Innovation and Practice of AI-Empowered Mathematics Course Teaching Models in Private Universities from the Perspective of Smart Education

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Abstract: In private universities, mathematics courses face challenges such as uneven student foundations, low learning motivation, and difficulty in personalized instruction due to large class sizes. From a smart education perspective, this study follows a "theoretical analysis–model construction–practical verification–countermeasure suggestions" logic to explore AI-empowered teaching. It proposes a "three-stage, four-element" model centered on pre-class intelligent diagnosis, in-class human-AI collaboration, and post-class data feedback. A semester-long controlled experiment in an Advanced Mathematics course shows that compared with traditional teaching, the AI-empowered model significantly improves grade distribution, pass rate, excellence rate, and learning engagement. Practical countermeasures are offered in platform construction, teacher competence, resource governance, and evaluation mechanisms.

Keywords: Smart Education; Private Universities; Artificial Intelligence; Mathematics Courses; Teaching Model Innovation

1. Introduction

Digital education transformation has become a national strategy. Private universities face three difficulties in mathematics courses: uneven student foundations, low motivation, and difficulty in personalized instruction due to large classes. AI offers solutions through precise diagnosis and adaptive learning, yet existing research lacks systematic teaching models and verifiable evidence. Following a "theoretical analysis–model construction–practical verification–countermeasure suggestions" logic, this paper explores AI empowerment mechanisms, constructs an operable teaching model, and tests its effects, aiming to provide a reference for intelligent transformation of mathematics courses in private universities.

2. Analysis of Theoretical Foundations and Practical Difficulties

2.1 Smart Education and AI-Empowered Mathematics Teaching

Smart education uses data collection and feedback across the entire learning process to achieve data-driven decisions, precise adaptation, human-AI collaboration, and continuous evolution. AI-empowered mathematics teaching does not replace teachers but reconstructs the teaching-learning-evaluation relationship: it helps teachers analyze learning conditions and design differentiated instruction; provides students with adaptive learning paths, instant Q&A, and personalized exercises; and enables process-oriented, data-based evaluation. In essence, AI uses data as a link to transform "teaching-determined learning" into "teaching according to learning needs.".

2.2 Practical Difficulties in Mathematics Course Teaching in Private Universities

From the preliminary research at a private university, the difficulties in the teaching of mathematics course in private universities can be summarized into the four dimensions shown in Table 1. The four difficulties are mixed up with each other, and just increasing the hours of classes or even strengthening the supervision of the classes can not really remove these difficulties from the root. Hence, intelligent technologies are needed to reconstruct the teaching structure.

2.3 Mechanisms Through Which AI Empowers Mathematics Teaching

AI affects mathematics teaching in private universities in the three mechanisms mentioned above. (1) The diagnostic mechanism can find out the weak knowledge points of students' learning precisely, because it bases on the knowledge graphs and assessment data, it changes the “ambiguous learning conditions” into the “computable learning conditions”. (2) The adaptive mechanism can dynamically recommend the stratified resource and personalized exercises by means of the learner profile, the teaching supply can fit the individual needs very well. (3) The feedback mechanism can form a closed teaching loop of “diagnosis-intervention-feedback” by means of accompanying data collection, it can support the teachers for continuously improving the teaching as we can. Together, the three mechanisms point at the goal of the aiming at the “personalization under large-scale teaching conditions.”

Table 1. Analysis of Difficulties in Mathematics Course Teaching in Private Universities

Dimension of Difficulty	Specific Manifestations	Limitations of Traditional Teaching
Student foundation	Wide variation in entrance mathematics proficiency and many knowledge gaps	Unified teaching progress makes stratified adaptation difficult
Learning motivation	Strong fear of difficulty and low classroom participation	Lack of personalized motivation and immediate feedback
Teacher-student ratio and class size	Large class size and high student-teacher ratio	Difficult to provide process-oriented individual guidance
Evaluation methods	Emphasis on results over process and delayed feedback	Difficult to support dynamic adjustment of teaching

3. Construction of an AI-Empowered Mathematics Course Teaching Model

3.1 Design Concepts and Principles of the Model

The model design follows following four principles, 1) placing student development at the center and make sure that the technology serves to teaching purposes not the other way around; 2) adhering to human-AI collaboration and strengthening the leading role of teachers in value guidance, thinking cultivation and emotional support; 3) emphasizing a data driven closed loop so that every teaching decision is based on the data; 4) focusing on operability and scalability, so that the model can be implemented under the existing conditions of private universities..

