Eng Int Syst (2025) 1: 47–56

Engineering
Intelligent Systems

Application and Innovation of Internet of Things Technology in English Teaching Scenarios

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This study was conducted to explore and determine the effectiveness of applying the Internet of Things (IoT) technology in the teaching of English language teaching, and its impact on students' English proficiency and motivation to learn. The study constructs an intelligent assessment system, integrating cutting-edge sensing technology and intelligent devices, to collect in real-time and analyze a range of information such as individual learning performance, interactivity in the teaching and learning environment, and the characteristics of individual learning behaviors during classroom teaching activities. At the software level, this study relies on three core components: the data management platform, the intelligent analysis module and the user-friendly interface to realize efficient data management and deep mining. The Intelligent Analysis Module utilizes advanced algorithms, including CNN-based emotion parsing algorithms, fused DNN-HMM speech recognition technology, and phoneme-level oral expression evaluation criteria, to accurately parse and quantitatively evaluate students' emotional state, speech information, and oral proficiency in English. In addition, we designed a personalized teaching module based on the results obtained by the intelligent analysis module. The implementation of the personalized teaching program is an iterative process that relies on the in-depth interpretation of the data provided by the intelligent analysis module, and accordingly develops and adjusts the teaching strategies to meet the unique learning needs and developmental trajectory of each student. The experimental design involves two groups of students with comparable English proficiency. The interactive English teaching mode supported by IoT technology was used for the experimental group, while the conventional teaching mode was maintained for the control group. At the end of the experiment and the post-test phase, results were analyzed and showed that compared with the control group, the students in the experimental group demonstrated significant improvement in English understanding ability, interest in learning and motivation to learn.

Keywords: Internet of Things, English language teaching, teaching scenarios, application innovation

1. INTRODUCTION

In today's era of globalization and the rapid development of informatization, the status of English as an international common language is becoming increasingly prominent, highlighting the importance of delivering effective English teaching. However, the traditional mode used to teach English is often limited by factors such as teachers' competence [1], the availability of adequate teaching resources, and a teaching environment conducive to learning. These factors make it difficult to meet the ever-increasing learning needs of today's students [2]. Therefore, finding new teaching modes and technical means to improve the effectiveness of English teaching has become an urgent task for the education sector.

The emergence of Internet of Things (IoT) technology brings new opportunities and challenges to the realm of English teaching, and its application and innovation in English teaching scenarios has great potential [3]. As an emerging information technology, IoT technology can achieve intelligent management and control by connecting various entities and objects to the Internet. With the continuous development of IoT technology, its application in the field of education is attracting an increasing amount of attention. English teaching, as an important part of education, is expected to realize the innovation of teaching mode and the improvement of teaching quality with the help of IoT

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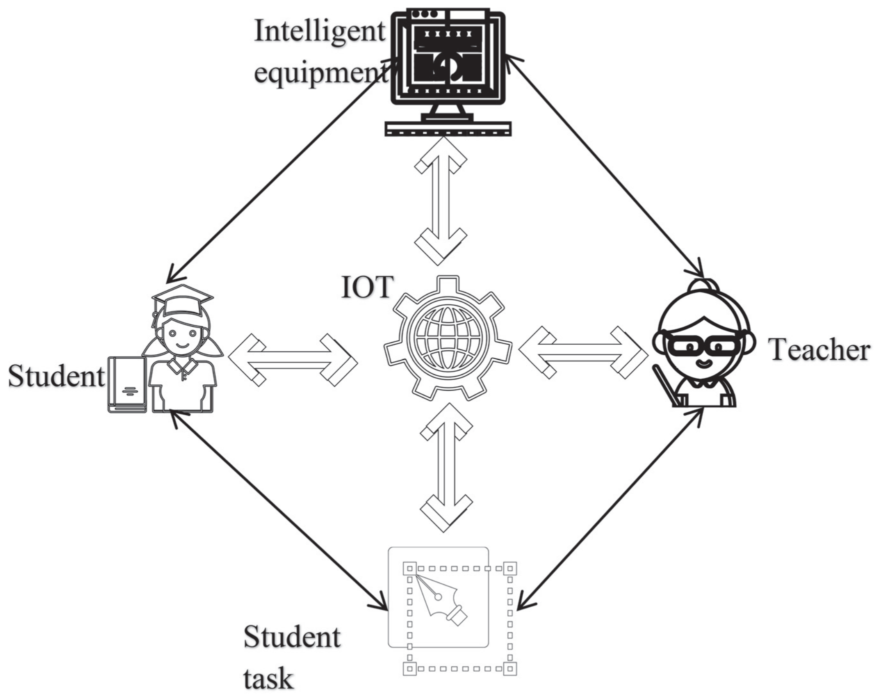

Figure 1 Model for the application of IoT in education and teaching.

technology. At present, the application of IoT technology in English teaching focuses mainly on smart classrooms, personalized learning and cross-border education. Smart classrooms create highly immersive and interactive learning environments for English teaching by integrating advanced tools such as smart sensing devices, interactive whiteboards and environment monitoring systems. The application model of IoT in education and teaching is shown in Figure 1 [4].

