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Artificial Intelligence Aided Diagnosis and Feedback System in English Teaching

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Because English isnow the main language used for international communication, the innovation of its teaching methods is particularly important given the increase of globalization and technological progress. This study explores the ways that digital technology and intelligent teaching can improve the efficiency and effect of language learning. After conducting an in-depth analysis of digital technology applications in education, the theoretical basis of intelligent assisted instruction, and its practical application in the teaching of English, this study designed and implemented a series of experiments. After collecting data from specific target groups, the study constructed an artificial intelligence-(AI-) assisted diagnosis and feedback system with advanced algorithms and technologies, aimed at providing personalized learning paths and real-time feedback for learners of English. The results show that the system can significantly improve learners' English ability, especially in terms of accuracy and fluency of language use. Through the evaluation and analysis of the model performance, the study further verified the intelligent CAI(Computer-Assisted Instruction) system's potential to improve the quality and efficiency of education. It is anticipated that this research will provide innovative pedagogy for the teaching of English, and also offer theoretical and practical references for the development and application of educational technology in the future.

Keywords: artificial intelligence (AI) assisted instruction, English teaching, diagnosis and feedback system, intelligent teaching technology, personalized learning path

1. INTRODUCTION

In today's society, characterized by the acceleration of globalization, English teaching has become a core issue in the field of global education. With the rapid development of technology, especially in the fields of information technology and artificial intelligence (AI), the traditional teaching mode is facing both unprecedented challenges and opportunities. The integration of digital and intelligent technology has brought a new dimension to language learning, making it possible to offer personalized learning and real-time feedback. In this context, using AI to assist English teaching not only improves teaching efficiency, but also enhances the learning experience, especially when diagnosing learning outcomes and providing feedback to learners. With the expansion of globalization, English, as the common language of international communication, plays a vital role in personal career development, cultural exchange and international communication. Therefore, the exploration of the latest scientific and technological advancements available to optimize English teaching has become a hot spot in the fields of educational science and technology research. At the same time, with the increasing demands of educators and learners for teaching quality and better learning outcomes, how to achieve more accurate learning diagnosis and an effective feedback mechanism through technical means has become the key to improving the quality of English teaching. These background factors jointly promote the demand for the research of AI-aided diagnosis and feedback system in English teaching, in order to find more scientific and efficient teaching

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methods and meet the modern society's new requirements for English teaching.

In the era of AI, English teaching is experiencing unprecedented reform and development. Ruan suggested English teaching reform and model design specifically for the era of artificial intelligence, emphasizing the application potential of AI technology in education reform [1]. Sun, Anbarasan, & Praveen Kumar further designed an online intelligent English teaching platform based on AI technology, with the aim of improving teaching efficiency and learning experience [2]. Sun&Li (2020) explored the possibility of using artificial intelligence to build an ecological environment for English teaching within the big data context, which reflected the new trend of building an educational ecosystem driven by data [3].

In regard to the intelligent processing of English teaching content, Li used support vector machine (SVM) technology to identify and classify English teaching content, which improved the accuracy of teaching content processing [4]. Zhang proposed an innovative English teaching model based on a machine learning neural network and image super-resolution technology, and demonstrated that technology can improve teaching quality [5]. Luo & Zhu [6] and Choi [7] use deep learning and computerized correction feedback systems to further improve the accuracy of English teaching content identification and error analysis.

In the design and application of an intelligent feedback system, Ma used machine learning technology to analyze students' feedback, and provides suggestions on course selection for English teaching in higher vocational education [8]. Zhang [9] and Li& Gou [10] proposed an English word-learning feedback system based on a smart phone APP and an English teaching system based on video feedback method, and emphasized the important role of feedback in improving learning efficiency. In addition, Zhang& Gao discussed the use of big data analysis to evaluate the classroom teaching quality and feedback system, showing that big data technology can be used to improve teaching quality [11].

To establish an English teaching ecological environment and data-driven model, Chen constructed a multi-dimensional corpus data-driven English language teaching model, which demonstrated the importance of data analysis in the optimization of teaching content [12]. Seterington, Woods, & McLean [13] and Chen, Chen & Tsai [14] promoted the improved learning outcomes of online discussion by means of an interactive feedback model and an instant semantic analysis feedback system. Tseng, Cheng & Wang explored the real-time facial expression recognition technology through dense and tight activation blocks, which further enhanced the ability of teaching interaction and analysis of students' emotions [15].

These studies explored the application of AI technology in English teaching from many perspectives: from the intelligent processing of teaching content to the design of personalized learning path, and then to the development of an intelligent feedback system. AI technology not only improves teaching efficiency and quality;it also stimulates students' learning motivation and brings revolutionary changes to the field of English teaching [16].

The purpose of this study is to conduct an in-depth analysis and evaluation of the effect of applying AI technology for auxiliary diagnosis and feedback in English teaching. By designing, developing and implementing a teaching assistant system based on AI, this study aims to improve educators' understanding of learners' learning process, optimize teaching strategies, and provide learners with personalized learning experience and immediate feedback.

In regard to theory, this study expands the theoretical framework for the effectiveness of an intelligent teaching system in the field of educational technology, providing new insights and theoretical support for the application of AI in language teaching. In practice, the research results are expected to provide new perspectives and tools for English teaching practice, so that educators can diagnose learners' needs more accurately and adjust teaching methods and contents accordingly, thereby improving teaching outcomes and learners' satisfaction. This study also aims to promote the innovative development of educational technology, help to drive the progress of education in a more intelligent and personalized direction, and provide guidance and a feasible reference for a future education model.

