Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 4447209, 11 pages
https://doi.org/10.1155/2022/4447209

*Research Article*

# Factors Influencing Analysis for Level of Engineering English Education Based on Artificial Intelligence Technology

**Mengqing Zhu**

*College of Foreign Languages Jilin Agricultural University, Changchun, Jilin 130118, China*

Correspondence should be addressed to Mengqing Zhu; zhumengqing@jlau.edu.cn

Received 21 July 2022; Revised 26 August 2022; Accepted 1 September 2022; Published 16 September 2022

Academic Editor: Gengxin Sun



The essence of English for engineering is English for professional purposes (ESP). The assessment of the level of education in engineering English classrooms is one of the key issues currently being discussed in all schools. While the traditional English classroom teaching model has been criticized due to many problems, the changes in the new English curriculum and the changes in the assessment methods have also created new demands on the English teaching methods. The artificial intelligence technology brings a new direction for the optimization of English classroom, and it also provides new support for the realization of intelligent and collaborative English classroom teaching. In view of the current situation that the college English teaching evaluation mode is still dominated by summative evaluation, this paper summarizes the current problems of poor teaching effect, unbalanced ability cultivation, and mismatch between evaluation and teaching in engineering English. On this basis, it adopts the BPNN network combined with the interactive mechanism of English teaching to establish a multi-dimensional interactive English learning framework of teacher, student, corpus, and AI resource base. And the BPNN algorithm process was optimized using the gray wolf algorithm to improve the engineering English teaching model. Finally, an experiment on teaching engineering English was conducted within a university, and the experimental results showed that teaching objectives, teaching contents, teaching methods, and teaching effects had important effects on teaching effectiveness. In addition, the teaching framework constructed using the improved BPNN algorithm was better in terms of the learning effect at the same time, especially in writing, during the teaching process. Finally, the experimental results show that BPNN optimized by gray wolf algorithm can achieve better teaching effect than BPNN.

## 1. Introduction

In the past 20 years, especially since 2009, English for specific purposes has spread and developed rapidly in mainland China and has become a hot spot for university English teaching and research [1, 2]. ESP is different from English for general purpose, which has its own unique curriculum characteristics and teaching requirements. The literature [3] argues that it has two distinctive features: first, learners have a clear learning purpose, i.e., learners need to achieve the ability to use English within certain disciplines due to the needs of specific industries; second, it has special content, i.e., specialized content. The literature [4] summarizes the four characteristics of ESP: "it belongs to the category of applied linguistics, it is closely related to a certain discipline, it better reflects the needs of learners, and English emphasizes applied skills" [5].

During the teaching process, how to make students overcome language barriers, such as mastering difficult to read and remember professional vocabulary, analyzing obscure and complex long sentences, understanding descriptions of professional tools and machines and professional English reading materials, and verbally describing professional work processes, are all factors to be considered in each class design [6]. The introduction of modern information technology is of great importance to make the teaching of professional English intuitive and easy to understand, to improve learners' English input and output and to generate continuous interest and self-motivation in learning [7, 8].

Information-based teaching is to use computers, multimedia technology, and network information technology as carriers and means of teaching activities, to use these advanced technologies to enrich the teaching content of professional English, to improve teaching methods, to enhance teaching means, and to give full play to the advantages of both for a better teaching effect [9].

For a long time, English learning has been closely linked with technology [10]. When computers were first introduced, the United States began experimenting with computer-assisted learning and teaching (CAL), of which computer-assisted language teaching (CALL) is one of the many areas of CAL research [11]. CALL represents a new way of teaching language, in which learners use a computer screen to learn the language learning resources provided by the computer, and the computer also acts as an intelligent assistant to the language teacher's teaching or research, which can be said to be a significant change to the traditional way of teaching language [12]. CALL has made full use of computer science, information technology, psychology, and further integration with automatic analysis technology, the Internet (WWW), natural language processing, and other technologies to make the CALL system more intelligent (e.g., to achieve oral responses and speech scoring), which has led to the development of CALL as artificial intelligence computer-assisted ICALL is a combination of language teaching, which has contributed to the modernization of language teaching [13].