However, the application of IoT technology as an innovation in English language teaching still faces many challenges such as the protection of students' privacy, ensuring data security, improving teachers' ICT literacy, and avoiding over-reliance on technology. The aim of this study is to examine and analyze in depth the specific application scenarios of IoT technology in respect to various aspects of English teaching, reveal its innovative value and potential problems, and on this basis, construct a set of new English teaching models that align with modern education concepts while fully exploiting the advantages of IoT technology, and propose targeted strategies and solutions [5].

This paper undertakes an analysis of application scenarios of IoT technology in English language teaching, including smart classrooms, personalized learning and cross-border education. Smart classrooms create highly immersive and interactive learning environments for English teaching by integrating advanced tools such as smart sensing devices, interactive whiteboards and environment monitoring systems. Personalized learning, on the other hand, involves the design of learning paths based on student learning data collected by IoT technology so that individual learning plans can be optimized. Cross-border education, on the other hand, is a model achieved through IoT technology that allows students and teachers from different countries to communicate and collaborate, providing a new way for students to expand their international horizons [6].

This study makes several contributions to the body of knowledge about the teaching of English: we propose an intelligent assessment system based on IoT technology to provide teachers with targeted teaching improvement suggestions by capturing and analyzing data related teaching activities in real time. We design personalized learning paths to individualize English teaching by combining students' interests, abilities and learning progress. We explore the application of Internet of Things (IoT) technology in cross-border education to overcome geographical boundaries and promote international exchanges and cooperation in English teaching.

2. LITERATURE REVIEW

2.1 Analysis of Teaching and Learning Scenarios for IoT

The widespread application and in-depth exploration of IoT technology in education has become a hot topic in academia, attracting the attention of many researchers. In recent years, a significant amount of research has explored the topic in a comprehensive and multi-level manner. For example, one research team [7] highlights the subversive change made by IoT technology to the education paradigm, evident in their research results. They found that IoT has successfully challenged the traditional education model through the ubiquitous connectivity network, real-time data transmission function, and intelligent decision-making assistance system, injecting a strong kinetic energy into the intelligent transformation of the education environment and teaching practices.

With the integration of various sensors and smart devices, IoT technology is able to sense and regulate the teaching

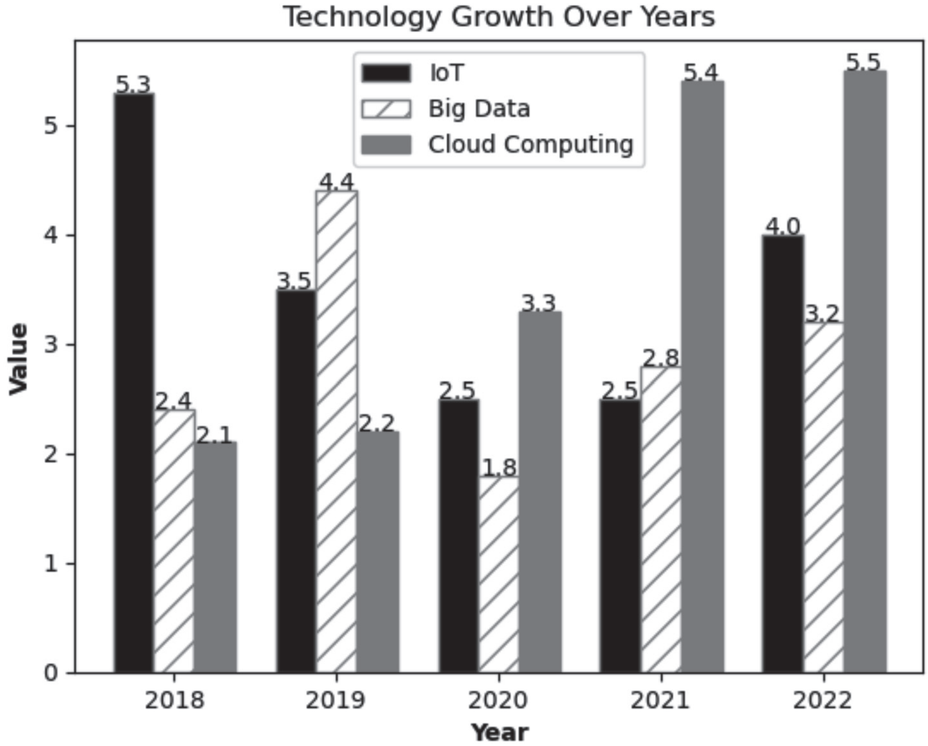

Figure 2 Proportion of various technologies.