This study focuses on the development and evaluation of an AI-aided diagnosis and feedback system for English teaching. The research content covers the application of digital technology in education, and the research will clarify the theoretical basis of intelligent assistant teaching technology and the strategies and methods used to integrate AI technology in English teaching practices. Following an in-depth exploration of adaptive learning theory, a cognitive diagnosis model, and the effectiveness of a feedback system in the learning process, a system that can provide personalized feedback and suggestions according to learners' learning situation is constructed. The development of the system is based on advanced AI algorithms, and involves data collection, preprocessing, model construction, system implementation and final performance evaluation. The study also includes the evaluation of the application effect of the system in a real teaching environment, in order to determine its contribution to improving English teaching and learning outcomes, and learners' learning efficiency. This study also explores the impact of the proposed system on educators' teaching strategies and methods, and its potential value in improving the overall teaching quality.

2. OVERVIEW OF DIGITAL TECHNOLOGY AND INTELLIGENT ASSISTED INSTRUCTION

2.1 The Application of Digital Technology in Education

2.1.1 Digital Teaching Resources and Platforms

Digital teaching resources and platforms are playing an increasingly significant role in the modern education system, especially in the field of English teaching. These resources and platforms greatly enrich the teaching content and enhance the learning experience by providing a variety of learning materials and interactive tools. Digital teaching resources include online courses, e-books, interactive exercises, video lectures and other forms, which make learning more flexible

and personalized and assist students to learn according to their own pace and interests. The teaching platform provides a centralized environment for educators and learners, including not only learning management system (LMS) and curriculum management system (CMS), but also platforms specially designed for language learning, such as multimedia interactive teaching software and online language learning community. These platforms usually have functions enabling the tracking learning progress, evaluating learning achievements and providing immediate feedback, so that educators can monitor the learning process more effectively and adjust teaching strategies in time.

The application of digital teaching resources and platforms improves the efficiency and quality of teaching, and also promotes educational equity. Through the Internet, learners from different regions and backgrounds can access high-quality teaching resources, which greatly narrows the educational gap between urban and rural areas and regions. In addition, these digital tools and resources also help educators to offer large-scale online open courses (MOOCs), enabling learners around the world to share knowledge and learning experiences.

In short, digital teaching resources and platforms have become an indispensable part of modern education. By providing rich learning materials and advanced teaching tools, they not only enhance the effectiveness and interest of learning, but also contribute to educational equity and the global sharing of educational resources.

2.1.2 Teaching Management System and Learning Analysis

Learning Management Systems, LMS) and Learning Analytics, LA) play a vital role in the modern educational environment. By collecting and analyzing learners' data and behavior patterns, these technologies provide educators with in-depth insight and help them optimize teaching methods and learning processes.

(1) Teaching Management System (LMS)

LMS provides an integrated platform for educational institutions, teachers and students, and supports curriculum design, assignment, tracking of learning progress, and performance management. These systems can facilitate the effective organization and presentation of course content, and provide a space for communication and collaboration, such as forums and instant messages, to enhance interactive teaching. The widespread application of LMS makes distance teaching and online learning more feasible and efficient, and greatly improves the flexibility and accessibility of teaching.

(2) Learning analysis (LA)

Learning analysis uses big data technology and machine learning algorithms to analyze learners' interaction, participation and achievements, aiming at identifying learning patterns, predicting learning outcomes, and supporting decision-making through these insights. Learning analysis can help educators identify students' learning difficulties, adjust teaching strategies accordingly, and provide students with personalized learning paths and support. For example, by analyzing learners' behavior data on the online platform, educators can identify what is too difficult or too simple for students, and make appropriate adjustments.

The combination of a teaching management system and learning analysis can greatly improve the educational outcomes. The structured teaching and learning environment provided by LMS, together with the insights obtained from learning analysis, constitute a powerful tool set. In practice, educators can use LMS to manage courses and evaluate students' homework, and at the same time use learning analysis tools to analyze students' learning behavior and achievements, so as to better understand students' learning needs and progress.

2.2 The Theoretical Basis of Intelligent Assisted Instruction

2.2.1 Adaptive Learning Theory

Adaptive learning theory focuses on how to achieve the personalized adjustment of educational content and learning experience via technical platforms so as to adapt to each learner's unique needs, abilities and learning speed. This theory is based on the fact that learners have significant differences in the path, speed and style of knowledge acquisition, and advocates the use of technical means to identify these differences and adjust teaching methods and contents accordingly.

An adaptive learning environment usually relies on complex algorithms and data analysis techniques, such as AI and machine learning, to analyze learners' interactive data, identify their learning patterns, predict learning outcomes, and provide personalized learning resources and activities accordingly. The goal of this method is to create a learning environment that can automatically adapt to changes in learners' abilities and needs, so as to optimize the learning process and improve learning efficiency and effectiveness.

The key principles of the adaptive learning theory are:

(1) Learner Centered: emphasis is placed on the needs and abilities of learners as the center of designing and implementing learning activities.

(2) Real-time feedback: through continuous monitoring and analysis of learners' activities, immediate feedback and guidance are given to help learners adjust their learning strategies.

(3) Personalized path: a customized learning path is suggested according to learners' progress and performance, including adapting to learners' content, level of difficulty, and format.

(4) Dynamic adjustment: The learning environment can dynamically adjust learning content and strategies according to learners' interactions and achievements.

The educational platform and tools applying the adaptive learning theory can provide a more flexible and efficient learning method, especially in a large-scale and diversified learning environment. By accurately identifying learners' needs and providing corresponding support, adaptive learning helps to achieve a more personalized educational experience and maximize the potential of each learner.

2.2.2 Cognitive Diagnosis Model (CDM)

The cognitive diagnostic model (CDM) is a set of statistical models used to evaluate learners' mastery of specific knowledge and skills, in order to reveal learners' cognitive strengths and weaknesses. By accurately diagnosing learners' abilities, CDM provides a theoretical basis for personalized teaching and learning support. These models determine learners' mastery of specific knowledge points or skills by analyzing their performance by means of tests or evaluations.