As the technology matures and research progresses, AI-supported English language education has transitioned from "technical inquiry" and "pedagogical practice" [14]. The research on "teaching practice" mainly focuses on the design of AI-supported English teaching models and learning paths and further explores the rules of teaching and learning English in an intelligent environment based on technical support to optimize learning effects and improve teaching quality. For example, in the English classroom teaching of literature [15], the use of the "criticism network" to design a flipped classroom creative collaborative teaching model was verified through practice to improve the effectiveness of students' English writing method. In addition, the practice of artificial intelligence to support English learning, Shanghai has tried to use artificial intelligence marking system English listening and the speaking test in the college entrance examination English test to help promote the change of the college entrance examination English speaking test [16]. Artificial intelligence has great potential in English education, and machine translation, natural language understanding, and speech recognition technologies have been applied to English learning [17]. Regarding how AI supports English learning, from the available studies, it is mainly reflected in AI support for listening training, AI support for speaking learning, and AI support for writing training [18]. The main contributions of this paper are summarized as follows: (a) from the perspective of the non-mechanism model, in view of the problems existing in the current use of neural networks in English teaching, this paper follows the basic principles and steps of neural network modeling in modeling, establishes a neural network model based on gray wolf optimization and improves the generalization ability, effectiveness, and robustness of the neural network model optimized by gray wolf. (b) Based on the BPNN network and the interactive mechanism of English teaching, a multi-dimensional interactive English learning framework of teachers, students, corpus, and artificial intelligence resource bank is established. (c) An engineering English teaching experiment was carried out in a university. The experimental results show that the teaching objectives, teaching contents, teaching methods, and teaching effects have an important impact on the teaching effect.

The rest of the paper is organized as follows: the second part discusses the framework of engineering English education based on artificial intelligence and the mechanism of teaching interaction in engineering English teaching. In the third part, an English teaching evaluation system based on the wolf pack algorithm to improve the BPNN network is investigated. The fourth part presents the conditions and experimental results of the teaching experiment. Finally, the fifth part concludes the whole paper.

## 2. Model Building of Artificial Intelligence and the Education Level of Engineering English Teaching

*2.1. Design of the ESP Information-Based Teaching Framework.* Artificial intelligence-based ESP teaching in the information environment should be understood as the integration of information technology and ESP course teaching, mainly integrating various ESP teaching resources, such as text, graphic images, audio, animation, video, and other media, reorganizing each teaching link and related elements, creating teaching situations, expanding the corresponding learning space and time, realizing the optimal allocation and design of resources and making the teacher-centered The teacher-centered teaching mode changes to a student-centered and teacher-led teaching mode, and follows the principles of authenticity, subjectivity, and openness of ESP teaching [19].

Authenticity means that the language carrier of ESP should be real and reliable, and the real language material should be used to teach foreign languages and create real contexts for students in order to stimulate their interest in learning [20]. The application of information technology not only provides authentic learning materials but also provides students with real audio and video materials. Applying these to ESP classroom teaching fully mobilizes students' eyes, ears, hands, mouth, and other organs to put students in an active and excited learning state, which can enhance students' interest in learning and improve learning efficiency [21]. Secondly, the teaching task should be authentic, that is, the "task" in classroom teaching must be consistent with the "task" in social practice. This requires ESP teaching to take the communicative tasks in social practice as the simulated objects of classroom teaching, such as the preparation of documents related to meetings, the presentation of products, and the explanation of the process of machine operation. Finally, the difficulty level of the material should be close to the real level of the learners. Today, with such advanced technology, it is easy to use information technology (e.g., the Internet, search engines, etc.) to find “original” authentic materials, but it is not easy to ensure that the difficulty of the selected materials is close to the real level of the learners. This requires the instructional designer to evaluate the difficulty level of the materials and make the final design after understanding the current level of the learners. The “evaluation methods” in formative evaluation are diversified, including the evaluation of teachers and educational administration departments on students, students’ self-evaluation, students’ mutual evaluation, students’ evaluation on teachers’ teaching attitude, teaching means, and teaching effect.

As shown in Figure 1, the subjectivity principle of ESP informatization teaching design mainly highlights the subject position of learners in the learning process and attaches importance to the analysis of different characteristics of learners in order to fully explore the internal potential of learners and stimulate and mobilize their initiative and enthusiasm for learning. Since learners are always the main subjects of teaching activities, teachers should consider the perspective of learners’ subjects when using information technology for teaching design, so as to promote learners’ personality development and all-round development. At the same time, there are also questionnaires and interviews on students’ learning motivation and interest, emotional attitude, learning strategies, autonomous learning ability, etc. In particular, the methods of “student self-evaluation” and “student mutual evaluation” can enable students to discover their achievements and problems in the learning process in time and then adjust their learning attitude, formulate learning plans and learning objectives and improve learning strategies and solve problems encountered in learning in a timely and effective manner.

