AI-Assisted Teaching Model for Personalized Computer Education Based on Deep Learning

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Abstract

This study investigates an AI-assisted, deep learning–based personalized teaching model for computer education. With the rapid expansion of artificial intelligence in the education sector, personalized learning has become increasingly important for improving instructional effectiveness. Sixty computer science students were selected and randomly assigned to an experimental group—receiving AI-assisted personalized instruction—and a control group using traditional teaching methods. Data were collected through a learning management system, a programming practice platform, and a structured questionnaire. Descriptive statistics, independent-sample difference tests, and correlation analyses were employed to evaluate outcomes.

The findings indicate that the experimental group outperformed the control group across key indicators, including learning-path adaptability, learning-effect improvement rate, and satisfaction with learning feedback. These results demonstrate that the AI-assisted teaching model significantly enhances learning effectiveness and learner engagement.

The study contributes a practical and data-driven framework for integrating AI into personalized computer education. However, limitations related to sample size, single-discipline focus, and short intervention duration suggest the need for broader, longitudinal, and cross-disciplinary future research.

Keywords: AI - assisted teaching, Deep learning, Personalized computer education, Teaching model, Learning effects

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Introduction

With the rapid development of artificial intelligence (AI) and educational innovation, personalized education models have emerged as a major focus, aiming to address individual learning differences. Deep learning, a key branch of AI, shows strong potential in computer education by enabling more accurate and tailored learning experiences (Alur et al., 2020).

Research Background and Significance

Rapid developments in artificial intelligence (AI) and deep learning have transformed the education sector, accelerating the shift from traditional, uniform instructional models toward data-driven, adaptive learning environments. In computer education—where learning processes are highly individualized due to differences in cognitive styles, programming habits, and problem-solving strategies—the limitations of conventional teaching methods have become increasingly evident. Traditional instruction often struggles to accommodate learners' diverse needs, resulting in uneven learning progress, low engagement, and inconsistent mastery of core skills.

AI-assisted teaching systems provide a promising solution by integrating deep learning algorithms with learning management platforms to collect, analyze, and interpret large-scale learning data in real time. Such systems can automatically identify students' knowledge gaps, behavioral patterns, and learning preferences, enabling the generation of personalized learning path that optimize pacing, content sequencing, and instructional strategies. Moreover, AI-enabled analytics allow for dynamic monitoring and timely feedback, helping instructors intervene more effectively and students adjust learning behaviors promptly.

The fast evolution of computer technology has increased the demand for versatile talent. Traditional education, limited in theory–practice integration and interdisciplinary training, struggles to meet this need (Liu, Chen, & Yao, 2022). Thus, exploring AI-assisted personalized models based on deep learning is significant for improving education quality and cultivating future-ready professionals (El Bahri et al., 2022).

Given these advances, this study focuses on evaluating an AI-assisted teaching model for personalized computer education based on deep learning, with three core objectives:

1. to design individualized learning pathways aligned with students' cognitive differences, interests, and learning habits;

2. to provide real-time monitoring, feedback, and instructional guidance; and

3. to leverage deep learning to analyze learning data and accurately assess learning outcomes for teaching improvement.

The significance of this research lies in its potential to enhance learning effectiveness, improve teaching precision, and provide empirical evidence for the integration of AI-driven personalized instruction in computer education. Findings from this study can inform curriculum design, support technology-enhanced learning reform, and contribute to the broader development of intelligent education systems.

Research Objectives

The study aims to evaluate an AI-assisted teaching model that:

1. Plans personalized learning paths based on students' cognitive differences, interests, and habits.
2. Provides real-time monitoring, feedback, and guidance.
3. Applies deep learning to analyze student data and accurately assess learning outcomes to support teaching improvement.

Theories and related research

A. Principles of Deep Learning Technology

Deep learning — a core subfield of machine learning—employs multilayer neural networks composed of input, hidden, and output layers to model complex cognitive processes. Through iterative adjustments of weights and biases, activation functions, and error backpropagation mechanisms, deep neural networks are capable of extracting high-level abstract features and learning nonlinear patterns from large datasets (Xuan, Zhu, & Xu, 2021). This capacity for hierarchical feature representation provides a technical foundation for building intelligent, adaptive teaching systems.