environment in real time. As shown in one of the studies [8], through the deployment of IoT sensing devices, the environmental parameters of the classroom, such as temperature, humidity, light intensity, and even air quality, can be automatically adjusted to the optimal learning state, thus creating a more humanized and efficient educational space. El Geddawy et al. [9] discusses in detail how IoT technology can transform the traditional classroom by establishing an intelligent sensory environment, organically integrating diversified sensors, smart devices and interactive platforms into the teaching scene to create a personalized learning experience for students. For example, IoT end devices such as smart desks, chairs, and electronic schoolbags are used to collect and analyze student behavioral data to support more accurate instructional interventions and personalized instructional design. Fang et al. [10] pointed out that the application of IoT technology is not only limited to the physical classroom, but also has great potential in distance education and blended learning scenarios. The researchers conducted an in-depth analysis to determine how IoT can optimize the course design and enhance the interactivity and effectiveness of online teaching through real-time tracking, and examined students' learning behavior paths. Focusing on how IoT can be combined with Virtual Reality (VR) and Augmented Reality (AR) technologies to create realistic simulated learning environments, IoT is revolutionizing the field of language learning in general and English language teaching in particular. For example, the Internet of Things (IoT) is integrated with VR/AR technologies to enable students to practice English conversations in simulated real-life situations, which significantly improves their practical language skills. To sum up, the application of IoT technology in the field of education has penetrated into the intelligent transformation of the teaching environment, the personalized customization of the teaching mode, and the diversified creation of learning situations, etc. With the continuous development and innovation of the technology, the penetration and integration of the IoT technology in the field of education is deepening. It not only facilitates the intelligent upgrading of the teaching environment, such as building intelligent classrooms through intelligent equipment; it also achieves the automatic adjustment of environmental parameters and dynamic sharing of resources and other functions, which greatly improves the comfort and convenience of the teaching environment. At the same time, it also promotes the personalized transformation of the teaching mode, with the help of IoT big data analysis of students' learning habits, interests, strengths and ability levels, so that teachers can accurately ascertain the learning needs of each student and carry out personalized teaching tailored to individuals [11]. The percentage of IoT technologies is shown in Figure 2.

2.2 Emerging Models of English Language Teaching

With the deep integration of Internet of Things (IoT) technology, the English teaching mode is experiencing an unprecedented innovative change. Gao et al. [12] reveals how IoT technology empowers the construction of intelligent English learning environments, which is manifested in the following ways: through the integration of advanced real-time speech recognition technology [13], it can significantly improve the precision and effect of English listening and speaking training, correct pronunciation, and provide instant feedback, making the teaching of English speaking and

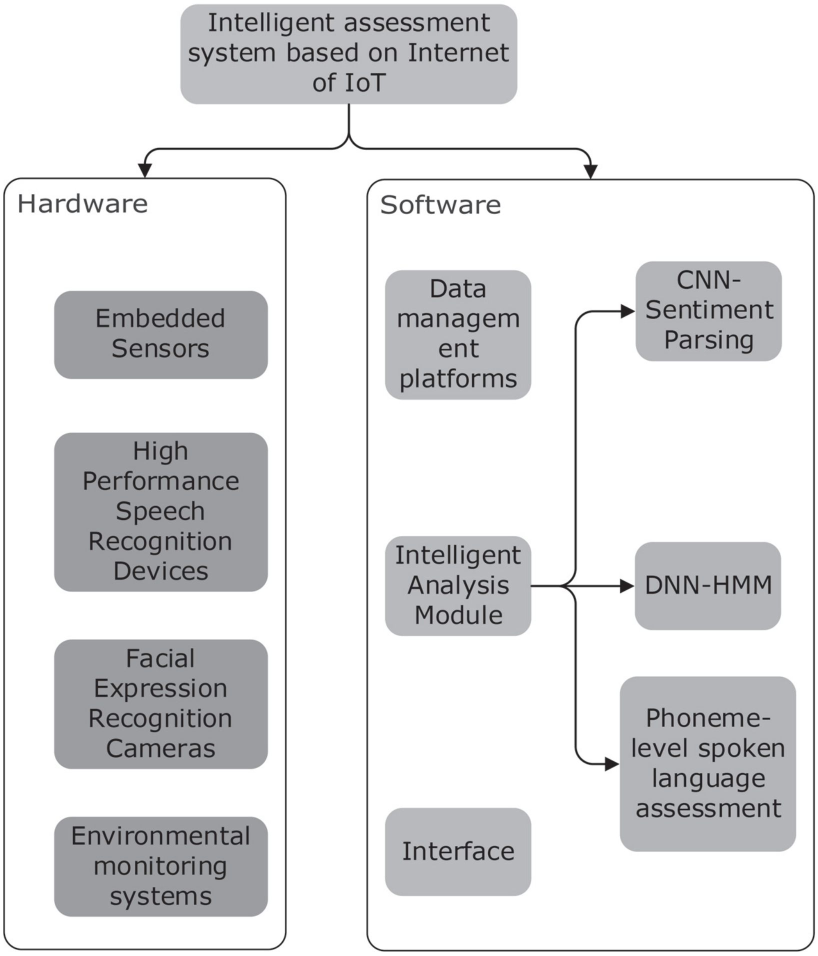

Figure 3 Modeling framework.

listening skills more interactive and targeted. In addition, Guo [14] also mentioned that the use of wearable devices and other IoT sensing devices to monitor students' physiological signals and emotional responses during English practice activities can help teachers acquire a deeper understanding of students' learning status, so as to scientifically adjust their teaching strategies and achieve the personalization and refinement of teaching methods.

