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Innovation of College English Teaching Methods Based on Deep Learning

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To provide innovative strategies to ensure the richness of teaching content, flexibility of teaching methods and efficiency of teaching process, this study uses an empirical experiment to explore the effectiveness of a college English teaching model based on deep learning. Two groups of 150 college students were selected as experimental subjects. One group received a personalized teaching mode based on deep learning, and the control group were taught by means of traditional pedagogy. The study compared the differences between the two groups in terms of English proficiency, learning attitudes and habits, learning efficiency, affective cognition and collaborative teamwork. The results show that the experimental group was significantly better than the control group according to all the evaluation indicators, indicating that the teaching model based on deep learning has significant advantages in improving the effectiveness of students' learning, improving learning attitudes and habits, improving learning efficiency, enhancing emotional cognitive stability and strengthening collaborative and cooperative team skills. These findings provide strong evidence for the improvement and optimization of college English teaching methods, and prove that the teaching model based on deep learning has great potential in promoting college students' English skills in the reading, writing and speaking of English.

Keywords: deep learning; college English; English teaching; innovative method

1. INTRODUCTION

With the rapid advancement of artificial intelligence technology, deep learning as its core pillar has recently achieved remarkable leaps. By constructing sophisticated models of multilayer neural networks, deep learning technologies can automatically mine and extract complex features deeply embedded in data, and they can be applied to many fields including image recognition, natural language processing, speech recognition, etc., and can, in some cases, overcome human cognitive limitations [1]. In the field of education, deep learning is gradually becoming a strong force driving the innovation of pedagogy, especially in the frontier fields of creating personalized learning experiences, building an intelligent auxiliary teaching system, and constructing knowledge maps, with unlimited potential. With the ability to process massive educational data, deep learning algorithms can accurately diagnose students' learning preferences, cognitive patterns and knowledge mastery levels, providing solid scientific support for of the fine-tuning of teaching strategies [2, 3].

With the tide of globalization, English, as the language of global communication, has become increasingly important. The teaching of college English teaching has a dual purpose: to consolidate students' English language skills, and to cultivate their intercultural communicative competence and critical thinking skills. Fortunately, the rapid progress of information technology offers great potential for the reform of college English teaching. In particular, the application of deep learning technology is expected to address the shortcomings of traditional teaching methods and lead us into a new era of highly personalized and intelligent teaching [4].

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This study will closely investigate the ways that deep learning empowers teachers to accurately identify the crux of teaching, design personalized (individual) learning paths that meet the unique needs of each student, and realize real-time adjustment and optimization of teaching activities with the help of intelligent teaching platforms, in order to improve both teaching quality and efficiency [5, 6].

The focus of this study is on the innovative integration of deep learning technology, taking four innovative points as breakthrough points to reshape the future pattern of college English teaching. The first innovation is the construction of a dynamic adaptive learning model, which is an intelligent system that can accurately capture each student's learning pattern and level of understanding, and then flexibly adjust the learning content and difficulty, thereby implementing and strengthening the concept of personalized teaching. Secondly, the research will develop interactive tools facilitating the improvement of language skills, simulating real-world communication and interaction through in-depth learning, not only to train students' oral and writing skills, but also to integrate cross-cultural communication elements and broaden students' international vision. Moreover, an intelligent evaluation and feedback mechanism will be constructed, which goes beyond simple knowledge detection and focuses more on evaluating students' critical thinking and ability to apply their language skills. Thereby promoting continuous improvement-of-learning cycle through timely feedback.

2. LITERATURE REVIEW

2.1 Deep Learning

Deep learning (DL), as a frontier branch of artificial neural networks (ANNs), cleverly reveals complex patterns inherent in data through the architecture of multi-layer nonlinear processing units. Its revolutionary contribution lies in the automatic discovery of high-level features of data without manual pre-definition, greatly decreasing the dependence on human expert knowledge. The architectural design of such models comprises input layers, multiple hidden layers, and output layers, each focusing on capturing feature representations of data at different levels of abstraction. Through the clever combination of a backpropagation algorithm and gradient descent optimization technique, the model can extract key weight parameters from a massive amount of trained data, showing excellent performance on prediction and classification tasks [7].

The customization of a personalized learning path by means of deep learning models, enables teachers of college English to determine each student's specific learning trajectory and level of understanding, and adjust the difficulty and progress of course content accordingly. This highly customized learning path design not only ensures the accurate matching of learning materials with students' current level of ability, but also increases the interest in learning and improves learning efficiency [8]. The combination of deep learning and natural language processing technology is particularly exciting as a means of improving students' English speaking and writing skills. By simulating real conversation scenarios and carefully analyzing grammar and semantics, the intelligent system can provide immediate feedback, and accurately guide students' pronunciation, sentence structure and use of grammar, and integrate cross-cultural communication strategies to comprehensively hone students' application of their communication skills [9]. By means of the Knowledge Graph-Driven Content Recommendation using the educational knowledge graph constructed by deep learning, college English teaching can describe the subject knowledge structure more finely, understand students' interests and learning needs, and thus recommend personalized learning resources. This improves the appropriateness and utilization of learning resources, band also encourages students to actively explore and broaden their learning boundaries, and stimulates their motivation to learn [10].