CDM usually includes the following key components:

(1) Cognitive attribute: This is the basic unit that constitutes learners' ability, such as specific skills, concepts or knowledge points.

(2) Q matrix: This is a table used to describe the relationship between topics and cognitive attributes. Each question is associated with a set of cognitive attributes, and this association shows the ability needed to solve the question.

(3) Proficiency analysis of learners: Based on the performance of learners in the test, CDM can generate a detailed analysis of their mastery of specific cognitive attributes.

The CDM is implemented with these steps:

(1) Define cognitive attributes: clearly identify and define the key cognitive attributes in the teaching content.

(2) Building Q matrix: build a matrix to correspond the test questions with related cognitive attributes.

(3) Data collection and analysis: collect data by evaluating learners' performance, and then use CDM to analyze the data to identify learners' abilities and cognitive weaknesses.

(4) Ability analysis: According to the analysis results, provide each learner's ability analysis report.

Through this process, CDM can provide educators with an in-depth understanding of learners' specific cognitive ability, so that they can design more effective teaching strategies and solve specific problems encountered by learners. In addition, the application of CDM helps to optimize the allocation of teaching resources and ensure that they are used efficiently.

In a word, the cognitive diagnosis model provides an accurate method for understanding learners' specific learning needs and challenges. By applying CDM, educators can devise teaching plans based on empirical data, while learners can obtain more targeted learning support and feedback, thus improving their learning outcomes

2.2.3 The role of Feedback System in the Learning Process

In the interaction between teaching and learning, the feedback system plays the role of a bridge, connecting educators' teaching goals with students' learning outcomes. By receiving feedback about their learning progress and understanding level, learners can better evaluate their learning strategies and methods and make corresponding adjustments to improve their learning efficiency. Positive feedback can enhance learners' sense of accomplishment and self-confidence, while constructive feedback can stimulate learners' willingness to overcome challenges, thus increasing their motivation to learn. Feedback is not only limited to simple hints of right or wrong, but also includes the correction of misunderstanding and the deepening of conceptual understanding, which helps the learning process to change from superficial learning to deep learning, and promotes the development of critical thinking and problem-solving ability. The feedback system can also provide educators with real-time data of learners' learning conditions and needs, so that educators can adjust teaching contents and methods in time to better meet learners' needs.

When designing and implementing the feedback system, it is necessary to ensure the timeliness and relevance of feedback to improve the learning effect. In addition, various forms of feedback, such as text, audio or video feedback, are adopted to meet the preferences of different learners and further enhance the learning experience and effect.

In short, the feedback system plays a vital role in the education process, as it helps learners to monitor and adjust themselves in the learning process, and helps educators to optimize teaching strategies according to learners' feedback, in order toachieve effective teaching and learning.

2.3 Application of Intelligent Assisted English Teaching

The application of intelligent assisted English teaching is a significant step in the progress of educational technology in the field of language learning. By integrating digital technology, a cognitive diagnosis model and a feedback system, it has brought revolutionary changes to English teaching. This progress not only improves teaching methods, but also greatly improves learning efficiency, especially in regard to personalized learning and real-time feedback.

An intelligent CAI English teaching system can accurately monitor and analyze students' learning behavior, ability level and progress by using advanced AI technology. Based on these analyses, the system can automatically adjust the teaching content and difficulty, and provide personalized learning paths that meet the needs of individual learners. For example, for vocabulary learning, the system can adjust the frequency and difficulty of review and testing according to the learners' mastery, so as to ensure that learners can obtain suitable learning materials at the right time.

The feedback mechanism in the intelligent assistant system can provide timely feedback information about learners' learning progress and level of understanding, help learners understand their learning status, and adjust their learning strategies in time. This kind of immediate feedback is particularly important for improving the four basic skills of language learning (listening, speaking, reading and writing) because it can help learners to correct mistakes quickly and improve their understanding of language rules.

In teaching practice, the application of intelligent assisted English teaching also includes using speech recognition and natural language processing technology to assist

pronunciation training and oral practice, supporting writing training through machine grading and feedback, and using virtual reality (VR) and augmented reality (AR) technology to create an immersive language learning environment. The application of these technologies makes learning livelier and more interesting, and also greatly improves the interactivity and practicality of language learning.

To sum up, the development of intelligent assisted English teaching has brought new perspectives and methods to traditional language teaching. By providing highly personalized learning experience and real-time interactive feedback, it has effectively improved learners' learning motivation and efficiency, and injected new vitality into the field of English teaching.

3. DATA COLLECTION AND EXPERIMENTAL DESIGN

3.1 Research Objectives and Assumptions

The purpose of this study is to explore the practical effect of the intelligent assistant teaching system in English teaching, focusing on the improvement of language skills and the increase of learning motivation.

Research objectives

(1) To evaluate the effectiveness of intelligent CAI system in improving learners' English listening, speaking, reading and writing skills.

(2) To determine whether an intelligent assistant teaching system has a significant impact onstudents' motivation to learn.

Research hypothesis

Based on the above objectives, the hypotheses are:

Hypothesis 1: Learners who use the intelligent CAI system will show more remarkable progress in English listening, speaking, reading and writing skills than those who use traditional teaching methods.

Hypothesis 2: With the assistance of the intelligent assistant teaching system, students' motivation to learn will be significantly enhanced.

3.2 Experimental Design and Implementation

3.2.1 Experimental Design

For this study, a comparative experimental framework was applied to the experimental group and the control group, with the aim of evaluating the effect of the intelligent assistant teaching system on English learning outcomes. The experiment was conducted for a period of 12 weeks, during which time the progress of students in both groups was regularly evaluated and monitored to compare the influence of an intelligent assistant system on learning effectiveness.