Han [15] focuses on the impact of Internet of Things (IoT) technology on the innovation of English teaching content and methods. He points out that the embedding of IoT technology makes the content of teaching materials no longer limited to static text and pictures, but can be updated in real time and keep pace with the times, and can facilitate intelligent screening and personalized delivery of teaching content according to the students' learning progress, interests and preferences, and differences in ability, so as to satisfy the learning needs of different students and enhance the effectiveness of teaching. The study conducted by Kong [16] demonstrates a new English teaching model formed by combining IoT technology with modern educational technologies such as gamified learning and virtual reality (VR). This model skillfully integrates IoT technology with immersive experiences, allowing students to simulate real English application scenarios in the virtual world, dramatically increasing their interest and motivation in learning, and making the process of English learning more interesting and productive. From another important perspective, Li [17] analyzes the key role of IoT in English teaching resource management. By building an intelligent educational resource management platform, IoT technology can achieve not only dynamic scheduling, real-time statistics and optimal allocation of educational resources; it also encourages the fair sharing and efficient use of educational resources. Particularly in regard to the equitable distribution of educational resources across regions and schools, IoT technology undoubtedly plays a positive role.

3. INTELLIGENT ASSESSMENT SYSTEM BASED ON IOT TECHNOLOGY

3.1 Modeling Framework

The modeling framework proposed in this paper is shown in Figure 3. In regard to hardware, the intelligent assessment system integrates a variety of cutting-edge sensing technologies and intelligent devices including, but not limited to, embedded sensors, high-performance speech recognition devices, facial expression recognition cameras, and environment monitoring systems, etc., which are able to accurately collect and record in real time various types of information about classroom teaching activities. These data cover a wide range of students' individual learning outcomes, the overall teaching and learning environment of the classroom, and even the subtle characteristics of students' learning behaviors, thus constructing a solid and diversified data support system for the assessment of teaching and learning [18, 19].

On the other hand, the software comprises: a data management platform, an intelligent analysis module and a user-friendly interface. The core function of the data management platform is to accept, securely store and pre-process the raw data transmitted from numerous IoT devices to ensure its accuracy and usefulness. The intelligent analysis module, as the central component of the whole system, adopts a variety of cutting-edge algorithms and technological solutions, including a Convolutional Neural Network (CNN)-based sentiment resolution algorithm to identify and quantify the emotional states and their changes exhibited by students during the learning process. Advanced speech recognition technology combining Deep Neural Networks and Hidden Markov Models (DNN-HMM) effectively achieves high-precision recognition and conversion of students' speech information [20, 21].

3.2 Core Technologies

3.2.1 DNN-HMM

We first use the DNN-HMM speech recognition technique to recognize and process the speech data acquired by the sensors. DNN-HMM combines deep neural networks (DNNs) and Hidden Markov Models (HMM) for speech recognition. DNN is used to learn the acoustic model while HMM is used to model the time-series properties of the speech signal. A basic DNN-HMM model can be represented as follows: $P(O|S) = \pi_{t=1}^{T} P(o_t|s_t)$,$P(S) = \pi_{t=1}^{T-1} P(s_{t+1|s_t})$ where O is the sequence of observations, S is the sequence of states, o_t is the observation at time ts_t is the state at time t, $P(o_t|s_t)$ is the probability of observing o_t in the state S_t computed by the DNN, and $P(s_{t+1}|s_t)$ is the probability of state transfer [22, 23].

In the DNN-HMM framework, deep neural networks (dnns) are mainly used to learn acoustic models, i.e., to learn the probability distributions from speech feature vectors to the corresponding articulatory states. The DNN learns how to map feature-extracted speech frames to a set of discrete HMM states by training a large-scale labeled speech database, where the features may be MFCCS (Meier Frequency Cepstrum Coefficients) or other advanced speech features. The output layer nodes of the DNN correspond to the individual states of the HMM, and each node outputs the probability of generating a particular feature vector in the current state, i.e., $P(O_t|S_t)$ in Equation, which is the DNN's estimation of the likelihood of observing the feature vector O_t when time t is in state S_t. On the other hand, Hidden Markov Models (HMMs) are used to capture the time series properties of speech signals. HMMs models have a predefined set of states that represent different stages or phoneme classes of articulation. An HMM has two components [24].

The state transfer probability $P(S_{t+1}|S_t)$, which indicates the probability of transferring from one state to another, reflects the continuity between phonemes and the linguistic structure of the speech signal.

The observation probability $P(O_t|S_t)$, as mentioned previously, is partly computed by the DNN instead of the GMM (Gaussian Mixture Model), allowing the model to characterize complex acoustic properties more accurately [25].

