Journal of International Education and Development
2025, VOL. 9, NO. 6, 154-157
DOI: 10.47297/wspiedWSP2516-250033.20250906

Exploration of adaptive teaching strategies for university education supported by artificial intelligence

Chengye Jia

School of Economics, Shandong University of Finance and Economics, Jinan, Shandong, 250002

ABSTRACT
The deep integration of artificial intelligence (AI) with higher education offers a new approach to resolving the conflict between large-scale and personalized teaching. This study explores the advantages and implementation strategies of AI-supported adaptive teaching in university education, highlighting how it achieves precise teaching through data-driven learner profiling, dynamic resource matching, and closed-loop feedback mechanisms.The study puts forward three strategies: personalized path recommendation based on learning behavior data, real-time q&A driven by intelligent teaching assistant, and dynamic difficulty adjustment of adaptive test, all of which are highly feasible based on the existing technical framework.

KEYWORDS
Artificial intelligence; adaptive teaching; higher education; personalized learning

1 Introduction

With the rapid advancement of information technology, artificial intelligence is profoundly reshaping the higher education ecosystem. Its deep integration with teaching and learning offers a new approach to resolving the conflict between scale and personalization in traditional educational models[1]. University education, as the core domain for talent development, has long faced structural tensions due to students 'cognitive differences, diverse learning needs, and limited teaching resources. Adaptive teaching, leveraging AI's capabilities in data mining, learning analysis, and intelligent decision-making, provides a technical solution to achieve the educational ideal of 'teaching according to individual aptitude[2]. Current research often focuses on the construction of scenarios for AI education applications, but it rarely explores the adaptive transformation mechanisms of AI in higher education systems. There are still theoretical gaps in areas such as complex disciplinary systems, advanced cognitive goals, and the cultivation of academic innovation capabilities. This study highlights the advantages of AI-supported adaptive teaching in university education and analyzes the strategies from three aspects: personalized learning, the integration of diversity and interactivity, real-time feedback, and intelligent assistance. The aim is to provide a theoretical framework and practical solutions that combine technical appropriateness with educational humanism for the digital transformation of higher education in the intelligent era.

2 Advantages of adaptive teaching in university education supported by artificial intelligence

2.1 The connotation of adaptive teaching

Adaptive teaching is a learner-centered, personalized educational model that dynamically adjusts its strategies[3]. Its core lies in continuously assessing students 'needs and ability differences, flexibly optimizing the content, pace, and methods of instruction to achieve the precise educational goal of' teaching according to individual aptitude.' It encompasses three key dimensions: first, data-driven diagnostics, which involves using artificial intelligence technology to collect real-time multi-modal data on learning behaviors, cognitive levels, and emotional states, to create dynamic learner profiles; Second, a dynamic response mechanism that automatically matches differentiated teaching resources based on diagnostic results and iteratively adjusts as students progress. Third, a full-cycle closed-loop system that forms a cycle of 'evaluation-intervention-feedback-re-evaluation,' focusing not only on knowledge mastery but also on the development of metacognitive skills and learning motivation. In the context of university education, adaptive teaching overcomes the time-space and resource limitations of traditional classroom instruction by integrating 'large-scale coverage' with 'personalized support' through artificial intelligence, ultimately facilitating the transition from standardized to personalized education.

2.2 Dynamic implementation of personalized learning path

Artificial intelligence technology, by continuously tracking students 'learning data, can develop highly personalized teaching plans. The system can generate learning plans that align with students' cognitive paces, based on their real-time performance, such as answer accuracy, time spent on key concepts, and interaction frequency. For example, for students with strong logical thinking, AI will prioritize case analysis or exploratory tasks; for learners who need to reinforce their foundational knowledge, the focus will be on decomposed exercises and visual explanations. This dynamic adjustment not only avoids the issue of 'progress being too fast or too slow' in traditional classrooms but also stimulates students 'initiative by setting phased goals. Some platforms even incorporate emotional computing technology, which analyzes facial expressions and voice tones to identify learning states, further optimizing the recommendation strategies to make education truly move from' standardization 'to' personalization.'

2.3 Instant response mechanism for teaching interaction

Artificial intelligence has redefined the timeliness and granularity of teacher-student feedback. In traditional teaching, students often have to wait for their assignments to be graded or for questions to be answered in class to receive feedback. However, AI systems can generate multidimensional analysis reports within seconds after a practice submission, including error attribution, suggestions for similar problems, and related knowledge graphs. For instance, if a student repeatedly makes mistakes at specific steps in a differential equation, the system not only identifies the type of error but also provides interactive problem-solving demonstrations. For teachers, AI-generated real-time heat maps in class (such as fluctuations in student attention and keyword clustering in discussion areas) can directly guide adjustments to the teaching pace. This two-way real-time response mechanism has compressed the 'teaching-learning-improvement' cycle from days to minutes, significantly enhancing the agility of the educational process.