3.2.2 Experimental Conditions and Setting of Control Group

In this study, two eighth-grade classes in a junior high school in A city were selected as the research subjectsto determine the effect of the intelligent assisted English teaching system. Prior to the experiment, a pre-test and information obtained from teachers confirmed that the two classes were similar in terms of students' English learning level.

Experimental group setup: Class A, with 37 students, was selected as the experimental group. During the 12-week experiment, these students used the intelligent assistant teaching system to learn English. The system provided personalized learning paths, real-time feedback, and course content that met students' learning needs, aiming to improve students' learning efficiency and academic outcomes through technical means.

Control group setting: Class B, with 35 students, was selected as the control group. In the same experimental period, the students in this group continued to be exposed to the traditional English teaching method without using the intelligent assistant teaching system. This included regular classroom lectures, written assignments and traditional learning materials to evaluate students' learning outcomes without the assistance of intelligent systems.

3.2.3 Data Types and Collection Tools

In this study, various types of data were collected to comprehensively evaluate the influence of the intelligent assistant teaching system on students' English learning outcomes. These data were used to support (or otherwise) the experimental hypotheses. The types of collected data and the corresponding collection tools are shown in Table 1 below.

The data analysis results enabled the researcher to obtain a comprehensive understanding of the specific impact of the intelligent assistant teaching system on students' English learning outcomes, including the improvement of academic performance, the change of learning motivation and the adjustment of learning behavior. Moreover, the study's results will provide a scientific basis for further research, discussion and educational practice.

3.2.4 Experimental Process

Step 1: Prepare before the experiment

Pre-test learning motivation questionnaire: Before the experiment, which involved using the intelligent assistant teaching system for the experimental group, and traditional methods for the control group, students in both groups were asked to complete a pre-test learning motivation questionnaire to evaluate their level of learning motivation before beginning to be exposed to one of the two modes of teaching.

Baseline test of English proficiency: Students in both groups were given a baseline test of English proficiency to ensure that the English proficiency of the two groups was roughly the same before the experiment.

Step 2: Experiment implementation

Application in the experimental group: Students in the experimental group began to use the intelligent assistant teaching system to learn English.

Table 1 Research data collection and related tools.

Data type	Describe	Collection tool
Academic achievement	Students' performance in English listening, speaking, reading and writing	Written test and oral test
Learning progress	Comparison of students' learning progress in intelligent system	System log analysis
Learning motivation	The change of students' motivation to learn English	Questionnaire survey (using Likert scale)
Learning behavior	Behavior patterns of students using intelligent assistant teaching system.	System log analysis and observation records
Student feedback	Evaluation of Students' Experience and Satisfaction with Intelligent CAI System	Questionnaires and interviews
Teacher observation	Teachers' observation of students' learning attitude and participation and the application of intelligent system in teaching.	Observation records, teacher interviews

Table 2 Examples of items inlearning motivation questionnaire.

Question content	Option
I am interested in learning English.	1–5 (strongly disagree to strongly agree)
I think learning English is beneficial to my future.	1–5 (strongly disagree to strongly agree)
I will take the initiative to learn English even if there is no external requirement.	1–5 (strongly disagree to strongly agree)

Table 3 Examples of items in student feedback questionnaire.

Question content	Option
After using the intelligent assistant teaching system, my English learning efficiency has been improved.	1–5 (strongly disagree to strongly agree)
I am satisfied with the user interface of the intelligent assistant teaching system.	1-5 (strongly disagree to strongly agree)
I will recommend the use of the intelligent assistant teaching system to others to learn English.	1-5 (strongly disagree to strongly agree)

Teaching in the control group: The students in the control group continued to be taught using conventional English teaching methods.

Step 3: End of the experiment

Post-test learning motivation questionnaire: At the end of the experiment, the post-test learning motivation questionnaire was distributed to the two groups of students again to evaluate whether their learning motivation had changed.

English proficiency test: Students in both groups were tested for their English proficiency after the experiment, and their learning outcomes before and after the experiment were compared.

Student feedback questionnaire: Questionnaires were distributed to students in the experimental group to collect their feedback on the intelligent assistant teaching system, including their user experience and level of satisfaction.

Sample items from the two questionnaires are shown in Table 2 and Table 3 below.

By means of the experiment, combined with pre-and post-test questionnaires, a comprehensive evaluation was conducted to determine the influence of the intelligent assistant teaching system on students' English learning motivation and learning outcomes, as well as students' experience and satisfaction with the system.

3.2.5 Data Preprocessing

(1) Data collection: Before and after the experiment, students' English listening, speaking, reading and writing scores and learning motivation scores were collected.

(2) Data cleaning: The integrity of the data was checked and any obvious errors or abnormal values were removed.

(3) The average score and standard deviation were calculated based on each class's listening, speaking, reading and writing scores and learning motivation scores to provide basic data for subsequent analysis. The process is shown in Equation (1) and Equation (2) below.

$$\bar{x} = \frac{\sum x_i}{n} \tag{1}$$

$$s = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n-1}} \tag{2}$$

x_i is the score for each student, and $\bar{x}$ is the average score., and n represents the total number of students, which is the average score. The pre-test results are shown in Tables 4 and 5 below.

Table 4 Average score and standard deviation of pre-test results.

Class	Listening	Standard deviation	Oral English	Standard deviation	Reading score	Deviation	Writing score	Standard deviation
group A	14.36	3.22	14.93	4.88	14.09	5.35	14.84	5.06
group B	15.61	5.34	15.15	5.29	15.08	5.18	15.59	4.96

Table 5 Average score and standard deviation of learning motivation.

Class	Average score of learning motivation	Standard deviation of learning motivation
Experimental group A	3.61	0.35
Control group B	3.44	0.36

(4) Data security and privacy protection: all data collection and processing stepswere conducted in compliance with the principle of privacy protection, and particular attention was paid to ensuring the confidentiality of student information.