Finally, ESP informatization teaching design should also follow the principle of openness. Attention should be paid to create a good teaching atmosphere, giving students sufficient free space for development, attaching importance to open thinking training, guiding students to use information technology, conducting exploratory, research and discovery learning, encouraging students to divide and cooperate in the process of completing classroom tasks, discussing, and analyzing.

*2.2. The Construction of the Interactive Mechanism Teaching Model.* Teaching interaction has an important value in the flipped classroom teaching model and is carried out throughout the flipped classroom teaching in Figure 2. Therefore, the quality of teaching interaction directly affects the implementation effect of the flipped classroom, and its role in the implementation of the flipped classroom is particularly significant, and its value before, during, and after class should not be underestimated. Because multiple assessments emphasize “the multiplicity of evaluation functions, the multiplicity of evaluation criteria and evaluation subjects, and the diversity of evaluation means, this evaluation system with diversified evaluation subjects, evaluation contents, and evaluation forms helps to cultivate students’ comprehensive English application ability and help students develop their independent learning ability and understand students’ feelings, attitudes, and learning strategies, in the process of growth and learning.”

(1) The value of preclass prestudy: for students, the teaching interaction enables them to understand and master the main contents of the class in advance, so that they can grasp the main points of learning and clarify their difficulties and make themselves more focused when listening and learning in class; for teachers, teaching interaction enables them to understand the learning situation of students in advance and understand the concentration of students’ learning issues and problems, so that they can teach the class. For teachers, teaching interactions enable them to understand students’ learning situation in advance, and to understand students’ concentrated learning problems and difficulties, so that they can grasp the key points during lectures and make lecture contents and lecture plans more relevant and improve classroom efficiency.

(2) Value in classroom learning: teaching interaction in the classroom can make students discuss learning problems together and enhance the cultivation of students’ feelings and facilitate the depth of knowledge internalization, which can make the cultivation of teachers’ feelings with students and make teachers’ lectures revolve around students’ difficult problems in real-time, and along with the progress of lectures, students’ problems will also change, and at this time, the value of teaching interaction can effectively solve students’ new problems and promote better internalization of knowledge.

(3) Value in postclass review: teaching interaction after class enables students to make up for knowledge gaps in the classroom, enables students to communicate and exchange with each other, promotes further internalization of knowledge, makes knowledge really become a skill of their own, facilitates teachers’ next teaching work, enables teachers to adjust teaching methods and ideas according to the situation and prepares corresponding test questions in time according to students’ feedback.

It is important for the teacher to have a good classroom atmosphere, and only if the atmosphere of the lecture is good, students can learn better and will learn more efficiently. It can be seen from the emergence of intelligent components instructional mode that the four reinteraction modes are interrelated, so that students can have information development participation between different intelligent modes. In the treatment of university English education, we will establish application scenarios to improve students’ desire, guide, and direct their learning in this treatment and advance good interaction between students and instructors. Teachers should scientifically analyze the