The whole speech recognition process can be decomposed into two steps: decoding process: through Viterbi algorithm or other decoding algorithms (e.g., WFST, CTC, etc.), based on the observation probabilities output from the DNN and the state transfer probabilities of the HMM, find the hidden state sequence S that is most likely to produce the observation sequence O, that is, to find the most likely pronunciation sequence. Model training process: a large amount of labeled speech data is utilized to train the DNN through forced alignment or embedded training, so that it can accurately predict the observation probability in each state, and the state transfer matrix of the HMM is adjusted to ensure that the model as a whole more accurately matches the actual speech data distribution [26].

As shown in Figure 4, the DNN-HMM model cleverly combines the powerful representation learning capability of deep neural networks and the good modeling capability of Hidden Markov Models (hmms) for sequential data, which overcomes the limitations of GMM-hmms in modeling complex acoustic features, and thus significantly improves the performance and accuracy of the speech recognition system [27].

3.2.2 Sentiment Analysis Model

After speech recognition, we transform the text data converted from speech data. Sentiment analysis is an important class of tasks. Sentiment analysis algorithm based on Convolutional Neural Network (CNN) is a powerful text classification method that recognizes sentiment tendencies by learning local features in the text. In this algorithm, the textual data needs to be converted into a numerical form so that it can be processed by the neural network. This is usually achieved through word embeddings, where each word is mapped to a vector in a high-dimensional space denoted as $\mathbf{e}_i = \text{Embedding}(W_i)$ where $\mathbf{e}_i$ is the embedding vector of the word W_i. The convolutional layer uses a set of filters to extract local features (e.g., n-grams) from the text. Each filter performs a convolution operation on a different part of the text to extract specific features. $\mathbf{c}_i = \text{ReLU}(\mathbf{W}_c * \mathbf{e}_i + b_c)$ where $\mathbf{c}_i$ is the feature vector after the convolution operation, $\mathbf{W}_c$ is the weight matrix of the convolution layer, $\mathbf{b}_c$ is the bias term and relu is the activation function [28]. The pooling layer is used to reduce the dimensionality of the features and retain the most important information. The most common pooling operation is maximum pooling, which selects the maximum value in each feature map. $p = \text{MaxPooling}(\mathbf{c}_i)$ Where $\mathbf{P}$ is the pooled feature vector. The fully connected layer converts the pooled feature vectors into the final output, such as the probability of sentiment classification. $\mathbf{o} = \text{softmax}(\mathbf{W}_f \cdot \mathbf{P} + \mathbf{b}_f)$ Where $\mathbf{o}$ is the output vector, W_f is the weight matrix of the fully connected layer $\mathbf{b}_f$ is the bias term and the softmax function is used to normalize the output probability. During the training process, a loss function is needed to evaluate the performance

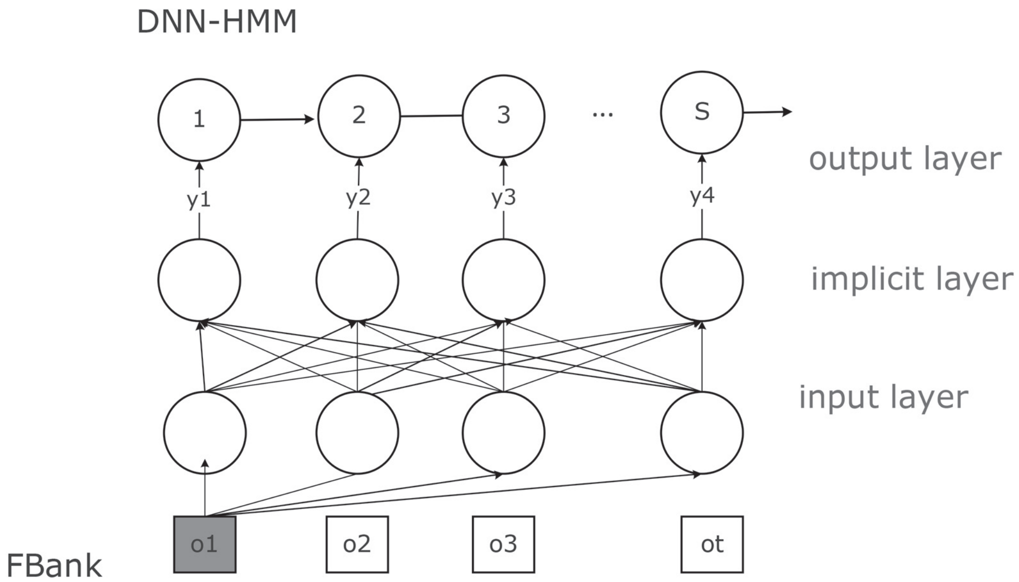

Figure 4 The DNN-HMM framework.