B. Research Status of Personalized Teaching Models

Personalized teaching models supported by artificial intelligence have progressed rapidly, driven by advances in data mining and machine learning. These models capture individual differences in student behavior, learning preferences, and performance, enabling systems to dynamically adjust learning pathways, recommend targeted content, and provide adaptive feedback. Although algorithmic capabilities have improved, research indicates that the effectiveness of AI-assisted personalized teaching still depends heavily on teachers' acceptance, pedagogical beliefs, and willingness to integrate technology into instruction (Aghaziarati, Nejatifar, & Abedi, 2023).

C. Application of Deep Learning in Personalized Teaching

Deep learning further enhances personalized instruction by enabling precise real-time analysis of student learning data. Neural models can infer learners' interests, proficiency levels, and cognitive styles, and thereby support the generation of adaptive learning paths and individualized content recommendations. Additionally, deep learning enables dynamic teaching environments in which instructional strategies continually adjust to student feedback, contributing to measurable improvements in engagement and learning outcomes (Yu et al., 2019).

D. Related Research Review

Recent studies demonstrate a broad range of deep-learning applications in intelligent education. These include academic performance prediction, intelligent tutoring systems, automated question generation (Huang, Chen, & Sun, 2018), and AI-generated content (AIGC) tools designed to support higher education. Earlier foundational work on intelligent tutoring (Sleeman & Brown, 1979) laid the groundwork for today's adaptive systems, which leverage deep neural networks to deliver refined feedback, personalized content recommendations, and continuous learning analytics. Collectively, this body of research highlights the transformative potential of deep learning in advancing personalized and data-driven education.

Research method

A. Population and sample

Description of Research Subjects: This study recruited 60 computer science students to examine the effects of an AI-assisted, deep-learning–based personalized teaching model on learning performance. The participants reflected natural variation in demographic characteristics such as age and gender, yet all were enrolled in computer science courses and possessed foundational computer literacy. This ensured that the sample was sufficiently diverse while maintaining consistent baseline knowledge relevant to the instructional content.

Grouping Procedure: The 60 students were evenly assigned to an experimental group and a control group, with 30 students in each. The experimental group received instruction through the AI-assisted personalized teaching model, whereas the control group was taught using traditional instructional methods. This parallel group design enabled direct comparison between the two pedagogical approaches, thereby providing a clear basis for evaluating the effectiveness of the AI-assisted model.

B. Research Instruments

Learning Management System (LMS): The school's existing LMS served as primary research instrument, providing automated records of students' learning duration, activity frequency, assignment submissions, and grades. By mining and analyzing LMS data, the study obtained detailed behavioral information on students' day-to-day learning processes. These data formed a comprehensive and reliable foundation for evaluating learning patterns and performance.

Programming Practice Platform: For programming-related components of the computer science curriculum, a specialized programming practice platform was employed to collect real-time records of students' coding and debugging activities. These data provided direct evidence of students' programming proficiency and practical problem-solving skills, making them essential for assessing learning outcomes in computer-based competencies.

C. Survey and Experimental preparation

C.1 Questionnaire Survey: A special questionnaire was designed and distributed to collect students' personal information (such as computer learning foundation, learning interests, etc.) and their subjective feelings about the learning process and effects. The questionnaire survey was conducted at the beginning and end of the research respectively to obtain students' attitudes and feedback information in different learning stages and provide supplementary data for the comprehensive evaluation of the impact of the teaching model.
The research flowchart is shown below:

