Article

AI-Empowered Blended Precision Teaching Model for Computer Courses: Construction and Empirical Study

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Abstract: Aiming at the prominent problems in computer courses at application-oriented undergraduate and vocational colleges-namely, significant student divergence, abstract theoretical content, delayed error correction in practice, and one-dimensional evaluation-this study, against the backdrop of educational digital transformation, integrates artificial intelligence techniques including learner analytics, intelligent code assessment, and personalised resource recommendation. It designs and implements a "three-dimensional, four-stage" AI-driven precision blended teaching model. A one-semester comparative teaching experiment was conducted between two parallel classes: the experimental class adopted the new model while the control class followed the traditional approach. Effects were examined through quantitative analysis of final grades, questionnaire surveys, and independent-samples t-tests. Results show that the model significantly improves students' course performance ($P < 0.05$), with the excellence rate rising by 17.32 percentage points and the failure rate decreasing by 12.68 percentage points. Students' autonomous learning, programming practice, and classroom engagement are also markedly enhanced. This study provides a replicable and quantitatively grounded reference for the smart teaching reform of computer-related courses.

Keywords: artificial intelligence; computer teaching; precision teaching; blended learning; empirical study; learner stratification

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1. Introduction

1.1. Research Background

In line with the strategic action plan for vocational education digitalisation, the Ministry of Education has explicitly called for deeper integration of AI, big data, and other emerging technologies into classroom instruction, so as to foster a new teaching ecology that accommodates individual differences and enables precision instruction [1]. Computer-related programmes-such as Java Programming, Computer Organisation, and Computer Networks-are characterised by intricate theoretical systems, high logical demands, and strong hands-on requirements, making them key areas for reform in engineering education [2].

At present, many ordinary undergraduate and vocational colleges face considerable heterogeneity among students in terms of prior knowledge, learning habits, and cognitive abilities; many students exhibit marked learning anxiety and limited practical problem-solving skills. Traditional teaching models, which follow a uniform syllabus, pace, and assignment structure, fail to address the differentiated needs of learners, resulting in low classroom efficiency and a pronounced polarisation of achievement [3].

1.2. Review of Current Research

A review of recent literature on computer teaching reform reveals that most studies remain at the level of conceptual elaboration and experiential summary, lacking robust operational models, quantitative experimental data, and statistical significance tests [4].

Consequently, research conclusions tend to be subjective. To address this gap, the present study constructs a standardised AI-based precision teaching framework and rigorously validates it through a controlled experimental design and statistical analysis, thereby enhancing the academic rigour of the findings.

1.3. Main Innovations

1. Proposes a "three-dimensional, four-stage" AI precision teaching architecture that covers the entire cycle of pre-class, in-class, post-class, and evaluation.
2. Integrates two core technologies-intelligent learner profiling and automated code assessment-to provide quantitative support for stratified instruction.
3. Adopts a controlled experimental design combined with independent-samples t-tests, ensuring quantifiable and reproducible conclusions.
4. Establishes a multi-dimensional formative evaluation system, effectively overcoming the inherent limitations of summative assessment [5].

2. Quantitative Diagnosis of Problems in Traditional Computer Teaching

2.1. Preliminary Learner Survey

A pre-course survey was conducted among 168 students from four computer-major classes (Grade 2024). The distribution of identified problems is shown in Table 1.

Table 1. Learning Pain Points under the Traditional Teaching Model (N = 168)

Problem Type	Proportion (%)	Specific Manifestation
Difficulty in understanding knowledge points	67.86	Obscure content such as computer organisation, addressing modes, and interface logic
Inability to independently fix coding errors	79.76	Weak debugging skills; habitual reliance on teacher assistance
Lack of differentiated homework	74.40	Uniform assignments that fail to accommodate both stronger and weaker students
Low classroom concentration	65.48	Monotonous teaching style; insufficient interaction
Inability to self-assess learning outcomes	82.14	Dependence solely on final exams; lack of formative feedback

As seen in Table 1, approximately 80% of students face difficulties in self-directed practice and lack adequate process feedback, making it impossible for the traditional model to deliver accurate diagnosis and individualised support.