2.2 Current Status and Challenges of College English Teaching

At present, although multimedia and network technologies have been introduced into the teaching of English in China's colleges [11], it is pointed out that these technologies are mostly used as supplementary tools, and have not fundamentally changed the traditional teacher-centered approach where teachers impart knowledge and students are passive recipients. This teaching mode ignores learners' individual differences and specific learning mode preferences. Therefore, although some classes seem active, it is difficult to improve the participation and learning efficiency of all students. Traditional teaching methods rely heavily on standardized textbooks, and the content often focuses solely on explaining language knowledge points, rather than combining this with the application of English in real-life scenarios [12]. This unrealistic pedagogy fails to stimulate students' interest and motivation, and does not help students to improve their English skills by using them in a real-life environment. Moreover, the updating of the curriculum cannot keep up with the pace of language development, especially for the rapidly changing network language, technical terms and other emerging language phenomena, teaching materials often lag behind, unable to reflect the latest dynamics of language use. With the acceleration of globalization and the rapid development of information technology, college students' need to have a high level of English proficiency [13]. Students are required to have more than just the basic English communication skills; there is an urgent need for students to acquire and apply advanced skills such as intercultural communication, formal English and a certain amount of colloquial English. However, the current teaching system is often too rigid and the curriculum fails to respond adequately to these diverse needs. This not only limits students overall ability to use English, but also affects their competitiveness in their future workplaces and academic fields.

On the other hand, an obvious change is occurring in the way that students are learning [14]. The research shows that with the abundance of Internet resources, students are more inclined to engage in independent learning and online learning. However, the unequal distribution of educational resources is a major obstacle. High-quality online courses, learning platforms and personalized learning resources are mostly concentrated in economically-developed regions or key universities, while students in other regions and ordinary colleges have difficulty accessing such resources. In addition, the traditional performance-assessment practices overemphasize scores and test-taking skills, neglecting the evaluation of students' ability to engage in autonomous learning and their practical application of the language. Current teaching practices do not cater for students' diverse and practical learning needs.

To sum up, currently, the teaching of college English has several significant problems: teaching methods are outdated, course contents are not keeping pace with the latest curriculum developments, and students' learning needs are not being met. Addressing these issues requires a concerted effort by educators, policymakers, and technology developers. First of all, there is a need to replace the teacher-oriented approach with one that is student-oriented; modern teaching methods such as the reversed classroom and project-based collaborative learning should be adopted; and students' critical thinking and enthusiasm for innovation should be encouraged. Secondly, teaching materials and course contents should be updated regularly in order to include more real-world application scenarios and emerging language trends. In this way, the learning can be applied in practice, and students will keep abreast of current language use. Furthermore, we should increase the investment in and integration of online educational resources, encourage resource sharing, reform the performance assessment system, introduce formative evaluation, and encourage and support the development of students' individual learning paths. Finally, teaching-education courses should include adequate training in the use of technology to enable teachers to use educational programs and platforms as tools to enhance their teaching, maintain student interest, and make learning more enjoyable. This will help to reform the current education system and address its shortcomings [15]. Through these measures, we hope to build a more flexible and efficient system for the teaching of English in ways that cater for the individual learning needs of college students.

2.3 Domestic and Foreign Research Trends

In recent years, the research and application of deep learning technology in the field of education has shown a vigorous development trend, and many studies in China and abroad have revealed its significant potential in improving educational effectiveness and personalized learning. Internationally, by using recurrent neural networks (RNNs) to build language models, personalized learning prediction frameworks can be created for language learners, demonstrating the potential of deep learning in adaptive learning path design [16]. This work offers a better understanding of learner behavior prediction, and establishes a theoretical and technical foundation for the design of subsequent personalized learning systems. In China, research has emphasized the positive impact of intelligent deep learning education platforms on students' learning outcomes, especially in improving English listening and speaking skills, highlighting the unique value of technology in language teaching [17]. This shows that deep learning effectively enhances the interactivity and practicality of language learning by simulating real conversation scenarios and offering real-time feedback mechanisms. In practice, U.S. online education giants Coursera and edX use deep learning algorithms to optimize course recommendation systems, customizing learning paths according to learners' historical behaviors and interests, significantly improving learning experience and satisfaction [18]. This practice demonstrates the power of deep learning in processing large-scale learning data and delivering personalized learning content. In China, Tsinghua University's "Rain Classroom" project is a typical application case, which has promoted and created personalized learning resources through in-depth analysis of students' learning behavior data, thereby greatly improving learning efficiency. The success of this project indicates the great effectiveness of deep learning technology in integrating educational big data, precise teaching strategy adjustment and personalized allocation of learning resources [19]. This is shown in Figure 1 above.

