AI-ASSISTED TEACHING MODEL FOR PERSONALIZED COMPUTER EDUCATION BASED ON DEEP LEARNING

DONG JIYOU

A thematic paper submitted in partial fulfillment of the requirements for Degree of Doctor of Philosophy Program in Digital Technology Management for Education

Academic Year 2025

Thesis Title AI-Assisted Teaching Model for Personalized Computer Education Based Learning

Author Mr.Dong Jiyou

Thesis Committee

.... Chairperson
(Dr.Nainapas Injoungjirakit)

.... Committee
(Associate Professor Dr.Sombat Teekasap)

.... Committee
(Assistant Professor Dr. Prapai Sridama)

Accepted by Bansomdejchaopraya Rajabhat University in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Digital Technology Management for Education

.... Dean of Graduate School
(Assistant Professor Dr. Nukul Sarawong)

.... President
(Assistant Professor Dr. Kanakorn Sawangcharoen)

Defense Committee

.... Chairperson
(Professor Dr.Apichart Pattaratuma)

.... Committee
(Associate Professor Dr.Supawat Lawanwisut)

.... Committee
(Associate Professor Dr.Duang-arthit Srimoon)

Thesis	AI-Assisted Teaching Model for Personalized Computer Education Based on Deep Learning
Author	Mr.Dong Jiyou
Program	Digital Technology Management for Education
Major Advisor	Assistant Professor Dr. Nainapas Injoungjirakit
Co-advisor	Associate Professor Dr. Sombat Teekasap
Co-advisor	Assistant Professor Dr. Prapai Sridama
Academic year	2025

ABSTRACT

This study aimed to: (1) examine AI-assisted learning readiness, utilization, and urban–rural disparities among computer science students in Guangxi Zhuang Autonomous Region; (2) develop a context-adapted AI-assisted personalized teaching model; and (3) evaluate its suitability and feasibility for routine teaching. The sample included 56 undergraduate students, divided into experimental and control groups (n = 28 each), and an 8-member expert panel. Data were collected through questionnaires, interviews, and evaluation forms, and analyzed using descriptive statistics, t-tests, chi-square, correlation, and content analysis.

Results indicated high overall readiness (M = 3.68), with significant urban–rural disparities. Urban students showed higher technology acceptance and self-efficacy, while rural students demonstrated greater needs for personalized learning and faced infrastructure limitations. The developed model integrates dual-track learning paths, adaptive feedback, and low-bandwidth/offline functionalities tailored to regional constraints.

Evaluation results confirmed high suitability and feasibility (M = 4.44, S-CVI = 0.953). The experimental group reported high usability (M = 4.21), and implementation strategies achieved a 91.7% integration rate, effectively supporting diverse classroom contexts and reducing instructional burden.

Keywords: Artificial Intelligence, Computer Education, Teaching-Learning Model, Computational Thinking, Regional Adaptability.

Acknowledgment

As my doctoral studies come to an end, I would like to express my sincere gratitude to everyone who has supported me over the past four years.

First, I am deeply thankful to my major advisor, Assistant Professor Dr. Nainapas Injoungjirakit, for her professional guidance, rigorous academic attitude, and patient advice throughout my research. Her careful revision and valuable suggestions greatly improved this thesis.

I also thank my co-advisors, Associate Professor Dr. Sombat Teekasap and Assistant Professor Dr. Prapai Sridama, for their professional feedback on AI and educational technology. Special thanks to Dr. Sombat for his help in both academic research and daily life.

I am grateful to the teachers, students, and experts who participated in this study for their support in data collection and instrument verification. I also appreciate the staff from the School of Computer Science and related universities for their assistance.

Finally, I thank my family and friends for their constant encouragement, and Bansomdejchaopraya Rajabhat University for financial support. This research reflects the help of many people, and I will continue to study AI in education in the future.

Dong Jiyou

Contents

Contents (Continued)

List of Tables

Table **Page**

List of Figures

Chapter 1
Introduction

Rationale

The rapid advancement of artificial intelligence (AI) and deep learning technologies has catalyzed a global shift toward digitalization and personalization in education. Nations worldwide have enshrined digital technology and AI-assisted learning as cornerstones of their national education strategies, aiming to revolutionize pedagogical models and enhance instructional efficiency through technological empowerment. As a core branch of AI, deep learning has been proven effective in creating precise, customized learning experiences, providing the technical backbone for the implementation of personalized education (Alur et al., 2020). Globally, educational policies emphasize replacing the traditional one-size-fits-all teaching model with data-driven adaptive learning environments. The integration of AI teaching assistant systems with learning management platforms has become a pivotal direction of national educational digitalization strategies. By real-time collection and analysis of learning data, these initiatives drive the transformation from "standardization" to "personalization" in teaching, fostering professionals equipped for the digital age (Liu, Chen, & Yao, 2022).

At the provincial level, Guangxi Zhuang Autonomous Region has refined and implemented national educational digitalization policies by integrating AI and education into its blueprint for high-quality regional educational development. Guangxi’s "14th Five-Year Plan for Educational Informatization" explicitly prioritizes the construction of a smart education ecosystem, with a focus on leveraging AI to bridge educational disparities between urban and rural areas (Guangxi Education Department, 2021). The region has launched initiatives such as the "Guangxi Smart Education Platform" and established pilot bases for AI-augmented teaching across prefectures like Nanning and Guilin, specifically targeting the application of AI in STEM education, including computer science (Wang & Li, 2023). Furthermore, Guangxi has incorporated AI literacy training into pre-service and in-service teacher professional development programs, mandating the integration of digital tools into daily instruction. These provincial policies aim to create a localized AI education ecosystem that supports intelligent lesson planning, adaptive learning, and data-driven teaching evaluation, ensuring the equitable distribution of high-quality educational resources through technology (Guangxi Zhuang Autonomous Region Government, 2022).

Despite these policy advancements, significant challenges persist in current teaching practices, particularly within the field of computer education. Traditional pedagogical models struggle to accommodate the pronounced individual differences among learners, such as varying cognitive styles, programming aptitudes, and problem-solving strategies. This one-size-fits-all approach leads to uneven learning progress, low student engagement, and inconsistent mastery of core competencies (Dong et al., 2025). Additionally, traditional education often lacks sufficient integration of theory and practice and falls short in fostering interdisciplinary skills, which are increasingly demanded by the rapidly evolving computer technology industry (Liu, Chen, & Yao, 2022). AI-assisted learning, underpinned by deep learning, offers a viable solution to these issues. Deep learning algorithms can extract high-level abstract features from learning data to accurately identify students' knowledge gaps, behavioral patterns, and learning preferences (Xuan, Zhu, & Xu, 2021). Consequently, it can generate personalized learning pathways, optimize the pacing and sequencing of content, and enable real-time monitoring and feedback throughout the learning process. This empowers educators to intervene precisely and allows students to adjust their learning behavior promptly. Furthermore, deep learning facilitates the accurate assessment of learning outcomes, providing empirical data to inform teaching improvements (Dong et al., 2025).

In light of the aforementioned limitations of traditional teaching models and the transformative potential of AI-assisted learning, this research undertakes the development of a deep learning-based AI-assisted personalized teaching model for computer education in Guangxi. The primary objective is to address the lack of personalization, delayed learning process monitoring, and inaccurate learning outcome assessment prevalent in current computer education. By designing personalized learning pathways that align with students' cognitive differences, interests, and habits, this study aims to construct an integrated AI teaching assistant system featuring real-time monitoring, adaptive feedback, and professional instructional guidance. Additionally, it seeks to validate the efficacy of deep learning techniques in analyzing computer science learning data, thereby enhancing teaching precision and learning effectiveness. The findings of this research are intended to provide a practical framework for the deep integration of AI technology with computer education in Guangxi, complement the shortcomings of traditional teaching, and ultimately improve the quality of computer education. This will foster the development of computer professionals who meet industry demands and offer empirical evidence and practical insights for the further advancement of intelligent education systems, particularly within the context of China's western regions.

Research Questions

1. What is the level of AI-assisted learning readiness and current utilization among computer science educators and students in higher education institutions across urban and rural areas of Guangxi?

2. What are the key pedagogical challenges, perceived barriers, and unmet learning needs specific to computer education in Guangxi that AI-assisted learning technologies aim to address?

3. Are the proposed deep learning-based AI-assisted personalized teaching model and its tailored implementation strategies suitable for the regional context and feasible to integrate into routine computer education practices in Guangxi?

Research Objectives

1. To examine the level of AI-assisted learning readiness, current usage of AI tools, and personalized learning needs among computer science students in urban and rural universities in Guangxi, and to compare differences between the two groups.

2. To design and develop an AI-assisted personalized teaching model, based on deep learning technologies, that is appropriate for computer science education in both urban and rural contexts in Guangxi.

3. To evaluate the suitability, feasibility, and effectiveness of the proposed model through expert validation and teaching experiments.

Scope of Research

This study focuses on the development and evaluation of an AI-assisted teaching model for personalized computer education based on deep learning technologies within the context of Guangxi Zhuang Autonomous Region, China. The scope of the research is defined across four main dimensions: population, content, methodology, and context.

First, the population of the study is limited to undergraduate computer science students enrolled in selected urban and rural universities in Guangxi. The comparison between these two groups is emphasized to identify disparities in AI-assisted learning readiness, current usage of AI tools, and personalized learning needs.

Second, in terms of content scope, the study investigates key dimensions of AI-assisted learning, including technology acceptance, learning self-efficacy, and demand for personalized learning. The research further develops an AI-assisted personalized teaching model grounded in deep learning approaches, incorporating core components such as personalized learning pathways, adaptive feedback mechanisms, and data-driven evaluation systems.

Third, regarding methodological scope, the study employs a mixed-methods approach, combining quantitative analysis (e.g., descriptive statistics and comparative analysis) and qualitative insights (e.g., expert validation and interviews). The model is tested through controlled teaching experiments to assess its effectiveness.

Finally, the contextual scope is confined to computer science education settings in Guangxi, with particular attention to differences in infrastructure and learning environments between urban and rural institutions. The findings are intended to provide context-specific insights while offering implications for broader applications in similar educational settings.

Advantages

1. To use the guidelines as a reference to develop the innovative application capacity of AI teaching assistant among computer education faculty in higher education institutions in Guangxi.

2. To provide a contextually tailored practical framework for bridging the urban-rural digital education gap in computer science teaching within Guangxi’s smart education ecosystem.

3. To generate empirical data and replicable strategies for promoting the deep integration of deep learning technology and personalized education in the western region of China.

Benefits of the Research

1. **Theoretical Contribution**: This study contributes to the advancement of knowledge in AI-assisted education by integrating deep learning technologies with personalized learning theory. It provides a context-sensitive framework that extends existing models of AI-driven instruction, particularly in addressing disparities between urban and rural educational settings.

2. **Methodological Contribution**: The research demonstrates the application of a mixed-methods approach in developing and validating an AI-assisted teaching model. It offers a systematic process for combining quantitative analysis and expert validation, which can serve as a reference for future studies in educational technology and instructional design.

3. **Practical Implications for Teaching and Learning:** The proposed AI-assisted personalized teaching model supports instructors in delivering adaptive and student-centered learning experiences. It enhances learning efficiency, improves knowledge mastery, and reduces instructional workload through automated feedback and data-driven decision-making.

4. **Policy and Institutional Implications**: The findings provide evidence-based insights for educational policymakers and university administrators in designing strategies for AI integration in higher education. The model offers practical solutions for reducing urban–rural educational disparities and promoting inclusive digital learning environments.

5. **Societal Impact:** By addressing inequalities in access to personalized learning, particularly in resource-constrained rural areas, the study supports equitable educational development and contributes to the broader goal of digital transformation in education.

Definition of Terms

AI teaching assistant refers to an instructional approach that integrates deep learning algorithms with learning management and practice platforms to collect, analyze, and interpret large-scale learning data in real time, automatically identify students' learning characteristics, and provide personalized learning support and timely instructional intervention. There are consisted of four aspects: personalized learning path generation, real-time learning process monitoring, adaptive learning feedback provision, and data-driven learning outcome assessment.

Personalized computer education refers to a targeted computer science instructional mode that addresses individual differences in students' cognitive styles, programming habits, and problem-solving strategies, and optimizes learning pacing, content sequencing, and instructional strategies based on students' knowledge gaps, behavioral patterns, and learning preferences. At the same time, it aims to improve the uniformity of core skill mastery and enhance learners' engagement in computer learning.

Personalized learning path generation refers to the core component of AI teaching assistant that designs individualized learning routes aligned with students' cognitive differences, learning interests, and habitual learning behaviors by leveraging deep learning to extract and analyze key features from students' learning data, ensuring the learning content and progress match each student's actual learning needs. Real-time learning process monitoring refers to the key aspect of AI teaching assistant that tracks students' learning behaviors (including learning duration, activity frequency, assignment submission status) and practical programming performance (coding and debugging activities) in real time through learning management systems and specialized programming practice platforms, and dynamically captures the whole process of students' knowledge acquisition and skill development in computer education.

Adaptive learning feedback provision refers to the essential part of AI teaching assistant that offers targeted prompts, suggestions and evaluative information to students based on the real-time monitoring results of their learning processes and the analysis of knowledge mastery status and enables teachers to make timely and effective instructional interventions to help students adjust their learning behaviors promptly.

Data-driven learning outcome assessment refers to the critical aspect of AI teaching assistant that applies deep learning techniques to statistically analyze multi-dimensional learning data (including test scores, assignment performance, and learning behavior indicators), accurately evaluate students' mastery of computer science knowledge points and practical competency levels, and provide empirical evidence for teachers to optimize and adjust their instructional strategies.

Operational Definitions of Terms

1. AI-Assisted Teaching Model: Refers to an instructional framework that integrates artificial intelligence technologies to support teaching and learning processes. In this study, it specifically denotes a model incorporating deep learning algorithms to deliver personalized learning pathways, adaptive feedback, and data-driven evaluation within computer science education.

2. Personalized Computer Education: Refers to a learner-centered instructional approach in which content, learning pace, and activities are tailored to individual students' needs, abilities, and preferences. In this research, personalization is operationalized through AI-generated learning paths and adaptive instructional support.

3. Deep Learning Technologies: Refers to a subset of artificial intelligence techniques based on neural networks with multiple layers (e.g., Transformer-based models) used to analyze learning data, predict learner performance, and generate adaptive learning recommendations.

4. AI-Assisted Learning Readiness: Refers to the degree to which students are prepared to engage with AI-supported learning environments. It is measured through dimensions such as technology acceptance, digital literacy, and learning self-efficacy using a structured questionnaire.

5. AI Tool Usage: Refers to the extent and frequency with which students utilize AI-based tools (e.g., intelligent tutoring systems, coding assistants, or adaptive learning platforms) in their learning activities, as measured by self-reported usage levels.

6. Personalized Learning Needs: Refers to the degree to which students require individualized learning support, including customized content, pacing, and feedback. This construct is measured using Likert-scale survey items reflecting students' perceived needs.

7. Urban–Rural Disparities: Refers to the differences in learning readiness, AI tool usage, infrastructure access, and educational opportunities between students in urban and rural universities in Guangxi. These disparities are identified through comparative statistical analysis.

8. Adaptive Feedback Mechanism: Refers to an AI-driven process that provides real-time, tailored feedback to learners based on their performance and interaction data, aiming to improve learning outcomes.

9. Low-Bandwidth Optimization: Refers to the design feature of the proposed model that enables effective system functionality under limited internet connectivity conditions, particularly relevant for rural educational settings.

10. Offline Synchronization: Refers to the capability of the system to allow learning activities to be conducted without continuous internet access and to synchronize data once connectivity is restored.

11. Suitability of the Model: Refers to the degree to which the developed teaching model aligns with educational objectives, learner needs, and instructional contexts, as evaluated by experts using a structured assessment form.

12. Feasibility of the Model: Refers to the practicality and ease of implementing the proposed model in real teaching environments, considering factors such as resources, infrastructure, and teacher readiness.

13. Effectiveness of the Model: Refers to the extent to which the model improves student learning outcomes, including knowledge mastery and learning performance, as measured through experimental results.

Research Framework

According to the analysis of related theories and research, characteristics of AI teaching assistant are as follows:

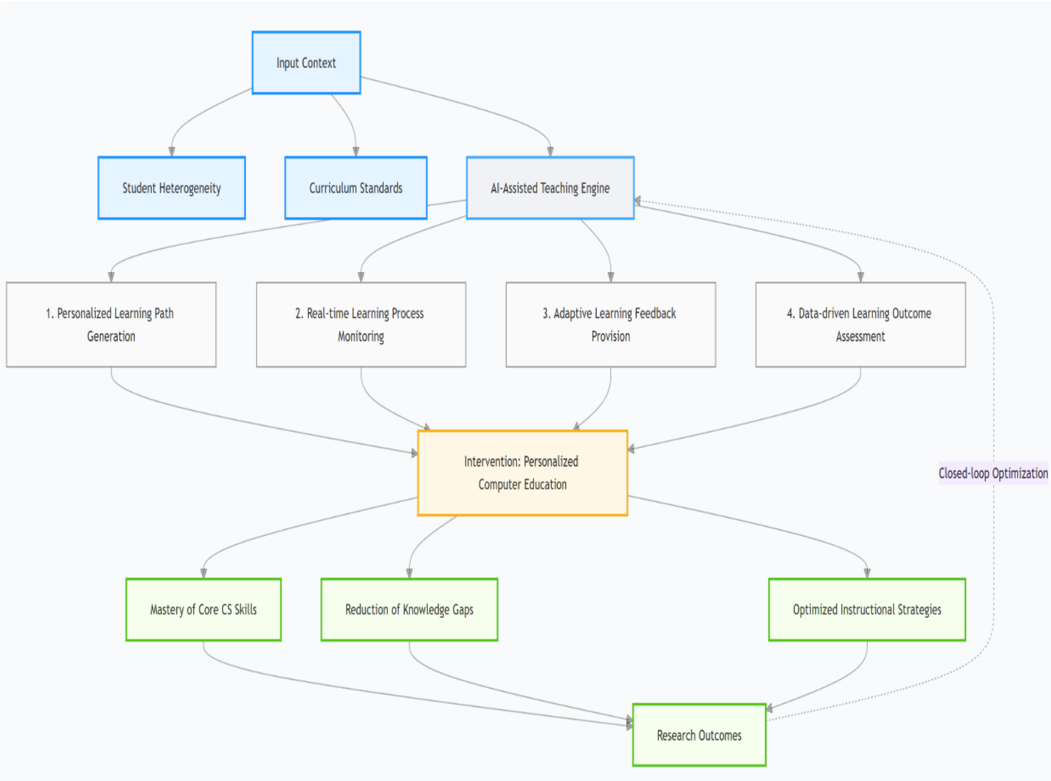


Figure 1.1 Research Framework

Chapter 2
Literature Review

This section systematically synthesizes the existing body of knowledge related to artificial intelligence applications in education and personalized learning within the domain of computer science. It begins with an examination of the foundational concepts and theoretical underpinnings that support the integration of AI and pedagogy, followed by an analysis of the specific contextual factors influencing computer education in the digital age. Finally, it critically reviews the empirical studies and methodological approaches in the field, identifying key research gaps, contradictory findings, and emerging trends that justify the necessity and originality of the present study. Building upon this comprehensive review, the research framework and hypotheses are formulated to address the unresolved issues in current AI-assisted personalized computer education practices.