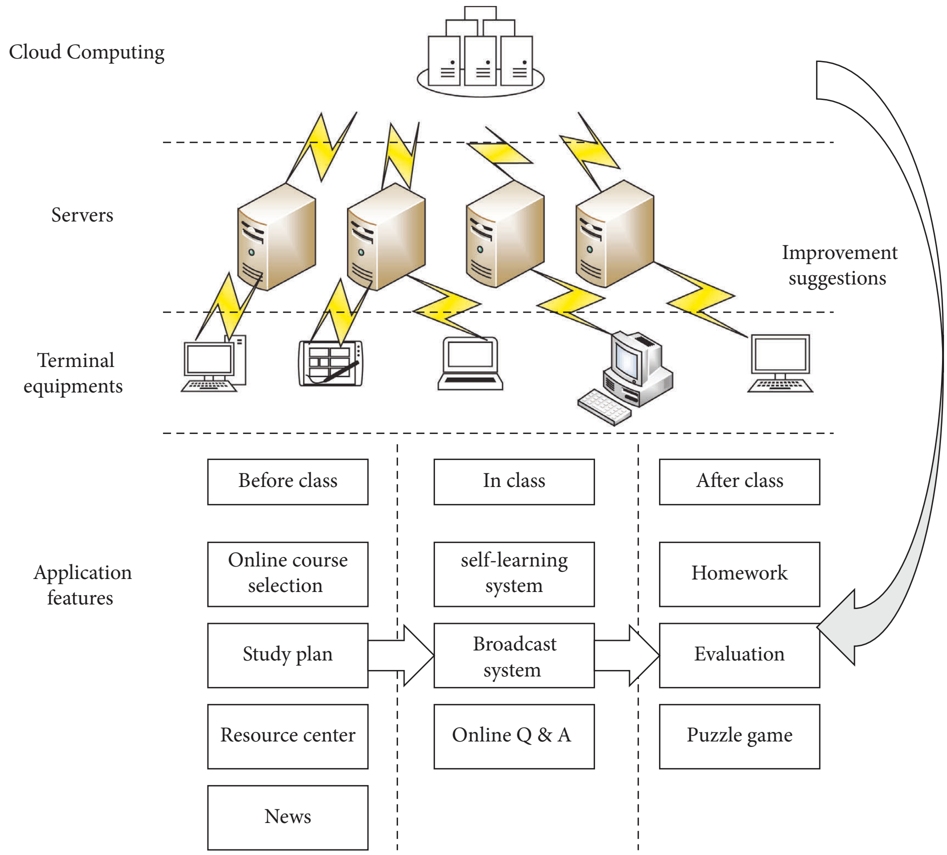


FIGURE 1: The structure of ESP teaching based on artificial intelligence.

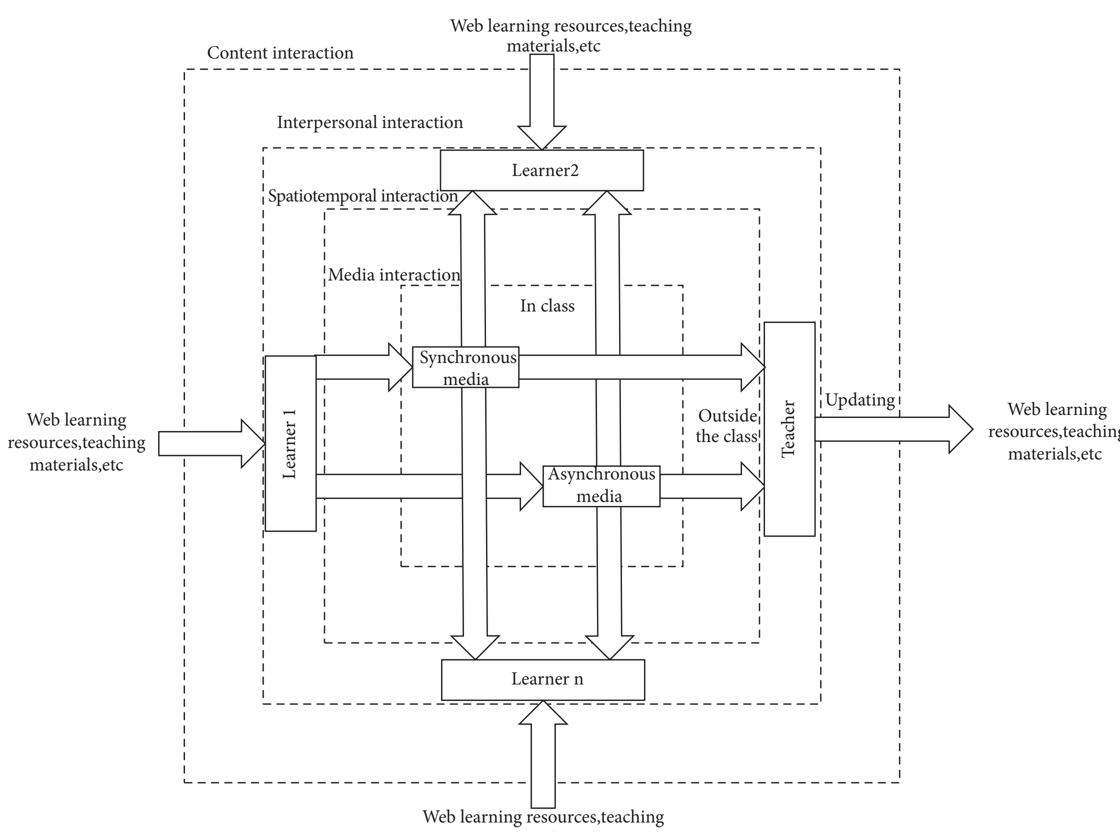


FIGURE 2: Interactive mechanism teaching mode.

teaching materials and innovatively reorganize and design the teaching content, so that the teaching contents are presented in a way that is conducive to the implementation of teaching interaction. Unlike the traditional ESP teaching, with the introduction of AI technology, the interaction mode becomes an interaction between students, teachers, teaching materials, and AI resource systems.

