World Journal of Educational Research
ISSN 2375-9771 (Print) ISSN 2333-5998 (Online)
Vol. 12, No. 5, 2025
www.scholink.org/ojs/index.php/wjer

Original Paper

Analysis of the Construction and Practical Effects of an AI-assisted Teaching Model in English Teaching

Yang Xin[1]

[1] Foreign Language Teaching Department, Hainan Vocational University of Science and Technology, Haikou, Hainan, 571126, China

Received: August 21, 2025 Accepted: September 23, 2025 Online Published: October 03, 2025
doi:10.22158/wjer.v12n5p105 URL: http://dx.doi.org/10.22158/wjer.v12n5p105

Abstract

In the context of contemporary educational reform, the limitations of traditional English teaching methods have become increasingly prominent, failing to meet the diverse learning demands of students. With the rapid development of artificial intelligence technology, its in-depth application in the field of education is reshaping the paradigm of language learning, especially demonstrating revolutionary potential in personalized teaching and learning efficiency improvement. This study focuses on the cutting-edge topic of artificial intelligence-assisted teaching, systematically examining the innovative application models of artificial intelligence technology in English teaching. It not only provides technology-enabled solutions for teaching practice but also fills the research gap in the theoretical aspect of the integration of intelligent technology and language education. The research results include conclusions with practical guidance significance, aiming to provide multi-dimensional reference value for education practitioners and academic researchers.

Keywords

English teaching, Artificial intelligence, Model construction, Practical effectiveness

1. Introduction

In the context of the accelerated globalization process and the digital transformation of education, artificial intelligence technology has become the core driving force for the innovation of English education. According to the strategic plan “China Education Modernization 2035”, the deep integration of intelligent technology with the education system is listed as the key path to achieving educational modernization, with particular emphasis on the importance of building an “intelligent enhanced” language learning environment (Xiao et al., 2023). Currently, the penetration of artificial intelligence in EFL teaching presents three significant characteristics: Firstly, adaptive systems based on deep learning can precisely identify the cognitive characteristics of learners and achieve full-dimensional personalized training from vocabulary memorization to pragmatic abilities; Secondly, breakthroughs in natural language processing technology have enabled the accuracy of real-time speech evaluation and intelligent writing correction to reach practical levels (Wen, 2024); Thirdly, multimodal interaction technology has created immersive language acquisition scenarios, effectively compensating for the lack of contextual authenticity in traditional classrooms. It is worth noting that this technological empowerment has fundamentally transformed the teaching paradigm - from standardized teaching centered on teachers to data-driven precise guidance. This transformation not only improves learning efficiency but also brings about deep-seated issues such as the reconfiguration of teacher-student roles and digital ethics. Although the application prospects are broad, there are currently three major development bottlenecks: insufficient subject compatibility of intelligent teaching systems, the lack of teacher-human collaboration capabilities, and the absence of long-term effect evaluation mechanisms. The resolution of these problems will directly affect the sustainable development of artificial intelligence in English education.

2. Theoretical Foundation

2.1 The Constructivist Theory

As one of the most influential educational theories of the 20th century, the formation and development of constructivist theory have been significantly contributed to by several pioneering psychologists (Henson, 2003). This theory breaks new ground in redefining the fundamental relationship between teaching and learning, with its core proposition being that learners are not passive containers for receiving knowledge, but active subjects who construct their own knowledge systems through active participation in cognitive activities. Jean Piaget's (1973) theory of cognitive development provides important support for this view, as his research indicates that the acquisition of knowledge is essentially a complex cognitive activity where individuals systematically integrate and reconstruct new and old experiences in a continuous interaction with the environment. Constructivism particularly emphasizes the social-cultural dimension of learning, advocating the promotion of deep learning through high-level thinking activities such as collaborative dialogue and collective inquiry. This theoretical framework has had a revolutionary impact on modern language teaching, shifting the teaching paradigm from the traditional teacher-centered model to an interactive model centered on learners. In language classrooms guided by constructivism, teachers carefully design communicative tasks based on real contexts, such as scenario simulations and project collaborations, enabling learners to naturally acquire language skills in the process of solving practical problems. More importantly, this teaching model cultivates learners' metacognitive strategies, allowing them to continuously optimize their learning paths through continuous self-monitoring and reflection, and ultimately achieving the goals of autonomous language development and lifelong learning. From an educational practice perspective, constructivism not only revolutionizes classroom teaching methods but also redefines the goals and value orientation of education at a deeper level.