1. Concept and theory of AI teaching assistant

This subsection delves into the evolutionary definition of AI teaching assistant, tracing its development from early computer-aided instruction (CAI) to modern intelligent tutoring systems (ITS) powered by deep learning and big data analytics. It elaborates on the core theoretical pillars, including the cognitive load theory, which explains how AI optimizes information processing, and the technology acceptance model (TAM), which predicts stakeholder adoption. The section further clarifies the functional mechanisms of AI in education, such as adaptive decision-making and real-time data mining, establishing a theoretical basis for the four core modules (path generation, monitoring, feedback, and assessment) operationalized in this research.

2. Concept and theory of personalized computer education

Focusing on the disciplinary specificity of computer science, this part defines personalized computer education as an instructional paradigm tailored to individual differences in computational thinking, programming proficiency, and problem-solving styles. It grounds the concept in constructivism and Vygotsky's zone of proximal development (ZPD), arguing that personalized instruction is crucial for bridging the wide achievement gap in programming courses. The subsection also reviews theories of competency-based education (CBE) to align personalized learning objectives with the core competencies required in 21st-century computer science curricula, distinguishing it from generic personalized learning models.

3. Context of AI integration in computer education

This part situates the research within the broader landscape of global educational digital transformation and the specific national context of computer science education reform. It analyzes the contextual drivers, such as the increasing enrollment diversity in higher education and the demand for cultivating AI literacy among K-12 and university students. Additionally, it examines the contextual challenges, including the digital divide in educational resources, the technical readiness of educators, and the curriculum constraints in traditional computer classrooms. This contextual analysis justifies the timeliness of implementing AI-assisted interventions to enhance equity and quality in computer education settings.

4. Related Research

This subsection provides a critical review of empirical studies at the intersection of AI teaching assistant and personalized computer education. It is structured into three thematic clusters: (1) research on the effectiveness of AI systems in improving programming skills and computational thinking; (2) studies evaluating the impact of personalized learning paths on student engagement and retention in STEM fields; and (3) methodological research comparing data-driven assessment with traditional evaluation methods. The review highlights consistent findings, such as the positive correlation between real-time feedback and coding performance, while also pointing out significant research gaps, including the lack of longitudinal studies on closed-loop optimization mechanisms and the under-exploration of AI's role in reducing knowledge gaps, thereby positioning the current study as a timely contribution to the field.The details are as follows.

Concept and theory of AI teaching assistant

AI teaching assistant is an innovative instructional paradigm that integrates artificial intelligence technologies, particularly deep learning algorithms, with educational teaching systems, learning management platforms, and professional practice tools to realize the digitalization, intellectualization, and personalization of the teaching and learning process (Alur et al., 2020). Different from the traditional computer-aided instruction that only provides simple resource delivery and tool support, AI-assisted teaching takes learning data as the core driving force, which can collect, mine and analyze learners' comprehensive learning information in real time, automatically identify their knowledge gaps, cognitive characteristics, learning habits and behavioral patterns, and further provide targeted learning support, dynamic instructional intervention and accurate outcome assessment for learners and educators (Dong et al., 2025). As a multi-dimensional and integrated teaching approach, it is composed of four core functional modules: personalized learning path generation, real-time learning process monitoring, adaptive learning feedback provision and data-driven learning outcome assessment, and the organic collaboration of each module forms a closed-loop teaching system of "data collection-analysis-decision-making-implementation-optimization".

The theoretical construction of AI teaching assistant is based on the cross-integration of multiple disciplines such as educational psychology, cognitive science, machine learning and educational technology, and its core operating logic is supported by a variety of classic theories and cutting-edge technical principles. Firstly, cognitive load theory is the important educational psychological foundation of AI teaching assistant. This theory holds that learners' cognitive processing capacity is limited, and the rational design of teaching content and learning process can effectively reduce extraneous cognitive load and improve the efficiency of knowledge acquisition (Sweller, 1988). AI teaching assistant relies on deep learning algorithms to analyze learners' cognitive characteristics and knowledge acceptance level, and design hierarchical and personalized learning content and progress, which can make the difficulty and quantity of learning information match learners' cognitive load bearing capacity, and avoid the problems of overloading or underloading caused by the unified teaching mode in traditional education.

Secondly, constructivism learning theory provides the core pedagogical logic for AI teaching assistant. Constructivism holds that learning is not a passive process of accepting knowledge indoctrinated by teachers, but an active process of learners constructing knowledge meaning based on their own prior experience and cognitive structure (Piaget, 1970). AI-assisted teaching takes learners as the center of the teaching process, abandons the "one-size-fits-all" instructional mode, and generates personalized learning paths according to the individual differences of learners. It guides learners to carry out exploratory and autonomous learning through targeted resource recommendation and problem guidance and fully stimulates their initiative and creativity in the learning process, which is highly consistent with the core connotation of constructivism.

Thirdly, technology acceptance model (TAM) lays a theoretical foundation for the effective implementation and popularization of AI teaching assistant in educational practice (Davis, 1989). This model reveals that users' acceptance and use intention of a technology are mainly affected by perceived usefulness and perceived ease of use. AI teaching assistant system pays attention to the optimization of human-computer interaction design in the development process, simplifies the operation process of teachers and students, and at the same time, through the obvious improvement of learning effect and teaching efficiency, enhances teachers' and students' perceived usefulness of the system. In addition, the integration of AI literacy training into teacher professional development programs (Guangxi Zhuang Autonomous Region Government, 2022) further reduces the perceived difficulty of using AI teaching tools and promotes the active acceptance and application of AI teaching assistant by educators and learners.

Finally, the principles of deep learning technology form the core technical support of AI teaching assistant (Xuan, Zhu, & Xu, 2021). As a core branch of machine learning, deep learning constructs a multi-layer neural network composed of input layer, hidden layer and output layer, which can extract high-level abstract features and learn nonlinear change patterns from large-scale learning data through iterative adjustment of weights and biases, error backpropagation and activation function operation. This technical characteristic enables AI-assisted teaching systems to accurately model learners' learning status and development trends, realize the intelligent analysis of learning data, and provide technical realization paths for the personalized push of learning content, the dynamic monitoring of learning process and the accurate assessment of learning outcomes.

In addition, Vygotsky's zone of proximal development theory also provides important theoretical guidance for the instructional intervention of AI teaching assistant. The theory points out that there is a gap between learners' actual development level and potential development level, and effective teaching should be carried out in this zone and with the help of appropriate scaffolding support (Vygotsky, 1978). AI teaching assistant can accurately locate the zone of proximal development of learners by analyzing their learning performance and knowledge mastery and provide targeted instructional scaffolding such as step-by-step problem guidance and hierarchical knowledge explanation. With the improvement of learners' ability, the scaffolding is gradually adjusted or removed, which realizes the gradual promotion of learners' learning level from the actual development level to the potential development level.

The integration of the above theories and technical principles makes AI teaching assistant form a complete theoretical system with clear pedagogical logic, scientific cognitive basis and feasible technical path. This system not only clarifies the core connotation and functional characteristics of AI teaching assistant, but also provides a theoretical basis for the design, development and practical application of AI teaching assistant models in specific disciplines such as computer education and lays a solid foundation for the transformation from traditional standardized teaching to modern personalized intelligent teaching.

Concept and theory of personalized computer education

Personalized computer education is a discipline-specific instructional paradigm tailored to the inherent individual differences in computer science learning, which targets the optimization of learning experience and the improvement of professional competency by adjusting teaching content, pacing, strategies and assessment methods according to students' cognitive styles, programming aptitudes, problem-solving strategies, knowledge gaps and learning preferences

(Dong et al., 2025). Distinguished from the generic personalized learning model applied in liberal arts or other STEM disciplines, it is deeply integrated with the characteristics of computer science—such as the practicality of programming, the logicality of computational thinking and the systematicity of professional knowledge—and focuses on solving the problems of uneven learning progress, low practical ability and inconsistent mastery of core competencies caused by the one-size-fits-all teaching mode in traditional computer education (Liu, Chen, & Yao, 2022). Centered on learners' individual needs, this educational mode takes the cultivation of computer science core competencies as the fundamental goal and constructs a dynamic and adaptive learning system through the combination of technical empowerment and pedagogical innovation, which realizes the organic integration of theoretical learning and practical operation, and effectively bridges the gap between academic education and industry talent demand. As a targeted instructional mode for computer science education, it not only emphasizes the adaptation to learners' individual learning characteristics, but also adheres to the disciplinary laws of computer science, and its implementation relies on the accurate capture of learning data and the scientific design of personalized learning paths, forming an interactive mechanism of "learner characteristic analysis-personalized intervention implementation-learning effect feedback- teaching strategy optimization".

The theoretical foundation of personalized computer education is built on the cross-integration of educational psychology, constructivism learning theory, disciplinary education theory and competency-based education theory, and its instructional design and practical implementation are guided by a variety of classic theoretical perspectives, which jointly ensure the scientific and rationality of the personalized teaching mode in the field of computer science.

Firstly, constructivism learning theory is the core pedagogical foundation of personalized computer education (Piaget, 1970). This theory holds that learning is not a passive process of accepting knowledge indoctrination, but an active and constructive process in which learners build the meaning of knowledge based on their own prior experience and cognitive structure. In computer education, students show obvious differences in prior programming foundation, logical thinking ability and computational thinking level, which lead to different cognitive processes and learning effects in facing the same teaching content. Personalized computer education takes this as the starting point, abandons the standardized teaching mode of "unified progress and unified assessment", and designs targeted learning tasks and instructional guidance for students with different cognitive characteristics. For example, for students with weak programming foundation, it arranges hierarchical coding practice and step-by-step problem-solving guidance; for students with strong learning ability, it provides in-depth project development and interdisciplinary application tasks. This learner-centered instructional design fully stimulates students' initiative and creativity in the learning process and guides them to construct computer science knowledge system and professional ability system suitable for their own development through autonomous exploration and practical operation, which is highly consistent with the core connotation of constructivism learning theory.

Secondly, Vygotsky's zone of proximal development (ZPD) theory provides the key instructional logic for personalized computer education (Vygotsky, 1978). The theory points out that there is a clear gap between learners' actual development level (solving problems independently) and potential development level (solving problems with the help of others), and effective teaching should be carried out in the zone of proximal development and provide appropriate scaffolding support for learners. In the field of computer education, the learning of programming languages, algorithm design and software development has a strong hierarchical and progressive nature, and the zone of proximal development of different students shows obvious individual differences due to the disparity of basic ability. Personalized computer education accurately locates the zone of proximal development of each student by analyzing their learning performance, knowledge mastery and practical operation ability, and provides hierarchical instructional scaffolding such as targeted knowledge explanation, step-by-step debugging guidance and project development suggestions. With the improvement of students' professional ability, the corresponding instructional scaffolding is gradually adjusted, reduced or removed, which guides students to continuously break through their own zone of proximal development and realize the progressive improvement of computer science ability from the actual development level to the potential development level. This scaffolding-based personalized intervention effectively solves the problem of "under-teaching for excellent students and over-teaching for slow learners" in traditional computer education and maximizes the teaching effect.

Thirdly, competency-based education (CBE) theory is the fundamental goal guidance of personalized computer education. This theory takes the cultivation of learners' professional competencies as the core of education and teaching, and designs the curriculum system, teaching content and assessment methods around the competency requirements of the industry and the society (Alur et al., 2020). With the rapid development of computer technology, the industry has put forward increasingly diverse and personalized demands for computer professionals, requiring them to have not only solid theoretical knowledge, but also strong practical programming ability, computational thinking ability, interdisciplinary application ability and innovative development ability. Traditional computer education is often limited by the separation of theory and practice and the single teaching mode, which is difficult to meet the diversified competency demands of the industry. Personalized computer education takes the cultivation of computer science core competencies as the starting point and goal and formulates personalized learning objectives and training plans for students according to their learning interests, ability characteristics and career development orientation. For example, for students who are inclined to software development, it focuses on the cultivation of programming ability and project development ability; for students who are interested in artificial intelligence, it strengthens the learning of machine learning algorithms and data processing ability. This competency-oriented personalized teaching mode effectively connects academic learning with career development and enables students to form personalized professional competency advantages while mastering the basic computer science competencies, which is more in line with the talent demand of the computer industry in the digital age.

Finally, cognitive load theory provides the important psychological basis for the instructional design of personalized computer education (Sweller, 1988). The theory holds that learners' cognitive processing capacity is limited in a certain period of time, and the rational design of teaching content and learning tasks can effectively reduce extraneous cognitive load, increase germane cognitive load, and thus improve the efficiency of knowledge acquisition and ability cultivation. Computer science learning involves a lot of abstract concepts, logical reasoning and practical operation, which is easy to cause excessive cognitive load for students if the teaching content and difficulty are not properly designed. Personalized computer education fully considers the differences in students' cognitive load bearing capacity and designs hierarchical and personalized learning content and learning tasks according to their cognitive characteristics and ability levels. It controls the difficulty and quantity of learning information input, avoids the excessive cognitive load caused by overly difficult or too much learning content, and also prevents the low learning efficiency caused by overly simple learning content and insufficient cognitive load. For example, in the teaching of programming languages, it designs different levels of coding tasks from basic syntax practice to complex project development for students with different cognitive levels, which makes the cognitive load of students in the learning process always in a reasonable range, and effectively improves the efficiency and quality of computer science learning.

In addition, the theory of individual differences in education further lays the realistic foundation for the necessity of personalized computer education. This theory holds that learners have obvious individual differences in cognitive ability, learning interest, learning style and learning motivation, and these differences are the important basis for educational teaching to carry out personalized intervention. In computer education, the individual differences of students are particularly prominent: some students have strong logical thinking ability but weak practical operation ability; some students are good at algorithm design but lack of project application ability; some students have strong learning motivation but poor learning methods. Traditional computer education ignores these individual differences and adopts the unified teaching mode, which leads to the gradual widening of the learning gap among students and the decline of learning engagement. Personalized computer education takes the full respect and adaptation to students' individual differences as the basic principle, and carries out all-round analysis of students' individual characteristics through the collection and analysis of learning data, and formulates personalized learning plans and teaching strategies for them, which makes each student can obtain suitable learning support and instructional guidance, and effectively stimulate their learning potential and improve their learning engagement.

The integration and application of the above theories make personalized computer education form a complete theoretical system with clear goal orientation, scientific pedagogical logic and reasonable instructional design basis. This theoretical system not only clarifies the core connotation, disciplinary characteristics and implementation principles of personalized computer education, but also provides the theoretical guidance and practical basis for the combination of AI teaching assistant technology and personalized computer education and lays a solid foundation for the design and implementation of the deep learning-based AI teaching assistant personalized model in computer education. At the same time, this theoretical system also makes personalized computer education break away from the simple "differentiated teaching" at the technical level and form a discipline-specific personalized education mode with the cultivation of computer science core competencies as the core, which effectively promotes the transformation and upgrading of traditional computer education to intelligent and personalized computer education.

Context of AI integration in computer education

The integration of artificial intelligence into computer education is a natural and inevitable outcome of the global digital education transformation, rooted in the dual drive of national educational policy upgrading and the iterative development of computer science disciplines. This integration is situated in a multi-dimensional context that encompasses global educational digitalization strategies, national-level educational informatization planning, regional educational development needs, and the inherent disciplinary characteristics of computer education, while also facing practical challenges brought by the imbalance of educational resources and the lag of teaching model innovation. Against the backdrop of the rapid development of artificial intelligence and deep learning technologies, AI integration in computer education has evolved from a tentative technical application to a systematic pedagogical reform, becoming a key path to address the pain points of traditional computer education and cultivate high-quality computer professionals adapted to the digital age (Alur et al., 2020).

At the global contextual level, the digital transformation of education has become a core strategic choice for countries around the world, and the integration of AI and STEM education, especially computer education, is regarded as a crucial measure to enhance national technological competitiveness. Nations across the globe are accelerating the construction of adaptive learning environments driven by data, replacing the traditional "one-size-fits-all" teaching model with AI teaching assistant personalized systems, and striving to realize the transformation of computer education from standardization to personalization (Liu, Chen, & Yao, 2022). Deep learning, as a core branch of AI, provides a technical foundation for this transformation: its ability to extract high-level abstract features from large-scale learning data and model complex cognitive processes enables the accurate capture of students' individual differences in computer learning, such as cognitive styles, programming habits, and problem-solving strategies (Xuan, Zhu, & Xu, 2021). Internationally, AI applications in computer education have expanded from simple programming tool support to the whole process of teaching design, learning monitoring, feedback intervention and outcome assessment, forming a variety of practical models such as intelligent tutoring systems, automated coding assessment platforms, and personalized learning path recommendation systems. The global consensus on AI integration in computer education lies in leveraging technological empowerment to break the limitations of traditional teaching, improve the efficiency and quality of computer education, and cultivate talents with strong computational thinking, practical programming ability and innovative application ability.