The AI resource library can effectively provide teachers with feedback on the current teaching situation and act as an assistant to help teachers enrich classroom content and make up for students' shortcomings in a targeted manner.

## 3. Research on the Evaluation Model of the Engineering English Teaching Level Based on the Improved BPNN Algorithm

*3.1. The Process of English Teaching Effectiveness Evaluation by the BPNN Model.* There are many kinds of artificial neural networks, BP neural network is a multilayer feedforward multilayer neural network. It has the largest application range among many neural networks with the most application scenarios. In the BP neural network, the neurons within each layer are not directly connected with each other. The neurons between the layers are interconnected by weights. BP neural network conducts forward through the data signal and reverse according to the error. In the data forward conduction process, the neural network transmits the data information content gradually from the input layer to the implicit layer to the output layer. Whenever there is a deviation between the output result and the expected result, the network system will transmit the output data information content back in the opposite direction and adjust the connection weights between the layers of the network system by the deviation of the output value from the expected value. Finally, the output value of the network system gradually approaches the desired value. Figure 3 shows the structure of the BP neural network.

The computational process of the BP neural network is considered as a computational process with a "mentor." The whole learning process consists of two parts. The first part is the forward operation of the data, which introduces the predefined sample data input values and the expected output values into the network to complete the forward calculation. Then, the second part is to compare the output value generated by the data input operation with the expected output value to calculate the error. When the error is greater than the specified range, the output result will be back propagated and the weights between neurons will be adjusted according to the error value. The above two parts of the calculation are repeated until the error between the real output value and the predicted output value is within the given accuracy range and the training is finished. The specific training process is shown in the following steps. An iteration period of the algorithm is

$$w^{k+1} = w^k + \Delta w = w^k - \eta^k \frac{\partial e^k}{\partial w^k}. \tag{1}$$

For nonlinear networks, choosing the learning rate is a very difficult task. For current networks, choosing too large a learning rate can easily lead to unstable learning; conversely, choosing too small a learning rate can lead to intolerably long training times. Unlike linear networks, a simple and easy method has not been found to solve the problem of choosing the learning rate for nonlinear networks. For fast training algorithms, there are usually margins for their default parameter values. The initial output and error of the network are calculated as

$$w_{ji}(n+1) = w_{ji}(n) + \eta(n) D(n). \tag{2}$$

The change of $\eta$ will affect the change of weight. Choosing the appropriate learning rate for a given problem is not an easy task. It is usually obtained empirically, and even then, a learning rate that is more effective at the beginning of the training may not necessarily be appropriate for later training as well. To solve this problem, networks have been used to automatically adjust the learning rate during the training process. Similar to the judgment condition when using the additional momentum method, when the new error exceeds the old error by a certain multiple, the learning rate will be reduced, otherwise its learning rate remains the same; when the new error is smaller than the old one, the learning rate will be increased. This method ensures that the network learns steadily so that its error continues to decrease and increase the learning rate so that it learns at a larger learning rate. Once the learning rate is adjusted too much, and the error is not guaranteed to continue decreasing, that is, the learning rate should be reduced until its learning process is stable. The weighted adjustment formula is

$$\Delta w(t+1) = \eta \frac{\partial e}{\partial w} + \alpha \Delta w(t). \tag{3}$$

Generally, $\alpha$ is about 0.9, where $\alpha$ is the momentum coefficient.

The maximum error rate of change can be any value greater than or equal to 1, typically 1.04. Therefore, conditional judgments must be added to the design of the training program for the additional momentum method in order to properly use its weight correction formula. The BPNN algorithm of self-adjusting LR can be described as

$$\begin{aligned} \Delta X &= L_r \frac{\partial E}{\partial X}, \\ \Delta X(k+1) &= mc \times \Delta X(k) + L_r \times mc \times \frac{\partial E}{\partial X}. \end{aligned} \tag{4}$$

Here, the momentum is $mc$.