3. CONSTRUCTION OF COLLEGE ENGLISH TEACHING MODEL BASED ON DEEP LEARNING

3.1 Intelligent Transformation of Teaching Content

The intelligent transformation of teaching content is a crucial step when constructing a college English teaching mode based on deep learning, which aims to improve teaching efficiency and personalized level through technical means, so as to make the learning experience richer and more efficient. This paper introduces an intelligent transformation model of course content that integrates deep learning technology. The model can dynamically adapt to students' learning progress and individual abilities, as well as continuously optimizing teaching resources and paths by analyzing learning behavior data, so as to achieve optimal learning outcomes. We will elaborate on four components of the model: model architecture, data processing, content recommendation algorithm and feedback adjustment mechanism.

When constructing the intelligent adaptation model of teaching content based on deep neural network, we design an intelligent system framework that comprehensively considers students' individual characteristics and learning needs. The model architecture is divided into four key steps from input to output: firstly, the input layer summarizes the students' multidimensional features, such as English basic level, interest preferences and learning habits, to form a feature vector. Then, the embedded layer intervenes to transform category variables such as interest preferences into dense vectors in a high-dimensional continuous space, paving the way for deep learning processing; then, one or more hidden layers are deployed through a multilayer perceptron. Nonlinearity is introduced by using an activation function such as ReLU, and feature extraction is deepened layer by layer to generate

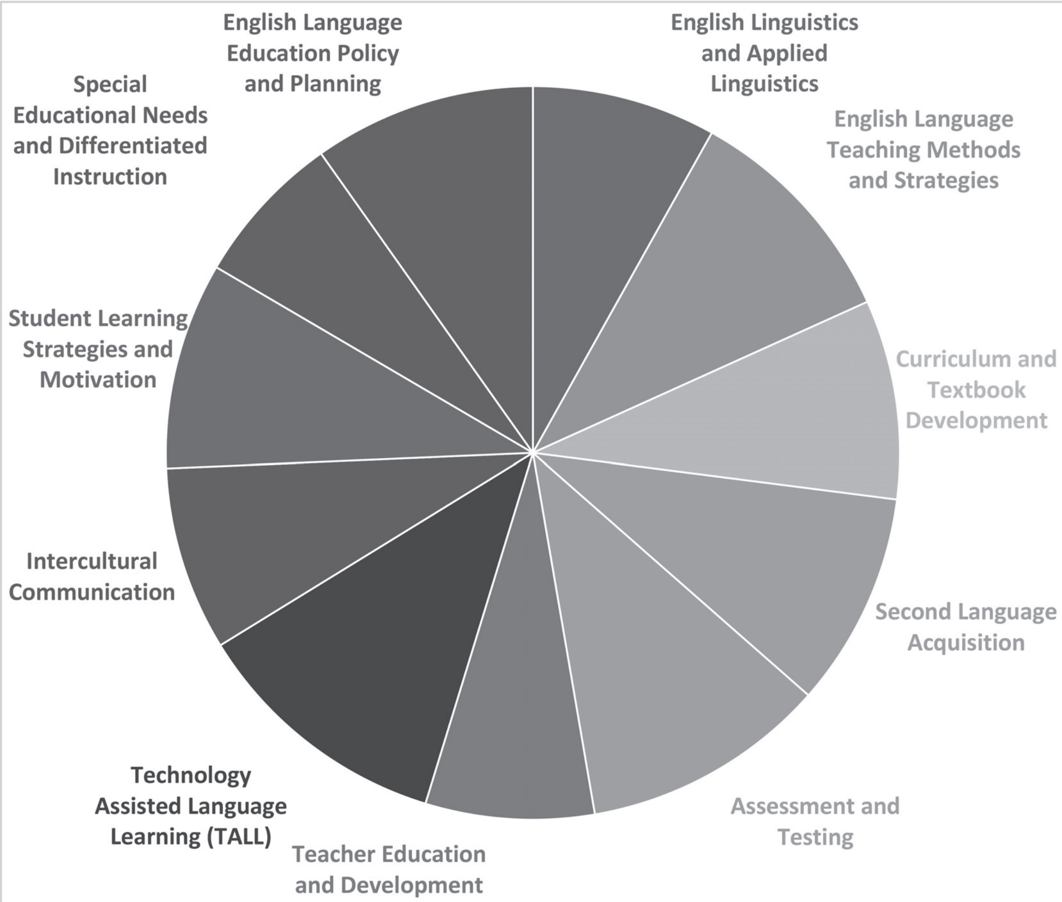

Figure 1 Number of achievements in English-related fields.