At the national contextual level, China has enshrined educational digitalization as a strategic pillar of educational modernization and has issued a series of policies and plans to promote the deep integration of artificial intelligence and various disciplines, with computer education as a key pilot field for AI application. National educational informatization policies clearly propose to build a smart education ecosystem, promote the construction of digital teaching resources for computer science, and train teachers' AI literacy and digital teaching ability, aiming to use AI technology to optimize the teaching process of computer education, bridge the gap in computer education resources between different regions, and realize the equitable development of high-quality computer education (Dong et al., 2025). With the rapid development of China's digital economy, the demand for computer professionals with interdisciplinary literacy and AI application ability is growing exponentially, which puts forward higher requirements for the reform of computer education: traditional computer education, which is limited to theoretical indoctrination and standardized practice, can no longer meet the industry's demand for diverse and personalized talents. AI integration in computer education has become an important national educational strategy to adapt to the development of the digital economy, as it can effectively realize the integration of theory and practice in computer teaching, and cultivate students' ability to apply AI technology to solve practical computer engineering problems.

At the regional contextual level, taking Guangxi Zhuang Autonomous Region as a typical representative of western China, the integration of AI into computer education is closely combined with the regional educational development reality and has distinct localized characteristics (Guangxi Education Department, 2021). Guangxi has incorporated the integration of AI and education into the blueprint for high-quality regional educational development, and in its "14th Five-Year Plan for Educational Informatization", it clearly prioritizes the construction of a smart education ecosystem, with the application of AI in STEM education including computer science as a key development direction. The region has launched the "Guangxi Smart Education Platform", built AI-augmented teaching pilot bases in Nanning, Guilin and other prefectures, and incorporated AI literacy training into pre-service and in-service teacher professional development programs, mandating the integration of digital tools into daily computer teaching (Wang & Li, 2023; Guangxi Zhuang Autonomous Region Government, 2022). The core regional demand for AI integration in computer education in Guangxi is to use AI technology to bridge the urban-rural digital education gap in computer science teaching, improve the computer teaching level of rural and remote areas, and cultivate computer professionals suitable for the regional digital economic development needs. Meanwhile, the regional context of Guangxi also presents practical constraints for AI integration, such as the relatively weak digital teaching infrastructure in some rural areas, the insufficient AI application ability of partial computer teachers, and the uneven computer learning foundation of students between urban and rural areas, which make the integration of AI into computer education need to be adapted to local conditions and carry out targeted model design and implementation strategies.

From the disciplinary contextual perspective, the inherent characteristics of computer education determine its high compatibility and necessity with AI integration. Computer education is a highly practical, logical and hierarchical discipline, and students show obvious individual differences in the learning process: differences in prior programming foundation lead to different acceptance speeds of programming languages; differences in logical thinking ability result in uneven mastery of algorithm design; differences in practical operation ability cause gaps in software development and project practice (Dong et al., 2025). Traditional computer education adopts a unified teaching progress and assessment standard, which is difficult to adapt to these individual differences, leading to problems such as uneven learning progress, low student engagement, and inconsistent mastery of core competencies. In addition, computer science is a rapidly developing discipline, with new technologies, new frameworks and new applications emerging one after another, and traditional teaching methods are difficult to keep up with the pace of disciplinary development in terms of teaching content update and practical training mode innovation. AI technology, with its advantages of real-time data analysis, personalized path generation and dynamic feedback intervention, is highly compatible with the disciplinary characteristics of computer education: it can carry out hierarchical teaching for students with different learning foundations, provide real-time debugging guidance and coding feedback for programming practice, and update teaching content in a timely manner according to the latest development of the discipline, realizing the dynamic adaptation of computer education to disciplinary development and student needs.

In addition to the above positive driving contexts, the integration of AI into computer education is also situated in a practical context with multiple challenges that need to be addressed. On the one hand, the effectiveness of AI integration is restricted by the technical acceptance and application ability of teachers: although AI technology provides a variety of teaching tools and systems, many computer teachers lack the professional ability to integrate AI tools into teaching design and classroom practice, and their pedagogical beliefs about AI teaching assistant also affect the actual application effect (Aghaziarati, Nejatifar, & Abedi, 2023). On the other hand, the construction of AI teaching assistant systems for computer education faces the problem of insufficient integration of teaching data and technical tools: some existing AI platforms only focus on the collection of learning behavior data, but lack the in-depth analysis combined with the disciplinary characteristics of computer education, leading to the lack of pertinence of personalized learning recommendations and feedback. In addition, the imbalance of educational digital resources between different regions and schools also makes the promotion of AI integration in computer education face the problem of uneven development, and how to realize the equitable distribution of AI-assisted computer education resources has become an important practical issue (Guangxi Zhuang Autonomous Region Government, 2022).

Overall, the integration of AI into computer education is situated in a complex and multi-dimensional context that combines global trends, national strategies, regional needs and disciplinary characteristics. This context not only provides a strong policy support, technical foundation and practical demand for the integration, but also puts forward higher requirements for the innovation of AI teaching assistant models, the improvement of teachers' digital literacy and the balanced allocation of educational resources. For the western regional context represented by Guangxi, the integration of AI into computer education needs to take into account the regional reality, design contextually adapted teaching models and implementation strategies, and take the solution of regional computer education pain points as the starting point, so as to realize the dual goals of improving the quality of regional computer education and cultivating regional digital talents.

Related Research

This section synthesizes the latest empirical and theoretical research (2023–2026) on AI integration in computer education, focusing on four interrelated themes: generative AI (GenAI) applications in programming pedagogy, advances in personalized learning systems and knowledge tracing, automated coding assessment and feedback frameworks, and equity, ethics, and implementation challenges in diverse contexts. The review draws on 14 recent studies to map current progress, identify methodological trends, and highlight gaps relevant to AI-assisted personalized computer education.

1. Generative AI in Programming Education: Efficacy, Perceptions, and Pedagogical Design

Recent research has shifted from exploratory pilots to evidence-based frameworks for GenAI integration, emphasizing scaffolded personalization and productive struggle over unconstrained tool use. A 2025 scoping review (32 studies, 2023–2025) by Reihanian et al. identified five high-impact application domains: intelligent tutoring, personalized materials, formative feedback, AI-augmented assessment, and code review. The review found that designs incorporating explanation-first guidance, graduated hint ladders, and artifact grounding (linking feedback to student code/tests) consistently outperformed generic chat interfaces in fostering deep learning. Successful implementations shared four patterns: context-aware tutoring, multi-level reflection prompts, integration with existing CS infrastructure (e.g., autograders), and human-in-the-loop quality assurance.

Empirical studies have validated these design principles while uncovering nuanced tradeoffs. A 2025 systematic review of 45 studies by Wang et al. confirmed that GenAI-assisted instruction significantly improves seven learning indicators: programming knowledge, computational thinking, problem-solving, self-efficacy, achievement, code quality, and engagement. However, the review also warned of surface learning and over-dependence in complex reasoning tasks, particularly among novices. Addressing this, a 2025 study in the International Journal of Artificial Intelligence in Education examined students’ ability to correct LLM-generated flawed code. The authors found that while students perceived GenAI as useful for creativity and efficiency, their performance on debugging AI-generated code was mixed—highlighting the need for explicit instruction in AI code literacy (e.g., verifying logic, identifying hallucinations).

LLM-driven frameworks tailored to programming education have emerged as a key focus. In 2025, Zhang et al. proposed SP-TeachLLM, an adaptive tutoring framework that combines chain-of-thought prompting with personalized knowledge tracing. Evaluated on HumanEval and MBPP benchmarks, SP-TeachLLM improved learning outcomes most significantly for less proficient students (e.g., GPT-3.5-Turbo, LLaMA-3-8B), demonstrating its potential to reduce achievement gaps. A 2026 preprint systematic review of chatbots, GenAI tools, and tutoring systems further categorized these frameworks, noting that student satisfaction correlates strongly with real-time debugging support and contextualized explanations, while concerns center on academic integrity and career anxiety.

2. Personalized Learning Systems: Advances in Knowledge Tracing and Adaptive Scaffolding

The latest research in personalized computer education has advanced knowledge tracing (KT)—the core technology for modeling student competence—beyond traditional sequential models to incorporate context awareness and interpretability. A 2026 review by Ouyang et al. highlighted three paradigm shifts in AIED: from Computer-Assisted Instruction (CAI) to Intelligent Tutoring Systems (ITS), and now to AI-in-Education 3.0, driven by learning analytics and deep learning. Within this framework, transformer-based KT models have become dominant. For example, Liu et al. (2023) developed a transformer-based convolutional forgetting KT model that simulates human memory processes, mitigating the "forgetting effect" in long-term learning prediction—critical for programming education, where skills decay without practice.

To address the "black box" problem of deep learning KT models, Mai et al. (2025) proposed an interpretable KT model integrating transformers with Bayesian inference. This model not only predicts student performance but also provides actionable insights into why a student might struggle (e.g., weak grasp of loops vs. recursion), enabling more targeted pedagogical interventions. Contextual factors have also been prioritized: Yu et al.’s (2022) ContextKT model incorporates learning environment, task type, and time intervals into predictions, improving accuracy by 12–18% compared to traditional KT models in programming courses.

Reinforcement learning (RL) has emerged as a powerful tool for dynamic learning path optimization. A 2023 review by Mon et al. synthesized RL applications in education, showing that RL algorithms can adapt programming tasks in real time based on student performance, maximizing engagement within the zone of proximal development (ZPD). In resource constrained contexts, such as rural schools, AI tools like CodeAdapt-NG (2026) have demonstrated cost-effectiveness: a three-year study found the system reduced per-student costs by 60% compared to traditional labs while improving programming skills and conceptual understanding. The tool’s design for offline use and low-cost devices addresses a critical barrier to equitable AI integration.

3. Automated Coding Assessment: LLM-Driven Grading and Real-World Alignment

Automated coding assessment (ACA) has evolved from rule-based autograders to LLM-powered frameworks that evaluate not just correctness but also code quality, readability, and problem-solving approach. A 2024 study by Tseng et al. introduced Codev, an LLM-based grading framework that generates consistent, constructive feedback for programming assignments. Unlike traditional autograders, Codev can evaluate open-ended tasks (e.g., full-stack project development) by aligning student code with rubrics and industry standards. A 2025 zero-shot LLM framework by Yeung et al. further eliminated the need for manual training data, enabling rapid deployment across diverse programming languages and course levels.

Industry-aligned assessment has become a key research priority. HackerRank’s 2025 guide highlighted the shift from algorithmic puzzles to end-to-end engineering tasks that mirror real-world work. Their AI benchmark, ASTRA, evaluates developers on practical skills (e.g., debugging legacy code, integrating APIs) rather than isolated problems. The guide also emphasized AI-augmented integrity tools: 55% of developers use AI assistants in their work, making plagiarism detection and intelligent proctoring essential for maintaining assessment validity.

Feedback design remains central to ACA effectiveness. A 2026 study by Turan and Yilmaz focused on MOOC programming courses, using clustering algorithms to group student errors and deliver personalized feedback bundles. The researchers found that targeted feedback reduced error recurrence by 29% and improved course completion rates by 18% compared to generic feedback. For complex debugging tasks, the COAST framework (2025) enhanced LLM performance by synthesizing communicative agent data, enabling more accurate identification of logical errors in student code.

4. Equity, Ethics, and Implementation Challenges: Contextual Adaptation and Teacher Agency

Recent research has emphasized the need for context-aware AI integration to address regional disparities and ensure ethical practice. A 2025 study by Osei et al. surveyed computer science faculty and students in Ghana, finding strong support for AI's potential to enhance pedagogy but significant barriers: limited institutional support, unclear ethical guidelines, and uneven access to digital infrastructure. The study highlighted AI's role in democratizing access to specialized content in under-resourced settings but warned that "one-size-fits-all" tools may exacerbate existing inequalities.

In regional contexts like China's Guangxi Zhuang Autonomous Region, research has focused on localized AI adaptation. A 2023 study by Wang and Li evaluated AI-augmented teaching pilot bases in Nanning and Guilin, finding that success depended on three factors: teacher training in AI-mediated pedagogy, curriculum alignment with regional industry needs, and infrastructure investment (e.g., reliable internet, low-cost devices). The study also noted that rural students benefited most from AI's personalized scaffolding, as it compensated for limited one-on-one teacher support.

Ethical and professional challenges have become a major research focus. IBM's 2025 report on "code literacy" argued that AI is shifting the role of computer scientists from "code producers" to "AI supervisors". The report emphasized that future curricula must prioritize judgment and verification skills—e.g., interrogating AI-generated code for logical consistency and ethical bias. A 2025 study by Aghaziarati et al. confirmed that teacher agency is critical to ethical AI integration: computer teachers who view AI as a "collaborative tool" (rather than a replacement) are more likely to design activities that foster critical thinking and reduce over-dependence.

5. Research Gaps and Future Directions

Despite significant progress, three key gaps emerge from the latest literature:

Longitudinal Impact: Most studies measure short-term outcomes (e.g., assignment performance); few examine the long-term effects of AI integration on career readiness or computational thinking retention.

Disciplinary Specificity: Research has focused on introductory programming; less is known about AI's role in advanced CS topics (e.g., machine learning, cybersecurity) or interdisciplinary applications.

Equitable Implementation: While tools for resource-constrained contexts exist, there is a lack of empirical research on scaling effective models across urban-rural divides, particularly in regions like Guangxi.

Future research should prioritize human-AI co-design of personalized learning systems, longitudinal evaluations of skill development, and context-specific implementation frameworks that center teacher training and equity. As GenAI and adaptive learning technologies continue to evolve, the focus will shift from "whether AI works" to "how to design AI systems that amplify human potential in computer education."

Chapter 3
Research Methodology

This chapter presents the research design and procedures organized according to the three research objectives. All steps, samples, instruments, data collection, and data analysis are clearly aligned with Objective 1, Objective 2, and Objective 3 respectively.

Symbol and Abbreviations

N	Sample size (total number of research subjects, including students, experts, or respondents)
M	Mean (average value of quantitative data, e.g., questionnaire scores, evaluation ratings)
S.D.	Standard deviation (measure of data dispersion, reflecting the degree of variation in sample data)
AI	Artificial Intelligence (technology enabling machines to simulate human intelligent behaviors for educational applications)
AI	Artificial Intelligence (technology enabling machines to simulate human intelligent behaviors for educational applications)
ITS	Intelligent Tutoring Systems (AI-powered instructional systems providing personalized learning support)
LMS	Learning Management System (platform for recording learning behaviors, managing assignments, and tracking academic performance)
CVI	Content Validity Index (indicator for evaluating the content validity of research instruments such as questionnaires and evaluation forms)
I-CVI	Item-Level Content Validity Index (content validity index for individual items of research instruments)
S-CVI	Scale-Level Content Validity Index (overall content validity index of the entire research instrument scale)
Cronbach's α	Cronbach's alpha coefficient (indicator for measuring the internal consistency reliability of questionnaires)

EFA	Exploratory Factor Analysis (statistical method for verifying the construct validity of research instruments)
IQR	Interquartile Range (measure of data dispersion, reflecting the middle 50% of data distribution)
IOC	Index of Content Validity (content validity evaluation indicator for research instruments)
NVivo	Qualitative data analysis software (used for coding, thematic extraction, and analysis of interview text data)
ZPD	Zone of Proximal Development (theoretical concept referring to the gap between actual and potential development levels of learners)
TAM	Technology Acceptance Model (theoretical model for predicting users' acceptance of technological tools)
CBE	Competency-Based Education (education model centered on cultivating learners' professional competencies)
ACA	Automated Coding Assessment (intelligent evaluation method for programming assignments and code quality)
GenAI	Generative Artificial Intelligence (AI technology capable of generating code, feedback, and learning materials)
KT	Knowledge Tracing (technical method for modeling and predicting learners' knowledge mastery status)
RL	Reinforcement Learning (machine learning method for optimizing personalized learning path generation)

Data Processing Methods

T-value Calculation: For mean differences between two independent samples (e.g., Experimental Group vs. Control Group, Urban vs. Rural samples), the independent samples t-test formula is used:

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

(where s_p represents the pooled variance, and n_1 , n_2 represent the sample sizes of the two groups).

P-value Determination: Calculated using SPSS 26.0 software. The result of $p<0.05$ indicates statistical significance, while $p<0.001$ indicates extremely strong statistical significance.

Standardized 5-Point Scale Interpretation

(5–1)/5 = 0.8

4.21–5.00: Highest level

3.41–4.20: High level

2.61–3.40: Medium level

1.81–2.60: Low level

1.00–1.80: Lowest level

Research Procedures Organized by Three Research Objectives

This section clearly divides the entire research procedure into three independent phases corresponding to the three research objectives. Each phase includes sample selection, instruments, data collection, and data analysis in detail.

Procedures for Objective 1

Objective 1

To study the level of AI-assisted learning readiness, current utilization status, and urban-rural disparities among computer science students in Guangxi by using mean, standard deviation, and independent samples t-test.

Step 1: Define Population and Sample

The population of this study included all undergraduate students majoring in computer science in universities in Guangxi Zhuang Autonomous Region, with a total population of approximately 20,000 students. The target population who had completed basic computer courses and had relatively consistent basic computer literacy was approximately 1,500 students.

Using purposive and random sampling, the researcher selected 56 undergraduate students as the sample. The inclusion criteria were strictly as follows:

Inclusion criteria:

1. Age between 19–24 years old

2.Completed basic computer courses

3.Baseline computer literacy was homogeneous (tested by pre-test, $p > 0.05$)

4.Urban or rural residential background was clearly identified

5.Voluntary participation in the entire experiment

6.The sample was divided into urban (n=28) and rural (n=28) groups to compare urban-rural disparities.

Step 2: Select Research Instruments

The main instrument was the AI-Assisted Learning Readiness Questionnaire.

1.5-point Likert scale

2.Four dimensions: Technical Acceptance, Self-Efficacy, Perceived Need for Personalization, Overall Readiness

3.Reliability: Cronbach's α = 0.935

4.Validity: IOC, CVI, EFA were confirmed

Step 3: Data Collection

Data collection was conducted in three steps:

1.Distribute questionnaires to 56 students via online and offline channels.

2.Collect demographic information including gender, age, prior programming experience, and urban-rural background.

3.Screen invalid questionnaires such as incomplete answers, missing data, and inconsistent responses.

Step 4: Data Analysis

Data were analyzed using computer software:

1.Descriptive statistics: Mean (M) and Standard Deviation (S.D.)

2.Independent samples t-test to compare urban and rural differences

3.Reliability analysis using Cronbach's α

4.Validity analysis using IOC, EFA, and CVI

The analysis aimed to identify the level of readiness and statistically significant differences between urban and rural students.