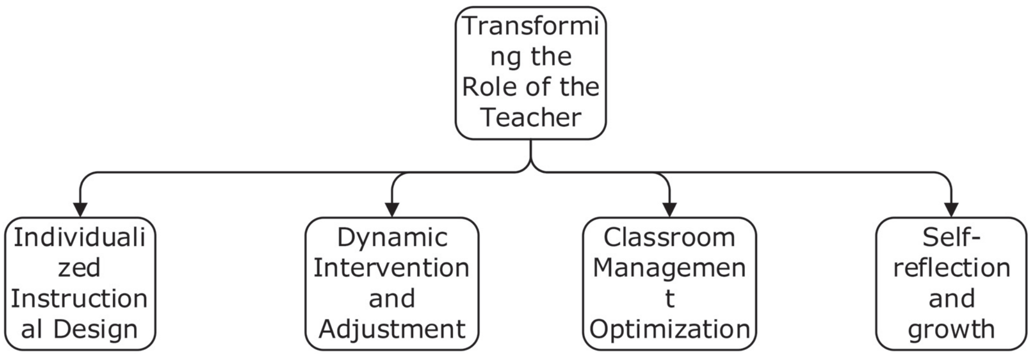

Figure 5 Changes in the role of the teacher.

of the model. For sentiment analysis, a cross-entropy loss function is usually used. Loss $= -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$ [29].

3.2.3 Evaluation of Phoneme Levels

The assessment of phoneme levels usually involves comparing the pronunciation with the standard pronunciation and giving a rating. This can be done by calculating the distance between the actual pronunciation and the standard pronunciation. A simplified scoring formula is: Score $= \sum_{i=1}^{N} \text{similarity}(p_i, p_i^*)$ where N is the number of phonemes, p_i is the phoneme pronounced by the student, p_i^* is the phoneme pronounced by the standard pronunciation, and similarity is a function that calculates the degree of similarity between two phonemes. This convergence of advanced technologies can powerfully analyze students' immediate emotional responses and oral expression abilities in a refined way, thus providing accurate and powerful support for teaching practice and assessment of learning effectiveness. By combining deep neural networks with Hidden Markov Models and other cutting-edge technologies, we are able to not only capture and understand the subtle emotional fluctuations of students in the language learning process, but also to assess the development of their speaking skills, including accuracy of pronunciation, fluency, appropriate intonation, and other dimensions. The application of such high-tech means undoubtedly greatly enhances the ability of educators to gain insight into students' needs and devise personalized teaching strategies, at the same time establishing a solid foundation for objectively and comprehensively evaluating students' language proficiency.

3.3 Transformation of Teachers' Roles

The transformation of the teacher's role, supported by the intelligent assessment system, is shown in Figure 5. Each component is explained below.

Accurate teaching orientation. In the past, teachers relied mainly on personal observation and experience to ascertain students' learning progress and difficulties. However, with the assistance of the intelligent assessment system, teachers can obtain a large amount of objective and accurate learning data in real time, such as students' oral pronunciation accuracy, vocabulary mastery, listening comprehension, reading speed, writing ability and other multi-dimensional data. Through in-depth analysis of these data, teachers can quickly and accurately identify the learning bottlenecks and weaknesses of each student.

Personalized Instructional Design. Based on the data provided by the Intelligent Assessment System, teachers can develop personalized teaching plans for each student's characteristics and needs. For example, if the system shows that a student has significant difficulty with pronunciation, the teacher can design a special pronunciation training program or provide individual tutoring. If the data shows that a student has problems understanding a specific grammar point, the teacher can reinforce that part of the lesson in subsequent lessons.

Dynamic Intervention and Adjustment. With the support of real-time data analysis, teachers can make dynamic adjustments to teaching content, teaching methods and teaching progress in a timely manner. For example, when the system prompts teachers to develop teaching strategies for a certain knowledge point, such as organizing appropriate group activities, mobilizing the classroom atmosphere at the right time, and introducing novel teaching methods to deal with inefficient periods, this can help maintain good classroom order and improve learning efficiency.

Self-reflection and growth. Through the Intelligent Assessment System, teachers can also obtain feedback on the effectiveness of their own teaching, including specific teaching practices, classroom control skills, and the appropriateness of homework assignments, so that they can continuously reflect on and optimize their teaching strategies and achieve their own professional growth.

In summary, the implementation of the intelligent assessment system enables teachers to take full advantage of big data analysis to make teaching decisions more scientifically and accurately, so as to promote the implementation of personalized teaching and tailored teaching, and to comprehensively improve the quality of teaching and the learning effectiveness of students.