hidden layer output; finally, at the output layer, the model predicts and recommends the most suitable course content or learning task set according to the students' current learning status, and adopts classification or regression strategies to flexibly adapt to different organizational forms of course content. This process not only achieve personalized matching of student learning paths, but also indicates the efficiency and intelligence of deep learning in the adaptation of educational content [20, 21]. The specific neural network architecture is shown in Figure 2.

In order to train the above model, a large amount of student learning data needs to be collected and preprocessed, including historical learning records, test scores, online interactions, etc. Suppose we have N samples, each containing M features, then dataset D can be represented as $D = \{(X_1,\ Y_1),\ (X_2, Y_2), ..., (X_N,\ Y_N)\}$ [22], where $X_i$is the ith student feature vector, Y_i is the corresponding optimal instructional content label.

We construct a content-based recommendation strategy. Specifically, the model first analyzes the teaching content deeply and extracts a series of key features expressed as vectors, where each component represents different dimensions of course content attributes. At the same time, students' learning habits, interest preferences and other key indicators are integrated into a feature vector X, which is used as a benchmark for personalized recommendation. In order to ensure the accuracy and relevance of recommendations, the model uses cosine similarity as a measure to calculate the similarity between student feature vectors and feature vectors of each teaching content, as shown in Equation (1) [23].

$$Similarity(X, C_j) = \frac{\sum_{j=1}^{k} X_i C_{ji}}{\sqrt{\sum_{i=1}^{k} X_i^2}\sqrt{\sum_{i=1}^{k} C_{ji}^2}} \tag{1}$$

This process ensures that the recommended content closely matches the students' characteristics, and selects the most similar one as the most suitable course content to recommend to the students.

However, the continuous optimization and self-evolution ability of the recommendation system is very important. The feedback loop mechanism is incorporated into the model design. By collecting the actual score set for student satisfaction with the recommended content [24], the back propagation algorithm is used to adjust the model parameters to quantify and minimize the gap between the predicted satisfaction and the actual feedback based on the mean square error (MSE) loss function, as shown in Equation (2).

$$L = \frac{1}{N}\sum_{i=1}^{N}(f_i - \widehat{f_i})^2 \tag{2}$$

Here, $\widehat{f_i}$ represents the estimated satisfaction of the students predicted by the model for a certain recommended content. Through iterative learning, the model learns from feedback after each recommendation, and gradually adjusts its internal

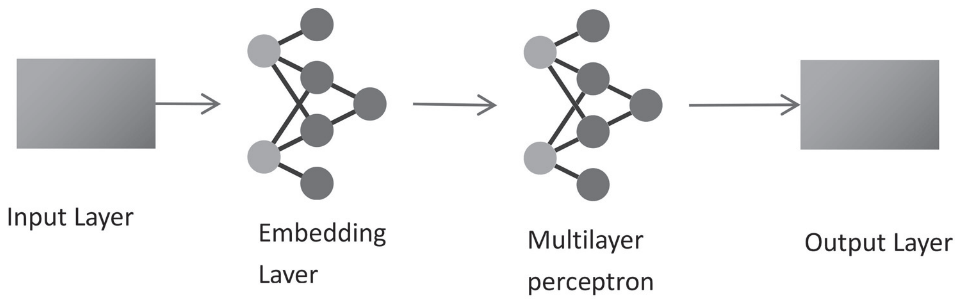

Figure 2 Neural network architecture.

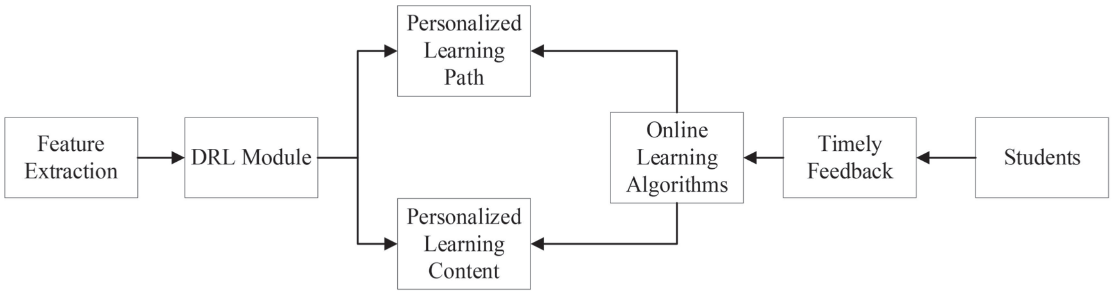

Figure 3 Innovation of teaching methods and strategies.

parameters to improve the fit between recommendations and students' real needs.