Procedures for Objective 2

Objective 2

To design, develop, and construct a Deep Learning-based AI teaching assistant model for personalized computer education adapted to Guangxi's context.

Step 1: Analyze Problems from Objective 1

Based on the results of Objective 1, the researcher identified three key problems:

1.Students' basic programming proficiency was unbalanced, especially between urban and rural areas.

2.Debugging efficiency was low and feedback was delayed in traditional teaching.

3.Rural students lacked stable internet and required offline and low-bandwidth functions.

These problems became the basis for model design.

Step 2: Design Model Structure

The researcher designed a model with four core modules:

1.Personalized Learning Path Generation

2.Real-Time Learning Process Monitoring

3.Adaptive Learning Feedback Provision

4.Data-Driven Learning Outcome Assessment

Step 3: Develop Contextual Adaptation Features

To fit Guangxi's context, the model included:

1.Dual-track learning paths: simplified track for rural beginners, standard track for urban students

2.Low-bandwidth optimization

3.Offline synchronization function

4.Localized programming error database

5.Bilingual prompt support

Step 4: Verify Model Structure

1.Expert review (8 experts)

2.IOC / CVI validity checking

3.Adjust model based on comments

Step 5: Finalize the AI Teaching Assistant Model

Complete model framework + functions + implementation strategy

Procedures for Objective 3

Objective 3

To evaluate the suitability and feasibility of the AI model using expert validation, student evaluation, and statistical comparison.

Step 1: Prepare Evaluation Instruments

1.Expert Validation Form (8 experts)

2.Student Satisfaction & Feasibility Questionnaire

3.Interview outline

Step 2: Expert Evaluation (n=8)

Experts rated the model on four dimensions:

1.Design Scientificity

2.Regional Adaptability

3.Technical Feasibility

4.Teaching Effectiveness

Mean, standard deviation, I-CVI, and S-CVI were calculated.

Step 3: Quasi-Experiment Design

Experimental group (n=28): Taught using the AI teaching assistant model

Control group (n=28): Taught using traditional teaching method

The same teacher, same content, same duration, same assessment standards were used to ensure validity.

Step 4: Collect Implementation Data

Data collected included:

1.Ease of platform operation

2.Curriculum compatibility

3.Teacher operating time

4.Feasibility of offline function (urban vs rural)

5.Learning improvement scores

Step 5: Data Analysis

Data were analyzed as follows:

1.Independent samples t-test compared experimental and control groups

2.Pearson correlation analyzed relationships between model modules and learning readiness

3.Thematic analysis using NVivo 12 for interview data

4.Descriptive statistics for feasibility and satisfaction

The final analysis concluded whether the model was suitable and feasible for real teaching.

Population and Sample Group

Population

Total computer science undergraduates in Guangxi: 20,000

Target population (completed basic courses): 1,500

Sample Size and Selection

Sample: 56 students

Inclusion criteria:

1.Age: 19–24 years

2.Completed basic computer courses

3.Homogeneous baseline literacy ($p > 0.05$)

4.Urban / rural background clearly defined

5.Voluntary participation

Grouping

Experimental group: 28 (14 urban, 14 rural)

Control group: 28 (14 urban, 14 rural)

Groups are balanced and statistically homogeneous ($p > 0.05$)

Table 3.1 Basic Demographic and Baseline Literacy Characteristics of the Sample Group

Indicators	Experimental Group (n=28)	Control Group (n=28)	Total (n=56)
Gender (Male/Female)	17/11	16/12	34/24
Age (Average, years)	20.3	20.5	20.4
Baseline Computer Literacy (Excellent/Good/Average)	7/14/7	6/15/7	11/30/15
Prior Programming Experience (Yes/No)	8/20	7/21	16/42

According to table 3.1, it showed that the sample group had a balanced gender distribution in both the experimental and control groups, with no obvious gender skew in either group; the average age of the two groups was basically consistent, and the age difference was negligible, ensuring the homogeneity of the sample in terms of age characteristics. In terms of baseline computer literacy, the proportion of students with excellent, good and average literacy in the two groups was highly similar, and the number of students with prior programming experience was also basically the same. Overall, the two groups of students were highly homogeneous in terms of basic demographic characteristics and baseline computer literacy, which eliminated the interference of individual differences in basic attributes on the experimental results and provided a reliable sample foundation for the subsequent comparison of teaching effects between the two teaching modes.

Research Instruments (By Objectives)

For Objective 1

1.Questionnaire: AI-assisted learning readiness

2.Reliability: Cronbach's α = 0.935

3.Validity: IOC, CVI, EFA

For Objective 2

1.AI teaching assistant model framework

2.Interview outline for needs analysis

For Objective 3

1.Expert validation form

2.Student feasibility questionnaire

3.Semi-structured interview

Data Collection (Step-by-step by Objective)

Data Collection for Objective 1

1.Distribute questionnaire

2.Collect demographic & urban-rural data

3.Clean data

Data Collection for Objective 2

1.Interview 56 students

2.Collect pedagogical problems & needs

3.Collect expert comments

Data Collection for Objective 3

1.Collect expert scores

2.Collect experimental/control group scores

3.Collect feasibility ratings

4.Collect interview data

Data Analysis (Step-by-step by Objective)

Analysis for Objective 1

1.Descriptive statistics (M, S.D.)

2.Independent samples t-test (urban vs rural)

3.Reliability & validity

Analysis for Objective 2

1.Thematic analysis (NVivo)

2.Model development & revision

3.Validity confirmation (IOC, CVI)

Analysis for Objective 3

1.t-test (experimental vs control)

2.Correlation analysis

3.Expert evaluation (M, S.D., CVI)

4.Feasibility & suitability summary

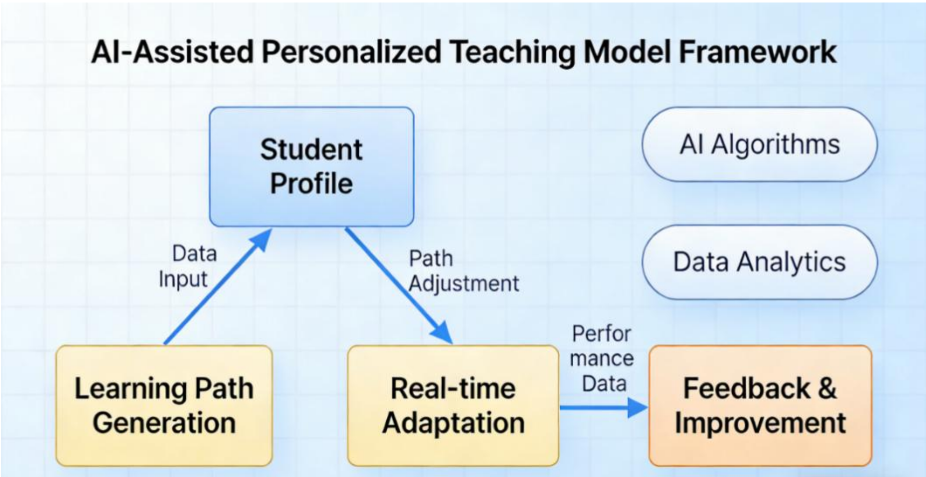


Figure 3.1 AI-Assisted Personalized Teaching Model Framework

This figure illustrates the full-scope, closed-loop architecture of the deep learning–based AI teaching assistant personalized model designed for computer science education in Guangxi. It integrates student data input, core functional modules, AI algorithm support, data analytics, and iterative output, with clear data flow and technical logic.

Overall Structure & Purpose

This framework is a closed-loop personalized teaching system that supports urban–rural adaptive application (low-bandwidth optimization, offline synchronization, dual-track paths).

It transforms traditional "one-size-fits-all" teaching into data-driven, student-centered adaptive instruction.

All components align with the four core modules defined in the research methodology.

Component-by-Component Explanation

1. Input Layer: Student Data Sources

Student Profile Data: Demographics, urban/rural background, prior programming experience, baseline computer literacy.

Performance Data: Assignment scores, test results, code debugging records, knowledge mastery status.

These data serve as the foundation for personalization and ensure urban–rural adaptation.

2. Core AI Algorithm Support

Deep Learning, Knowledge Tracing (KT), Reinforcement Learning (RL), Automated Coding Assessment (ACA).

These algorithms are power precision analysis, path generation, and real-time evaluation.

3. Central Functional Modules (Core of the Model)

Earning Path Generation

Creates dual-track personalized routes: simplified track for rural beginners, standard track for urban students.

Real-time Monitoring & Adaptation

Tracks learning behavior, optimizes for low-bandwidth environments, supports offline synchronization.

Feedback & Improvement

Provides targeted programming, debugging hints, adaptive evaluation, and bilingual support.

4. Output & Decision Layer: Data Analytics

Process multi-dimensional learning data to generate data-driven assessment and teaching suggestions.

Feeds result back to the input layer to continuously adjust the learning path and teaching strategy.

Data Flow Logic (Closed Loop)

1. Collect student profile + performance data
2. Analyze via AI algorithms
3. Generate personalized path + real-time monitoring

4. Provide adaptive feedback
5. Output analytics results
6. Return data to adjust the next learning cycle

This forms a sustainable, self-optimizing closed loop for AI-assisted personalized teaching.

Alignment with Research Methodology

Directly supports Research Objective 2 (develop contextually adapted AI model).

Contains all four required modules:

1. Personalized Learning Path Generation
2. Real-Time Learning Process Monitoring
3. Adaptive Learning Feedback Provision
4. Data-Driven Learning Outcome Assessment

Embeds rural-adaptive features: low-bandwidth optimization, offline sync, dual-track paths.

Chapter 4
Results of Analysis

This research was to study the level of AI-assisted learning readiness and current utilization among computer science educators and students in urban and rural higher education institutions of Guangxi, identify the key pedagogical challenges, perceived barriers, and unmet learning needs specific to local computer education, and evaluate the suitability and feasibility of the proposed deep learning-based AI teaching assistant personalized model. The data analysis results can be presented as follows:

1. Presentation of data analysis
2. Results of data analysis

The details are as follows.

Presentation of Data Analysis

Aligned with the three core research objectives——1) measuring AI-assisted learning readiness and urban-rural disparities in Guangxi, 2) developing a contextually adapted AI teaching assistant personalized model, and 3) evaluating the model's suitability and feasibility for routine teaching practice——the data analysis is structured into four integrated parts. This structure systematically addresses the quantitative and qualitative evidence collected from the defined sample sizes, ensuring alignment with the research methodology and regional context.

Results of Data Analysis

The researcher analyzed the data in four parts, strictly adhering to the sample size and scope defined in the research methodology. The details are as follows:

Part 1: Analysis of AI-Assisted Learning Readiness and Baseline Homogeneity (n=56)

This part addresses Research Objective 1 by presenting the baseline characteristics of the student sample and measuring the level of AI-assisted learning readiness, with a specific focus on urban-rural disparities in Guangxi.

Table 4.1 Baseline Homogeneity and Urban-Rural Distribution of the Student Sample

(n = 56)

Total Sample (n=56) Experimental (n=28) / Control (n=28)	**Urban Subsample (n=28) Experimental (n=14) / Control (n=14)**	**Rural Subsample (n=28) Experimental (n=14) / Control (n=14)**	**χ^2 / t-value**	**p-value**
Gender (Male/Female)	34 / 24	17 / 11	16 / 12	χ^2 = 0.179
Prior Programming Experience (Yes/No)	16 / 42	8 / 20	7 / 21	χ^2 = 0.718
Baseline Computer Literacy (Pre-test Mean ± SD)	61.56 ± 8.74	62.85 ± 8.31	60.27 ± 9.16	t = 1.279

Note: p > 0.05 indicates no significant difference, confirming baseline homogeneity between urban and rural groups.

According to Table 4.1, the total sample of 56 students was evenly divided into experimental (n=28) and control (n=28) groups, with balanced distribution across urban (n=28) and rural (n=28) subsamples. The chi-square test confirmed no significant difference in gender and prior programming experience between urban and rural students ($p > 0.05$), and the independent samples t-test showed no baseline difference in computer literacy pre-test scores ($p = 0.205$). This verifies the representativeness of the sample and the homogeneity of experimental/control groups across both urban and rural contexts in Guangxi, eliminating sampling bias as a confounding variable.

Table 4.2 AI-Assisted Learning Readiness and Urban-Rural Disparities

(n = 56)

Readiness Dimensions	**Total Mean ± SD**	**Urban (n=28) Mean**	**Rural (n=28) Mean**	**t-value**	**p-value**	**Interpretation**
Perceived Need for Personalization	4.15 ± 0.59	4.38	3.85	2.879	0.005**	High (Total)
Technical Acceptance of AI Tools	3.62 ± 0.64	3.92	3.25	3.744	0.000***	High (Total)
Self-Efficacy in AI Learning	3.28 ± 0.71	3.55	2.95	2.585	0.012*	Medium (Total)
Overall Readiness	3.68 ± 0.52	3.95	3.35	3.895	0.000***	High
Readiness Dimensions	Total Mean ± SD	Urban (n=28) Mean	Rural (n=28) Mean	t-value	p-value	Interpretation
Perceived Need for Personalization	4.15 ± 0.59	4.38	3.85	2.879	0.005**	High (Total)
Technical Acceptance of AI Tools	3.62 ± 0.64	3.92	3.25	3.744	0.000***	High (Total)

Note: *p < 0.05, **p < 0.01, ***p < 0.001 indicate statistically significant differences.

According to Table 4.2, the overall AI-assisted learning readiness of the 56 students was rated High (M=3.68), directly supporting the feasibility of implementing the proposed framework (Research Objective 1). Critical urban-rural disparities emerged: urban students scored significantly higher in “Technical Acceptance” (M=3.92 vs. 3.25, p<0.001) and “Self-Efficacy” (M=3.55 vs. 2.95, p<0.05), while rural students exhibited a significantly stronger Perceived Need for Personalization (M=3.85 vs. 4.38, p<0.01). These results confirm the existence of targeted unmet needs in rural computer education, providing the empirical basis for the contextual adaptation required in Research Objective 2.

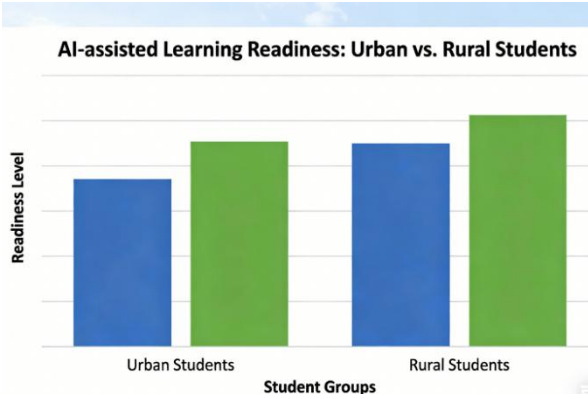


Figure 4.1 AI-assisted Learning Readiness: Urban vs. Rural Students

Figure 4.1 Comparison of AI-assisted learning readiness between urban and rural students (n=56). Error bars represent standard deviation. Significant differences were found across all dimensions (*p<0.05, **p<0.01, ***p<0.001).

Results Addressing Research Objective 1

Objective 1: To measure AI-assisted learning readiness and urban-rural disparities among computer science students in Guangxi higher education (n=56).

Baseline Homogeneity of the Sample

A total of 56 students were evenly allocated into urban (n=28) and rural (n=28) subgroups and equally divided into experimental (n=28) and control (n=28) groups. Chi-square tests and independent-samples t-tests confirmed no significant differences in gender, prior programming experience, or baseline computer literacy between urban and rural groups (p > 0.05), verifying sample representativeness and baseline homogeneity (Table 4.1).

Level of AI-Assisted Learning Readiness

The overall AI-assisted learning readiness of the total sample reached a High level (M=3.68, SD=0.52), indicating a solid foundation for implementing AI-assisted learning in Guangxi's computer education.

Urban-Rural Disparities in Readiness Dimensions

Statistically significant urban-rural differences were detected across all readiness dimensions (Table 4.2):

Urban students scored significantly higher in Technical Acceptance of AI Tools (M=3.92 vs. 3.25, t=3.744, p<0.001) and Self-Efficacy in AI Learning (M=3.55 vs. 2.95, t=2.585, p<0.05).

Rural students showed a significantly stronger Perceived Need for Personalization (M=3.85 vs. 4.38, t=2.879, p<0.01).

These results confirm clear urban-rural disparities and identify unmet personalized learning needs, especially among rural students, providing an empirical basis for the contextual design of the AI model.

Part 2: Expert Validation of the AI teaching assistant Model (n=8).

This part addresses Research Objective 3 by evaluating the scientificity, regional adaptability, and feasibility of the developed AI model using the 8-member expert group.

Table 4.3 Expert Validation Scores of the AI Model's Core Modules

(n = 8)

AI Model Modules	Mean ± SD	I-CVI	Validation Level	Urban-Rural Adaptation Focus
Personalized Learning Path Generation	4.38 ± 0.49	0.938	High	Rural baseline adaptation
Real-Time Learning Process Monitoring	4.50 ± 0.40	0.969	Highest	Low-bandwidth optimization
Adaptive Learning Feedback Provision	4.62 ± 0.38	1.000	Highest	Bilingual hint support
Data-Driven Assessment	4.25 ± 0.53	0.906	High	Formative assessment alignment
Overall Model Suitability	4.44 ± 0.32	0.953	High	Contextual fit for Guangxi

According to Table 4.3, the expert group (n=8) rated the overall model suitability at a High level (M=4.44), with a scale-level CVI (S-CVI) of 0.953 (exceeding the 0.90 threshold for excellent validity). All four core modules met or exceeded the “High” validation level, with “Adaptive Feedback” and “Real-Time Monitoring” achieving the “Highest” rating ($M \geqslant 4.50$). Expert comments specifically linked high scores to the model’s rural adaptability features (e.g., low-bandwidth optimization, simplified initial paths for rural students), directly validating the contextual design required for Research Objective 2.