This pretreatment process ensured the accuracy and reliability of data, laying a solid foundation for the analysis of experimental results.

4. MODEL CONSTRUCTION AND IMPLEMENTATION

4.1 Theoretical Basis of Model Construction

4.1.1 Selected Algorithm and Technical Description

Natural Language Processing (NLP): Emotional Analysis

Technical note: The Bert (Bidirectional Encoder Presentations from Transformers) model was used to analyze the emotion of students' written homework. The BERT model was selected because of its excellent performance on various NLP tasks. For the classification of emotion, Equation (3) is used:

$$P(y|x) = \text{softmax}(W_{\text{cls}} \cdot \text{BERT}(x) + b_{\text{cls}}) \tag{3}$$

where x is the input text data, y is the output of emotion classification (for example, positive or negative), and $\text{BERT}(x)$ is the weight and bias of the classification layer, W_{cls} and b_{cls} is the representation vector obtained after processing x by BERT model.

Machine Learning (ML): Prediction of Students' Learning Effectiveness

Technical note: Support Vector Machine (SVM) model is used to predict students' learning effectiveness. SVM is chosen because of its high efficiency and accuracy in classification. The goal of SVM is to find an optimal hyperplane, as shown in Equations (4) and (5).

$$\min_{\omega,b} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}\xi_i \tag{4}$$

$$\text{subject to } y_i(\omega \cdot x_i + b) \geq 1 - \xi_i, \xi_i \geq 0 \tag{5}$$

ω is the normal vector of the hyperplane, x_i and y_i are the training samples respectively, and the corresponding ξ_i is the relaxation variable and C is the regularization parameter.

Deep Learning (DL): Analysis of Learning Behavior Sequence.

Technical note: The long-term and short-term memory network (LSTM) was used to analyze students' learning behavior sequence. LSTM was selected for its advantages in processing time series data. The update of the LSTM unit can be carried out by the Equations (6)–(11).

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{6}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{7}$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{8}$$

$$C_t = f_t{}^* C_{t-1} + i_t * \tilde{C}_t \tag{9}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{10}$$

$$h_t = o_t{}^* \tanh(C_t) \tag{11}$$

f_t, i_t, and o_t are the activation values of the forgetting gate, the input gate, and the output gate, respectively. C_t is the cell state, h_t is the current hidden state, x_t is the input feature, σ is the sigmoid function, and tanh is the hyperbolic tangent function.

4.1.2 Feature Selection

In order to ensure the efficiency and accuracy of the model, feature selection methods based on statistics and machine learning techniques were adopted, such as Pearson Correlation Coefficient and tree-based feature selection method.

Pearson correlation coefficients

The Pearson correlation coefficient was used to determine the linear correlation between two variables, and the calculation Equation (12):

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2}\sqrt{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \tag{12}$$

X_i and Y_i is the observed value of two variables, $\bar{X}$ and $\bar{Y}$ are their average., and n is the number of observations. By calculating the correlation coefficient between features and target variables (such as academic performance improvement), the features highly related to the target variables are selected.

Tree-based feature selection

Tree-based models, such as random forests, can determine the importance of features in the training process. Feature importance can be calculated by Equation (13):

Table 6 System usage characteristics.

Feature category	Feature description	Reason for choice
Learning behavior	Number of times to complete homework	Frequent homework completion is associated with the improvement of academic performance.
Learning behavior	Active time on online learning platform	Longer study time usually means higher learning investment and better learning results.
Academic achievement	Baseline test scores	Students' initial ability level has an important influence on their learning progress.
Interactive feedback	Frequency of participation in discussions	Active classroom participation is positively related to the improvement of academic performance.

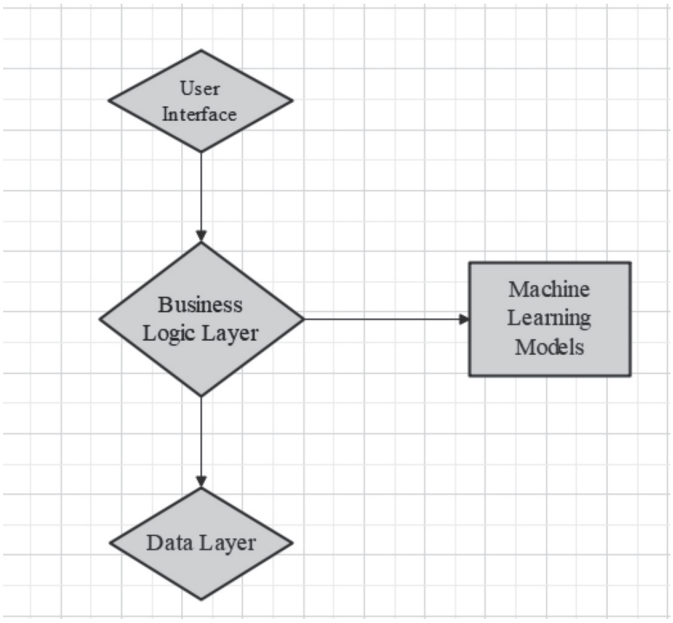

Figure 1 Architecture diagram of the system.

$$\text{Importance}(F) = \sum_{t \in T} \Delta\text{Accuracy}(F, t) \qquad (13)$$

where f is a feature, t is a set of trees, and $\Delta\text{Accuracy}(F, t)$ is the accuracy improvement brought by the feature F in tree t splitting. In this way, the features that contribute the most to the model performance can be identified.

Feature selection result

The key features selected based on the above methods are shown in Table 6 below.

Through the selection and analysis of the above characteristics, the intelligent assistant teaching system can understand students' learning behavior and needs more accurately, and then provide customized learning paths and feedback for each student to improve their English learning.

