Construction and Practical Verification of an Intelligent Teaching Model Based on Generative AI

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Abstract. Addressing the core challenge in current educational practice—the difficulty of balancing scalable instruction with personalized cultivation—this study proposes an innovative teaching paradigm deeply integrated with Generative Artificial Intelligence. This framework is structured around a "Selective Flipped Classroom" and a tri-method pedagogical integration of "PBL+TBL+CCBL." It establishes a closed-loop teaching system characterized by "data-driven decision-making, intelligent resource generation, and dynamic methodological synergy," powered by learning analytics as the diagnostic core and large language models as the generative core. The paper systematically elaborates the theoretical framework, design principles, and a comprehensive implementation pathway covering the entire "pre-class, in-class, and post-class" process. Empirical validation through a rigorous parallel-class controlled experiment demonstrates that the experimental class employing this model achieved significant improvement in overall academic performance (with an average score increase of 4.6 points and a 100% pass rate), particularly in preview effectiveness and knowledge transfer capability ($p < 0.01$). These results confirm the model's effectiveness in promoting precision teaching, process optimization, and educational equity. This research provides a comprehensive solution with both theoretical innovation and practical feasibility for constructing a learner-centered intelligent teaching paradigm in the era of "digital-intelligent integration."

Keywords: AI-assisted teaching, Large Language Model, Learning Analytics, Selective Flipped Classroom, Tri-Method Integrated Teaching Approach, Empirical Research.

1 Introduction

With the advancement of generative AI and learning analytics, education is entering a stage of "digital-intelligent integration." Traditional teaching models face challenges in delivering personalized support at scale and fostering higher-order thinking, creating a need for new, data-driven and intelligently-powered pedagogical structures [1,2].

Current research on AI-empowered education reveals significant yet fragmented progress. Studies on technology integration show promising but limited applications: multimodal analytics frameworks enable dynamic learning path adjustments [3], and

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LLMs enhance PBL through personalized scenario generation [4], yet these approaches often operate in isolation. Research on flipped classrooms confirms the efficacy of data-driven content selection [5], but frequently lacks mechanisms for personalized resource adaptation. Systematic reviews indicate that most studies focus on single-technology, single-method combinations, with few exploring the deep integration of multiple technologies and pedagogies [6].

Domestically, research emphasizes localized adaptation. Blended models leverage analytics to optimize in-class interaction [7], and integrated PBL-TBL approaches improve collaboration [8]. However, resource delivery often remains uniform, and applications of selective flipping or LLMs in CCBL frequently lack precision or synergy with other methods [9,10].

In summary, the current landscape has three main limitations: 1) siloed applications of intelligent technologies, lacking a dual-core diagnostic-generative mechanism; 2) unsystematic integration of pedagogies (PBL, TBL, CCBL) without synergistic design; and 3) empirical studies focusing on single outcomes rather than multi-dimensional process analysis. These gaps underscore the need for a comprehensive, integrated teaching paradigm.

This paper addresses these gaps by deeply embedding LLMs and learning analytics into a "Selective Flipped Classroom" and "PBL+TBL+CCBL" framework. It aims to build an intelligent teaching model capable of cognitive support and adaptive intervention. Through rigorous empirical comparison, the study validates the model's effectiveness in improving academic performance and procedural learning, offering an evidence-based, integrated paradigm for achieving tailored instruction and core competency development.

2 Theoretical Foundations for an Integrated Teaching Model Empowered by AI

This section outlines the core theoretical pillars of the proposed teaching model, which synergistically combines a data-driven selective flipped classroom with an intelligently enhanced tri-method pedagogical approach.

2.1 The Selective Flipped Classroom: Precision through Data and Generation

Moving beyond the traditional fully-flipped model, the selective flipped classroom advocates for a strategic, data-informed approach. Its implementation is powered by two AI-driven cores:

Learning Analytics as the Diagnostic Core: It analyzes multi-modal student data to diagnose learning states, thereby intelligently identifying *what* content to flip, *for whom*, and *when*.