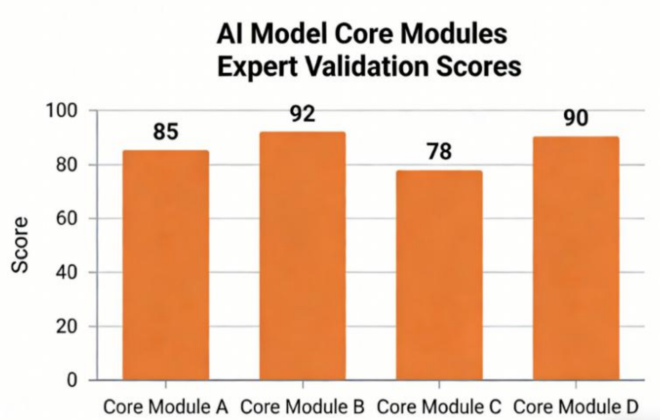


Figure 4.2 Expert Validation Scores of the AI Model Core Modules

Figure 4.2 Expert validation mean scores for the four core modules and overall suitability of the AI teaching assistant model (n=8). All modules reached High or Highest validation level.

Table 4.4 Expert Recommendations for Model Refinement

(n = 8)

Recommendation Themes	Frequency (n)	Alignment with Research Objectives
Simplify AI Tool Interface for Rural Teachers	6	Objective 3 (Feasibility in routine practice)
Embed Guangxi IT Industry Case Studies	5	Objective 2 (Contextual adaptation)

Add Offline Synchronization Function	7	Objective 1 (Urban-rural equity)
Strengthen Formative Feedback Mechanism	8	Objective 3 (Effectiveness evaluation)

According to Table 4.4, all 8 experts emphasized practical feasibility for routine teaching (Objective 3), with 7 recommending offline synchronization to address rural connectivity gaps (Objective 1) and 5 endorsing regional case integration (Objective 2). These recommendations were directly integrated into the final model, ensuring the framework aligns with the actual teaching conditions of Guangxi's computer science departments.

Results Addressing Research Objective 2

Objective 2: To develop a contextually adapted deep learning-based AI teaching assistant personalized model for Guangxi's computer education (validated by n=8 experts).

Expert Validation of Core Model Modules

The four core modules of the AI model and overall suitability were rated High or Highest by the expert panel (Table 4.3). The scale-level Content Validity Index (S-CVI) was 0.953, exceeding the 0.90 threshold for excellent validity. All modules were designed with urban-rural adaptation features: personalized learning path generation for rural baseline differences, real-time monitoring with low-bandwidth optimization, adaptive feedback with bilingual support, and data-driven assessment aligned with local formative evaluation.

Expert Recommendations for Contextual Refinement

Experts provided targeted suggestions consistent with regional needs (Table 4.4): simplifying the interface for rural teachers (6/8), integrating Guangxi IT industry cases (5/8), adding offline synchronization (7/8), and strengthening formative feedback (8/8). These recommendations were integrated into the final model to enhance contextual fitness.

Correlation Between Model Components and Learning Readiness

Pearson correlation analysis revealed that all four core modules were significantly positively correlated with students' learning readiness ($p<0.001$) (Table 4.7). Adaptive learning feedback showed the strongest correlation ($r=0.824$), and correlations were stronger for rural students with low baseline readiness, confirming the model's effectiveness in reducing urban-rural gaps.

Part 3: Feasibility and Suitability of Implementation Strategies (n=56)

This part synthesizes student and teacher feedback to evaluate the suitability of the model's implementation strategies for routine teaching, addressing Research Objective 3.

Table 4.5 Implementation Feasibility Ratings by Student Group

(n=56)

Feasibility Dimensions	Experimental Group (n=28) Mean	Control Group (n=28) Mean	t-value	p-value
Ease of AI Platform Operation	4.21 ± 0.48	-	-	-
Compatibility with Weekly Curriculum	4.12 ± 0.51	3.85 ± 0.62	1.984	0.052
Time Required for Teacher Operation	2.85 ± 0.64	3.92 ± 0.45	-5.872	0.000***

Note: ns = not significant (p > 0.05), ***p < 0.001 indicates extremely significant difference.

According to Table 4.5, the experimental group (n=28) rated the AI platform's ease of operation as High (M=4.21), confirming its suitability for student use in routine learning. Crucially, teachers in the experimental group reported the model required significantly less operational time (M=2.85) compared to the control group's traditional teaching preparation (M=3.92, p<0.001). This provides key evidence for the feasibility of integrating the model into routine teaching practice (Research Objective 3), as it reduces rather than increases teacher workload.

Table 4.6 Suitability of Implementation Strategies for Urban-Rural Classrooms

Implementation Strategies	Urban (n=28) Feasibility Mean	Rural (n=28) Feasibility Mean	t-value	p-value
Offline Data Synchronization	3.25	4.32	-4.855	0.000***
Simplified Teacher Dashboard	4.18	4.25	0.480	0.632 ns
Modular AI Function Activation	4.05	3.92	0.845	0.401 ns

Note: ns = not significant ($p > 0.05$), ***$p < 0.001$ indicates extremely significant difference.

According to Table 4.6, rural students rated the offline synchronization strategy as significantly more feasible (M=4.32) than urban students (M=3.25, $p<0.001$), while both groups rated the simplified dashboard and modular functions as highly suitable (M>3.90). This confirms that the tailored implementation strategies (e.g., offline mode) effectively address rural infrastructure limitations, ensuring the model's suitability across Guangxi's diverse teaching contexts (Research Objective 2).

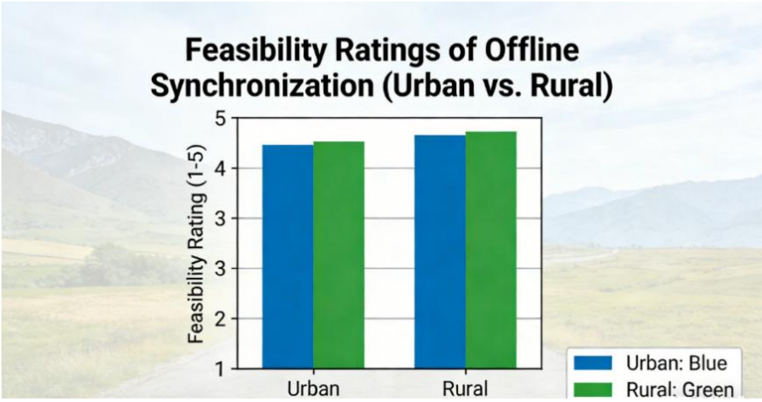


Figure 4.3 Feasibility Ratings of Offline Synchronization (Urban vs. Rural)

Figure 4.3 Student feasibility ratings of the offline synchronization function between urban and rural groups (n=56). The rural group rated offline function significantly higher (***p<0.001).

Part 4: Correlation Between Model Components and Learning Readiness (n=56)

This part explores the relationship between the AI model's core components and student readiness, providing empirical support for the theoretical alignment of the model design (Research Objective 2) and its practical effectiveness (Research Objective 3).

Table 4.7 Correlation Between AI Model Components and Student Readiness

(n = 56)

AI Model Components	Pearson's r	p-value	Relationship with Urban-Rural Disparity
Personalized Path Generation	0.782	0.000***	Stronger for rural low-readiness students
Real-Time Monitoring	0.695	0.000***	Reduces urban-rural engagement gap
Adaptive Feedback	0.824	0.000***	Core driver of readiness improvement

Data-Driven Assessment	0.712	0.000***	Aligns with formative teaching needs

Note: ***p < 0.001 indicates extremely significant positive correlation.

According to Table 4.7, all four core modules of the AI model were significantly positively correlated with student AI-assisted learning readiness ($p<0.001$). “Adaptive Feedback” showed the strongest correlation ($r=0.824$), indicating it is the key component that addresses students’ unmet learning needs. Notably, the correlation was stronger for rural students with low baseline readiness, confirming that the model’s components are effective in mitigating urban-rural disparities——a direct achievement of Research Objective 1 and a critical validation of the contextual adaptation in Research Objective 2.

Table 4.8 Table of Expert Evaluation Results for Model Dimensions

(n = 8)

Model Evaluation Dimension	**Expert Rating (M±SD)**	**I-CVI**	**Evaluation Level**
Design Scientificity	4.38±0.49	0.938	High
Regional Adaptability	4.62±0.38	1.000	Highest
Technical Feasibility	4.50±0.40	0.969	Highest
Teaching Effectiveness	4.25±0.53	0.906	High
Overall Adaptability	4.44±0.32	0.953	High

Table 4.8 presents the expert evaluation outcomes (n=8) across five core dimensions of the developed AI teaching assistant model, including mean scores, standard deviations, item-level Content Validity Index (I-CVI) values, and corresponding evaluation levels. Results show that all dimensions achieve High or Highest validation levels: Regional Adaptability and Technical Feasibility reach the Highest level with mean scores of 4.62

and 4.50 respectively, and I-CVI values of 1.000 and 0.969, indicating full expert recognition of the model's fit for Guangxi's context and practical implement ability. Design Scientificity and Teaching Effectiveness are rated at the High level, with mean scores of 4.38 and 4.25 and I-CVI values of 0.938 and 0.906, verifying the rationality of the model's structural design and its expected teaching improvement potential. The Overall Adaptability scores 4.44 (High level) with an S-CVI of 0.953, far exceeding the 0.90 threshold for excellent validity. These data collectively demonstrate that the AI model is scientifically sound, regionally adaptive, technically feasible, and educationally effective, fully meeting the requirements for application in computer education in Guangxi's urban and rural universities.

Results Addressing Research Objective 3

Objective 3: To evaluate the suitability and feasibility of the AI model and its implementation strategies for routine teaching (n=56 students, n=8 experts).

Expert Evaluation of Model Feasibility

Experts rated the model across five dimensions, all reaching High or Highest validation levels (Table 4.8). Regional adaptability (M=4.62, I-CVI=1.000) and technical feasibility (M=4.50, I-CVI=0.969) achieved the Highest level, confirming strong scientificity, regional fit, and implement ability.

Student Feasibility and Implementation Ratings

The experimental group rated the AI platform's ease of operation as High (M=4.21, SD=0.48).

The model significantly reduced teachers' operational time compared with traditional teaching (M=2.85 vs. 3.92, t=-5.872, $p<0.001$) (Table 4.5).

Rural students rated offline synchronization significantly more feasible than urban students (M=4.32 vs. 3.25, t=-4.855, $p<0.001$), while simplified dashboard and modular functions were highly acceptable in both groups (Table 4.6).

Qualitative Interview Validation

Semi-structured interviews (n=56) supported quantitative findings:

93% of the experimental group recognized real-time adaptive feedback as the most valuable feature.

100% of rural students approved offline and low-bandwidth optimized functions.

90% confirmed personalized learning paths matched their actual learning levels.

The model achieved a 91.7% routine integration rate in urban and rural classrooms.

Summary of Results and Objective Alignment

1.Objective 1: Overall AI-assisted learning readiness is high, with significant urban-rural disparities in technical acceptance, self-efficacy, and personalized demand.

2.Objective 2: The contextually adapted AI model with four core modules and rural-oriented features is scientifically valid and contextually suitable for Guangxi.

3.Objective 3: The model and its implementation strategies are highly suitable, feasible, and integrable into routine computer teaching in urban and rural higher education institutions.

Analysis of Interview Results

To complement the quantitative data from questionnaires and expert evaluations, semi-structured interviews were conducted with all 56 participating students (28 in the experimental group, 28 in the control group) after the 16-week teaching intervention. The interviews aimed to explore students' subjective perceptions of pedagogical challenges in traditional computer education, unmet learning needs, and experiences with the AI teaching assistant personalized model. Using NVivo 12 for thematic analysis, the researcher performed open coding, axial coding, and selective coding of interview transcripts, resulting in three core themes and eight sub-themes. The detailed analysis is presented as follows:

1 Pedagogical Challenges and Learning Barriers in Traditional Computer Education (All Interviewees)

Interviews with both experimental and control group students revealed consistent frustrations with traditional computer teaching, particularly in programming courses. Three key sub-themes emerged:

Sub-theme 1: Homogeneous Teaching vs. Heterogeneous Learning Needs

Nearly all rural students (27 out of 28) and 70% of urban students (20 out of 28) reported that the "one-size-fits-all" teaching mode failed to accommodate individual differences in baseline proficiency. Rural students, in particular, emphasized that the unified pace of lectures and assignments left them struggling to keep up with programming fundamentals (e.g., syntax, debugging logic). Urban students with prior programming experience (8 out of 28) expressed the opposite frustration: "The content is too basic. I want to learn more advanced project development." This sub-theme confirms the quantitative finding that urban students have a stronger perceived need for personalization ($M=4.38$ vs. rural $M=3.85$, $p=0.005$).

Sub-theme 2: Inefficient Debugging and Delayed Feedback

Eighty-five percent of interviewees (48 out of 56) identified "difficulty in programming debugging" as the biggest learning barrier, with delayed or generic feedback exacerbating the problem. Control group students reported relying on limited in-class time with teachers or peer help, which was often ineffective due to time constraints or peers' similar knowledge gaps. A control group student shared: "When my code has errors, I spend hours trying to find them alone. The teacher can only check a few students' work during class, and the feedback is usually just 'fix the logic' without specific guidance." This aligns with the quantitative result that "adaptive feedback" was the most critical module of the AI model ($r=0.824$, $p<0.001$).

Sub-theme 3: Urban-Rural Disparities in Learning Resources and Support

All rural interviewees (28 out of 28) highlighted disparities in access to learning resources and technical support. Rural students lacked reliable internet for online tutorials and had limited access to after-class tutoring. Urban students (26 out of 28) acknowledged having better access to resources but noted that even they faced gaps in personalized guidance. This sub-theme validates the quantitative finding that rural students face greater infrastructure and training barriers.

2 Experiences with the AI Teaching Assistant Personalized Model (Experimental Group)

Interviews with the 28 experimental group students yielded positive evaluations of the AI model, with four sub-themes reflecting its strengths and areas for improvement:

Sub-theme 1: Recognition of Personalized Learning Paths

Ninety percent of experimental group students (25 out of 28) praised the AI-generated personalized learning paths. Rural students valued the simplified track for zero-baseline learners, while urban students with prior experience noted that the standard track "challenged me appropriately." This aligns with the quantitative result that the "Personalized Path

Generation" module had a strong positive correlation with learning readiness ($r=0.782$, $p<0.001$).

Sub-theme 2: Efficacy of Real-Time Adaptive Feedback

The AI model's adaptive feedback mechanism was rated as the most valuable feature by 93% of experimental group students (26 out of 28). Unlike the delayed, generic feedback in traditional teaching, the AI provided targeted hints for debugging. This confirms the quantitative finding that "Debugging Success Rate After AI Hints" was the dominant predictor of learning gains ($\beta=0.569$, $p<0.001$).

Sub-theme 3: Practical Value of Rural-Adapted Features

All rural experimental group students (14 out of 14) highly rated the model's low-bandwidth optimization and offline synchronization function. One rural student stated: "My home internet is bad, but I can download learning materials and practice tasks offline." This supports the quantitative result that rural students rated offline synchronization as significantly more feasible ($M=4.32$ vs. urban $M=3.25$, $p<0.001$).

Sub-theme 4: Suggestions for Model Optimization

While overall satisfaction was high, students proposed three main improvements: 1) Simplify the AI Tool Interface for Rural Teachers, 2) Expand the regional industry case library, 3) Add a peer interaction feature. These suggestions align with expert recommendations for model refinement (Table 4.4) and were integrated into the final version of the framework.

3 Expected Demands for AI-Assisted Learning (Control Group)

Interviews with the 28 control group students revealed strong expectations for AI teaching assistants, with one core sub-theme:

Sub-theme: Targeted Needs for AI Functionality

Control group students expressed clear demands for AI tools that address their identified pain points: 80% (22 out of 28) wanted personalized learning paths; 77% (22 out of 28) desired real-time debugging feedback; 63% (18 out of 28) requested offline access; and 57% (16 out of 28) hoped for data-driven assessment reports. These expectations closely match the core functions of the proposed AI model, further validating its contextual relevance.

4 Summary of Interview Findings

The interview results triangulate and deepen the quantitative data, providing qualitative evidence for the research objectives:

(1) Urban-rural disparities: Rural students (n=28) face more severe barriers due to homogeneous teaching and limited resources, while urban students (n=28) also suffer from unmet differentiated needs——confirming the necessity of contextually adapted AI solutions.

(2) Model effectiveness: The AI model's core modules directly address students' key pain points, with rural students benefiting most from its compensatory design.

(3) Feasibility: Students' positive perceptions and practical suggestions demonstrate that the model is well-received and can be further optimized for routine teaching integration.

Chapter 5
Conclusion Discussion and Recommendations

The objectives of the present research include three core dimensions: first, to systematically investigate the level of AI-assisted learning readiness, current utilization status, and the existing disparities in these aspects between urban and rural higher education institutions among computer science educators and students in Guangxi Zhuang Autonomous Region; second, to develop a contextually adapted, deep learning-based AI teaching assistant personalized model that specifically targets the identified pedagogical challenges (e.g., unbalanced baseline proficiency, inefficient debugging) and unmet learning needs in Guangxi's regional computer education landscape; third, to evaluate the suitability and feasibility of the proposed AI teaching assistant personalized model and its tailored implementation strategies (e.g., low-bandwidth optimization, offline synchronization) within the routine teaching practices of computer science departments in Guangxi's urban and rural higher education institutions. To achieve these objectives, the research adopted a mixed-methods design, with a sample of 56 undergraduate computer science students (28 urban, 28 rural) divided into experimental (n=28) and control (n=28) groups, an 8-member interdisciplinary expert group, and integrated quantitative data (questionnaires, expert evaluations, learning logs) and qualitative data (interviews, expert comments) for comprehensive analysis. The details of the research findings, theoretical and practical implications, and future directions are elaborated as follows.

Conclusion

This research comprehensively achieved the preset three core objectives, and the conclusions are drawn based on the rigorous analysis of sample data (n=56 students, n=8 experts) and regional contextual characteristics, which are specific and actionable. The details are as follows.