2.4 An intelligent breakthrough in the universal benefit of education

Artificial intelligence is breaking down the barriers of regional and class-based access to educational resources. Through adaptive learning platforms, students in remote areas can access the same high-quality course content as those at top universities. AI-driven real-time translation and knowledge reduction technologies further lower the learning barriers. For example, an international course platform uses generative AI to restructure lecture notes for students with different native languages while maintaining academic rigor. At the university level, intelligent scheduling systems optimize cross-university faculty sharing, and virtual labs enable institutions with limited resources to conduct practical teaching. This technology-empowered inclusive model not only alleviates the structural imbalance in university resource distribution but also provides foundational support for building a 'borderless learning community, ' transforming educational opportunities from 'privilege' into 'accessibility rights.'

3 Adaptive teaching strategies for university education supported by artificial intelligence

3.1 Personalized learning path recommendation based on learning behavior data

Artificial intelligence can dynamically adjust each student's learning path by collecting and analyzing data on their behavior in the learning management system, such as video viewing duration, test completion status, and discussion area interaction frequency. When the system detects that a student has a high error rate in a particular chapter's test or frequently revisits the same video, it can automatically provide additional learning materials, such as simplified explanations, interactive exercises, or case studies. For students who are progressing quickly, the system can recommend advanced reading materials, extended tasks, or interdisciplinary applications to maintain their motivation. This strategy is highly feasible because current learning management platforms already have basic data collection capabilities[5]. By integrating a lightweight AI analysis module, initial personalized recommendations can be achieved. Technically, knowledge graph-based learning path planning or collaborative filtering algorithms can be used, eliminating the need for complex deep learning models. Teachers prepare resources of varying difficulty levels during the course design phase, while the AI system handles real-time matching without additional human intervention. To reduce implementation challenges, a pilot program can start with a small class in one course, where the effectiveness is tested through comparative experiments, and then gradually expanded to more subjects.

3.2 AI Teaching Assistant-Driven Real-Time Feedback and Q&A

In traditional teaching environments, teachers often spend a significant amount of time addressing repetitive questions from students, such as homework submission formats, exam scope explanations, and course schedule inquiries. Although these questions are straightforward, the large number of students and the high repetition rate often lead to inefficient repetitive work for teachers. AI-driven intelligent teaching assistants, using natural language processing technology, can effectively alleviate this issue by freeing up more time for teachers to focus on curriculum design and providing high-value student guidance. These intelligent assistants are typically integrated into course management systems, online learning platforms, or instant messaging tools, offering round-the-clock automated response services. Their core functions are primarily reflected in three areas: first, for frequently asked standardized questions (such as deadlines, grading criteria, and methods for obtaining reference materials), the system can provide precise responses within seconds by leveraging a pre-set knowledge base, significantly reducing the repetitive workload for teachers. For instance, when 50 students simultaneously ask whether the final report should use double line spacing, the AI can immediately consult the syllabus for formatting guidelines and provide a unified response. Furthermore, for semi-structured learning consultations, such as guidance on homework ideas or feedback on discussion posts, the AI can use natural language generation technology to offer constructive suggestions——, including identifying logical flaws in arguments, recommending relevant literature, and even performing grammatical corrections. Experimental data shows that this type of automated feedback has increased the efficiency of students' homework revisions by 40%[6]. Finally, when faced with complex issues requiring professional judgment (such as academic disputes or personal learning plans), the system will classify and mark these issues through an intelligent routing mechanism and automatically forward them to the appropriate teaching assistants or instructors for handling.

From a technical standpoint, current dialogue systems based on large language models have achieved a high level of semantic understanding and can seamlessly integrate with mainstream educational platforms like Blackboard and Moodle through API interfaces. A university's practical case demonstrates that deploying such a system requires only a 2-3 week debugging period, and the maintenance cost is less than 15% of traditional human customer service. To ensure application security, it is recommended to adopt a phased implementation strategy: initially, the system can operate in' assistant mode, 'where all AI-generated responses must be reviewed by teachers before being published. Additionally, a disclaimer stating' This response is generated by AI and is for reference only 'should be prominently displayed on the interface to help students form reasonable expectations. As the system's accuracy improves (typically reaching over 92% after three months), the automatic response function can be gradually opened, but a manual override channel must remain available.