3.2 Framework of the “Three-Stage, Four-Element” Teaching Model

Based on the above mechanisms, this paper constructs a teaching model centered on “pre-class intelligent diagnosis – in-class human-AI collaboration – post-class data feedback,” supported by intelligent technologies, teaching resources, teacher-student role reconstruction, and diversified evaluation. The pre-class stage uses knowledge graphs and pre-tests to identify knowledge gaps and generate stratified preview tasks; the in-class stage features human-AI collaboration, where teachers guide thinking and AI provides real-time dashboards, intelligent problem-solving support, and dynamic grouping; the post-class stage updates learner profiles, recommends adaptive exercises, and generates diagnostic reports, forming a continuous closed loop. The overall framework is shown in Figure 1.

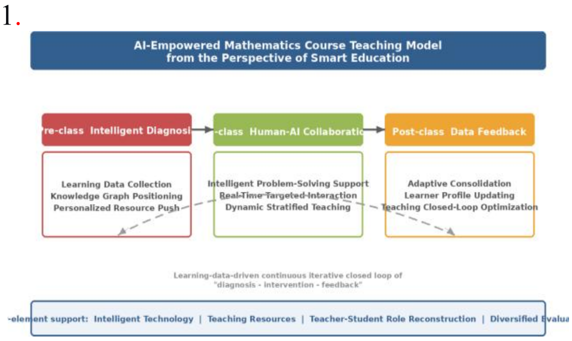

Figure 1 Framework of the “Three-Stage, Four-Element” AI-Empowered Mathematics Course Teaching Model

3.3 Key Technical Support and Learning-Effectiveness Evaluation Model

In this paper, in order to quantitatively evaluate the teaching effect, the author builds a learning-effectiveness evaluation model of comprehensive. Let the student comprehensive learning-effectiveness index E be the knowledge mastery K, ability development A and learning engagement P with weight of index,expressed as:

$$E = w^1 \cdot K + w^2 \cdot A + w^3 \cdot P \tag{1}$$

where w^1、w^2、w^3 are weighting coefficients satisfying $w^1 + w^2 + w^3 = 1$， In this study, after expert consultation and data calibration, the weights are set as $w^1 = 0.5$、$w^2 = 0.3$、$w^3 = 0.2$。All sub-indicators are normalized to a scale of 0–100. Furthermore, the growth of students’ knowledge mastery with effective learning time t can be described by a learning curve:

$$K(t) = K_{m}ax \cdot \left(1 - e^{(-\lambda t)}\right) \quad (2)$$

Where $K_{m}ax$ is the upper limit of knowledge mastery, and λ is the learning-rate coefficient. AI-based personalized recommendation accelerates knowledge mastery by increasing the proportion of effective learning time and the learning-rate coefficient λ. Teaching value-added is measured by the difference between the comprehensive effectiveness of the post-test and the pre-test, denoted as $\Delta E = E_{p}ost - E_{p}re$, which serves as the core indicator for evaluating the effect of AI-empowered teaching.。

4. Teaching Practice and Effect Analysis

4.1 Practice Design and Sample

A 16-week controlled experiment was conducted in an Advanced Mathematics course at a private university. From natural classes of the same major and cohort with no significant difference in entrance scores, 96 students were assigned to an experimental group (using the “three-stage, four-element” AI-empowered model) and 96 to a control group (traditional lecture-based teaching). Both groups shared the same instructor, textbook, class hours, and assessment standards. Data collection included pre-test and final scores, learning engagement indices, platform logs, and interview.

4.2 Analysis of Teaching Effectiveness

Figure 2 shows that AI-empowered teaching reduced the failure rate from 14.6% to 5.2%, increased the good/excellent rate from 29.1% to 51.1%, and shifted the grade distribution rightward, benefiting both remedial support and excellence development.