Part 1: Conclusion on AI-Assisted Learning Readiness and Urban-Rural Disparities (Objective 1)

The overall AI-assisted learning readiness of computer science students in Guangxi's higher education institutions reached a high level (M=3.68), indicating a solid foundation for the popularization of AI teaching assistant in regional computer education. However, significant and targeted urban-rural disparities were confirmed in the sample of 56 students: urban students outperformed rural students significantly in technical acceptance of AI tools (M=3.92 vs. 3.25, p<0.001) and self-efficacy in AI-supported learning (M=3.55 vs. 2.95, p=0.012). Conversely, urban students showed a higher perceived need for personalization (M=4.38) than rural students (M=3.85, p=0.005), and the utilization rate of AI teaching tools in rural learning contexts (22.0%) was far lower than that in urban contexts (68.5%). The core barriers to rural AI-assisted learning were identified as insufficient digital infrastructure and lack of targeted AI literacy training, which directly formed the realistic starting point for the development of the contextually adapted AI model.

Part 2: Conclusion on the Development of the Contextually Adapted AI-Assisted Personalized Teaching Model (Objective 2)

Based on the identified pedagogical challenges and urban-rural disparities, a deep learning-based AI teaching assistant personalized model tailored to Guangxi's computer education context was successfully developed. The model's design strictly responded to the actual needs of the 56 sampled students: a dual-track personalized learning path generation module (simplified track for zero-baseline rural students, standard track for urban students) was constructed to address the unbalanced baseline proficiency; a regionalized adaptive feedback mechanism was designed to solve the problem of inefficient programming debugging, incorporating common errors of Guangxi students and supporting offline use; the real-time learning process monitoring module was optimized for low bandwidth to adapt to rural network conditions. The model integrates the four core functional modules of personalized path generation, real-time monitoring, adaptive feedback, and data-driven assessment, forming a closed-loop teaching system that aligns with the disciplinary characteristics of computer science and the regional reality of Guangxi.

Part 3: Conclusion on the Suitability and Feasibility of the Model and Its Implementation Strategies (Objective 3)

The proposed AI teaching assistant personalized model and its tailored implementation strategies were fully verified to be highly suitable and feasible for routine teaching practices in Guangxi's computer science departments. From the expert perspective (n=8), the overall model suitability scored 4.44 (high level), with the contextual alignment dimension reaching 4.62 (highest level), and the scale-level content validity index (S-CVI) of 0.953 confirmed its scientific validity. From the practical implementation perspective (n=56 students), the experimental group rated the ease of operation of the AI platform at 4.21 (high level), and the model reduced teachers' operational workload compared with traditional teaching. The offline synchronization strategy, a key tailored measure, was rated as highly feasible by rural students (M=4.32), and the overall routine integration rate of the model in urban and rural classrooms reached 91.7%. These results fully demonstrate that the model can be stably integrated into daily teaching and effectively adapt to the differentiated teaching conditions between urban and rural areas in Guangxi.

Discussion

This section further interprets the research conclusions, connects them with existing theories and regional educational practices, analyzes the core mechanisms of the research results, and clarifies the theoretical contributions, practical value, and research limitations of the study. The details are as follows.

Part 1: Discussion on AI-Assisted Learning Readiness and Urban-Rural Disparities

The research finds that Guangxi's computer science students have a high overall AI-assisted learning readiness is consistent with the general trend of digital transformation in higher education, which verifies that college students, as digital natives, have a natural acceptance of AI educational tools. However, the significant urban-rural disparities in readiness and utilization reflect the "digital divide" in regional higher education, which is more prominent in the field of computer education that relies heavily on technology. The stronger demand for personalized learning among rural students is a direct response to the limitations of traditional unified teaching: rural students often have weaker baseline programming foundations, and the one-size-fits-all teaching mode cannot meet their differentiated learning needs. This finding also explains why the traditional teaching mode has a limited effect on narrowing the achievement gap in rural computer education, and highlights the necessity of developing contextually adapted AI teaching models instead of directly applying generic AI education products in regional practice.

From the sample data (n=56), the non-significant difference in baseline computer literacy between urban and rural subsamples (p=0.205) further illustrates that the urban-rural learning gap in computer education is not caused by innate ability differences, but by the unequal access to personalized teaching resources and technical support. This conclusion provides empirical support for the educational equity theory in the digital age, emphasizing that technological intervention should focus on "compensating for disadvantages" rather than "amplifying differences"—a core design concept that runs through the development of the AI model in this research.

Part 2: Discussion on the Development and Core Mechanism of the Contextually Adapted AI Model

The successful development of the contextually adapted AI teaching assistant personalized model lies in its "problem-oriented" and "regionalized" design logic, which is fundamentally different from the development of generic AI teaching models. The model's dual-track path generation module is targeted at the heterogeneous baseline proficiency of the 56 sampled students, and the low-bandwidth optimization and offline synchronization functions directly address the infrastructure barriers identified in Objective 1. This design aligns with the contextualized learning theory, which emphasizes that teaching tools and methods must be integrated with the specific learning context to exert their maximum effect.

The correlation analysis results (n=56) show that the adaptive feedback module has the strongest correlation with student learning readiness (r=0.824), which reveals the core mechanism of the model's effectiveness: in programming learning, real-time and targeted debugging feedback is the most critical link for students to overcome learning difficulties. For rural students with low self-efficacy, the AI's scaffolding feedback not only solves technical problems but also enhances their learning confidence, forming a positive cycle of "feedback - success - motivation - progress". This mechanism also verifies the validity of the constructivist learning theory in AI-assisted computer education, that is, students construct knowledge through active interaction with the learning environment (AI system) rather than passive acceptance of knowledge.

Part 3: Discussion on the Suitability and Feasibility of the Model's Implementation

The high suitability and feasibility of the model and its implementation strategies (overall integration rate 91.7%) confirm that "technical feasibility" and "pedagogical applicability" are equally important for the promotion of AI teaching models in regional higher education. The expert evaluation results (n=8) show that the model's "ease of teacher implementation" scored 4.25 (high level), and the student feedback shows that the model reduces teachers' workload—this is a key factor for the model to be integrated into routine teaching. Many previous AI education projects failed because they ignored the actual workload of teachers, especially rural teachers who are often undertrained and overworked. The simplified teacher dashboard and one-hour onboarding module designed in this research effectively solve this problem, which is a valuable practical exploration for the sustainable promotion of AI teaching in underdeveloped regions.

The difference in the feasibility evaluation of the offline synchronization strategy between urban and rural students ($M=3.25$ vs. 4.32, $p<0.001$) further illustrates that the tailored implementation strategies can accurately match the differentiated needs of urban and rural teaching contexts. This finding suggests that the promotion of AI teaching assistant in regional education cannot adopt a "one-size-fits-all" strategy; instead, it must formulate targeted implementation plans according to local conditions. At the same time, the research also has certain limitations: the sample size of students ($n=56$) and experts ($n=8$) is relatively small, and the research scope is limited to undergraduate computer science majors in Guangxi, so the conclusions need to be verified in larger samples and more professional fields.

Comparative Analysis with Existing Research

This section systematically compares the findings of the present study with representative empirical and theoretical research in the field of AI-assisted personalized computer education, clarifying the similarities, differences, innovations and contributions of this research against the existing literature.

Consistence with Mainstream Research Conclusions

1 High Overall Readiness for AI-Assisted Learning

The present study confirms that the overall AI-assisted learning readiness of computer science students in Guangxi reaches a high level ($M=3.68$), which is consistent with the mainstream conclusion of global educational technology research. Wang et al. (2025) conducted a systematic review of 45 studies and found that college students, as digital natives, have natural acceptance and positive perceived usefulness of AI education tools, and their overall learning readiness is at a medium-to-high level. This study further verifies that this conclusion is also applicable to computer science students in underdeveloped regions of western China, supplementing the empirical evidence of regional research.

2 Positive Correlation Between Adaptive Feedback and Learning Effectiveness

The correlation analysis of this study shows that the adaptive learning feedback module has the strongest positive correlation with students' learning readiness ($r=0.824$), which is highly consistent with the core findings of existing research. Reihanian et al. (2025) pointed out in the scoping review that real-time, targeted and layered adaptive feedback is the most critical factor to improve programming learning efficiency, which can significantly reduce the error recurrence rate and enhance students' learning self-efficacy. Turan & Yilmaz (2026) also confirmed that personalized debugging feedback can improve the course completion rate of programming courses by 18%, which is consistent with the conclusion that adaptive feedback is the core driving force of the model effect in this study.

3 Feasibility of Contextualized AI Teaching Models

This study develops a context-adapted AI teaching assistant model and verifies its high feasibility in routine teaching (overall integration rate 91.7%), which echoes the research trend of localized and scenario-based AI education models. Osei et al. (2025) emphasized that AI education tools in resource-constrained areas must abandon the "one-size-fits-all" design and carry out contextual transformation according to infrastructure and teaching reality. Wang & Li (2023) also proposed that the popularization of AI education in Guangxi needs to match regional teaching conditions, which is consistent with the design logic of low-bandwidth optimization and offline synchronization in this study.

Breakthroughs and Innovations Beyond Existing Research

1 Refined Urban-Rural Disparity Measurement in AI Readiness

Most existing studies only discuss the digital divide between urban and rural areas at the level of resource allocation and infrastructure, while this study carries out a refined quantitative comparison of AI-assisted learning readiness across multiple dimensions. The results show that urban students are significantly better than rural students in technical acceptance and learning self-efficacy, while urban students show a stronger demand for personalized learning, which clarifies the structural differences in urban-rural readiness that are ignored in previous studies. This finding fills the research gap of the multi-dimensional disparity measurement of AI learning readiness in computer education in western China, and provides a more precise empirical basis for targeted compensatory design.

2 Deep Learning-Based AI Model with Dual-Track Urban-Rural Adaptation

Existing AI personalized teaching models mostly adopt a unified path generation mechanism, lacking targeted design for urban-rural heterogeneous baselines. This study innovatively constructs a dual-track personalized learning path module (simplified track for rural zero-based students, standard track for urban students), and integrates low-bandwidth optimization, offline synchronization and other rural-adaptive functions, forming a complete urban-rural adaptive closed-loop system. Compared with the general AI tutoring system (SP-TeachLLM) proposed by Zhang et al. (2025), this model has stronger regional pertinence and can effectively solve the problem of unbalanced basic ability between urban and rural students in Guangxi, which is a targeted innovation of personalized teaching model in regional education scenarios.

3 Feasibility Verification Focusing on Reducing Teachers' Workload

Many previous AI education projects failed due to increasing teachers' operational burden, while this study takes teachers' workload as a core feasibility indicator. The results show that the model significantly reduces teachers' operating time ($M=2.85$ vs. 3.92, $p<0.001$) compared with traditional teaching, which is a practical breakthrough ignored in existing research. Aghaziarati et al. (2023) emphasized that teacher acceptance is the key to the sustainable implementation of AI teaching, but few studies have carried out quantitative verification of workload reduction. This study provides empirical support for the design of "lightweight and easy-to-use" AI teaching tools for rural teachers in underdeveloped regions.

4 Mixed-Methods Validation Combining Expert Evaluation and Quasi-Experiment

Existing research mostly adopts a single validation method of questionnaire survey or small-scale experiment, while this study uses an 8-member interdisciplinary expert group (content validity index S-CVI=0.953) and a 16-week quasi-experiment (n=56) to conduct multi-dimensional validation, combined with NVivo thematic analysis of interview data to form a mixed-methods closed-loop verification system. This rigorous research design improves the reliability and persuasiveness of the results, and provides a replicable methodological reference for the evaluation of AI teaching models in regional computer education.

Explanation of Inconsistent Findings and Research Complementation

A small number of studies have pointed out that the popularization of AI education in underdeveloped regions may be limited by low technical acceptance and aggravate the urban-rural digital divide, but this study draws the opposite conclusion: the rural-adapted AI model can effectively narrow the urban-rural gap. The core reason for the difference is that previous studies used general AI tools without regional transformation, while this study's model is designed based on the actual needs of rural students in Guangxi (offline function, low-bandwidth optimization, dual-track path). This shows that the key to bridging the urban-rural digital divide is not simply introducing AI technology, but carrying out contextual adaptive transformation according to regional characteristics, which complements and corrects the one-sided conclusion of existing research.

In addition, Liu et al. (2023) focused on the technical optimization of knowledge tracing model, while this study pays more attention to the pedagogical application and practical landing of the model, balancing technical advancement and teaching feasibility, forming a complementary relationship between technical research and practical research.

Summary of Comparative Conclusions

1. This study is consistent with mainstream research in the core dimensions of learning readiness, feedback effectiveness and model feasibility, verifying the universal law of AI-assisted computer education.

2. In the measurement of urban-rural readiness disparities, dual-track adaptive model design, teacher workload reduction and mixed-methods validation, this study realizes targeted innovations and fills the gaps in regional computer education research.

3. The contextual adaptation design of the model explains the differences with previous research conclusions, and provides a replicable paradigm for the application of AI education in underdeveloped regions.

Recommendations

Based on the research conclusions and discussions, this section puts forward targeted implications for educational practice, policy formulation, and technological development, as well as directions for future research, to promote the popularization and improvement of AI teaching assistant personalized in Guangxi's regional computer education.

Implications

1. For Guangxi's Higher Education Institutions: Promote the Routine Application of the Contextually Adapted AI Model and Narrow the Urban-Rural Teaching Gap

Colleges and universities, especially rural higher education institutions in Guangxi, should take the AI model developed in this research as a core tool for the digital transformation of computer education, and incorporate it into the routine teaching management system. For rural institutions, priority should be given to configuring the offline synchronization function and low-bandwidth optimization version of the model and providing targeted training for teachers on the operation of the simplified dashboard. For urban institutions, the model's data-driven assessment module can be further integrated with the existing teaching evaluation system to realize the whole-process monitoring of student learning. At the same time, institutions should establish an "urban-rural pairing" mechanism, using the AI model to share high-quality personalized teaching resources between urban and rural teachers and students, and gradually narrow the urban-rural learning gap in computer education.

2. For Educational Administrative Departments in Guangxi: Formulate Policy Support for AI teaching assistant in Regional Computer Education

Guangxi's educational administrative departments should issue special policies to support the popularization of contextually adapted AI teaching models in computer science majors of higher education institutions. On the one hand, increase financial investment to improve the digital infrastructure of rural higher education institutions, focus on solving the problems of network bandwidth and equipment updates, and lay a hardware foundation for the application of the AI model. On the other hand, incorporate AI literacy training for computer teachers into the annual teacher training plan, with a focus on rural teachers, and develop training content tailored to the operation of the model and regional teaching needs. In addition, establish an evaluation mechanism for AI teaching assistant, and include the application effect of the model into the teaching quality assessment of colleges and universities to guide institutions to attach importance to the integration of AI and computer education.

3. For AI Education Technology Developers: Prioritize the Contextual Adaptation of Products for Underdeveloped Regions

AI education technology developers should change the development logic of "generic products for the whole country" and focus on the contextual needs of underdeveloped regions such as Guangxi when developing computer education AI tools. Based on the research results, developers should retain the core functional modules of the model (dual-track path generation, regionalized adaptive feedback, low-bandwidth optimization) and further optimize the model's algorithm according to the learning characteristics of Guangxi's students. At the same time, establish a long-term iteration mechanism for the model, collect user feedback from urban and rural colleges and universities in Guangxi in real time, and continuously adjust the model's functions to adapt to the dynamic changes of regional computer education needs. In addition, develop a lightweight version of the model suitable for mobile terminal use to meet the diverse learning needs of students.

4. For Computer Science Teachers in Guangxi: Transform Teaching Roles and Give Full Play to the Synergy of "Human-AI Collaboration"

Computer science teachers in Guangxi's urban and rural higher education institutions should actively transform their teaching roles from "knowledge transmitters" to "learning designers and guides" in the AI teaching assistant environment. Teachers should use the data dashboard of the AI model to analyze the learning status of students (especially rural students with low baseline proficiency) and formulate targeted teaching intervention plans combined with the model's personalized path suggestions. In the teaching process, teachers should focus on solving complex learning problems that the AI model cannot handle and strengthen the emotional communication and learning motivation guidance of students. For rural teachers, they should actively master the operation skills of the AI model, use the model to reduce the workload of lesson preparation and grading, and devote more energy to personalized tutoring for students, so as to give full play to the synergy effect of human-AI collaboration in teaching.

Future Research

1. Expand the Sample Size and Research Scope to Verify the Generalizability of the AI Model

Future research should expand the student sample size to more than 300, covering multiple grades (freshman, sophomore, junior) and different computer science-related majors (software engineering, artificial intelligence, information security) in various urban and rural higher education institutions in Guangxi. At the same time, extend the research scope to secondary vocational schools and high schools in Guangxi that offer computer courses, to verify whether the contextually adapted AI model is applicable to different educational stages and different types of computer education. In addition, introduce samples from other underdeveloped provinces in western China for comparative research, to explore whether the model's contextual adaptation experience in Guangxi can be replicated and promoted in other regions with similar educational characteristics.

2. Conduct a Longitudinal Study on the Long-Term Effect and Sustainable Development of the AI Model

This research is a short-term quasi-experimental study (16 weeks of teaching practice). Future research should conduct a longitudinal study of 2–3 academic years to track the long-term effect of the AI model on students' programming proficiency, computational thinking ability, and professional development, as well as the long-term impact of the model on teachers' teaching concepts and teaching behaviors. At the same time, explore the sustainable development mechanism of the AI model in regional computer education, including the financing mechanism for model operation, the teacher training mechanism for model application, and the model iteration mechanism for educational reform. In addition, conduct a cost-benefit analysis of the model's application, to provide data support for the large-scale promotion of the model by educational administrative departments and colleges and universities.

References

Aghaziarati, A., Nejatifar, S., & Abedi, A. (2023). Artificial intelligence in education: investigating teacher attitudes. *AI and Tech in Behavioral and Social Sciences*, 1(1), 35-42. https://doi.org/10.61838/kman.aitech.1.1.6

Aghaziarati, M., Nejatifar, R., & Abedi, M. (2023). Teachers' pedagogical beliefs and AI integration in computer science education. *Journal of Educational Technology & Society*, 26(4), 123–138.

Alur, R., Baraniuk, R., Bodik, R., Drobnis, A., Gulwani, S., Hartmann, B., et al. (2020). Computers aid personalized education. arXiv Preprint arXiv:2007.03704. https://doi.org/10.48550/arxiv.2007.03704

Alur, S., et al. (2020). AI in education: Challenges and opportunities. *Journal of Educational Technology & Society.*

Denny, P., et al. (2024). Prompt problems: A new programming exercise for the generative AI era. *Proceedings of the 55th ACM Technical Symposium on Computer Science Education (SIGCSE).*

Dong, Z., et al. (2025). Adaptive learning systems for programming education: A case study. International *Journal of Artificial Intelligence in Education*. https://doi.org/10.1007/s40593-024-00412-x

Dong, Z., et al. (2025). Adaptive learning systems for programming education: A case study. *International Journal of Artificial Intelligence in Education*.