2.2. Major Deficiencies of the Traditional Model

Uniform pace: Insufficient consideration of student diversity; absence of a stratified teaching mechanism.

Delayed feedback: Coding errors and cognitive gaps are only addressed during after-class Q&A sessions.

Fixed resources: No personalised recommendation channel; students at different levels cannot access suitably challenging content.

One-sided evaluation: Excessive emphasis on final exam scores; insufficient attention to the learning process.

3. Construction of the AI-Empowered Precision Blended Teaching Model

3.1. Overall Architecture

The proposed model consists of a "three-dimensional technological base + four-stage teaching closed loop". The three dimensions are: big-data learner profiling, an AI intelligent assessment system, and a personalised resource library. The four stages are:

pre-class precision diagnosis, in-class precision instruction, post-class precision push, and whole-process precision evaluation (As shown in Figure 1).

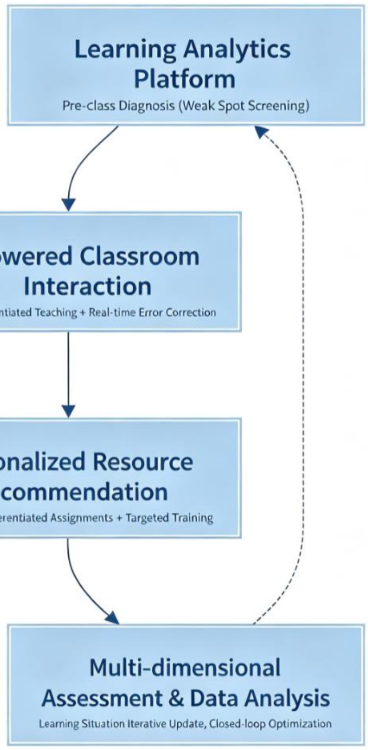

Figure 1. Architecture of the AI-empowered Blended Precision Teaching Model for Computer Courses

3.2. Pre-Class: AI-Based Precision Learner Diagnosis

The AI platform automatically aggregates data on preview video viewing duration, exercise accuracy, and knowledge points of incorrect answers, generating a class-level knowledge heatmap and individual learner profiles. Based on these, students are dynamically divided into three tiers:

Tier A (advanced): solid foundation; assigned extended projects and complex algorithmic cases.

Tier B (consolidating): average foundation; assigned comprehensive practical tasks.

Tier C (remedial): weak foundation; provided with micro-lectures, basic question types, and targeted error-correction exercises.

3.3. In-Class: Intelligent Interaction and Real-Time Error Correction

Teachers deliver targeted lectures based on pre-class weak-point data, reducing general theoretical exposition. During lab sessions, an AI code-assessment module is introduced, which can:

instantly detect syntax errors;

intelligently flag logical flaws;

automatically score code standardisation;

classify error types and map them to corresponding knowledge points.

This design significantly reduces the teacher's real-time Q&A burden and shortens the time students spend on debugging.

3.4. Post-Class: Differentiated Resource Delivery

Based on each student's daily error records and weak knowledge points, the AI system automatically compiles personalised homework packages-truly achieving "one unique assignment per student". A 24-hour intelligent Q&A bot is also deployed to prevent learning gaps after class.

3.5. Whole Process: Multi-Dimensional Quantitative Evaluation

A weighted evaluation structure is established: formative assessment accounts for 60% and summative assessment for 40%. Formative dimensions include pre-class preview behaviour, classroom interaction frequency, lab project scores, code accuracy, error correction performance, and after-class study duration. Summative dimensions cover the final written examination and comprehensive project practical assessment.

4. Empirical Teaching Experiment Design

4.1. Experimental Subjects

Two natural classes from the Grade 2024 computer major were selected for the comparative experiment:

Experimental group (82 students): adopted the AI-empowered precision blended teaching model.

Control group (80 students): continued with the traditional lecture-plus-lab approach.