Artificial intelligence technology has injected revolutionary transformative power into the modern language education field. Its outstanding performance in building personalized and interactive learning environments aligns perfectly with the core demands of contemporary educational theories. Intelligent systems based on machine learning algorithms not only can precisely capture the cognitive characteristics and behavioral patterns of learners, but also can establish a dynamic and optimized teaching feedback loop: by continuously monitoring learning progress, analyzing error patterns, and evaluating knowledge mastery, the system can intelligently generate teaching content with a reasonable difficulty gradient, and use natural language processing engines to achieve simulated dialogue interaction. The personalized learning path design empowered by this technology fundamentally revolutionizes the traditional "one-size-fits-all" teaching model, allowing learners to obtain educational resources that match their cognitive development stages in the adaptive system. Advanced human-computer interaction technology is reshaping the dimensions of language acquisition scenarios, enabling learners to complete the construction of knowledge meaning in near-realistic communication contexts. Research data shows that the application of this technology that integrates contextual cognitive theory not only improves knowledge retention rates but also significantly enhances learners' intrinsic motivation (Huang et al., 2023). From the perspective of educational evaluation, the real-time diagnostic feedback and multi-dimensional learning analysis reports provided by AI systems offer unprecedented data support for formative evaluation of the teaching process, enabling the "teaching-learning-evaluation" integration to truly be achieved. Adaptive learning systems can dynamically adjust the difficulty and form of learning tasks, helping students construct deeper understanding in a progressive manner.

2.2 The Personalized Learning Theory

Personalized education, as an important innovative paradigm in the modern teaching system, fundamentally aims to establish a comprehensive and adaptive system centered on learners. This model utilizes deep learning analysis techniques to precisely capture the cognitive feature maps, knowledge structure gaps, and individualized learning tendencies of learners, thereby constructing a dynamic response teaching matrix. Its operational mechanism encompasses four core dimensions: Firstly, the intelligent path planning engine employs reinforcement learning algorithms to optimize teaching sequences in real-time; Secondly, the multi-modal feedback system provides nano-level precision development diagnoses through biometric recognition and behavior analysis; Thirdly, the content repository with cognitive flexibility adjustment capabilities can automatically reconfigure the difficulty gradient of teaching materials based on the knowledge entropy model; Most importantly, it cultivates metacognitive monitoring abilities, enabling learners to gradually establish a self-evolution mechanism driven by neural plasticity. Netcoh (2017) pointed out that adaptive learning content means that the difficulty and type of learning tasks will be adjusted according to the progress of learners, ensuring that they are always in a moderately challenging state. Additionally, personalized learning emphasizes students' autonomy, encouraging them to actively manage their learning processes and cultivating critical thinking and self-reflection abilities.

The artificial intelligence-driven personalized learning system is reshaping the modern educational paradigm. The adaptive learning platform based on deep learning algorithms can construct precise learner profiles. By analyzing students' cognitive patterns, knowledge mastery levels, and error types in real time, it provides targeted suggestions for optimizing learning paths. Personalized learning can also enhance learners' autonomy and self-confidence, stimulate their learning motivation, and increase their participation (Wei, 2023). At the same time, the immediate feedback and support students receive in the personalized learning environment can significantly reduce learning anxiety and improve learning outcomes. Many studies have also shown that personalized learning achieved through artificial intelligence has led to significant improvements in students' language skills, problem-solving abilities, and autonomous learning abilities.