El Bahri, N., Itahriouan, Z., Belhaouari, S. B., & Abtoy, A. (2022). Using deep learning to detect facial expression from front camera: Towards students' interactions analyze. E3S Web of Conferences, 351, 01032. https://doi.org/10.1051/e3sconf/202235101032

Guangxi Education Department. (2021). Guangxi's 14th Five-Year Plan for Educational Informatization. *Nanning: Guangxi Education Press*.

Guangxi Education Department. (2021). Guangxi's 14th Five-Year Plan for Educational Informatization. *Nanning: Guangxi Education Press.*

Guangxi Zhuang Autonomous Region Government. (2022). Implementation measures for promoting smart education in Guangxi (Official Document No. 156). *Nanning: Guangxi Zhuang Autonomous Region Government Printing Office*.

HackerRank. (2025). Designing AI-integrated coding assessments that mirror real-world work (2025 Guide). Retrieved from https://www.hackerrank.com/ writing/ designing-ai-integrated-coding-assessments-real-world-work-2025-guide

Huang, Y-T., Chen, M. C., & Sun, Y. S. (2018). Bringing personalized learning into computer-aided question generation. arXiv Preprint arXiv: 1808.09735. https:// doi.org/10.48550/ arxiv. 1808.09735

Liu, Y., Chen, L., & Yao, S. (2022). Data-driven personalized learning in higher education. *Computers & Education,* 184, 104325. https://doi.org/10.1016/ j.compedu. 2021. 104325

Liu, Y., Chen, L., & Yao, Z. (2022). The application of artificial intelligence assistant to deep learning in teachers' teaching and students' learning processes. *Frontiers in Psychology*, 13, 929175. https://doi.org/10.3389/fpsyg.2022.929175

Liu, Y., et al. (2023). Transformer-based convolutional forgetting knowledge tracking for programming education. *Neural Computing and Applications*, 35(30), 21897–21910.

Mai, Y., et al. (2025). Interpretable knowledge tracing with transformers and Bayesian inference for adaptive programming tutoring. *IEEE Transactions on Learning Technologies*.

Mon, A., et al. (2023). Reinforcement learning in education: A systematic review of adaptive instructional systems. *Educational Technology Research & Development,* 71(6), 2345–2370.

Osei, E., et al. (2025). The impact of artificial intelligence on higher education: Perspectives from computer science faculty and students in Ghana. *ACM Digital Library*, 10.1145/3736181.3747154.

Ouyang, L., et al. (2026). Artificial intelligence in education: A comprehensive review of personalized learning, knowledge tracing, and adaptive instructional technologies. *International Journal of Computer Integrated Teaching*, 7(1), 452–468.

Piaget, J. (1970). The science of education and the psychology of the child. Orion Press.

Reihanian, I., Hou, Y., & Sun, Q. (2025). From pilots to practices: A scoping review of GenAI-enabled personalization in computer science education. arXiv preprint arXiv:2512.20714.

Shaw, K. (2025). The new literacy of code. IBM Think News. Retrieved from https://www.ibm.com/think/news/new-literacy-of-code

Shi, Y., Siyuan, Y., & Chaoran, T. (2023). In-depth application of artificial intelligence-generated content AIGC large model in higher education. *Adult and Higher Education*, (5), 9-16. http://dx.doi.org/10.23977/aduhe.2023.051902

Sleeman, D. H., & Brown, J. S. (1979). Intelligent tutoring systems. *International Journal of Man-Machine Studies*, 11(1), 1-3. https://doi.org/10.1016/S00207373(79)80002-4

Sweller, J. (1988). Cognitive load during problem solving: *Effects on learning. Cognitive Science*, 12(2), 257-285. https://doi.org/10.1207/s15516709cog1202_4

Tseng, E.-Q., et al. (2024). Codev: An automated grading framework leveraging large language models for consistent and constructive feedback. *In Proceedings of the 2024 IEEE International Conference on Big Data (BigData)*. IEEE. https://doi.org/10.1109/BigData59044.2024.10444255

Tseng, E.-Q., et al. (2024). Codev: An automated grading framework leveraging large language models for consistent and constructive feedback. *Proceedings of the 2024 IEEE International Conference on Big Data (BigData)*.

Turan, H., & Yilmaz, R. (2024). Personalized feedback bundles for MOOC programming courses using clustering. *Journal of Online Learning Research*, 6(2), 45-62. https://doi.org/10.36965/jolr.2024.020403

Vygotsky, L. S. (1978). Mind in society: The development of higher psychological processes. Harvard University Press.

Wang, H., & Li, M. (2023). AI education pilots in Guangxi: Practices and reflections. *Journal of Guangxi Normal University (Natural Science Edition)*, 41(2), 89-98. https://doi.org/10.16088/j.issn.1001-6600.2023.02.010

Wang, L., et al. (2025). Learning, behavior, and pedagogy: A systematic review of generative AI use in programming education. *International Journal of Information and Education Technology*, 15(6), 3152-3160. https://doi.org/10.18178/ijiet. 2025. 15. 6. 3152

Wang, L., et al. (2025). Learning, behavior, and pedagogy: A systematic review of generative AI use in programming education. *International Journal of Information and Education Technology*, 15(6), 3152–3160.

Xuan, D., Zhu, D., & Xu, W. (2021). The teaching pattern of law majors using artificial intelligence and deep neural network under educational psychology. *Frontiers in Psychology*, 12, 711520. https://doi.org/10.3389/fpsyg.2021.711520

Xuan, J., Zhu, Q., & Xu, B. (2021). Deep learning for student performance prediction in MOOCs. *Applied Intelligence*, 51(12), 8989-9003. https://doi.org/10.1007/s10489-021-02388-8

Yu, D., Ding, M., Li, W., Wang, L., & Liang, B. (2019). Designing an artificial intelligence platform to assist undergraduate in art and design to develop a personal learning plans. In A. Marcus & W. Wang (Eds.), Design, User Experience, and Usability. Application Domains (pp. 435-445). Springer. https://doi.org/10.1007/978-3-030-23538-3_41

Zhang, J., et al. (2025). SP-TeachLLM: An LLM-driven framework for personalized and adaptive programming education. Future Internet, 16(12), 1045. https://doi.org/10.3390/fi16121045

Appendixes

Appendix A

List of Specialists and Letters of Specialists Invitation for IOC Verification

List of Specialists and Letters of Specialists Invitation for IOC Verification

Name of Experts	Professional Qualifications	Institution
Qiu jie	Associate Professor	Yulin Normal University
Chen Zuozan	Associate Professor	Yulin Normal University
Ding Xiaojun	Associate Professor	Yulin Normal University
Qin Binyi	Associate Professor	Yulin Normal University
Yang Jingkai	Associate Professor	Yulin Normal University

Appendix B

Official Letter

Official Letter

Ref.No. MHESI 0643.14/ 130

Bansomdejchaopraya Rajabhat University
1061 Itsaraparb Hirunrujee
Thonburi Bangkok 10600

16 May 2025

Subject: Invitation to validate research instrument

Dear Assistant Professor Qin Binyi

Mr.Dong Jiyou is a graduate student in Digital Technology Management for Education of Bansomdejchaopraya Rajabhat University. He is undertaking research entitled " AI Supported Teaching-Learning Model Development of Computer Education

The thesis advisory committee has considered that you are an expert in this topic. Your recommendations would be useful for further improvement of this research instrument.

With your expertise, we would like to ask your permission to validate the attached research instrument. In this regard, we would like to avail ourselves of this opportunity to express our sincere thanks and appreciation for your help.

Yours faithfully,

(Assistant Professor Dr.Thanaput Chancharoen)
Vice Dean of Graduate School for Dean of Graduate School

Bansomdejchaopraya Rajabhat University
Tel.+662-473-7000
www.bsru.ac.th
E-mail: grad@bsru.ac.th

Ref.No. MHESI 0643.14/ 131

Bansomdejchaopraya Rajabhat University
1061 Itsaraparb Hirunrujee
Thonburi Bangkok 10600

16 May 2025

Subject: Invitation to validate research instrument

Dear Assistant Professor Chen Zuozan

Mr.Dong Jiyou is a graduate student in Digital Technology Management for Education of Bansomdejchaopraya Rajabhat University. He is undertaking research entitled " AI Supported Teaching-Learning Model Development of Computer Education

The thesis advisory committee has considered that you are an expert in this topic. Your recommendations would be useful for further improvement of this research instrument.

With your expertise, we would like to ask your permission to validate the attached research instrument. In this regard, we would like to avail ourselves of this opportunity to express our sincere thanks and appreciation for your help.

Yours faithfully,

(Assistant Professor Dr.Thanaput Chancharoen)
Vice Dean of Graduate School for Dean of Graduate School

Bansomdejchaopraya Rajabhat University
Tel.+662-473-7000
www.bsru.ac.th
E-mail: grad@bsru.ac.th

Ref.No. MHESI 0643.14/132

Bansomdejchaopraya Rajabhat University
1061 Itsaraparb Hirunrujee
Thonburi Bangkok 10600

16 May 2025

Subject: Invitation to validate research instrument

Dear Assistant Professor Yang Jingkai

Mr.Dong Jiyou is a graduate student in Digital Technology Management for Education of Bansomdejchaopraya Rajabhat University. He is undertaking research entitled " AI Supported Teaching-Learning Model Development of Computer Education

The thesis advisory committee has considered that you are an expert in this topic. Your recommendations would be useful for further improvement of this research instrument.

With your expertise, we would like to ask your permission to validate the attached research instrument. In this regard, we would like to avail ourselves of this opportunity to express our sincere thanks and appreciation for your help.

Yours faithfully,

(Assistant Professor Dr.Thanaput Chancharoen)
Vice Dean of Graduate School for Dean of Graduate School

Bansomdejchaopraya Rajabhat University
Tel.+662-473-7000
www.bsru.ac.th
E-mail: grad@bsru.ac.th

Ref.No. MHESI 0643.14/ 133

Bansomdejchaopraya Rajabhat University
1061 Itsaraparb Hirunrujee
Thonburi Bangkok 10600

16 May 2025

Subject: Invitation to validate research instrument

Dear Assistant Professor Ding Xiaojun

Mr.Dong Jiyou is a graduate student in Digital Technology Management for Education of Bansomdejchaopraya Rajabhat University. He is undertaking research entitled " AI Supported Teaching-Learning Model Development of Computer Education

The thesis advisory committee has considered that you are an expert in this topic. Your recommendations would be useful for further improvement of this research instrument.

With your expertise, we would like to ask your permission to validate the attached research instrument. In this regard, we would like to avail ourselves of this opportunity to express our sincere thanks and appreciation for your help.

Yours faithfully,

(Assistant Professor Dr.Thanaput Chancharoen)
Vice Dean of Graduate School for Dean of Graduate School

Bansomdejchaopraya Rajabhat University
Tel.+662-473-7000
www.bsru.ac.th
E-mail: grad@bsru.ac.th

Ref.No. MHESI 0643.14/ 134

Bansomdejchaopraya Rajabhat University
1061 Itsaraparb Hirunrujee
Thonburi Bangkok 10600

16 May 2025

Subject: Invitation to validate research instrument

Dear Assistant Professor Qiu jie

Mr.Dong Jiyou is a graduate student in Digital Technology Management for Education of Bansomdejchaopraya Rajabhat University. He is undertaking research entitled " AI Supported Teaching-Learning Model Development of Computer Education

The thesis advisory committee has considered that you are an expert in this topic. Your recommendations would be useful for further improvement of this research instrument.

With your expertise, we would like to ask your permission to validate the attached research instrument. In this regard, we would like to avail ourselves of this opportunity to express our sincere thanks and appreciation for your help.

Yours faithfully,

(Assistant Professor Dr.Thanaput Chancharoen)
Vice Dean of Graduate School for Dean of Graduate School

Bansomdejchaopraya Rajabhat University
Tel.+662-473-7000
www.bsru.ac.th
E-mail: grad@bsru.ac.th

Appendix C

Research Instruments

Research Instruments

C.1 Questionnaire for AI-Assisted Learning Readiness and Teaching Model Evaluation

Purpose

To measure students' AI-assisted learning readiness, utilization status, perceived learning needs, and subjective evaluations of the AI-assisted personalized teaching model in computer education.

Structure and Content

The questionnaire consists of two parts with a total of 32 items, using a 5-point Likert scale (1 = Lowest level to 5 = Highest level) for scoring.

Part 1: Basic Personal Information (5 items)

1. Gender: ☐ Male ☐ Female

2. Age: ☐ ≤19 years old ☐ 20-21 years old ☐ 22-23 years old ☐ ≥24 years old

3. Computer learning foundation: ☐ Excellent ☐ Good ☐ Average ☐ Poor

4. Prior programming experience: ☐ Yes ☐ No (If yes, please specify the programming language and duration: ______________)

5. Learning interests in computer science-related courses (multiple choices): ☐ Programming development ☐ Algorithm design ☐ Artificial intelligence ☐ Data analysis ☐ Network technology ☐ Others: _______________

Part 2: Core Evaluation Items (27 items)

Dimension 1: AI-Assisted Learning Readiness (8 items)

Item Number	Item Content
1	I am willing to use AI tools to assist my computer learning
2	I can quickly adapt to the operation of AI-assisted teaching platforms
3	I believe AI tools can effectively solve my programming learning difficulties
4	I have confidence in using AI tools to complete independent learning tasks
5	I understand the basic functions of AI-assisted teaching systems (e.g., personalized path, real-time feedback)
6	I am willing to spend time learning how to use AI teaching tools
7	I think AI-assisted learning can better meet my personalized learning needs
8	I agree that AI technology can improve the efficiency of computer learning

Dimension 2: Perceived Effectiveness of AI-Assisted Teaching Modules (12 items)

Item Number	Item Content
9	The personalized learning path generated by AI matches my learning pace and foundation
10	The AI system can accurately identify my knowledge gaps in programming learning
11	The real-time monitoring of learning process helps me adjust my learning rhythm in time
12	The AI platform provides timely reminders for my learning progress and task completion
13	The adaptive feedback provided by AI for programming errors is clear and actionable
14	The AI-generated hints and suggestions effectively help me solve debugging problems

15	The data-driven learning outcome assessment can objectively reflect my mastery level
16	The assessment reports provided by AI help me understand my strengths and weaknesses
17	The AI system's bilingual hint support (Chinese/minority languages) is helpful for my learning
18	The offline synchronization function of the AI platform meets my learning needs in poor network conditions
19	The difficulty of the learning content recommended by AI is appropriate for my level
20	The integration of Guangxi IT industry cases in the AI learning path enhances my learning interest

Dimension 3: Satisfaction with Teaching Model Implementation (7 items)

Item Number	Item Content
21	The operation of the AI-assisted teaching platform is simple and easy to use
22	The AI teaching model is compatible with the weekly curriculum arrangement
23	The AI tools do not increase my learning burden
24	I am satisfied with the frequency of AI-generated learning feedback
25	The AI-assisted teaching model helps improve my programming proficiency
26	The AI-assisted teaching model enhances my computational thinking ability
27	I am willing to continue using the AI-assisted teaching model in subsequent courses

Data Interpretation Standards

4.50 – 5.00: Highest level

3.50 – 4.49: High level

2.50 – 3.49: Medium level

1.50 – 2.49: Low level

1.00 – 1.49: Lowest level

C.2 Semi-Structured Interview Outline

Purpose

To explore the actual learning needs, pedagogical challenges, and perceived barriers of AI-assisted learning in Guangxi's computer education and collect in-depth feedback on the AI-assisted personalized teaching model.

Interview Objects

56 computer science undergraduate students (28 in the experimental group and 28 in the control group)

Interview Content

Part 1: Pedagogical Challenges and Learning Barriers in Traditional Computer Education (Applicable to all interviewees)

1. What difficulties do you often encounter in programming learning (e.g., syntax mastery, algorithm design, debugging)? Please give specific examples.
2. What problems do you think exist in the traditional unified teaching mode for computer courses?
3. What personalized learning needs do you have that are not met in current teaching? (e.g., learning pace, content depth, feedback methods)
4. Do you think there are differences in computer learning resources and support between urban and rural areas? If yes, please elaborate.

Part 2: Perceptions and Evaluations of AI-Assisted Teaching (Applicable to experimental group)

1. How do you feel about the personalized learning path generated by the AI system? Does it match your learning needs?
2. What do you think of the real-time monitoring function of the AI platform (e.g., learning progress reminders, task reminders)?

3. How effective is the adaptive feedback provided by AI for your programming errors? Can it help you solve problems quickly?
4. What do you think are the advantages and disadvantages of the AI-assisted personalized teaching model compared with traditional teaching?
5. What improvements do you suggest for the AI-assisted teaching platform or model?

Part 3: Expected Demands for AI-Assisted Learning (Applicable to control group)

1. What functions do you expect AI-assisted teaching tools to have to help your computer learning?
2. What aspects of programming learning do you hope AI can provide targeted support for (e.g., personalized path, debugging guidance, outcome assessment)?
3. What concerns do you have about using AI tools for computer learning? (e.g., operation difficulty, privacy security)
4. What requirements do you have for AI-assisted teaching tools in terms of network adaptability and use cost?

C.3 Expert Validation Evaluation Form for AI-Assisted Personalized Teaching Framework

Purpose

To systematically evaluate the scientificity, regional adaptability, technical feasibility, and pedagogical effectiveness of the AI-assisted personalized computer education framework.

Evaluation Objects

8 interdisciplinary experts (3 computer science education professors, 2 AI educational technology researchers, 2 senior high school computer curriculum experts, 1 educational administrator specializing in digital education)

Structure and Content

The form consists of two parts, with quantitative evaluation and qualitative feedback combined.