Both classes shared the same instructor, textbook, class hours, and lab environment. Their pre-test average scores showed no significant difference ($P > 0.05$), confirming comparability.

4.2. Experimental Duration

The experiment lasted one full semester, i.e., 16 teaching weeks.

4.3. Research Instruments

Data were collected through the course's final unified examination, a self-designed learner perception questionnaire, automatically logged data from the AI teaching platform, and analysed using SPSS 26.0.

5. Experimental Results and Quantitative Data Analysis

5.1. Final Examination Performance Comparison

As shown in Table 2, the experimental group outperformed the control group in mean score, excellence rate, and pass rate, while the failure rate dropped substantially, indicating that the new model effectively alleviates score polarisation.

Table 2. Comparison of Final Examination Score Distributions

Group	Mean Score	Excellence Rate (≥85)	Pass Rate	Failure Rate
Control	72.36	16.25%	83.75%	16.25%
Experimental	78.92	33.57%	96.43%	3.57%
Improvement	+6.56	+17.32%	+12.68%	–12.68%

5.2. Independent-Samples T-Test

Table 3. Independent-samples T-test Results for the Two Groups

Group	Mean	Std. Deviation	t-value	p-value	Significance
Control	72.36	8.62	–4.268	0.000	$p < 0.05$, significant
Experimental	78.92	7.15	–	–	–

The results demonstrate a statistically significant difference between the two groups, confirming that the improvement attributable to the AI model is not due to sampling error.

5.3. Questionnaire Analysis of Student Perceived Ability Improvement

An anonymous post-experiment questionnaire was administered, yielding 162 valid responses. The results are summarised in Table 4 (As shown in Table 3).

Table 4. Student Self-reported Improvement Rates

Survey Dimension	Positive Endorsement Rate
Clearer understanding of knowledge points	91.36%
Enhanced ability to debug programs independently	94.44%
Better alignment of learning content with personal level	92.59%
Improved classroom learning efficiency	88.89%
Reduced learning anxiety	86.41%

6. Analysis of Teaching Reform Effectiveness

6.1. Structural Improvement in Academic Performance

After implementing the new model, the number of low-scoring students decreased markedly, while the proportion of high-scoring students increased significantly, effectively reversing the long-standing polarisation in computer courses.

6.2. Systematic Enhancement of Practical Skills

With the aid of AI real-time assessment tools, students' programming behaviour shifted from passive copying to proactive error detection, independent debugging, and logical reflection, thereby substantially strengthening their programming competence.

6.3. Data-Driven Teaching Decision-Making

Teachers moved beyond experience-based intuition and began to rely on accumulated learner data to inform the selection of key content and strategies for tackling difficult points, making instruction more targeted.

6.4. Rationality and Comprehensiveness of the Evaluation System

Complete process data were retained, replacing the traditional "one final exam determines everything" approach. This better aligns with the goal of cultivating application-oriented talents by tracking ability growth trajectories.

7. Implementation Safeguards

Digital capacity building for teachers: regular training on AI teaching platforms and intelligent assessment tools.

Dynamic updating of course resources: adjust project-based case libraries according to the latest industry competency requirements.

Tiered support mechanism: for Tier C students, set up AI-based early warnings and provide one-to-one tutoring.

Data compliance management: strictly define the scope and usage rights of learner data collection, ensuring compliance with educational data security regulations.

8. Conclusions and Future Directions

The AI-based three-dimensional, four-stage precision blended teaching model designed and validated in this study has been shown, through controlled experimentation and statistical testing, to effectively address the core issues of homogenised pacing, delayed feedback, and unbalanced evaluation commonly found in computer course instruction. After application, students' course performance, programming practical skills, and autonomous learning awareness all improved significantly, indicating strong potential for broader adoption.

In future work, we plan to further incorporate large language model-powered intelligent Q&A systems, adaptive learning path planning algorithms, and virtual simulation environments, so as to deepen the integration of AI technologies with computer education and provide more robust technological support and practical evidence for the comprehensive digital transformation of computer teaching.

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