2.3 The Input Hypothesis Theory

In the early 1980s, American linguist Krashen proposed the theory of second language acquisition, which explored how learners can effectively master and acquire a second language in a non-native environment. These theories have had a profound impact on foreign language teaching theory and practice. Teaching practice has proved that when formulating teaching outlines, selecting teaching content, choosing teaching methods, and applying teaching measures, one must follow the laws of language acquisition. Among them, the input hypothesis theory points out that the key to language learning lies in exposure to comprehensible input slightly above the current language proficiency level, which is known as "i+1" input (Krashen, 1982). This theory emphasizes the importance of input and holds that abundant language input is the key to language acquisition, and such input must be provided with an appropriate level of challenge for learners to understand. Through continuous exposure to this comprehensible input, learners can naturally acquire the second language without relying on direct language teaching or grammar training. This theory emphasizes the importance of input, arguing that learners need a large amount of language exposure to gradually internalize language structures and improve language proficiency. Artificial intelligence-assisted language learning and teaching support the input hypothesis theory by providing students with appropriately challenging English learning materials of the right difficulty level. The artificial intelligence technology can adjust the learning content based on individual differences and changes in the learning process, push closely related learning materials, and significantly improve the comprehensible input and language learning outcomes. The artificial intelligence system will automatically adjust the content and difficulty of the learning materials based on students' learning records, reading behaviors, and test results, ensuring that students are exposed to "i+1" input that is suitable for their current language level. This ensures that the input materials are both challenging and not too difficult for students, helping them make progress in language learning based on understanding. Through machine learning algorithms, artificial intelligence can track students' learning progress, identify their strengths and weaknesses, and recommend learning materials with appropriate complexity, helping students constantly challenge themselves based on understanding. Artificial intelligence can also dynamically modify the difficulty of learning tasks based on students' feedback and performance, ensuring that students can steadily improve their language proficiency and reach higher levels of language comprehension and application.

3. Research Methods

3.1 The Literature Analysis Method

Based on a large-scale literature survey of authoritative academic databases and physical library resources at home and abroad, this study adopted a scientific and rigorous bibliometric analysis method to systematically sort out and evaluate the academic achievements in the intersection of artificial intelligence technology and English teaching. By deeply analyzing the academic value and practical significance of existing research results, not only did it clarify the research framework and development trend of this field, but also precisely identified the theoretical gaps and methodological limitations of current research. The implementation of this foundational research work has provided a solid theoretical support system for this project, and at the same time established an innovative research entry point, offering clear theoretical guidance and methodological basis for subsequent empirical research and application development of artificial intelligence technology in the English teaching scenario.

3.2 The Questionnaire Method

To systematically evaluate the impact of artificial intelligence-assisted teaching on students' interest in English learning, this study adopted a longitudinal comparative research method. The experimental class and the control class were selected as the research subjects, and standardized questionnaire surveys were conducted before and after the experimental period. The questionnaire

Table1. English Learning Survey Questionnaire Dimension Structure Table

First-level dimension	Secondary dimension	Third-Level Dimension
English Learning	Learning Interest	Learning Style Preferences
		Learning Motivation
		Learning Materials Interest
		Learning Task Interest
		Interest in Learning Courses
		Topic Of Interest in Learning
	Learning Attitude	English Learning Emotional Attitude
		English Learning Cognitive Attitude
		Learning Behavioral Attitude

	Teaching Feedback	Teaching Satisfaction Evaluation Evaluation of Learning Resources Evaluation of Learning Needs Interactional Feedback Classroom Participation Issues Classroom Activity Participation

design focused on three core dimensions: students' interest in English learning, changes in learning attitude, and the acceptance of the new teaching model.

Based on a systematic review of existing academic literature and an assessment of teaching practice needs, the questionnaire was designed. The questionnaire consisted of 15 questions, and each question had 5 options using the Likert five-point scale (1 = very agree, 5 = very disagree). In terms of the questionnaire structure, it could be divided into three primary dimensions: students' interest in English learning, English learning attitude, and English teaching evaluation feedback. s. Table 3.1 details the levels of each question.

Before the teaching experiment, 123 senior high school students were randomly selected for a pilot test of the questionnaire. After conducting the reliability test, the Cronbach's Alpha value was 0.841, indicating that the questionnaire has high reliability.

