and increased precision.

The text analysis results show that the average scores of the integrity and innovation of the post-test instructional design schemes of the experimental group students increased by 32.6% and 28.9% respectively compared with the pre-test, and the teaching reflection depth index increased by 41.2% compared with the pre-test, which forms triangular verification with the quantitative research results and further confirms the robustness of the research results.

5.5 Mediating effect test of AI-generated feedback

To test the mediating effect of AI-generated feedback between teaching mode and the improvement of pre-service teachers' teaching competence, this study adopted Hayes' PROCESS macro program (Model 4), with teaching mode as the independent variable (experimental group=1, control group=0), total teaching competence score as the dependent variable, and AI-generated feedback quality as the mediating variable. The Bootstrap method was used for repeated sampling 5000 times, and the test results are shown in Table 4.

With gender and previous grades of pedagogy basic courses as covariates for control, the mediating effect of AI-generated feedback was tested again. The results show that the 95% confidence interval of the indirect effect still does not contain 0 ([0.342, 0.651]), indicating that the mediating effect is robust.

Table 4 Mediating Effect Test Results of AI-Generated Feedback

Path	Effect Value	Standard Error	95% Confidence Interval
Total Effect	0.872	0.086	[0.702, 1.042]
Direct Effect	0.385	0.097	[0.193, 0.577]
Indirect Effect	0.487	0.078	[0.342, 0.651]

The results show that the 95% confidence interval of the indirect effect of AI-generated feedback does not contain 0, indicating that AI-generated feedback has a significant partial mediating effect between teaching mode and the improvement of pre-service teachers' teaching competence, with the mediating effect accounting for 55.85% of the total effect. This responds to research question RQ3, confirms that the real-time feedback generated by AI is the core mechanism of the AI-enabled mode to improve pre-service teachers' teaching competence, and also provides empirical basis for the intelligent application of formative assessment theory.

5.6 Predictive effect of learning behavior data on the growth trajectory of teaching competence

To verify the predictive effect of AI learning behavior data on the growth trajectory of pre-service teachers' teaching competence, this study took the improvement range of teaching competence (post-test total score - pre-test total score) as the dependent variable, and learning engagement, AI tool use frequency, simulated teaching times, and feedback iteration times as predictive variables to construct a multiple linear regression model.

The prerequisite test results of the regression model show that the residuals conform to the normal distribution, there is no significant heteroscedasticity and autocorrelation, and the VIF values of all variables are less than 2, so there is no multicollinearity problem, which meets the prerequisites for regression analysis. The specific regression results are shown in Table 5.

Table 5 Regression Analysis Results of Learning Behavior Data on Teaching Competence Improvement

Predictive Variable	B-value	Standard Error	t-value	p-value	VIF
Constant Term	0.215	0.187	1.149	0.253	-
Learning Engagement	0.186	0.072	2.583	0.011*	1.235
AI Tool Use Frequency	0.247	0.078	3.167	0.002**	1.321
Simulated Teaching Times	0.352	0.081	4.346	<0.001***	1.287
Feedback Iteration Times	0.289	0.075	3.853	<0.001***	1.304

*Note: Model R^2=0.624, adjusted R^2=0.607, F=36.782, p<0.001**; *p<0.05, **p<0.01, ***p<0.001.*

The results show that the overall regression model is significant, which can explain 62.4% of the variation in the improvement range of pre-service teachers' teaching competence. Among them, simulated teaching times, feedback iteration times, AI tool use frequency, and learning engagement all have a significant positive predictive effect on teaching competence improvement. This result responds to research question RQ4, confirms that the multimodal data of pre-service teachers' AI learning behaviors can effectively predict the growth trajectory of their teaching competence, and provides empirical support for the AI-driven mechanism model of teaching competence development.