To sum up, this recommendation system combining content feature representation, attention mechanism and feedback optimization can finely customize students' learning path, and ensures the continuous improvement of recommendation outcomes through the continuous learning feedback mechanism, providing strong technical support for education personalization, indicating that education technology is moving towards a more intelligent and humanized direction [25].

3.1.1 Innovation of Teaching Methods and Strategies

When exploring the innovative path of intelligent teaching methods and strategies, we are not limited to the improvement of oral skills, but comprehensively utilize deep learning technologies, such as deep reinforcement learning (DRL) and sequence-to-sequence (Seq2Seq) model, to construct a comprehensive teaching assistance system, aimed at improving the quality and efficiency of college English teaching in all areas, with special attention to the construction of interactive and personalized learning paths and the strengthening of an instant feedback mechanism. Its framework is shown in Figure 3.

In terms of oral skill improvement, the model based on deep reinforcement learning achieves the dynamic adjustment of dialogue strategy through a formula that contains a deeper mechanism, as shown in Equation (3) [26].

$$\Delta\theta = \alpha \cdot \nabla \cdot (r + \gamma \cdot Q(s', a', \theta) - Q(s, a, \theta)) \tag{3}$$

Here, $\Delta\theta$ is the update amount of the parameter θ, γ is the learning rate, ∇ is the gradient, r is the immediate reward, and γ is the discount factor, s$'$ and a$'$ represent the state and action of the next step. This update rule ensures that the model gradually optimizes dialogue strategies after each interaction based on student reactions and learning outcomes to more accurately match student abilities and improve the adaptability and learning effects of interactions [27].

To achieve a more precise personalized learning path planning, we introduce a variant of the sequence-to-sequence model that incorporates the attention mechanism, as shown in Equations (4)–(6).

$$h_t = \text{Encoder}(x_t, h_{t-1}) \tag{4}$$

$$c_t = \text{Attention}(h_1, h_2, \ldots, h_t) \tag{5}$$

$$y_t = \text{Decoder}(h_t, c_t) \tag{6}$$

The optimization of the immediate feedback mechanism is also supported by deep learning, by integrating online learning algorithms such as Adam, as shown in Equations (7)–(9) [28, 29].

$$m_t \beta_1 \cdot m_{t-1} + (1 - \beta_1) \cdot \nabla_t \tag{7}$$

$$v_t = \beta_2 \cdot v_{t-1} + (1 - \beta_2) \cdot (\nabla_t)^2 \tag{8}$$

$$w_{t+1} = w_t - \frac{\eta}{\sqrt{v_t} + \epsilon} \cdot m_t \tag{9}$$

3.2 Innovation of Evaluation System

Among the educational innovations led by deep learning, models for the evaluation of real-time learning effectiveness and comprehensive ability have become essential for the improvement of teaching quality and efficiency. Traditional assessment models are limited to static testing and one-dimensional performance analysis, while modern educational concepts advocate dynamic and comprehensive insight into students' learning processes and potential. Therefore, we adopt ensemble learning strategies, especially XGBoost (Extreme Gradient Boosting Tree), a powerful machine learning tool, to build a comprehensive evaluation system

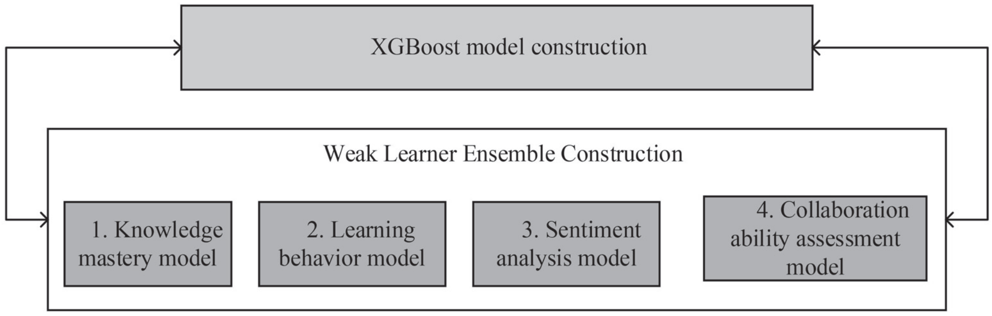

Figure 4 XGBoost model framework.

that comprehensively captures multidimensional learning dynamics and real-time feedback on the students' progress.