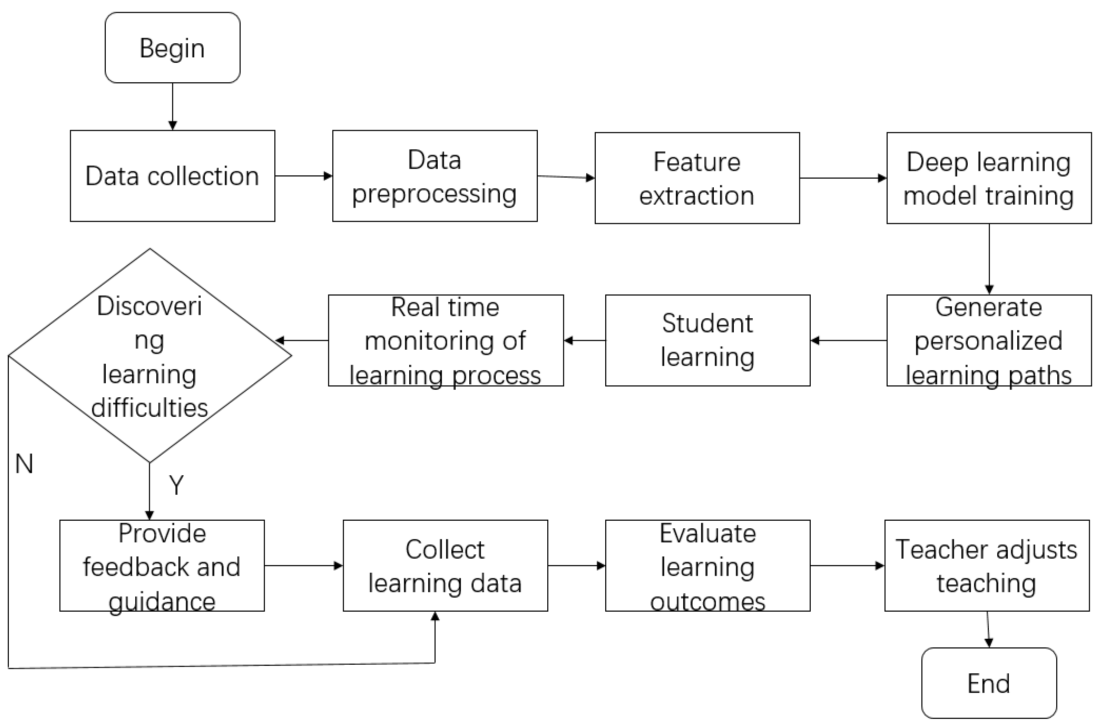

Figure 1 Research Flowchart

C.1.1. Questionnaire Design: The questionnaire aimed to collect students' personal information and perceptions of the learning process and effects. It included: (a) personal details (age, gender, computing background, learning interests) and (b) perceptions of learning (difficulty, satisfaction, suitability of learning path). Both multiple-choice and short-answer formats were used.

C.1.2 Questionnaire Distribution and Collection: Surveys were administered at the beginning and end of the study using both online (via LMS) and offline (classroom) methods. Invalid responses (incomplete or random) were removed during preliminary sorting.

C.1.3 Questionnaire Data Processing: Valid responses were coded and categorized. For example, computing background was classified into categories, and text responses were transformed into quantifiable data for statistical analysis.

C.2 Experimental preparation

C.2.1 Grouping of Experimental Subjects: Sixty computer science students with basic computing knowledge and diverse backgrounds were selected and evenly divided into an experimental group and a control group (30 each).

C2.2 Implementation of the Experimental Process:

Experimental Group: Taught with an AI-assisted personalized learning model. The system tracked learning behaviors (time, frequency, coding, debugging) and achievements (assignments, tests) in real time.

Control Group: Taught with traditional methods, with the same learning behavior and achievement data recorded via the LMS and practice platform.

C.2.3 Data Collection: Learning behaviors and achievements were gathered from the LMS and practice platform, while personal information was obtained via questionnaires. Data were cleaned, standardized, and coded.

Learning behavior data were collected via the learning management system (LMS) and a programming practice platform. The LMS recorded weekly learning time, frequency, and assignment submissions, while the platform tracked coding and debugging activities, reflecting students' engagement and skill development. Data were regularly cleaned to remove errors, unreasonable time records, and duplicates, ensuring accuracy.

While learning achievement data, assignment and test grades (including chapter tests, mid-term, and final exams) were obtained from the LMS. To enhance comparability, grades were standardized and weighted to generate a comprehensive score representing students' overall performance.

And students' personal information was collected via a questionnaire, covering age, gender, prior computing experience, and learning interests. Responses were coded into quantitative categories (e.g., programming competition participation, certificates) to support statistical analysis and modeling.

C2.4 Data Analysis: Descriptive statistics (means, medians, standard deviations) were calculated for the experimental and control groups to compare learning behaviors, achievements, and personal information. Visualizations such as box plots and histograms were used to display distributions, quartiles, outliers, and frequency patterns, providing an overview for further analysis.