Large Language Models as the Generative Core: Based on diagnostic insights, LLMs dynamically produce or adapt personalized pre-class learning resources (e.g., simplified explanations, advanced readings), enabling truly differentiated preparation.

2.2 Intelligent Enhancement of the PBL+TBL+CCBL Tri-Method

The model elevates three established pedagogical methods through AI:

PBL (Problem-Based Learning): LLMs act as intelligent tutors, generating authentic, multi-level problem scenarios and providing heuristic guidance during student inquiry.

TBL (Team-Based Learning): Learning analytics informs optimal team formation. LLMs then facilitate collaboration by helping teams organize ideas and refine outputs, while analytics monitors group engagement and equity[11, 12].

CCBL (Course Content-Based Learning): LLMs serve as a teaching assistant, instantly generating diverse instructional strategies (e.g., cases, simulations, visualizations) tailored to specific content types (conceptual, theoretical, practical).

This integration creates a closed-loop system of "AI-Powered Problem Guidance, Team Collaboration, and Content-Specific Instruction."

3 Implementation Path of the Fusion Teaching System Centered on Large Models and Learning Analytics

The implementation of this model is a dynamic, intelligent, and closed-loop system that runs through the entire cycle of "pre-class, in-class, and post-class." Its core lies in using learning analytics technology to achieve precise diagnosis and decision-making, and leveraging large language models to achieve large-scale, personalized resource generation and interactive support, ultimately completing knowledge internalization and ability sublimation through the "PBL+TBL+CCBL" tri-method teaching approach.

3.1 Pre-class: Data-Driven Systematic Learning Design and Personalized Preparation

Learning Analytics-Driven Precise Flipping Decisions and Target Layering. First, instead of deciding flipped content based on experience, teachers rely on learning analytics technology to conduct in-depth mining of class-wide and individual student learning data. The system analyzes data such as past grades, homework error points, and online learning behaviors to automatically generate a learning diagnostics report, accurately identifying common difficulties, error-prone points for the class, and individual knowledge gaps. Based on this, teachers make flipping decisions according to the "Precise Adaptation Principle."

Large Model-Supported Personalized Resource Generation and Precise Delivery. After determining the flipped content, the large language model plays a core role. Teachers only need to input core knowledge points and target student group characteristics, and the large model can automatically generate diverse preparatory materials, such as conceptual explanatory micro-lecture scripts, comparison tables, and mind maps. This transforms resources from "uniform supply" to "personalized generation."

Learning Condition Prediction and Intervention Preparation. All student learning behaviors on the platform, such as video viewing duration, test accuracy rates, and the frequency and content of questions asked to the large model-driven Q&A robot, are recorded and analyzed in real time. The learning analytics system automatically alerts teachers about students experiencing difficulties or insufficient engagement and generates reports for teacher reference, enabling teachers to grasp the learning situation before class and prepare adequately for in-class intervention.

3.2 In-class: Human-Machine Collaborative Multi-dimensional Interaction and Ability Training

Three-Stage Progression: Deep Interaction Path Based on Real-Time Learning Feedback. Stage 1: Connection and Clarification (PBL + Selective Flipping). Based on the preview test data provided by the learning analytics system, teachers use the PBL teaching method to design problem chains around common errors and difficulties. The large model can assist teachers in quickly generating a series of follow-up questions targeting these points of confusion.

Stage 2: Evaluation and Deepening (TBL + Learning Analytics). Teachers use the platform to anonymously display representative answers submitted before class. Subsequently, the TBL teaching method is applied for group evaluation. During this process, learning analytics technology can monitor the discussion heat and keywords of each group in real time. If a group's discussion stalls, the system can automatically issue an alert.

Stage 3: Transfer and Creation (TBL + CCBL + Large Model). After completing the new content delivery in class, the teacher poses more challenging comprehensive application problems. Students again engage in group discussions and are encouraged to use AI tools like large language models for assistance, while the teacher focuses on guiding their critical evaluation and creative use of the content generated by the large models.