6. Discussion

6.1 Analysis of core research results

The results of this study fully respond to the four research questions raised, and the core conclusions can be summarized into four points:

First, this study confirms that the AI deeply embedded blended teaching mode can significantly improve pre-service teachers' instructional design competence, classroom implementation competence, and AI application literacy, with a significantly better effect than the traditional blended teaching mode. This aligns with findings on intelligent technology's impact (Boerboom et al., 2024; Cheung et al., 2024) but extends them by deeply embedding AI into teacher education curricula, filling a gap in AI-blended teaching research specific to this context. At the same time, this result also verifies the rationality of the reconstruction of the TPACK framework in the AI context in this study, and confirms that deep integration of AI knowledge with subject pedagogy enhances pre-service teachers' core professional competence.

Second, this study finds that the real-time feedback generated by AI has a significant partial mediating effect in the improvement of pre-service teachers' teaching competence, with the mediating effect accounting for 55.85%. This result confirms the core conclusion of Henderson et al. (2025) on AI-based formative assessment, and further clarifies that AI feedback is the core mechanism of the intelligent blended teaching mode, explaining the internal logic of "why AI technology can improve pre-service teachers' teaching competence". Different from traditional formative assessment which relies on teachers' subjective judgment and has lagging feedback, the AI real-time feedback in this study realizes whole-process and personalized assessment support. This finding also provides empirical support for the data-based upgrading of formative assessment theory.

Third, this study confirms that the multimodal data of pre-service teachers' AI learning behaviors can effectively predict the growth trajectory of their teaching competence, among which the number of simulated teaching times and feedback iteration times have the strongest predictive effect. This finding complements the research on multimodal learning analytics by Kleinknecht et al. (2023), further clarifies that high-frequency practice and continuous feedback are the core paths for the improvement of pre-service teachers' teaching competence, and provides empirical basis for the process assessment and precise intervention of pre-service teachers' teaching competence. At the same time, this result also verifies the effectiveness of the AI-driven mechanism model for teaching competence development constructed in this study, and confirms that the closed-loop logic of "perception-analysis-feedback-adjustment-promotion" is practical and feasible.

Fourth, the three-dimensional curriculum system and intelligent blended teaching closed loop constructed in this study realize the dual improvement of pre-service teachers' teaching competence and AI application literacy, making up for the lack of digital literacy cultivation in traditional pedagogy courses. This is consistent with the research views on virtual simulation training of Grossman et al. (2024), but this study breaks through the optimization of a single training link, constructs an AI empowerment system covering the whole course process, and puts forward a practice mode with more localized adaptability.

The qualitative research results further confirm the quantitative research conclusions. Interviews and text analysis show that the AI-enabled blended teaching mode can not only improve the objective competence indicators of pre-service teachers, but also improve students' learning experience and teachers' teaching efficiency, further verifying the practical feasibility of the mode. Students in the experimental group generally reported that the AI virtual training scenario provided them with more practice opportunities, and the AI real-time feedback could help them quickly find their own shortcomings and adjust learning strategies in a timely manner. Teachers believed that the embedding of AI technology reduced the workload of teaching feedback, allowing them to devote more energy to personalized guidance, and improving teaching efficiency and quality.

6.2 Theoretical contributions and expansion of blended learning theory

This study advances blended learning theory by shifting from simple "online-offline integration" to "intelligent-driven personalization." By embedding AI as a core driver for data collection, diagnosis, and feedback, it operationalizes a closed-loop system ("pre-class diagnosis, in-class interaction, post-class iteration"), optimizing the process for personalized support.

Furthermore, this study reconstructs the TPACK framework for the AI era by positioning AI not merely as a general technological tool but as a core technical element and feedback agent. The significant improvements observed in both teaching competence and AI application literacy confirm that the deep integration of AI-specific knowledge with pedagogical and content knowledge expands pre-service teachers' professional capacity. Finally, the study upgrades formative assessment theory by demonstrating the efficacy of AI-driven, multimodal, real-time feedback. The finding that AI-generated feedback accounts for 55.85% of the total effect on competence improvement provides robust empirical support for transitioning from teacher-led periodic assessment to AI-enabled continuous, data-informed formative evaluation.