4.2 System Development and Implementation

4.2.1 System Architecture Design

Presentation layer

Function: Responsible for direct interaction with users and providing graphical user interface (GUI).

Technology: Web technology (HTML5, CSS3 and JavaScript) was adopted to build a responsive interface to ensure that students and teachers can access the system through different devices (such as computers, tablets and smart phones).

Business logic layer

Function: Processing the core functions of the system, including course content recommendation, learning progress tracking and performance analysis.

Technology: Python and frameworks such as Flask or Django are used to process back-end logic, and machine learning libraries (such as scikit-learn and TensorFlow) are combined for the training and prediction of algorithm models.

Data layer

Function: Responsible for storing and managing data in the system, including student information, learning activity records and learning materials.

Technology: A relational database management system (such as PostgreSQL or MySQL) is used for data storage to ensure data consistency, security and efficient access.

System architecture diagram

The architecture diagram of the system is simplified as shown in Figure 1 below.

Users interact with the system through the interface, when performing activities such as taking courses, completing tests and viewing feedback.

The business logic layer processes user requests and calls the machine learning model for data analysis and decision support.

The data layer stores all relevant data and provides data support for the business logic layer and the machine learning model.

Through this architecture design, the intelligent CAI system can efficiently process a large number of learning data, provide students with personalized learning experiences, and provide teachers with strong teaching support and a function that tracks students' progress.

4.2.2 Algorithm Implementation and Integration

(1) BERT model is used for sentiment analysis.

Implementation steps:

Data preparation: Students' written homework and oral expression is converted into a format that the model can handle.

Model loading: The pre-trained BERT model is used to load the corresponding weights and configurations.

Fine-tuning: For the specific task of emotional analysis, the BERT model is fine-tuned so as to adapt to the specific context of students' homework.

Emotional analysis: The processed text is input into the model to obtain the prediction result for emotional tendency.

Integration: The trained emotional analysis model is integrated into the business logic layer, and this model is called for analysis when the system needs to evaluate the emotional tendency related to students' homework.

(2) Support Vector Machine (SVM) model predicts students' learning effectiveness.

Implementation steps:

Feature extraction: According to the result of feature selection in 4.1.2, relevant features are extracted from students' learning behavior data.

Data processing: The selected features are standardized to ensure the consistency of model input.

SVM training: The extracted features and students' academic performance are used as labels to train the SVM model.

Performance evaluation: The prediction performance of the model is evaluated by cross-validation and other methods to ensure its accuracy and generalization ability.

Integration: The trained SVM model is integrated into the business logic layer to predict students' learning effectiveness in real time, so as to provide personalized learning suggestions.

(3) LSTM model is used to analyze the learning behavior sequence

Implementation steps:

Sequence construction: Based on the records of students' learning activities, the learning behavior sequence is constructed.

Model configuration: The parameters of LSTM model, such as the size of hidden layer and learning rate, are set.

LSTM training: The learning behavior sequence is used as input to train the LSTM model to identify learning patterns.

Behavior pattern analysis: The trained LSTM model is used to analyze students' learning behavior and identify potential learning obstacles and advantages.

Integration: The LSTM model is integrated into the business logic layer to analyze students' learning behavior sequence, and provide teachers with in-depth insights about students' learning status.

4.2.3 User Interface and Interaction Design

Design points:

(1) Intuitive navigation: The navigation structure of the system is clear and easy to understand, so that users can quickly find the required functions, such as learning module, score feedback and personalized recommendation.

(2) Personalized learning dashboard: A customized learning dashboard is provided for each user, showing learning progress, immediate feedback and recommending learning resources.

(3) Interactive learning content: Rich media elements (such as videos, animations and interactive tests) are used to enhance the attractiveness of learning content and teaching effect.

(4) Immediate feedback mechanism: The system provides timely learning feedback, including exercise scores, progress tips and error analysis, to help students adjust their learning strategies in time.

Specific design elements

(1) Home page: This shows an overview of the system, including the latest learning activities, upcoming tests and personalized learning suggestions.

(2) Learning module: Course content is organized in a modular way, andhelps students to choose learning paths according to their interests and learning needs.

(3) Practice and test interface: A clear and easy-to-operate practice and test interface is designed to support various types of questions, such as multiple-choice questions, fill-in-the-blank questions and short-answer questions.

(4) Feedback and analysis page: This shows the learning feedback and progress analysis in detail, including the trend of academic performance, the mastery of knowledge points and learning suggestions.

Interactive logic

Adaptive learning path: Course content and difficulty can be automatically adjusted according to students' learning feedback and grades.

Interactive learning support: Instant learning support and answers to questions are provided via question-and-answer sessions, discussion forums and virtual assistants.

Achievement system and incentive: An achievement system and learning incentive measures, such as medals, points and leaderboards, are established to strengthen learning motivation.