XGBoost (eXtreme Gradient Boosting) is an advanced version of ensemble learning, which gradually enhances prediction performance by increasing the set of weak learners (such as decision trees) and assigning weights according to their contributions. This is shown in Equation (10). The final prediction G(x) is the weighted sum of all weak learner outputs, each from the set of weak learners, with weights depending on its contribution to the overall prediction. This framework enhances prediction accuracy while maintaining model interpretability and facilitating understanding of evaluation logic by teachers and students [29, 30].

$$G(x) = \sum_{t=1}^{T} \alpha_t G_t(x), \quad G_t \in \mathcal{H} \tag{10}$$

The core of constructing comprehensive ability assessment model lies in integrating multi-dimensional learning data to depict a student's learning profile. This includes, but is not limited to, the following key aspects: Knowledge Comprehension Level (K), quantified by test scores, assignment ratings, and online test results; Learning Habit (L, V, I, L), which relates to login frequency, learning period, video viewing time, and forum interaction; emotional cognition (E), which uses natural language processing technology to deeply analyze student feedback and diaries to capture emotional changes; and collaboration (C), which assesses contribution to team projects and peer evaluations. The integration of these various data provides a rich perspective for in-depth understanding of students' learning process and provides a sound basis for the formulation of personalized teaching strategies.

Through XGBoost, a special weak learner framework is constructed comprising the features shown in Figure 4. The knowledge mastery model is Equation (11).

$$K = F(K) = \sum_{i} w_i \phi_i(K_i) \tag{11}$$

Where ϕ_i is the function for grades and assignments, and w_i is the weight. Similarly, the learning behavior model is constructed by analyzing logins, video viewing, etc., forming a behavior pattern recognizer using Equation (12) [31].

$$B = G(L, V, I) = \sum_{j} \eta_j \psi_j(L_j, V_j, I_j) \tag{12}$$

ψ_j represents the learning behavior feature functions, weights. Affective analysis model and collaborative ability evaluation also follow similar construction logic to form a comprehensive evaluation system.

The value of real-time assessment lies in the immediate discovery of bottlenecks and potentials to achieve precise teaching interventions. The XGBoost model iterates rapidly, enabling new data input (assignments, interactions), and immediately updates the evaluation with Equation (13).

$$G_{new}(x) = G_{old}(x) + sum_{t=1}^{T} delta_t \alpha_t G_t(x) \tag{13}$$

δ_t forecasts in real time the new data impact factors. This enables educators to keep track of student dynamics in real time, provide personalized resources that can be described as U(r) interest matching, W(r) resource value, and ensure that each student receives the most appropriate learning path to maximize learning efficiency and effectiveness.

4. EXPERIMENTAL EVALUATION

4.1 Experimental Design

In order to verify the effectiveness of the college English teaching model based on deep learning, an empirical experiment was designed to compare the differences between the experimental group and the control group in English learning outcomes, learning attitudes and learning efficiency. The experimental design followed the principle of randomized control to ensure that there was no significant difference between the two groups of students at the initial level, thereby strengthening the scientific rigor and reliability of the experimental results.

The purpose of this experiment was to evaluate the effectiveness of a personalized teaching model based on deep learning in improving college students' overall English language skills, and compare it with the traditional teaching model. The study was conducted over a semester (16 weeks), and the participants were 150 first-year English majors from two universities, ensuring a balance in basic level knowledge, age, gender, etc. Essentially, the aim of the experiment was to determine whether a personalized teaching path, a dynamic content recommendation system and an immediate feedback mechanism influenced learning outcomes, and further analyze the development of students' emotional cognition, the change of learning habits and the improvement of collaborative ability under this new teaching mode. Through carefully designed experimental arrangements, the two different

Table 1 Statistics of basic information of students.

Group	Gender	Age	Initial English proficiency mean	Number of students
experimental group	equal no. of males and females	20 years old	75 points	150
control group	equal no. of males and females	20 years old	75 points	150

Table 2 Comparison of pre-test and post-test English comprehensive proficiency.

Group	Test type	Average hearing score	Reading average	Writing average	Increase or decrease in overall mean score
experimental group	pre-test	70	75	72	-
experimental group	post-test	80	85	82	+10
control group	pre-test	70	75	72	-
control group	post-test	75	80	79	+5

teaching models were the strictly controlled independent variables, observation-dependent variables included, but were not limited to, quantitative indicators of learning outcomes (e.g., final grade and homework average), survey feedback on learning attitudes, improvement in learning efficiency, positive changes in emotional state, optimization of learning behavior habits, and improvement in collaborative teamwork skills, to comprehensively test the role of teaching innovation based on deep learning in fostering students' all-round development.