3.4 Data Flow

The data flow of the system can be outlined as follows: in a classroom teaching environment, using cutting-edge IoT technology, various hardware devices are able to monitor and record core activity data including student interactions, engagement, behavioral performance, and course content in real time to form an initial data set. Subsequently, these instantly generated huge amounts of data are transmitted to the data processing platform in the cloud via a secure and reliable wireless network, ensuring real-time data availability and integrity. In the data processing and analysis phase, the system uses an intelligent analysis engine to perform a series of pre-processing tasks on the collected raw data, such as data cleaning to remove invalid or erroneous information, followed by normalization and organization, laying the foundation for in-depth mining of data value. On this basis, the system uses complex data analysis algorithms to deeply analyze students' learning behaviors and effects during teaching activities, and automatically generates detailed and meticulous learning reports. In the feedback section, the system displays the complex analysis results in the form of charts, dashboards and other forms of vivid and intuitive display on the user interface of the teacher's end, so that the abstract data becomes easy to understand. Teachers can easily access quantitative assessment information about classroom status, individual student performance and overall teaching effectiveness, and receive teaching improvement suggestions based on data analysis. In the end, after receiving these instructive data-driven information, teachers can make well-informed teaching decisions based on the precise feedback provided by the system, make timely adjustments to teaching strategies, and implement more personalized teaching plans, aiming to improve the overall quality of teaching and effectively promote the learning progress and performance of each student.

4. IMPLEMENTATION OF INDIVIDUALIZED INSTRUCTIONAL PROGRAMS

The implementation of a personalized instructional program is an iterative cycle that relies on an in-depth interpretation of the data provided by the intelligent analytics module and the development and adjustment of instructional strategies according to the unique learning needs and developmental trajectory of each student.

For the targeting process, we set S to represent an individual student and D to represent the data set collected by the intelligent analysis module, including the student's learning ability C, interest preference I, and existing knowledge level K. The personalized teaching goal T can be represented by the function f, which is a function that analyzes the data and reasoning based on the data set D in order to refine the teaching goal that meets the characteristics of the individual student: $T = f(D)$. Assuming that R represents all available teaching resources, the personalized teaching content P for student S can be represented by the function g, which is a matching and optimization function that generates personalized teaching content suitable for the student according to the determined teaching objectives T, combining the existing teaching resource base R and the individual characteristics of the student S (including information such as learning ability C, interest preference I, and the existing knowledge level K, etc.): $P = g(T, R, S)$. Dynamic adjustment and feedback loop: In terms of personalized teaching, it is crucial to monitor and evaluate the learning effect E of students in real time. This process can be represented by the assessment function h, which obtains real-time feedback by comparing the impact of the actual content P on the learning outcomes of the student S: $E = h(P, S)$. The obtained feedback E is then fed back to the intelligent analysis module to update the dataset D, forming a closed-loop control system that continuously optimizes and adjusts the personalized teaching objectives T and the teaching content P to achieve the most optimal teaching effect: $D' = D \cup E$, $T' = f(D')$, $P' = g(T', R, S)$.

5. FINDINGS AND ANALYSIS

5.1 Model Design and Implementation

In order to determine the effect of IoT technology in English teaching, this study adopts a mixed method research

Table 1 Results for the general English language proficiency pre-test.

Groups	Number of people	Average score	Standard deviation
Experimental group	100	74.1	7.8
Control subjects	100	73.5	8.4

Table 2 Results of English general ability test after the experiment.

Groups	Number of people	Average score	Standard deviation
Experimental group	30	86.7	6.5
Control subjects	30	77.3	8.1

approach, combining a questionnaire survey with a rigorous experimental design. The research sample consists of students from two grades of an English teaching class in a city university. The sample consists of 200 students, with a balanced ratio of 100 males and 100 females. The experimental design includes random division into an experimental group and a control group, with 100 subjects in each group. The experimental group adopts an English teaching model based on IoT technology, while the control group adopts a traditional teaching model. The experimental period lasts for six months from January to July 2023, with two English classes per week, each lasting 40 minutes.

As can be seen from Table 1, there are 100 subjects in the experimental group, and their average score in the English general ability test is 74.1, which means that the overall English level of the group is close to this score. The standard deviation is 7.8, indicating that the differences in English proficiency among the members of the experimental group are relatively small, but there is still a certain degree of dispersion, that is, the difference in English proficiency among individuals fluctuates within a range of about ± 7.8 points. The control group also consisted of 30 subjects, and their average score was 73.5 points, which was slightly lower than that of the experimental group by 0.6 points, although their overall English proficiency was relatively similar. The standard deviation of the control group is 8.4, which is slightly higher than that of the experimental group, indicating that the differences in English proficiency between members of the control group are greater than those of the experimental group. Specifically, the English proficiency scores of individuals in the control group may fluctuate around the mean by about 8.4 points. This higher standard deviation suggests that there is a greater variability in English proficiency among individuals in the control group. From the analysis of the above data, the average performance of the experimental group and the control group in terms of overall English proficiency is similar, but in terms of intra-group consistency, the distribution of scores in the experimental group is more concentrated.