6.3 Possible challenges

Practical challenges involve technological maturity, teacher adaptation, and data privacy. Mitigations include multimodal validation, faculty training, strict data governance, and student AI literacy workshops.

6.4 Implications for teacher education reform

Teacher education reform must integrate AI advancements dynamically, shifting blended learning from superficial integration to data-driven intelligent personalization. Evaluation should emphasize formative, AI-supported process tracking, and pre-service digital literacy—particularly human-machine collaborative teaching—should be systematically cultivated through dedicated coursework.

7. Conclusion

Taking the core pedagogy course of teacher education as the carrier, aiming at the practical dilemmas of traditional pedagogy courses such as insufficient practice opportunities, lagging feedback, and extensive evaluation, this study constructs an AI-enabled blended teaching mode and curriculum system, and verifies the effectiveness of the mode through an 18-week quasi-experimental study.

Key findings confirm that the AI-enabled blended teaching mode significantly outperforms traditional approaches in enhancing instructional design, classroom implementation, and AI literacy. AI-generated real-time feedback accounted for 55.85% of the total effect, establishing it as the core mechanism. Multimodal learning behavior data—particularly simulated teaching frequency and feedback iterations—effectively predicted competence growth trajectories ($R^2=0.624$). Theoretically, this study expands blended learning theory, reconstructs the TPACK framework, and upgrades formative assessment for the AI era. Practically, it offers a replicable paradigm for AI integration in teacher education.

This study has limitations. First, primary outcomes relied on self-reported questionnaires, which, despite strong psychometric properties, are susceptible to subjective biases. Although the study triangulated findings with behavioral data and qualitative analysis, future research should incorporate objective performance metrics to further validate these results. Specifically, independent expert ratings of recorded teaching sessions using standardized observational protocols (e.g., the Classroom Assessment Scoring System, CLASS) would provide a more robust measure of actual teaching competence. Additionally, objective assessments of AI literacy through performance-based tasks could complement self-report scales. Second, the research sample only comes from a single local university in the eastern region, so the universality of the conclusions needs to be further verified. The research period is only one semester, so it is difficult to observe the long-term impact of the mode on pre-service teachers' teaching practice after employment. The rapid iteration of AI technology may also lead to the need for continuous updating of some contents of the curriculum scheme. Follow-up research will further expand the sample scope, carry out multi-center comparative experiments in normal universities and colleges in different regions and at different levels, and conduct long-term follow-up research at the same time, to continuously optimize the practice mode of AI-enabled teacher education courses and provide support for the construction of a high-quality teacher education system in China.

Ethical Statement

This study was conducted in strict adherence to international ethical guidelines, including the principles outlined in the Declaration of Helsinki. The research protocol received formal approval from the Academic Ethics Committee of the School of Education at [University of Shaoxing] (Ethics Approval No. JY2025018). Prior to participation, all students were fully informed about the study's purpose, procedures, data collection and usage, and their rights as research participants. Written informed consent was obtained from every subject, who were explicitly assured of their right to withdraw from the study at any time without any penalty or adverse consequences. To ensure data confidentiality and protect participant privacy, all personal identifying information was anonymized, and all collected data were securely stored in password-protected files and used exclusively for the purposes of this academic research.

Conflict of Interest

The authors declare that they have no conflicts of interest in this work.

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Appendix

Technical Specifications and Limitations of the AI System: The AI-enabled teaching platform integrated three core technological components. First, the speech analysis module utilized the iFlytek Open Platform (version 2.0) automatic speech recognition (ASR) engine, which performed real-time transcription and extracted prosodic features including speech rate, pause frequency, and pitch variation. Second, the text analysis module employed an NLP pipeline based on a pre-trained BERT architecture fine-tuned on a corpus of Chinese educational texts, conducting semantic similarity scoring against rubric-based criteria. Third, the affective computing module used OpenFace 2.0 to detect facial action units and infer basic engagement levels.

Inherent limitations include reduced ASR accuracy with strong dialects or background noise, constrained NLP assessment of constructs like "innovation" due to training data distribution, and probabilistic affective estimates that cannot access internal cognitive states.