Data collection links use multi-dimensional and digital means to comprehensiveness of learning activities. Specific measures included: tracking the interaction of each student in real time by means of an intelligent online learning platform, collecting detailed behavior data indicated by login frequency, accumulated video viewing time and even online communication activity; organizing online tests regularly to quantify and record the students' knowledge mastery and growth at various stages. At the same time, a questionnaire survey was combined with natural language processing technology to conduct an in-depth analysis of the learners' emotional fluctuations and attitude changes, and provide detailed psychological portrait to guide teaching strategies. Moreover, each student's collaborative and cooperative skills and contribution to a team project were measured objectively via a peer evaluation mechanism that determined the extent to which soft skills had been fostered. By means of these various data collection methods, a comprehensive and multi-level basis was established to plot the growth blueprint of students in deep learning mode, and provide solid data support for the evaluation of educational outcomes.

The first week of the experiment was the pre-test phase, in which all participants were tested to determine their English proficiency in listening/comprehension, reading and writing, to establish baseline data. At the same time, through basic information collection and learning habits questionnaire, combined with NLP technology to analyze students' daily feedback, a baseline was established of students' emotional state, for subsequent analysis. The students were then divided into two groups - the experimental group and the control group – and the experiment was conducted over 12 weeks. The experimental group experienced tailor-made deep-learning-driven teaching comprising personalized content adaptation, instant feedback mechanism, sequence-to-sequence model-guided customized learning path, and oral interaction optimized by deep reinforcement learning, intended to improve learning efficiency and interactivity. In addition, teamwork skills were fostered through group discussions and team projects monitored by collaborative learning platforms. On the other hand, the control group were instructed using the traditional teaching model, and the fixed curriculum content was maintained and as well as progress evaluation as a baseline for comparison. The post-test phase was initiated at week 16 to quantify the improvement brought about by the instructional intervention by repeating the comprehensive English proficiency test of the pre-test. In addition, the re-distribution of the learning attitude and habit questionnaire, combined with NLP technology in-depth analysis of student feedback, revealed any changes in learning behavior and emotional cognition. Team project performance and peer evaluation were the key indicators used to evaluate the difference of collaborative ability between the two groups of students.

The students' privacy was protected throughout the whole experiment. All data was anonymized, and compliance with relevant laws and regulations was ensured. All participants signed informed consent forms in advance and were fully apprised of the details of the experiment. At the same time, psychological counselling services were made available to ensure the psychological well-being of students. In regard to educational equity, the teaching resources were made available to the control group after the end of the experiment to ensure that all students could benefit from the research results.

4.2 Experimental Results

Table 1 shows the basic information of the experimental group and the control group. The number of students in both groups is 150, the age is 20 years, the gender distribution is half male and half female, and the average initial English level is 75 points. From these data, we can see that the experimental group and the control group have similar backgrounds and conditions in the initial state, which helped us to better compare and analyze the results of subsequent experiments.

Table 2 shows the scores for overall English proficiency of the experimental group and the control group in the pre-test and post-test. On the pretest, students in both groups

Table 3 Results of the questionnaire on learning attitudes and habits.

Group	Proportion of students more inclined to active learning	On-time completion rate	Increased interest in English learning
experimental group	65%	90%	20%
control group	50%	80%	10%

Table 4 Changes in learning efficiency.

Group	Online learning platform activity increase (login times/week)	Increase in video viewing time (minutes/week)	Job completion speed increase (%)
experimental group	+3	+20	15%
control group	+1	+10	8%

Table 5 Cognitive analysis of emotion.

Group	Percentage of positive emotional feedback	Percentage of negative emotional feedback	Emotional stability index (before-and-after difference)
experimental group	85%	10%	+15
control group	75%	15%	+5

Table 6 Team Collaboration Assessment.

Group	Average team project rating	Proportion of positive peer feedback	Collaborative problem-solving score
experimental group	88 points	80%	90 points
control group	82 points	70%	85 points

scored an average of 70, 75 and 72 in listening, reading and writing. In the post-test, the experimental group's mean scores increased to 80, 85, and 82 points, respectively, with an overall mean score increase or decrease of +10 points; the control group's mean scores increased to 75, 80, and 79 points, respectively, with an overall mean score increase or decrease of +5. These post-test data show that the experimental group improved more than the control group in regard to overall English proficiency.

Table 3 shows the questionnaire results for the experimental group and the control group in terms of learning attitudes and habits. 65% of the students in the experimental group were more inclined to engage in active learning, compared with 50% in the control group; the punctuality of completing homework in the experimental group was 90% compared with 80% in the control group; the amount of interest in English learning of the experimental group was 20% compared with 10% of the control group. These data suggest that the experimental group outperformed the control group in terms of learning attitudes and habits.