BP networks typically use an implicit layer of an $S$-shaped activation function, which is often referred to as a "squash" function that compresses an infinite range of inputs into a finite range of outputs. It is characterized by a slope close to 0 when the input is large, which results in a small gradient amplitude in the algorithm and may bring the correction process of the network weights to a near halt.

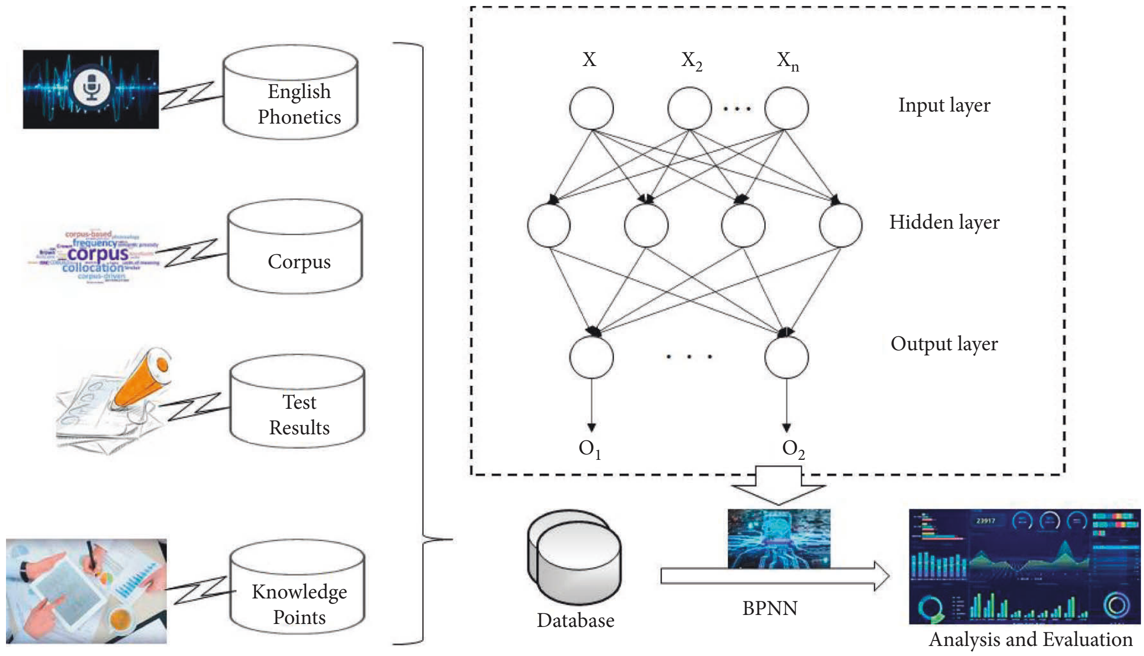


Figure 3: Basic BPNN network structure.

The flexible BP algorithm takes only the sign of the partial derivative and does not consider the magnitude of the partial derivative. The sign of the partial derivative determines the direction of the weight update, while the magnitude of the weight change is determined by an independent "update value."

$$f(x) = \left(\frac{0.5}{\lambda}\right)\sin(\lambda x) + \left(\frac{0.5}{\lambda}\right). \tag{5}$$

In this way, the BP algorithm converges relatively fast and the algorithm is not complicated, and it does not need to consume more memory.

*3.2. A Framework for English Teaching Evaluation Based on the Optimized BP Neural Network with the Gray Wolf Algorithm.* Organisms in nature have gradually evolved the most suitable way of survival for their own species in the process of adapting to the environment, and humans have learned a large number of working methods that can be used in production and life by observing the information exchange characteristics or life styles of other species. The gray wolf algorithm, as a new type of a group intelligence optimization algorithm, is proposed by scholars based on the strict hierarchy and a precise cooperative hunting mode of the gray wolf population. It is inspired by the prey hunting behavior of the gray wolf pack. The gray wolf algorithm simulates the bottom-up pyramidal social hierarchy in the gray wolf population and the mechanism of information sharing during the hunting process of the gray wolf population. This algorithm has fewer parameters, strong convergence, and easy to implement global search. Since the gray wolf algorithm was proposed, it has achieved good results in the fields of parameter optimization and image classification.