Method Synergy: Intelligent Adaptation of Teaching Strategies Guided by CCBL. Throughout the in-class session, "PBL+TBL" serves as the main thread. Meanwhile, CCBL, assisted by the large model, achieves precision and diversity in teaching strategies. Teachers can instruct the large model to quickly generate and recommend the most suitable teaching strategies based on different knowledge types, such as case-based teaching, project-based learning, gamified learning, or visual demonstrations.

Comprehensive Practice: Higher-Order Ability Generation Path Based on Project-Driven. In addition to the embedded seminars in regular classes, specialized project-driven thematic seminar courses are set up, aiming to achieve the transition from knowledge application to ability innovation.

The course teaching team releases carefully designed seminar topics two weeks in advance, such as "Optimal Selection Strategy for Nuclear Warhead Size" or "Pilot Seat Pressure Distribution Model Analysis" and other complex cases derived from actual scenarios. Students, in groups, cooperate to form complete solutions through literature review, data analysis, and internal discussion.

In the special seminar courses, each group presents their results. Students in the audience raise questions, make supplements and conduct debates through various forms such as on-site questions or Rain Classroom bullet screens. This process creates an intensive academic thinking atmosphere. Through intensive "teacher-student - student-student" theoretical dialogues, the understanding of the essence of mathematical theories is significantly deepened, and the innovative ability to solve complex problems using comprehensive knowledge is effectively improved.

3.3 Post-class: Data-Driven Dual-Driven Learning System and Teaching Closed Loop

"Content Deepening and Extension" Drives Knowledge Internalization. Based on in-class performance and learning analytics results, teachers precisely push personalized extension resources generated by the large language model through the platform. This makes the deepening and transfer of knowledge more targeted.

"Student Question-Driven" Trains Higher-Order Thinking. In the question discussion area established on the platform, students are encouraged to actively raise theoretical puzzles or critical reflections. The large language model first addresses and synthesizes common questions, forming a virtuous cycle of interaction characterized by "student questioning – preliminary AI response/peer assistance – teacher highlighting key insights."

Teaching Reflection and Model Optimization Intelligent Closed Loop. The learning analytics engine integrates multimodal data from the entire cycle, generating visual class-wide learning situation panorama reports and individual learning path maps. This data-driven report provides teachers with objective and comprehensive evidence for reflecting on the rationality of "selective flipping" decisions and the effectiveness of the tri-method teaching approach synergy, thereby continuously optimizing the design and implementation of the next teaching cycle, forming a self-evolving and continuously improving intelligent teaching closed loop.

4 Empirical Verification of AI-Assisted Teaching Strategies

To scientifically evaluate the effectiveness of the integrated teaching model proposed in this paper, a rigorous comparative teaching experiment was designed, and quantitative analysis methods were used to empirically test the teaching effects from multiple dimensions.

4.1 Experimental Design and Methods

This study employed a pre-test-post-test control group design. Two natural classes with no significant differences in entrance scores, previous course GPAs, etc., were selected as research subjects. Among them, the Experimental Class (n=25) implemented the AI-integrated "Selective Flipped Classroom" and "PBL+TBL+CCBL" tri-method teaching approach; the Control Class (n=40) adopted a traditional teacher-led instruction model. The experiment lasted one semester. Data collection covered the entire teaching process, including preparation tests, class performance, homework, and final exam scores, ensuring the integrity and traceability of the data chain. All data were analyzed using

MATLAB R2023a, including descriptive statistics, independent samples t-tests, correlation analysis, and effect size calculation.

4.2 Results and Analysis

Significant Improvement in Overall Academic Performance. To examine the overall difference in total academic scores between the two classes, we first conducted descriptive and inferential statistics. Table 1 details the key statistical indicators for both classes.