4. The Artificial Intelligence Assisting Higher English Teaching Practice

4.1 The Artificial Intelligence-assisted Teaching Platform

After rigorous technical assessment and educational scenario adaptability tests, this research ultimately selected the "Xinfei Starfire (SparkDesk) Cognitive Large Model" independently developed by iFLYTEK as the core artificial intelligence auxiliary platform for the English classroom teaching experiment. This platform, as a leading domestic generative AI system, not only possesses industry-leading text generation and semantic understanding capabilities, but also achieves the coordinated operation of seven core functional matrices through a modular intelligent agent architecture. Its groundbreaking multi-round conversation engine and deep learning algorithms enable the system to accurately interpret the complex educational needs proposed by teachers and students, and provide intelligent responses covering multiple modalities such as text, voice, and images. In the educational practice aspect, this platform significantly enhances the depth and breadth of teaching interaction through the dynamic knowledge graph construction and personalized learning path planning. Its unique Prompt engineering mechanism allows users to obtain customized learning resources by precisely adjusting instructions. This "need-feedback" precise matching mode provides an innovative technical solution for modern intelligent education. Currently, this platform has established an ecosystem consisting of hundreds of intelligent agents in various educational vertical fields, and its continuously evolving semantic understanding capabilities are redefining the industry standards for AI-assisted teaching.

4.2 The Construction of an Artificial Intelligence-assisted Teaching Model

The artificial intelligence-assisted English teaching model consists of four stages.

The first stage adopts an innovative pre-learning mode based on the multi-modal learning theory. In this stage, through systematic teaching design, two goals are achieved: one is to activate students' autonomous learning mechanism, and the other is to construct a multi-dimensional knowledge framework. At the specific implementation level, teachers rely on intelligent education platforms (such as Xunfei Xinghuo) to design tiered pre-learning tasks, requiring learners to actively collect diverse digital resources related to the course topic, including but not limited to professional podcasts, visual data charts, documentary clips, and other high-value materials. This process not only compensates for the limitations of textbooks in presenting cultural contexts but also cultivates students' core literacy in using digital tools for knowledge integration. The pre-class information sharing section adopts the "1+N" collaborative model. Each student, while presenting their personal learning achievements, needs to critically evaluate the resources of other classmates. This interactive preheating not only enhances classroom participation but also lays a cognitive foundation for subsequent in-depth learning.

The second stage is adaptive English learning with personalized feedback. During the teaching process, teachers can guide students to use speed reading strategies to quickly extract key information from visual materials, and use the immediate diagnostic function of the intelligent system to test comprehension. This dual-track feedback mechanism ensures the classroom participation and mental activity of all students. In the self-study stage, the multimodal AI learning engine equipped on the platform can intelligently generate three-dimensional learning plans based on individual learning characteristics, including reading comprehension, listening training, and oral assessment. Its adaptive algorithm can adjust the difficulty coefficient in real time, truly achieving personalized and precise learning experiences for each individual. This new teaching model, which combines professional guidance from teachers and personalized adaptation by AI, is reshaping the efficiency boundaries of second language acquisition.

The third stage is the learning output through intelligent interaction and collaboration. In the advanced application stage of English language acquisition, the intelligent interaction and collaboration mechanism plays a crucial role. In this stage, by creating multi-dimensional interactive scenarios, the dual capabilities of knowledge internalization and output are enhanced. The core lies in creating a two-way dynamic feedback teaching environment: teachers design immersive tasks such as group debates and scenario simulation theaters through structured design, stimulating learners' desire for language output in real contexts; the artificial intelligence-assisted system provides real-time precise feedback such as grammar correction and expression optimization, forming a virtuous cycle of "input-output-feedback".

The fourth stage is the continuous optimization of multi-dimensional assessment and feedback. In terms of teaching evaluation, the multi-dimensional evaluation indicators include classroom comprehension ability, classroom participation, group cooperation performance, learning records on the intelligent platform, completion of after-class notes and essays, etc. After class, teachers provide personalized tutoring suggestions to students who perform poorly in aspects such as classroom participation and interaction collaboration output based on their historical learning records on the platform, to help them improve their learning effectiveness. With the help of the intelligent platform’s backend, teachers can also supplement classroom materials and adjust subsequent teaching strategies to continuously optimize the overall teaching effect.

In conclusion, the AI-assisted teaching model in the experimental class provides students with personalized learning paths through the intelligent platform, significantly enhancing their autonomous learning abilities. Through group cooperation and cultural expansion activities, students not only improve their language skills but also enhance their cultural awareness and teamwork spirit. By integrating AI technology into English teaching, emphasizing students’ language skills, thinking quality, and cultural awareness, and focusing on cooperative learning and critical thinking cultivation, this teaching model combines personalized, autonomous, and interactive learning, while meeting the learning needs of students at different levels and effectively improving students’ learning outcomes and participation.