C2.5 Difference Test: Independent sample t-tests (for normally distributed data with equal variance) or non-parametric tests (e.g., Mann–Whitney U) were applied to examine group differences in learning achievements, knowledge mastery, adaptability, and satisfaction. Normality and homogeneity of variance tests were conducted before selecting the appropriate method.

C2.6 Correlation Analysis: Correlations between learning behaviors (e.g., learning time, frequency, coding, debugging) and learning outcomes (e.g., assignment and test grades, knowledge mastery) were calculated. For instance, significant positive correlations between learning time and mastery rates, or coding frequency and assignment grades, indicated the impact of practice on performance.

Research Results

Collecting data of controlled group and experiment group was done in 30 days.

Key Indicators are:

Knowledge Point Mastery Rate (%): Calculated from students’ test and assignment performance across course knowledge points.

Learning Path Adaptability Rate (%): For the experimental group, measures how well the AI-planned path matches students’ needs, based on completion, efficiency, and feedback.

Learning Effect Improvement Rate (%): Compares effectiveness before and after using the model (or between groups), e.g., by score improvement ratio.

Learning Feedback Satisfaction Rate (%): Derived from questionnaires and feedback on prompts and suggestions provided by the model.

Hypothesis T-test for Learning Path Adaptability Rate

Hypotheses:

H0: No significant difference in learning effect improvement between groups ($\mu 1 - \mu 2 = 0$).

H1: Significant difference exists.

Data Grouping:

Group 1: Learning effect improvement rates included values such as 20, 18, 19, 17, 16, etc. (*n = 30*)

The formula for calculating the mean $\bar{x}_1$ is: $\bar{x}_1 = \frac{1}{n_1}\sum_{i=1}^{n_1} x_i$

$\bar{x}_1$ =1/30(20+18+19+17+16+16+17+13+14+16+14+13+14+13+13+14+13+13+12+13+14+ 13+13+13+13+14) =14.4

The formula for calculating the variance s_1^2 is: $s_1^2 = \frac{1}{n_1 - 1} \sum_{i=1}^{n_1} (x_i - \bar{x}_1)^2$

$$s_1^2 = \frac{1}{30-1} \times [(20 - 14.4)^2 + (18 - 14.4)^2 + \cdots + (13 - 14.4)^2]$$
$$\approx 9.96$$

Group 2: Learning effect improvement rate data (the last 30 students' data): 15, 14, 13, 13, 5, 8, 13, 8, 5, 8, 12, 8, 12, 8, 8, 8, 8, 8, 12, 8, 13, 8, 12, 8, 8, 8, 8, 8, 12, 8, 13, 8, 12, 8, 8, 8. Sample size n_2 (*n=30*)

The formula for calculating the mean $\bar{x}_2$ is: $\bar{x}_2 = \frac{1}{n_2} \sum_{j=1}^{n_2} x_j$

$\bar{x}_2$=8

The formula for calculating the variance s_2^2 is: $s_2^2 = \frac{1}{n_2 - 1} \sum_{j=1}^{n_2} (x_j - \bar{x}_2)^2$

$$s_2^2 = \frac{1}{30-1} \times [(15 - 8)^2 + (14 - 8)^2 + \cdots + (8 - 8)^2]$$
$$\approx 9$$

Data conforms to normal distribution and variance homogeneity testing.

Shapiro - Wilk test was used to test normality: Assume that after performing the Shapiro - Wilk test on the two groups of data, the p - value p>0.05 for both group, then the data of both groups are considered to conform to normal distribution.

Levene test was used to test variance homogeneity: Assume that after performing the Levene test on the two groups of data, the p - value p>0.05, then the variances of the two groups are homogeneous.

Appropriate t - test method according to the data distribution and calculating.

Since the data conforms to normal distribution and the variances are homogeneous, an independent - sample t - test is used. The formula for calculating the t - statistic is:

$$t = \frac{(\bar{x}_1 - \bar{x}_2) - (\mu_1 - \mu_2)}{s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

Where μ_1-μ_2=0 (under the null hypothesis), and s_p is the pooled variance, calculated as:

$$s_p = \sqrt{\frac{(n_1-1)s_1^2+(n_2-1)s_2^2}{n_1+n_2-2}}$$

$$s_p = \sqrt{\frac{(30-1)\times 9.96+(30-1)\times 9}{30+30-2}}$$

$$t = \frac{(14.4-8)-0}{3.13\sqrt{\frac{1}{30}+\frac{1}{30}}}$$

Calculating degrees of freedom and determining the p - value

Degrees of freedom: $df=n_1+n_2$-2=30+30-2=58.