Table 1. Comparison of Overall Score Distribution Statistics

Statistical Metric	Control Class (*n*=40)	Experimental Class (*n*=25)	Improvement	p-value
Mean Score	78.6	83.2	+4.6	0.005
Standard Deviation	8.24	6.87	-1.37	-
Pass Rate (≥60)	87.5%	100%	+12.5%	0.032
Excellence Rate (≥85)	42.5%	60.0%	+17.5%	0.041

*Note: * $p < 0.05$, ** $p < 0.01$*

As shown in Table 1, the average score of the experimental class was significantly higher than that of the control class (83.2 vs. 78.6), and an independent samples t-test indicated that this difference was statistically significant ($p = 0.005 < 0.01$). Furthermore, the pass rate and excellence rate of the experimental class were both significantly improved. It is particularly noteworthy that the minimum score in the experimental class was 12.3 points higher than that in the control class, and the standard deviation was smaller. This indicates that while improving overall performance, the intelligent teaching model had a particularly prominent effect on supporting students with weak foundations, effectively promoting educational equity.

To more intuitively display the differences in score distribution, we plotted box plots and normal distribution fitting curves, as shown in Figure 1.

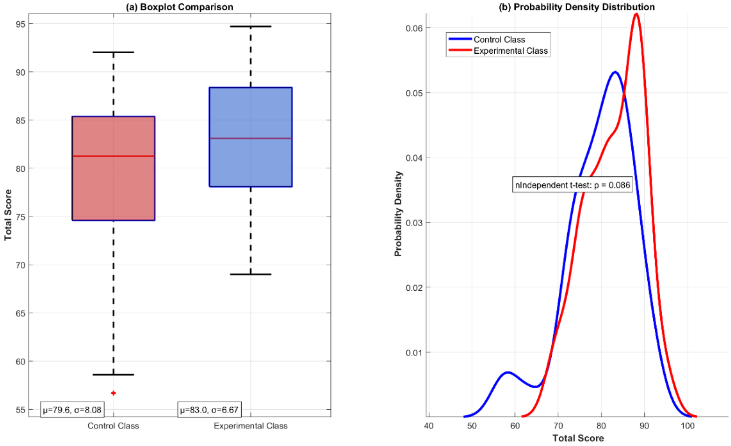

Fig. 1. Comparison of total score distributions between two classes. (a) Boxplot; (b) Probability density distribution.

Figure 1(a) clearly shows that the overall box position of the experimental class is higher. Figure 1(b) further shows that the score distribution curve of the experimental class is shifted to the right overall, with a higher peak and a slimmer shape, which corroborates the conclusion of "higher mean score and smaller standard deviation" in Table 1.

Differential Effects in Key Teaching Modules. To deeply explore the impact of the intelligent teaching model on different teaching modules, we analyzed the various dimensions that constitute the total score. Figure 2 shows the comparison of scoring rates for each module via a radar chart.

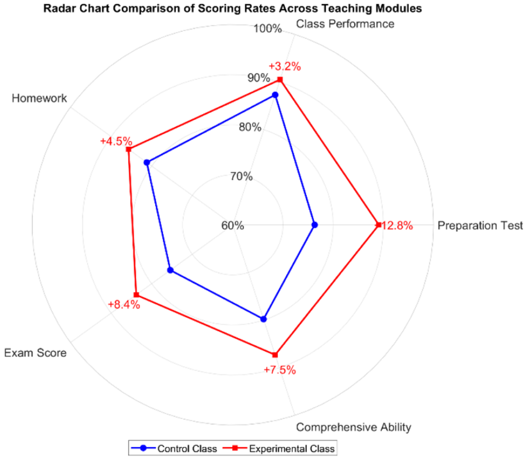

Fig. 2. Radar chart comparison of scoring rates across teaching modules.

From Figure 2, it can be intuitively seen that the experimental class's scoring rate is higher than that of the control class in all teaching modules, with the most significant improvements especially in Preparation Test (+12.8%) and Exam Score (+8.4%). This result strongly proves that the personalized preview resources supported by the large language model and the knowledge internalization brought about by in-depth interaction in class have a decisive impact on the final learning outcome.