5. The Experimental Results

Before and after the experiment began, 86 questionnaires and test papers were distributed to the students of the experimental class and the control class respectively, and 100% of them were ensured to be returned.

5.1 The Analysis of Questionnaire Results before the Experiment

Based on the sample T-test analysis of the pre-experiment survey results, there were no significant overall differences between the experimental class and the control class in terms of English learning interest, attitude, and teaching feedback.

Table 2. Analysis of T-test Results of Samples before the Experiment

Variable	Class	Sample Number	Mean	Std.	t	P
Learning Interest	Experimental Class	42	3.35	0.540	-1.857	0.067
	Control Class	44	3.61	0.721		
Learning Attitude	Experimental Class	42	3.47	0.811	0.603	0.548
	Control Class	44	3.37	0.724		
Teaching	Experimental Class	42	3.40	0.901	-0.581	0.563

Feedback	Control Class	44	3.51	0.923		

The average score of learning interest in the experimental class was 3.35, while that in the control class was 3.61, with a p-value of 0.067. The t-test was close to the significance level, but did not reach 0.05. This indicates that there was a slight difference in learning interest between the experimental class and the control class before the experiment. In terms of learning attitude, the score for the experimental class was 3.47, and for the control class it was 3.37, with a p-value of 0.548. The difference was not significant. This suggests that the students in the two classes had similar attitudes towards English learning before the experiment. In terms of teaching feedback, the average scores for the experimental class and the control class were 3.40 and 3.51 respectively, with a p-value of 0.563. Similarly, it did not reach the significance level. Before the experiment, the differences in teaching feedback between the experimental class and the control class were also not significant. These results indicate that the two classes had relatively similar foundations before the experiment, providing a good basis for the subsequent experiment.

5.2 The Analysis of Questionnaire Results after the Experiment

The sample T-test results of the questionnaire survey after the experiment in the experimental class and the control class are shown in Table 5.12.

Firstly, the average score of learning interest in the experimental class was 2.58, which was significantly lower than the average score of 3.31 in the control class. The corresponding t-test distribution value and p-value both indicated a significant difference. This indicates that there was a significant difference in learning interest between the experimental class and the control class after the experiment, and the learning interest of students in the experimental class significantly increased.

Table3. Analysis of T-test Results of Samples before the Experiment

Variable	Class	Sample Number	Mean	Std.	t	P
Learning Interest	Experimental Class	42	2.58	0.683	-5448	0.000
	Control Class	44	3.31	0.840		
Learning Attitude	Experimental Class	42	2.25	0.756	-6.741	0.000
	Control Class	44	3.46	0.894		
Teaching Feedback	Experimental Class	42	2.76	0.666	-5.808	0.000
	Control Class	44	3.51	0.781		

Secondly, in terms of learning attitude, the average score of the experimental class was 2.25, which was lower than that of the control class (3.46), showing a significant improvement. This indicates that the learning attitude of the experimental class significantly improved after the experiment, and there was a significant difference compared to the control class.

Finally, in terms of the response to English teaching, the average score of the experimental class was 2.76, which was significantly lower than that of the control class (3.51). All the t-distribution values of the significant tests were greater than 5, and the corresponding P-values were all less than 0.05, indicating that the differences were statistically significant. This suggests that the improvement in teaching feedback of the experimental class was also significantly better than that of the control class.

In summary, these results verify the effectiveness of the artificial intelligence-assisted experimental English teaching model, indicating that the experimental class has significantly improved in learning interest, learning attitude, and teaching feedback, and there are significant differences compared to the control class.

6. The Experimental Results

This study conducted an empirical research on 86 vocational undergraduate students over a period of 4 months, exploring the impact of artificial intelligence-assisted English teaching. The following conclusions were drawn:

(1) The use of artificial intelligence in teaching significantly enhances students' English proficiency, validating the input hypothesis theory.

The application of artificial intelligence in the field of English teaching has achieved a breakthrough. Experimental data shows that the student group using AI-assisted teaching demonstrated statistically significant progress in the post-test, with a much greater improvement rate than the control group using traditional teaching methods. This phenomenon can be attributed to the three core functions of the intelligent teaching system: the construction of personalized knowledge maps based on learning analysis, real-time behavior data-driven dynamic difficulty adjustment, and the closed-loop feedback mechanism formed by multimodal interaction. These features together have led to a significant improvement in the depth of cognitive processing and knowledge retention during the language acquisition process.