Determining the p – value: By looking up the t - distribution table or using statistical software (such as R language, Python's scipy.stats library), according to t =5.83, with degrees of freedom df =58, the p - value is obtained as less than 0.05.

Since the p - value is less than 0.05, the null hypothesis is rejected, and it is considered that there is a significant difference in the learning effect improvement rate between the two groups of students.

Hypothesis T-test for Learning Feedback Satisfaction Rate: Similarly, calculate the Learning Feedback Satisfaction Rate using the above formula. Obtained through calculation: t =12.12, df =58 according to that, the p - value is obtained as less than 0.05. Since the p - value is less than 0.05, the null hypothesis is rejected, and it is considered that there is a significant difference in the learning feedback satisfaction rate between the two groups of students.

Confidence interval analysis: Calculate the confidence interval for an independent - sample T - test, when the population variance is unknown and the sample size is not very large, the formula for calculating the confidence interval of the difference between population means is:

$$(\bar{x}_1-\bar{x}_2) \pm t_{\alpha/2,df} \times s_p\sqrt{\frac{1}{n_1}+\frac{1}{n_2}}$$

where $\bar{x}_1$ and $\bar{x}_2$ are the means of the two groups of samples, $t_{\alpha/2,df}$ is the two - sided t quantile corresponding to a confidence level of 1-α with degrees of freedom df , s_p is the pooled variance, and n_1 and n_2 are the sizes of the two groups of samples.

Given that $\bar{x}_1 = 91, \bar{x}_2 = 74, s_p \approx 4.14, n_1 = n_2 = 30$, and the degrees of freedom $df=n_1+n_2$-2=30+30-2=58. Assuming we choose a commonly used confidence level of 95%, then α=0.05 and $\alpha/2$=0.025. By looking up the t - distribution table, we can get $t_{0.025,58} \approx 2.002$.

Substituting the above values into the confidence interval formula, thus:

$$(91-74) \pm 2.002 \times 4.14\sqrt{\frac{1}{30}+\frac{1}{30}}$$

$$= 17 \pm 2.99$$

So, the 95% confidence interval for the difference between the population means is (14.01,19.99).

Conclusions of confidence interval analysis: Since the 95% confidence interval excludes 0, the null hypothesis is rejected, indicating a significant difference in learning feedback satisfaction between the two groups. The interval (14.01–19.99) also estimates the magnitude of this difference, showing the extent of variation in satisfaction levels.

Discussion

This study examined the effectiveness of an AI-assisted teaching model designed to: (1) generate individualized learning pathways based on students’ cognitive characteristics, interests, and learning habits; (2) provide real-time monitoring, adaptive feedback, and instructional guidance; and (3) apply deep learning techniques to analyze learning data and accurately assess learning outcomes to support teaching improvement.

Across 60 computer science students—divided into experimental (AI-assisted) and control (traditional instruction) groups—data were collected through the learning management system, a programming practice platform, and a structured questionnaire. Analysis revealed that the AI-assisted group demonstrated significantly higher scores in learning-path adaptability, improvement in learning effectiveness, and satisfaction with feedback mechanisms.

Furthermore, correlation analysis indicated strong positive relationships between system-captured learning behaviors (e.g., engagement frequency, coding performance, and feedback responsiveness) and students' academic outcomes. These findings confirm that the AI-assisted model not only enhances the personalization of learning paths but also strengthens real-time learning support and improves the accuracy of outcome assessment through deep learning analytics.

Overall, the research validates the model as an effective tool for improving instructional quality and advancing personalized computer education, demonstrating clear alignment with the study’s three core objectives.

Significance

The study demonstrates how deep learning can support personalized computer education by customizing paths, monitoring progress, and improving outcomes. It provides a basis for future research on enhancing and extending AI-assisted teaching models.

Future Directions

Future studies should involve larger, more diverse populations, apply the model to other fields, and further optimize its performance.

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