Enhanced Correlation Between Learning Process and Results. We further calculated the Pearson correlation coefficients between various learning process indicators and the total score to test whether the intelligent teaching model changed students' learning behavior patterns. Figure 3 displays the correlation matrices of the two classes in the form of heatmaps.

Comparing Figure 3(a) and (b), it can be found that the correlation coefficients between "Preparation Test," "Class Performance," and "Total Score" in the experimental class are significantly higher than those in the control class (for example, the preparation test correlation increased from 0.68 to 0.82). This indicates that under the intelligent teaching model, the connection between students' procedural learning investment and final academic outcomes is closer, forming a healthier "process-outcome" strongly associated learning ecosystem.

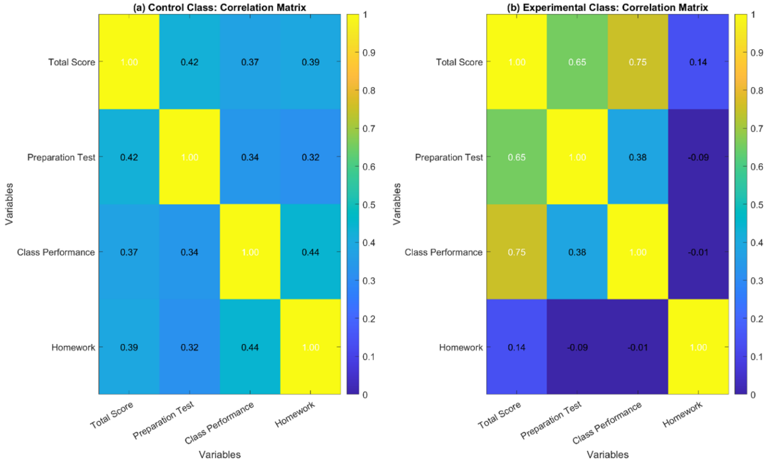

Fig. 3. Heatmaps of correlation between learning behaviors and total scores. (a) Control class; (b) Experimental class.

4.3 Discussion

Through rigorous empirical analysis, this study draws the following main conclusions:

Effectiveness Verification. The integrated teaching approach combining AI, "Selective Flipped Classroom," and the "PBL+TBL+CCBL" tri-method can significantly improve students' overall academic level. Statistical tests confirm that the experimental class significantly outperformed the control class on key indicators such as average score, pass rate, and excellence rate.

Key Path Revelation. The intelligent reconstruction of the preparation module is a key lever for the success of this model. The resource generation and interaction supported by the large language model greatly enhance the efficiency and depth of independent learning, laying a solid foundation for higher-order thinking training in class.

Process Optimization Proof. This model effectively constructs a strong correlation between "procedural learning and summative assessment." Students pay more attention to their usual learning investment, and the learning process becomes more scientific and effective.

Promotion of Educational Equity. The reduction in the standard deviation of scores and the significant increase in the minimum score in the experimental class indicate that this model can provide effective personalized support for students with different starting points, promoting the optimization of the score distribution while improving the mean, which has important significance for educational equity.

In summary, the empirical results verify the theoretical rationality and practical effectiveness of the integrated teaching model proposed in this paper from multiple perspectives, providing strong data support and practical examples for deepening teaching reform and constructing a "student-centered" intelligent teaching paradigm in the AI era.

5 Summary and Outlook

This study constructed and empirically validated an integrated teaching model driven by large language models and learning analytics technology as its dual core. It systematically elaborated on the model's core advantages in achieving precision in instruction, intelligence in interaction, and data-driven decision-making. Empirical results demonstrate that this model can significantly enhance students' overall academic performance (with an average score increase of 4.6 points), achieve a 100% pass rate, and show substantial supportive effects for students with learning difficulties. This model represents not only an upgrade to blended teaching but also a successful exploration of a new "digital-intelligence integrated" teaching paradigm. These research efforts will continue to advance this teaching model toward deeper levels of intelligent and human-centric development, ultimately contributing to the organic integration of scalable education and personalized cultivation.

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