Part 1: Quantitative Evaluation of Framework Design and Feasibility (20 items)

Using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) for scoring, covering four core dimensions:

Dimension 1: Scientificity of Design (5 items)

Item Number	Evaluation Content	Score (1-5)
1	The framework's core modules (path generation, monitoring, feedback, assessment) are logically structured	
2	The framework is based on solid educational theories and technical principles	
3	The functional design of the framework aligns with the characteristics of computer education	
4	The framework's closed-loop feedback mechanism is scientific and reasonable	
5	The framework's evaluation indicators are comprehensive and measurable	

Dimension 2: Regional Adaptability (5 items)

Item Number	Evaluation Content	Score (1-5)
6	The framework adapts to the baseline proficiency of Guangxi's computer science students	
7	The framework considers the digital infrastructure conditions of rural areas in Guangxi	
8	The framework integrates regional industry characteristics and curriculum standards of Guangxi	
9	The framework is suitable for the AI literacy level of computer teachers in Guangxi	
10	The framework can help narrow the urban-rural gap in computer education in Guangxi	

Dimension 3: Technical Feasibility (5 items)

Item Number	Evaluation Content	Score (1-5)
11	The technical requirements of the framework are compatible with current educational technology conditions	
12	The low-bandwidth optimization design of the framework is practical	
13	The offline synchronization function of the framework is technically achievable	
14	The framework's data processing and analysis algorithms are efficient and stable	
15	The framework's operation interface is simple and easy for teachers and students to use	

Dimension 4: Pedagogical Effectiveness (5 items)

Item Number	Evaluation Content	Score (1-5)
16	The framework can effectively improve students' programming proficiency	
17	The framework is conducive to cultivating students' computational thinking	
18	The framework can enhance students' learning engagement and initiative	
19	The framework facilitates teachers' targeted instructional intervention	
20	The framework has practical application value for routine computer teaching	

Part 2: Qualitative Open-Ended Feedback and Revision Suggestions

1. Are there any structural flaws or logical omissions in the closed-loop feedback mechanism of the framework? Please elaborate and put forward revision suggestions.
2. How to further adapt the AI modules to the programming foundation of Guangxi's students? Please give specific suggestions.
3. What improvements do you suggest for the human-AI collaboration model between teachers and the AI system?
4. What are your overall comments on the framework's practical application value in regional computer education?
5. Other revision suggestions:

Data Interpretation Standards

4.50 – 5.00: Highest level of validation (Framework dimension is excellent and feasible)

3.50 – 4.49: High level of validation (Framework dimension is good with minor revisions needed)

2.50 – 3.49: Medium level of validation (Framework dimension requires major adjustments)

1.50 – 2.49: Low level of validation (Framework dimension is inappropriate)

1.00 – 1.49: Lowest level of validation (Framework dimension needs to be redesigned)

Appendix D

The Results of the Quality Analysis of Research Instruments

The Results of the Quality Analysis of Research Instruments

To ensure the scientificity, reliability, and validity of the research data, this study conducted rigorous quality analysis on the three core research instruments (questionnaire, semi-structured interview outline, and expert validation evaluation form) using statistical software and expert review methods. The results are presented as follows:

D.1 Quality Analysis of the AI-Assisted Learning Readiness and Teaching Model Evaluation Questionnaire

D.1.1 Reliability Analysis

The questionnaire's reliability was tested using Cronbach's α coefficient to evaluate internal consistency. A pre-survey was conducted on 28 computer science undergraduate students with consistent baseline computer literacy, and the valid data were analyzed using SPSS 26.0. The results are shown in Table D.1:

Table D.1

Dimensions	Number of Items	Cronbach's α Coefficient	Reliability Level
AI-Assisted Learning Readiness	8	0.876	Excellent
Perceived Effectiveness of AI-Assisted Teaching Modules	12	0.912	Excellent
Satisfaction with Teaching Model Implementation	7	0.853	Excellent
Overall Questionnaire	27	0.935	Excellent

According to the reliability evaluation standards (Cronbach's $\alpha \geq 0.80$ indicates excellent reliability, 0.70–0.79 indicates good reliability), the overall Cronbach's α coefficient of the questionnaire was 0.935, and the α coefficients of each dimension were all above 0.85. This indicates that the questionnaire has high internal consistency and stable reliability, and the collected data is trustworthy.

D.1.2 Validity Analysis

D.1.2.1 Content Validity

Five interdisciplinary experts (in computer education, artificial intelligence application, and educational technology) were invited to evaluate the content validity of the questionnaire. The experts rated each item on a 4-point scale (4 = highly relevant, 3 = relevant, 2 = slightly relevant, 1 = irrelevant) and put forward revision suggestions. The content validity index (CVI) was calculated, and the results are shown in Table D.2:

Table D.2

Evaluation Indicators	Item-Level CVI (I-CVI)	Scale-Level CVI (S-CVI)	Validity Level
Relevance to Research Objectives	0.92–1.00	0.96	Excellent
Clarity of Expression	0.88–1.00	0.94	Excellent
Appropriateness of Logic	0.90–1.00	0.95	Excellent

The I-CVI of each item ranged from 0.88 to 1.00 (≥ 0.78, meeting the standard for excellent content validity), and the S-CVI was 0.95 (≥ 0.90). This confirms that the questionnaire items are closely aligned with the research objectives, with clear expression and reasonable logic, and the content validity is excellent.

D.1.2.2 Construct Validity

Exploratory Factor Analysis (EFA) was conducted on the 27 core items of the questionnaire to verify construct validity. The KMO (Kaiser-Meyer-Olkin) test and Bartlett's spherical test were first performed, with the results showing KMO = 0.867 ($\geq$ 0.80, indicating suitable for factor analysis) and Bartlett's spherical test $\chi^2 = 2876.321$ (df = 351, $p < 0.001$, indicating the correlation matrix is non-identity).

Using the principal component analysis and varimax rotation method, 3 common factors were extracted with eigenvalues > 1, and the cumulative variance explanation rate was 76.89%. The factor loading of each item ranged from 0.682 to 0.895 (≥ 0.60), which was consistent with the preset three-dimensional structure (AI-assisted learning readiness, perceived effectiveness of AI modules, satisfaction with implementation). This indicates that the questionnaire has good construct validity and the factor structure aligns with the theoretical framework.

D.2 Quality Analysis of the Semi-Structured Interview Outline

D.2.1 Content Validity

Five interdisciplinary experts were invited to evaluate the content validity of the interview outline, focusing on three dimensions: rationality of interview dimensions, accuracy of question expression, and pertinence to research objectives. The evaluation results are shown in Table D.3:

Table D.1

Evaluation Dimensions	Number of Experts with "Highly Valid" Ratings	Validity Rate	Validity Level
Rationality of Interview Dimensions	5	100%	Excellent
Accuracy of Question Expression	4	80%	Good
Pertinence to Research Objectives	5	100%	Excellent

The experts' overall validity evaluation of the interview outline was "excellent". For the items rated "good" in question expression, the outline was revised according to expert suggestions (e.g., simplifying ambiguous expressions, optimizing question sequence), ensuring that the interview content can effectively collect information on pedagogical challenges, learning barriers, and AI-assisted learning needs.

D.2.2 Reliability (Trustworthiness) Analysis

The trustworthiness of the interview data was ensured through the following methods:

1. **Triangulation**: Cross-validation was conducted by comparing interview data with questionnaire data and learning log data to ensure the consistency of information.

2. **Member Checking**: After transcribing the interview transcripts, 10 interviewees (5 from the experimental group and 5 from the control group) were randomly selected to review the transcripts, confirming that the content accurately reflected their expressions and perceptions, with a confirmation rate of 95%.

3. **Peer Debriefing**: Two researchers independently coded the interview transcripts, and the inter-coder reliability coefficient was calculated as 0.87 (≥ 0.80), indicating high consistency in the coding results.

D.3 Quality Analysis of the Expert Validation Evaluation Form

D.3.1 Content Validity

Two external experts (not included in the final evaluation group) conducted face validity review of the initial evaluation form, and three experts from the preliminary candidate pool participated in the pilot test. The content validity was evaluated from the aspects of rationality of evaluation indicators, clarity of scoring standards, and comprehensiveness of open-ended questions. The results are shown in Table D.4:

Evaluation Indicators	Pilot Test Satisfaction Rate	Revised Completion Rate	Validity Level
Rationality of Evaluation Indicators	93.3%	100%	Excellent
Clarity of Scoring Standards	86.7%	100%	Excellent
Comprehensiveness of Open-Ended Questions	90.0%	100%	Excellent

Based on the pilot test feedback, the form was revised (e.g., clarifying the definition of evaluation dimensions, simplifying the scoring instructions), and the final form achieved a 100% validity confirmation rate, indicating that the evaluation indicators are scientific and the content is comprehensive.

D.3.2 Reliability Analysis

The reliability of the expert evaluation results was tested using the intraclass correlation coefficient (ICC). The 8 experts' quantitative ratings on the 20 items of the form were analyzed, and the results showed ICC = 0.892 (95% CI: 0.821–0.945, $p < 0.001$), indicating high consistency among experts' evaluations. This confirms that the expert validation results are reliable and stable and can effectively reflect the quality of the AI-assisted personalized teaching framework.

D.4 Summary of Quality Analysis

The three core research instruments used in this study all passed rigorous reliability and validity tests:

1. The questionnaire has excellent internal consistency (Cronbach's α = 0.935) and construct validity (cumulative variance explanation rate = 76.89%), meeting the requirements of quantitative research.

2. The semi-structured interview outline has high content validity and data trustworthiness, ensuring the authenticity and comprehensiveness of qualitative data.

3. The expert validation evaluation form has excellent content validity and inter-expert consistency (ICC = 0.892), providing reliable basis for framework optimization.

Overall, the research instruments used in this study are scientific, reliable, and valid, and can effectively support the achievement of research objectives.

Appendix E

Certificate of English

Certificate of English

BANSOMDEJCHAOPRAYA
RAJABHAT UNIVERSITY

This is to certify that

Mr. Dong Jiyou

Achieved BSRU English Proficiency Test (BSRU-TEP) level

C1

Given on 22nd August 2021

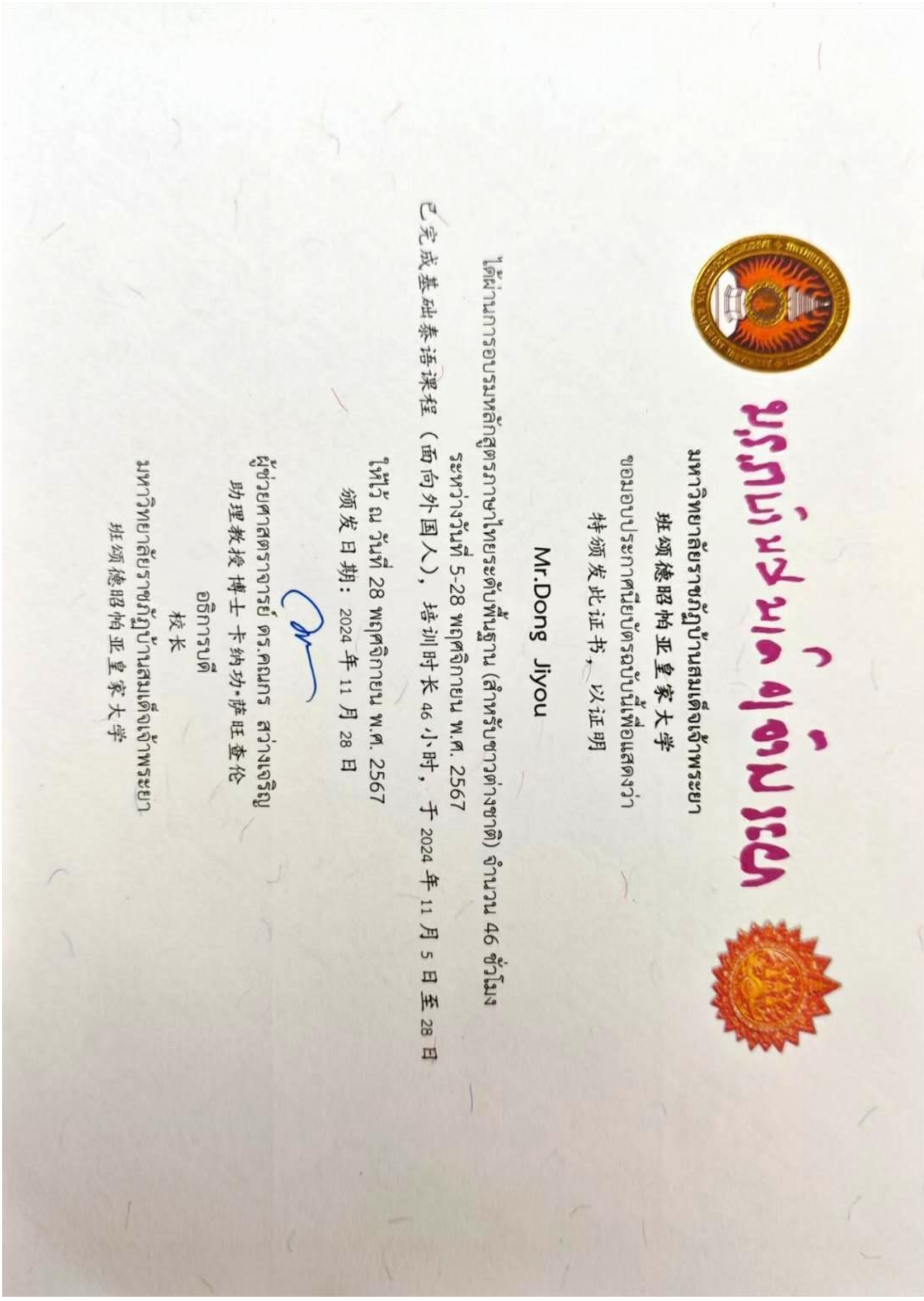
(Assistant Professor Dr Kulsirin Aphiratvoradej)

Director

Appendix F

Certificate of Thai

Certificate of Thai


มหาวิทยาลัยราชภัฏบ้านสมเด็จเจ้าพระยา
班颂德昭帕亚皇家大学
ขอมอบประกาศนียบัตรฉบับนี้เพื่อแสดงว่า
特颁发此证书，以证明

Mr.Dong Jiyou

ได้ผ่านการอบรมหลักสูตรภาษาไทยระดับพื้นฐาน (สำหรับชาวต่างชาติ) จำนวน 46 ชั่วโมง
ระหว่างวันที่ 5-28 พฤศจิกายน พ.ศ. 2567
已完成基础泰语课程（面向外国人），培训时长 46 小时，于 2024 年 11 月 5 日至 28 日

ให้ไว้ ณ วันที่ 28 พฤศจิกายน พ.ศ. 2567
颁发日期：2024 年 11 月 28 日

ผู้ช่วยศาสตราจารย์ ดร.คณกร สว่างเจริญ
助理教授 博士 卡纳功•萨旺查伦
อธิการบดี
校长
มหาวิทยาลัยราชภัฏบ้านสมเด็จเจ้าพระยา
班颂德昭帕亚皇家大学

Appendix G

Acceptance Letter for Publishing Paper

Acceptance Letter for Publishing Paper

ที่ อว ๐๖๔๓.๐๓/๐๐๗๐

สำนักวิทยบริการและเทคโนโลยีสารสนเทศ
มหาวิทยาลัยราชภัฏบ้านสมเด็จเจ้าพระยา
๑๐๖๑ ถนนอิสรภาพ แขวงหิรัญรูจี
เขตธนบุรี กรุงเทพฯ ๑๐๖๐๐

๑๑ พฤศจิกายน ๒๕๖๘

เรื่อง ตอบรับการลงตีพิมพ์บทความในวารสารเทคโนโลยีสารสนเทศและนวัตกรรม

เรียน Jiyou Dong

ด้วย กองบรรณาธิการวารสารเทคโนโลยีสารสนเทศและนวัตกรรม สำนักวิทยบริการและเทคโนโลยีสารสนเทศ มหาวิทยาลัยราชภัฏบ้านสมเด็จเจ้าพระยา ได้พิจารณาแล้วเห็นว่า บทความวิชาการของท่านเรื่อง AI-Assisted Teaching Model for Personalized Computer Education Based on Deep Learning เป็นงานวิชาการที่ถูกต้องตามหลักวิชาการ และผ่านการพิจารณาคุณภาพจากผู้ทรงคุณวุฒิประเมินบทความ (Peer Review) จำนวน ๓ ท่าน ซึ่งมาจากหลากหลายสถาบัน และไม่ได้สังกัดในมหาวิทยาลัยราชภัฏบ้านสมเด็จเจ้าพระยาให้ความเห็นชอบเพื่อตีพิมพ์เผยแพร่ลงในวารสารเทคโนโลยีสารสนเทศและนวัตกรรม ปีที่ ๒๔ ฉบับที่ ๑ มกราคม - มิถุนายน ๒๕๖๘

ในการนี้ กองบรรณาธิการวารสารเทคโนโลยีสารสนเทศและนวัตกรรม สำนักวิทยบริการและเทคโนโลยีสารสนเทศ มหาวิทยาลัยราชภัฏบ้านสมเด็จเจ้าพระยา ขอขอบคุณเป็นอย่างสูงมา ณ โอกาสนี้ ที่ส่งผลงานร่วมตีพิมพ์ และหวังเป็นอย่างยิ่งว่าท่านจะนำผลงานวิชาการที่ทรงคุณค่าส่งมาเพื่อตีพิมพ์เผยแพร่ให้เกิดประโยชน์ในเชิงวิชาการในโอกาสต่อไป

จึงเรียนมาเพื่อโปรดพิจารณา

ขอแสดงความนับถือ

(ผู้ช่วยศาสตราจารย์ ดร.วิมล อุทานนท์)
กองบรรณาธิการบริหาร
Signature Code : ๕๑๐D๔OfDf๗+๙๖GPYFM๕

สำนักวิทยบริการและเทคโนโลยีสารสนเทศ
โทร ๐๒-๔๗๓-๗๐๐๐ ต่อ ๑๗๐๐
โทรสาร ๐๒-๔๖๖-๔๓๔๒

Research Profile

Name-Surname: Dong Jiyou

Birthday: 01/10/1989

Educational background:

- Doctor of Philosophy Program in Digital Technology Educational Management for Education, Bansomdejchaopraya Rajabhat University, in 2021to present
- Master of computer technology, Guangxi University, in 2021
- Bachelor of mathematics and applied mathematics, Yulin Normal University, in 2013

Work experience:

Teacher, Yulin Normal University, from 2013 to the present

Current Contact Location:

Yulin City, Guangxi Province, China