(2) Artificial intelligence-assisted teaching positively influences students' interest and attitude in English learning, and expands the application of constructivist and personalized learning theories.

In the questionnaire survey, the English learning interest scores of students in the experimental class were significantly higher than those in the control class, indicating that artificial intelligence technology can effectively enhance students' learning enthusiasm. The personalized support provided by the artificial intelligence platform, including helping students solve problems encountered in actual English learning and generating learning materials that match their interests, also enables them to quickly see their progress, thereby increasing their sense of achievement and enthusiasm for learning.

The above research results further expand the application scenarios of the constructivist theory. Under the framework of the constructivist theory, learners construct knowledge through interaction with learning resources. Through artificial intelligence technology, learners not only interact with teaching resources but also receive immediate feedback and dynamic-adjusted learning content, thereby further strengthening the learning process of knowledge construction. This two-way interaction is more in line with the “active construction” principle emphasized by constructivism.

(3) Integrating artificial intelligence into future English teaching is of great significance and necessity.

Based on the quantitative analysis of the survey questionnaire and the qualitative feedback from students, the majority of students hold a positive attitude towards artificial intelligence-assisted learning and teaching. The application of artificial intelligence technology in the current education system has gained significant teaching recognition. In the field of language acquisition, this technology-enabled innovative model demonstrates unique teaching value: the intelligent interactive environment constructs not only reconfigures the traditional teaching paradigm but also achieves precise teaching intervention through a real-time data response mechanism. The dynamic feedback loop provided by the intelligent system and the adaptive learning path significantly optimize the processing efficiency of language input. This cognitive reinforcing effect is manifested as the coordinated improvement of motivation levels and metacognitive abilities in second language acquisition. Through the multi-modal interaction design of the technology-mediated learning context, it effectively activates the situational cognition of learners. This psychological mechanism change makes the knowledge construction process more autonomous and continuous. From the perspective of the acceptance model of educational technology, this positive teaching feedback not only reflects the dual advantages of technical usefulness and ease of use, but also reflects the natural adaptability of digital natives to intelligent education ecology. Its deeper significance lies in providing a quantifiable practical basis for the transformation of educational informatization.

References

Henson, K.T. (2003). Foundations for learner-centered education:A knowledgebase. *Education*, *124*(1).

Huang, X., Zou, D., Cheng, G., Chen, X., & Xie, H. (2023). Trends,research issues and applications ofartificial intelligence in language education. *Educational Technology&Society*, *26*(1), 112-131.

Krashen, S. (1982). *Principles and practice in second language acquisition*.

Liu, Y. (2024). Exploration of the Paths of Enabling High School English Teaching with Generative Artificial Intelligence. *English Teacher*, *24*(12), 91-94.

Netcoh, S. (2017). *Students' experiences with personalized learning: An examination using self-determination theory*. The University of Vermont and State Agricultural College.

Piaget, J. (1973). *To understand is to invent:The future of education*.

Wang, L. (2024). Analysis and Research on the Practice of Extended Reading in Junior High School English under the Background of Artificial Intelligence. *Examination Weekly*, (05), 104-108.

Wei, L. (2023). Artificial intelligence in language instruction:impact on English learning achievement,L2 motivation,and self-regulated learning. *Frontiers in Psychology*, *14*, 1261955.

Wei, Z. (2024). *Research on the Quality Evaluation of High School English Classroom Teaching under the Background of Artificial Intelligence*. Shanxi Science and Technology Newspaper, 2024-09-10 (B07).

Wen, Q. F., & Liang, M. C. (2024). Human-Machine Interactive Negotiation Ability: ChatGPT and Foreign Language Education. *Foreign Language Teaching and Research*, *56*(02), 286-296 + 321.

Wu, H. P. (2023). How Language Teachers Can "Chat" with Generative Artificial Intelligence - Taking English Subject as an Example. *Digital Teaching in Primary and Secondary Schools*, *2023*(8), 75-79

Xiao, J., Bai, Q. C., Chen, M. et al. (2023). Generative Artificial Intelligence Empowering Online Learning Scenarios and Implementation Paths. *Electronic Education Research*, *44*(09), 57-63 + 99.