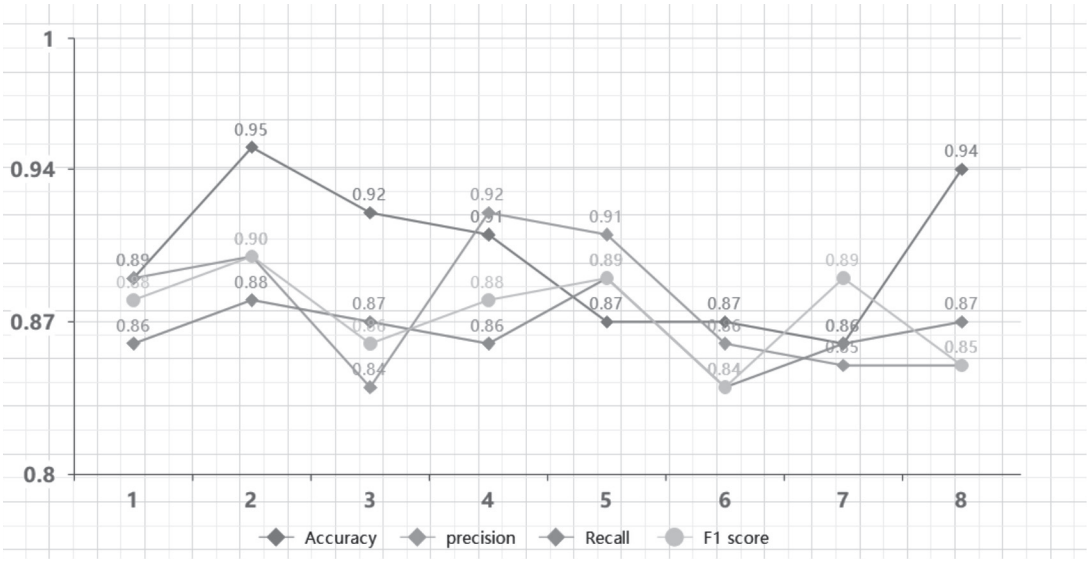

Figure 2 Partial K-fold cross-validation process.

Technical realization

Front-end technology stack: Modern JavaScript frameworks such as React or Vue.js are used to develop responsive web pages to ensure a good user experience.

Back-end integration: Communication with back-end logic through RESTful API achieves dynamic loading of data and immediate response to the user's operation.

5. ANALYSIS AND EVALUATION OF RESULTS

5.1 Model Performance Evaluation

5.1.1 Definition of Evaluation Indicators

When evaluating the performance of the intelligent CAI system, the following key indicators are adopted:

Accuracy: the proportion of students' learning effectiveness correctly predicted by the model. This is calculated with following Equation (14):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{14}$$

where TP, TN, FP and FN respectively represent the number of true cases, true negative cases, false positive cases and false negative cases.

Precision: the proportion that is really positive among all samples predicted by the model, calculated with Equation (15):

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{15}$$

Recall: the proportion of all the samples that are actually positive that the model correctly predicts as positive, calculated with Equation (16):

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{16}$$

F1 Score: the harmonic average of accuracy and recall, which is used to comprehensively evaluate the performance of the model, as shown in Equation (17):

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{17}$$

5.1.2 Performance Test Results

The cross-validation method is used to test the performance of the model in the intelligent assistant teaching system. Specifically, the data set is divided into training set and test set, and K-fold cross-validation is used to evaluate the generalization ability of the model. Part of the validation process is shown in Figure 2 below.

The final evaluation is shown in Figure 3 below.

Performance evaluation method

Data preparation: the data set collected by the research is used, including students' learning behavior data, grades and feedback data.

Model training and verification: each model is trained with a training set, and its performance is verified on a test set.

Evaluation and comparison: the above indicators are calculated, the performance of different models is analyzed, and the best model is found.

Through the above evaluation process, we can fully understand the performance of each model in the intelligent assisted instruction system and provide a scientific basis for the subsequent system optimization and improvement.

5.2 Analysis and Discussion of Results

5.2.1 Statistical Analysis of Experimental Results

According to the implementation of the intelligent assistant teaching system, the pre-test and post-test of Class A and Class B were conducted to evaluate the influence of the system on students' English learning achievement and learning motivation. The average scores, standard deviations and

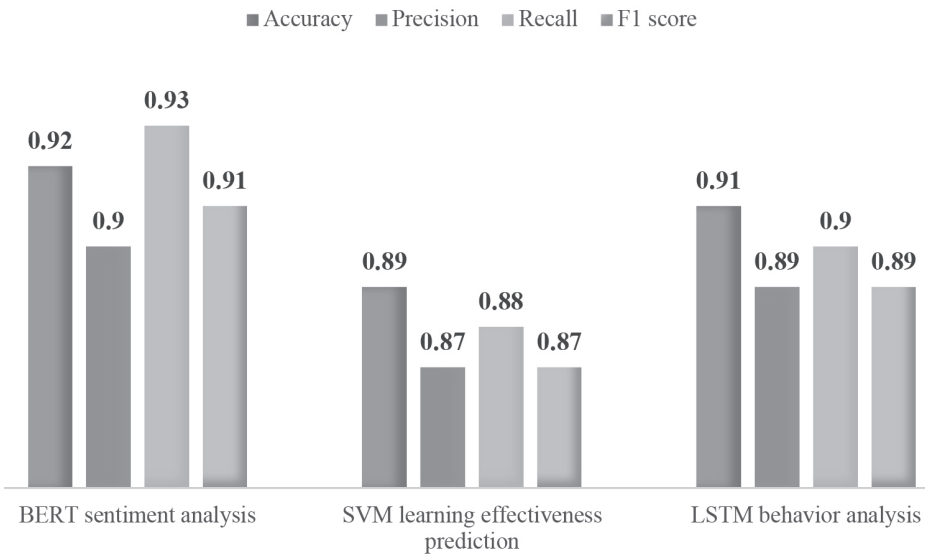

Figure 3 Performance data of each model.

Table 7 Average score and standard deviation of post-test results.

Class	Listening	Standard deviation	Oral English	Standard deviation	Reading score	Deviation	Writing score	Standard deviation
Experimental group A	16.5	3.0	16.8	4.5	17.2	4.8	17.0	4.6
Control group B	17.2	4.9	17.5	5.1	17.8	5.0	17.4	4.7

Table 8 Average score and standard deviation for learning motivation.

Class	Average score of learning motivation	Standard deviation of learning motivation
Experimental group A	3.8	0.3
Control group B	3.7	0.32

learning motivation scores obtained from the post-test are shown in Tables 7 and 8.