Table 4 shows the changes in learning efficiency between the experimental group and the control group. The activity of the online learning platform of the experimental group increased by 3 times/week, the video viewing time increased by 20 minutes/week, and the homework completion speed increased by 15%. The activity of the online learning platform of the control group increased by 1 time/week, the video viewing time increased by 10 minutes/week, and the homework completion speed increased by 8%. These data indicate that the experimental group improved their learning efficiency more so than the control group.

Table 5 shows the results of analysis of emotional cognition of the experimental and control groups. The experimental group had 85% positive emotional feedback, 10% negative emotional feedback, and an emotional stability index of +15. The control group had 75% positive emotional feedback, 15% negative emotional feedback, and an emotional stability index of +5. These data suggest that the experimental group performed better than the control group in regard to emotional cognition.

Table 6 shows the evaluation of the experimental group and the control group in terms of teamwork ability. The average score for the team item in experimental group was 88, while that of the control group was 82; the positive feedback rate of peer evaluation of the experimental group was 80%, while that of control group was 70%; the score the collaborative problem-solving ability of the experimental group was 90, while that of control group was 85. These data suggest that the experimental group performed better than the control group in terms of teamwork.

In the overall level of English skills (speaking, listening, writing), the experimental group's overall average score increased by +10 points, while the control group's score increased by +5, indicating that the experimental group's English learning improved more significantly. In terms of learning attitude and habit, the experimental group tended to be more active in learning, and the punctuality rate of completing homework and the proportion of increasing interest in English learning were higher than those of the control group. In terms of learning efficiency, the experimental group's online learning platform activity, video viewing time and homework completion speed were all improved, more so than those of the control group. In terms of emotional cognition, the experimental group had a higher proportion of positive emotional feedback, a lower proportion of negative emotional feedback, and a higher emotional stability index. In terms of team cooperation ability, the average score of team project, the amount of positive peer evaluation feedback and the score for the collaborative problem-solving ability of the experimental group were higher than those in the control group.

In conclusion, the experimental results show that the new teaching method can effectively improve students' English learning, improve learning attitudes and habits, improve learning efficiency, enhance emotional cognitive stability, and enhance team cooperation ability. These findings are of great significance to the improvement and optimization of English teaching methods.

5. CONCLUSION

With the rapid development of science and technology, AI technology, especially deep learning technology, has gradually penetrated the field of education and triggered profound changes in teaching models. The excellent performance of deep learning technology in image recognition, speech recognition, natural language processing, etc. provides unprecedented opportunities for the education industry. In the field of English teaching, deep learning technology can predict students' learning needs by analyzing students' learning data, so as to realize personalized teaching content recommendation and dynamic adjustment of their learning path, which can significantly improve teaching efficiency and learning outcomes. The traditional college English teaching model relies on mainly teachers taking the leading role and students passively accepting knowledge, which greatly limits students' initiative and creativity. In addition, the teaching resources under the traditional teaching mode are relatively limited and cannot meet the students' individual learning needs. Therefore, the college English teaching mode based on deep learning can improve teaching efficiency and personalized learning through technical means, so as to make the learning experience richer and more efficient. The results of this study reveal the significant advantages of the deep-learning-based college English teaching model in improving students' English learning. The experimental group performed better than the control group in English proficiency in all areas of English learning, learning attitude and habit, learning efficiency, affective cognition and team cooperation ability, which proved that the application of deep learning technology in college English teaching has important practical value. First, in the overall level of English skills (speaking, listening, writing), the experimental group's overall average score increased by +10 points, while the control group's score increased by +5, indicating that the experimental group's improvement in English learning was more significant. This result indicates that the teaching model based on deep learning can effectively improve students' overall English ability, including listening, reading and writing. Secondly, in terms of learning attitude and habit, the experimental group tended to be more actively engaged in learning, and the punctual submission of completed homework and the amount of increasing interest in English learning were higher than those of the control group. This shows that the teaching model based on deep learning can stimulate students' interest and initiative in learning and encourage them to develop good learning habits. In addition, in regard to learning efficiency, the activity of online learning platform, video viewing time and homework completion speed of the experimental group were all improved more so than those of the control group. This shows that teaching models based on deep learning can improve students' learning efficiency and enable them to use learning resources and time more effectively. In terms of emotional cognition, the experimental group had a higher proportion of positive emotional feedback, a lower proportion of negative emotional feedback, and a higher emotional stability index. This shows that the teaching model based on deep learning can promote students' positive emotional attitude and emotional stability, and enhance their learning motivation and self-confidence. Finally, in terms of team cooperation ability, the average score of team project, the amount of positive peer evaluation feedback and the score of collaborative problem-solving ability of the experimental group were higher than those of the control group. This shows that the teaching model based on deep learning can foster students' ability to cooperate and collaborate.

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