References

Black, P., & Wiliam, D. (1998). Inside the black box: Raising standards through classroom assessment. *Phi Delta Kappan, 80*(2), 139-148.

Boerboom, J., Blijleven, H., & Jochems, W. (2024). Data-driven adaptive blended learning: The effects of learning analytics dashboards on student performance and self-regulated learning. *Computers & Education, 201,* 104897.

Cheung, S. K., Huang, R., & Hew, K. F. (2024). Human-AI collaboration in teacher education: A systematic review of AI applications in pre-service teacher training. *Computers & Education, 209,* 104987.

Cohen, L., Manion, L., & Morrison, K. (2018). *Research methods in education* (8th ed.). Routledge.

Feng, X. Y., Wang, R. X., & Wu, Y. J. (2018). A review of domestic and international research on blended teaching: Based on the analytical framework of blended teaching. *Journal of Distance Education, 36*(3), 13-24.

Garrison, D. R., & Vaughan, N. D. (2008). *Blended learning in higher education: Framework, principles, and guidelines.* Jossey-Bass.

Grossman, P., Hammerness, K., & McDonald, M. (2024). AI-enhanced clinical practice in teacher education: Redesigning field experiences with virtual simulations. *Educational Technology Research and Development, 72*(3), 789-812.

He, K. K. (2019). The significant impact of emerging information technologies since the 21st century on the in-depth reform of education. *E-education Research, 40*(3), 5-12.

Henderson, M., Ryve, A., & Nilsson, P. (2025). AI-based formative assessment in pre-service teacher education: Effects on reflective practice and teaching performance. *British Journal of Educational Technology, 56*(1), 345-362.

Jung, Y., Lee, J., & Park, S. (2022). Does blended learning always work? A meta-analysis of the effects of blended learning on K-12 and higher education outcomes. *British Journal of Educational Technology, 53*(4), 1245-1264.

Katsampoxaki-Hodgetts, K., Kotsidis, K., Papadakis, S., & Anastasiades, P. (2025). Reimagining preschool pedagogy: AI-enhanced teaching through multiliteracies-informed curriculum innovation. In V. Lamanauskas (Ed.), *Science and technology education: Expectations and experiences* (pp. 104-119). Scientia Socialis. https://doi.org/10.33225/BalticSTE/2025.104

Kleinknecht, M., Gröschner, A., & Seidel, T. (2023). Multimodal learning analytics for pre-service teachers' classroom management skills: Validating AI-based feedback with classroom observations. *Educational Technology Research and Development, 71*(5), 1457-1482.

Luckin, R., Holmes, W., Griffiths, M., & Woolf, B. P. (2016). *Intelligence unleashed: An argument for AI in education*. Pearson.

Mishra, P., & Koehler, M. J. (2006). Technological pedagogical content knowledge: A framework for teacher knowledge. *Teachers College Record, 108*(6), 1017-1054.

Piaget, J. (1970). *Science of education and the psychology of the child*. Viking Press.

Rienties, B., Héliot, Y., & Jindal-Snape, D. (2023). Virtual simulation in pre-service teacher training:

A systematic review and meta-analysis. *Computers & Education, 198,* 104789.
Uğraş, H., Uğraş, M., Papadakis, S., & Kalogiannakis, M. (2024). ChatGPT-supported education in primary schools: The potential of ChatGPT for sustainable practices. *Sustainability, 16*(22), Article 9855. https://doi.org/10.3390/su162209855
Wang, Y. L., & Wu, W. D. (2023). Practical dilemmas and reform paths of subject pedagogy courses. *Research in Educational Development, 43*(12), 60-67.
Zacharis, G., & Papadakis, S. (2025). Can AI grade like a human? Validity, reliability, and fairness in university coursework assessment. *Educational Process: International Journal, 19,* Article e2025591. https://doi.org/10.22521/edupij.2025.19.591
Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education, 16*(1), 1-27.

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