As shown in Figure 4, the post-test results indicate that the average scores of students in Class A and Class B have improved in terms of listening, speaking, reading and writing. Compared with the pre-test data, it shows that the intelligent assistant teaching system has a significant role in promoting students' English ability. In particular, the improvement of reading and writing is obvious, which may be because the personalized learning materials and real-time feedback provided by the intelligent system have effectively helped students strengthen their learning in these two aspects.

In addition, the average score of learning motivation also showed an upward trend. The average score of learning motivation in Class A rose from 3.61 to 3.8, and that of Class B rose from 3.44 to 3.7, which indicated that the intelligent assistant teaching system improved students' academic performance and effectively improved their learning motivation.

By comparing the pre-test and post-test data, it can be concluded that the intelligent assistant teaching system has a positive impact on improving students' English learning performance and learning motivation.

5.2.2 Interpretation of the Educational Significance of the Results

(1) Effectiveness of personalized learning path: The experimental results show that personalized learning path provided by the intelligent assistant teaching system can significantly improve students' English learning outcomes. This demonstrates the importance of personalized learning in meeting students' different learning needs and the potential of using technology to realize personalized learning path.

(2) The influence of immediate feedback on learning effectiveness: The immediate feedback mechanism provided by the system helps students to know their learning situation and existing problems in time, so that they can quickly adjust their learning strategies and improve their learning efficiency, thus highlighting the necessity of building an effective feedback mechanism.

(3) The role of technology in promoting learning motivation: In regard to learning motivation, the intelligent assistant teaching system has improved students' academic achievements and enhanced their learning motivation, thus suggesting to educators the important value of technology in stimulating students' learning interest and enhancing their learning motivation.

(4) Teacher's role change in the intelligent teaching environment: With the introduction and application of intelligent technology, the teacher's role has changed from being the direct transmitter of knowledge to the learning guide and facilitator. Teachers can use the data and analysis

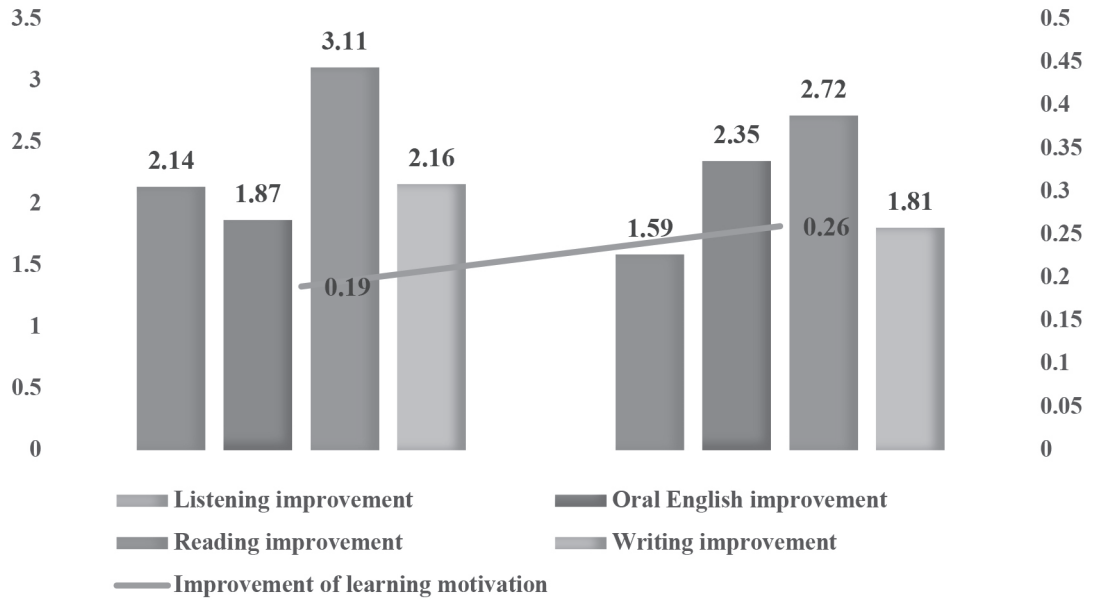

Figure 4 Analysis on the improvement of achievement and learning motivation.

provided by the system to support students' learning more effectively and optimize teaching strategies.

(5) Insight on the allocation of educational resources: The research shows that the use of intelligent assistant teaching system can effectively improve students' learning outcomes, suggesting that educational resources should be more invested in the development and application of educational technology and intelligent systems to promote the overall improvement of educational quality.

6. CONCLUSION

This study discusses and examines the application of an intelligent assistant teaching system in English teaching, and experimentally verifies the effectiveness of the system in improving students' English learning achievement and learning motivation. By means of well-designed models and algorithms, the system can provide students with personalized learning paths, instant feedback and interactive learning experiences. The results show that the students who participated in the intelligent assisted instruction system significantly improved their skills in listening, speaking, reading and writing English, and their learning motivation has also been effectively stimulated.

The research also reveals the changing role of teachers in the intelligent teaching environment. Instead of being the traditional transmitters of knowledge, they now have the role of guide and learning facilitator. Moreover, the study emphasizes the rational allocation of educational resources in the intelligent assisted teaching environment. These findings provide valuable experience for the design and implementation of intelligent assistant teaching system, and also provide guidance for the development direction of educational technology in the future.

However, this study also has several limitations. The experiment focuses on students in specific grades and disciplines, and may not fully represent the diversity of all educational backgrounds and learning needs. Future research could consider a wider range of application scenarios and different learning groups, so as to further verify and optimize the effect of the intelligent assisted instruction system. The long-term impact of specific technologies and algorithms used in intelligent systems also needs more in-depth research and analysis.

In a word, this study provides strong evidence for the application of an intelligent assistant teaching system in English teaching and demonstrates its potential to improve students' motivation and learning outcomes. With the continuous progress of educational technology, it is expected that the intelligent assistant teaching system will play a greater role in future educational practice and provide students with a more efficient and personalized learning experience.

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