5.2 Analysis and Interpretation of Results

On the basis of ensuring that the English proficiency of the experimental group is comparable to that of the control group, this study formally entered the experimental stage. Relying on the Internet of Things (IoT) technology, the experimental group implemented an interactive English teaching model, the core features of which include: teachers use IoT devices and platforms to dynamically monitor students' learning status, adjust the pace and difficulty of the teaching in a timely manner, and select appropriate teaching content and methods based on students' real-time feedback. Students can actively participate in classroom interactions and discussions through the IoT technology platform, communicate with teachers and classmates in real time, ask questions, share ideas, and display their own learning outcomes and experiences. After the completion of the experiment, a detailed questionnaire survey was conducted of the two groups of college students. Questionnaire items related to students' interest in English learning, motivation, habits, challenges, needs and satisfaction, etc. Following the experiment, the learning outcomes of the two groups of students after the experiment were compared by means of interviews and written tests. As can be seen from Table 2, the average score of the experimental group on the comprehensive English proficiency test after the experiment increased significantly to 86.7, and the standard deviation decreased to 6.5, which shows that the overall English proficiency of the experimental group has been greatly improved, and the proficiency difference of the members in the group has also been reduced. In contrast, the mean score of the control group after the experiment was 77.3, which was also an improvement, albeit much lower than that of the experimental group, and the difference in proficiency within the group was still large (standard deviation 8.1). T-test results showed that the difference between the experimental group and the control group in the mean score of the post-experiment English comprehensive proficiency test was statistically significant ($t = 4.89$, $p = 0.008$), indicating that the teaching methods or interventions adopted by the experimental group were significantly more effective than those for the experimental group. Therefore, the teaching methods or interventions used are significantly better than those for the control group.

According to Table 3, the experimental group showed higher satisfaction in the English learning satisfaction questionnaire, with a mean score of 4.7 and a small standard deviation, indicating that most of the subjects gave positive and consistent feedback on the method or measure. The mean score of the control group was 3.3, with a lower satisfaction level and a relatively large difference of opinion within the group. The improvement in satisfaction of the experimental group relative to the control group was also statistically significant.

As indicated in Table 4, the experimental group showed greater increase in both interest and motivation in English learning than the control group, and the increases were statistically significant. This suggests that the teaching

Table 3 Results of the English Learning Satisfaction Questionnaire after the experiment.

Groups	Number of people	Average score	Standard deviation
Experimental group	30	4.7	0.4
Control subjects	30	3.3	0.6

Table 4 Summary of the analysis of the experimental results

Perspectives	Norm	Experimental group	Control subjects	T-value	T-value
General English Proficiency	Average post-test scores	86.7	77.3	4.89	0.008
	Post-experiment test standard deviation	6.5	8.1		
	Difference between post-experiment and pre-experiment mean scores	12.6	3.8	4.22	0.015
Interest in learning English	Mean scores for the post-experiment questionnaire	4.3	3.5	3.80	0.025
	Post-experiment questionnaire standard deviation	0.5	7.0		
	difference between post-experiment and pre-experiment mean scores	0.7	0.1	3.40	0.035
English Learning Motivation	Mean scores for the post-experiment questionnaire	4.2	3.4	3.65	0.028
	Post-experiment questionnaire standard deviation	0.6	0.8		
	Post-experiment and pre-experiment mean score difference	0.6	0.1	3.10	0.045

Table 5 Post-experiment results for English listening comprehension test.

Groups	Number of people	Average score	Standard deviation
Experimental group	30	82.5	6.8
Control subjects	30	75.0	7.5

Table 6 Post-experiment results for the assessment of oral expression in English.

Groups	Number of people	Average score	Standard deviation
Experimental group	30	83.2	6.2
Control subjects	30	74.8	7.8

methods or interventions used with the experimental group not only improved students' general English proficiency, but also played a positive role in stimulating students' interest in learning and maintaining their motivation.

As can be seen from Tables 5 and Tables 6, the experimental group also showed obvious advantages in the tests specifically for English listening comprehension and oral expression. Whether it is listening comprehension or oral expression, the average scores of the experimental group are significantly improved compared with those of the control group, which once again verifies the effectiveness of the methods or measures adopted by the experimental group in improving students' practical application of English.

6. CONCLUSION

With the rapid development of educational informatization, this study explored the potential of Internet of Things (IoT) technology in English teaching. We innovatively built an intelligent assessment system that integrates a variety of cutting-edge sensing technologies and intelligent devices. It can not only capture and analyze diverse information such as individual learning performance, teaching environment and subtle learning behaviors in classroom activities in real time, but also establish a three-layer architecture consisting of a data management platform, an intelligent analysis module and a user-friendly interface. In particular, the intelligent analysis module uses advanced CNN sentiment analysis algorithms, DNN-HMM hybrid speech recognition technology and phoneme-level oral expression evaluation criteria to achieve a fine quantitative assessment of students' emotional state, voice information and English speaking skills. Based on this, we developed a personalized teaching module to design and implement personalized teaching plans through a dynamic iteration mechanism, and adjust teaching strategies based on the in-depth data analysis provided by the intelligent analysis module to meet the learning needs and development paths of each student. The results show that the experimental group using IoT technology to support interactive English teaching is significantly better than the control group using traditional teaching methods in terms of English comprehension ability, learning interest and motivation. This shows that the application of IoT technology in English teaching can not only improve teaching quality and student participation, but also effectively promote and stimulate students' English learning ability and enthusiasm.

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