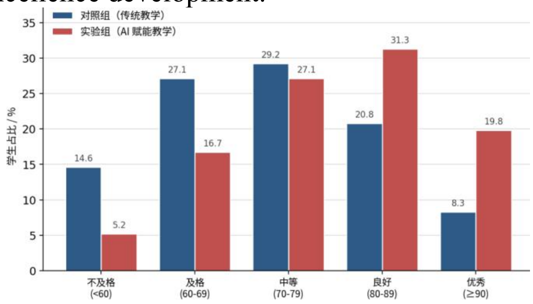

Figure 2. Comparison of Final Score Distributions Between the Experimental and Control Groups

As shown in Figure 3, the experimental group’s learning engagement index steadily increased from Week 3 to approximately 98 by semester end, while the control group fluctuated between 60 and 70, indicating that personalized recommendations and immediate feedback enhanced sustained engagement.

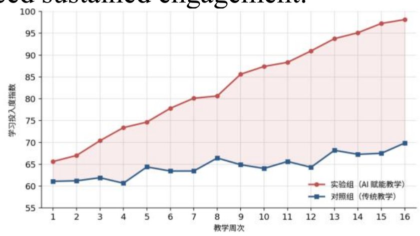

Figure 3. Curve of Teaching Weeks and Learning Engagement Index

Table 2 shows that the experimental group outperformed the control group in all key indicators ($p < 0.01$), verifying the model's effectiveness.

Table 2. Comparison of Key Indicators Between the Experimental and Control Groups

Evaluation Indicator	Control Group	Experimental Group	improvement
Final average score	71.3	81.6	+10.3
Pass rate / %	85.4	94.8	+9.4
Excellence rate / %	8.3	19.8	+11.5
Teaching value-added ΔE	12.7	24.5	+11.8
Learning engagement at the end of the semester	69.9	98.1	+28.2

4.3 Teacher-Student Feedback and Qualitative Analysis

Student feedback indicated that personalized exercise recommendations aligned well with their ability levels and that intelligent Q&A reduced fear of difficulty. Teachers reported that the learning-condition dashboard significantly eased lesson preparation and enabled greater focus on thinking guidance and key-point instruction. However, issues such as uneven platform resource coverage and some students’ over-reliance on AI tools were also noted, suggesting the need for corresponding governance and guidance mechanisms.

5. Countermeasures for Promoting AI-Empowered Mathematics Teaching

To promote AI-empowered mathematics teaching in private universities, four countermeasures are proposed: strengthen smart teaching platforms and data integration (knowledge graphs, learning analytics, unified data standards); enhance teachers’ AI literacy through training and case repositories, shifting their role from knowledge transmitters to learning designers; establish a stratified, modular resource repository with quality review and dynamic updating mechanisms; and build a diversified process-oriented evaluation system incorporating behavioral data, ability development, and engagement, while guiding students to avoid over-reliance on AI tools. Additionally, an implementation mechanism of “small-scale pilot–iterative optimization–phased promotion” should be adopted to ensure steady, context-appropriate rollout.

6. Conclusions and Prospects

This paper explores AI-empowered mathematics teaching in private universities from a smart education perspective. Three main conclusions are drawn: AI addresses core difficulties (uneven foundations, low motivation, lack of personalization) through diagnosis, adaptation, and feedback mechanisms; the “three-stage, four-element” teaching model provides an operable pathway for personalized instruction under large-class conditions; a controlled experiment shows significant improvements in grade distribution, pass rate, excellence rate, and learning engagement. Future research will introduce generative AI for intelligent tutoring, expand sample scope and course types for multi-center validation, and construct multidimensional learner profiles (knowledge, ability, thinking, affect) to shift evaluation from outcome-oriented to literacy-oriented, further supporting the intelligent transformation of mathematics courses in private universities.

Acknowledgments

This research was supported by the Project of Liaoning Private Education Association(LMJX2025213). The authors gratefully acknowledge this support.

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