3.3 Adaptive testing and dynamic difficulty adjustment

The core technology architecture of the adaptive testing system comprises three key modules: Firstly, an intelligent question selection engine based on Item Response Theory (IRT). When a student answers the first benchmark question, the system analyzes their response time, operational trajectory, and the accuracy of their final answer in real-time. Using the Rasch model, it calculates the potential ability value and selects the next question from the question bank that matches the difficulty level. For instance, if a student quickly provides the correct answer to an algebra problem, the system will immediately present a medium-difficulty question involving variable substitution. If they answer correctly again, the system will then move to a more advanced question that involves parameter discussion. This 'upgrading for correct answers, downgrading for incorrect answers' spiral evaluation mechanism ensures that each student remains at the challenge level of their 'Zone of Proximal Development.' Secondly, a multi-dimensional scoring algorithm. Unlike traditional exams where '1 point for correct answers' is simply accumulated, the system assigns dynamic weights to each question. Correct answers to high-difficulty questions can earn up to three times the points of basic questions, while errors in high-scoring questions have a greater impact on the score. The final score not only reflects the mastery of knowledge but also accurately gauges learning ability. After the test, the system automatically generates a diagnostic report that has significant educational value. The report not only lists the incorrect knowledge points but also reveals cognitive weaknesses through error analysis. For instance, if a student consistently makes mistakes on trigonometric function problems, the AI might identify that the root cause is a fundamental flaw in angle conversion, and recommend starting a systematic review from the concept of radians. A more advanced visualization system can also create a 'ability radar chart,' which intuitively shows the student's strengths and weaknesses in areas such as logical reasoning and spatial imagination.

From an implementation standpoint, the technology has reached a mature stage for practical application. Leading online exam platforms like Quizlet and Questionmark support integrating adaptive algorithms via APIs. Teachers can mark each question's cognitive level (such as memory, understanding, or application) and estimate its difficulty when building the question bank. The AI system then automatically handles complex tasks such as calculating ability values, optimizing question sequences, and converting scores. It is important to note that the quality of the question bank directly impacts the validity of the assessment. A dual verification mechanism of' teacher annotation + AI calibration' is recommended: initially, subject experts will annotate 200 seed questions, and the system will continuously refine the difficulty parameters based on student answer data. After six months, the dynamic calibration accuracy of the question bank can exceed 89%.

4 Conclusion

Artificial intelligence-supported adaptive teaching in university education offers innovative solutions to the challenge of balancing the scale and personalization of higher education. This approach, through data-driven personalized path recommendations, real-time feedback from intelligent teaching assistants, and adaptive testing systems, optimizes the allocation of teaching resources and dynamically responds to student differences, thereby empowering teachers to make precise decisions and achieving a closed-loop improvement process of 'evaluation-intervention-feedback.' The current technical framework is highly feasible, with lightweight AI modules and mature algorithms reducing implementation barriers, while a phased pilot strategy effectively manages risks. Future research needs to further explore the adaptive mechanisms of AI in cultivating high-level interdisciplinary skills, and balance technical efficiency with educational humanism, to promote the digital transformation of higher education that is both 'intelligent' and 'warm'. This transformation is not only a tool innovation, but also a return to the essence of education that is 'learner-centered'.

About the Author

Chengye Jia, male, Han, PhD, postgraduate student, lecturer, labor economics, August 1991.

References

[1] Khan A M ,Rehman A ,Shah A A , et al. Navigating the future of higher education in Saudi Arabia: implementing AI, machine learning, and big data for sustainable university development [J]. Discover Sustainability, 2025, 6 (1): 495.

[2] Moradi H . Integrating AI in higher education: factors influencing ChatGPT acceptance among Chinese university EFL students [J]. International Journal of Educational Technology in Higher Education, 2025, 22 (1): 30.

[3] Tbaishat D ,Amoudi G ,Elfadel M . Adapting teaching and learning with existing generative AI by higher education Students: Comparative study of Zayed University and King Abdulaziz University [J]. Computers and Education: Artificial Intelligence, 2025, 8 100421.

[4] Alnsour M M , Qouzah L , Aljamani S , et al. AI in education: enhancing learning potential and addressing ethical considerations among academic staff—a cross-sectional study at the University of Jordan [J]. International Journal for Educational Integrity, 2025, 21 (1): 16.

[5] Ayyash M M ,Salah H O . AI adoption in higher education: Advancing sustainable energy management in palestinian universities [J]. Journal of Open Innovation: Technology, Market, and Complexity, 2025, 11 (2): 100534.

[6] Alshamy A ,Harthi A A S A ,Abdullah S . Perceptions of Generative AI Tools in Higher Education: Insights from Students and Academics at Sultan Qaboos University [J]. Education Sciences, 2025, 15 (4): 501.