The optimization of the BP neural network using the GWO algorithm can effectively improve its convergence speed and accuracy. The optimal solution of the BP neural network is obtained when the gray wolf reaches the location of the prey, i.e., when the gray wolf is in the best hunting position. Gray wolf optimization algorithm is a swarm intelligence algorithm that can find the global optimal solution. It has the characteristics of accelerating the convergence speed of the model and improving the accuracy. It takes the weight and threshold of the BP neural network as the position information of gray wolf. According to the position judgment of gray wolf on the prey, constantly updating the position is equivalent to constantly updating the weight and threshold to finally find the global optimal solution.

The gray wolves not only have a strict social hierarchy within the group but also have an extremely orderly mechanism of command transmission and information sharing in the hunting process. In the process of predation, the gray wolf firstly determines the target and chases it. In the process of chasing, it gradually approaches the prey and surrounds it and tries to interfere with it. When the disturbance is successful, it tries to attack the prey until it is successfully captured. During the hunting process of the gray wolf pack, when the head wolf in the layer captures the position of the prey, it will unite with the other two leaders and direct the whole pack, so that the whole pack will surround the prey from all directions and further hunt the target. The mathematical expression describing the above behavior is

$$\begin{cases} D_\alpha = \left|C_1 \cdot X_\alpha(t) - X(t)\right|, \\ D_\beta = \left|C_2 \cdot X_\beta(t) - X(t)\right|, \\ D_\delta = \left|C_3 \cdot X_\delta(t) - X(t)\right|. \end{cases} \tag{6}$$

There are many kinds of excitation functions for BP neural networks, and the excitation function chosen in this paper is logsig function, which is expressed as follows. The expressions are as follows:

$$f(x) = \frac{1}{1 + e^{-x}}. \quad (7)$$

The optimization of the BP neural network by the GWO algorithm can effectively improve its convergence speed and accuracy, so that the neural network can quickly jump out of the local optimal solution in the operation process. When the gray wolf reaches the location of the prey, that is, when the gray wolf is in the best hunting position, the optimal solution of the BP neural network is obtained, the structure is shown in Figure 4.

## 4. Analysis of Test Results

*4.1. Experimental Environment and Simulation Settings.* In order to test the effect of the BPNN network framework optimized based on the GWO algorithm on the quality of engineering English teaching, 150 non-English majors from a university were selected for this experiment. A preschool test was administered to the students before the experiment, and the students were grouped according to their preschool test scores, so that the overall mean scores and standard deviations of each group were consistent. The students in these three groups were divided into experimental, control, and standard groups, with 50 students in each group. The experiments were conducted to compare the student performance of the traditional teaching model with that of the new classroom quality monitoring model, so as to compare the effectiveness of the teaching method in this paper. Before the experiment, the students in the experimental class and the control class were tested on their English proficiency with the full-scale CET-4 questions to understand the basic situation of the students in each class. The test results were calculated and analyzed with SPSS, and the significant difference was $p < 0.05$.

*4.2. Verification of the Superiority of the Algorithm Analysis of English Teaching Quality Evaluation Indexes.* After many experiments, the neural network parameters optimized by GWO are as follows: the number of wolves is 200; The upper and lower bounds of the initial position are 3 and—3; The maximum number of iterations is 150; The network structure is 10-9-1, that is, the input layer has 10 nodes (number of variables), 9 hidden layer nodes, and 1 output node.

In the teaching process, the teacher's behavior was studied to determine the impact of different aspects of the teacher's teaching on the students' abilities in various areas. The teacher's teaching skills were divided into four main areas: teaching objectives, teaching content, teaching methods, and teaching effect. Figure 5 shows that teaching objectives had the greatest overall impact on students and had a more significant impact on students' independent learning ability and listening and speaking ability, and it can be seen that teaching objectives effectively mobilized students' motivation and improved their learning motivation. However, their ability to improve reading in the learning process is not enough, probably because the motivation process avoids a lot of reading training. The second major influence on students is teaching content, which is well prepared by teachers to improve students' learning efficiency and thus reduce learning time. Good teaching content can effectively improve students' reading ability, which makes up for the lack of teaching objectives, and the teaching effect has less influence on the students' learning effect.

Figure 6 shows that the variation of different optimization algorithms on the suggested accuracy of AI repository shows that the optimization effect does not improve significantly with the increase of optimization generations using the traditional optimization algorithm, which means that the number of generations to be optimized needs to be much more than that of the BPNN network to achieve better results. The original BPNN converges after about 45 iterations while the improved BPNN network based on the GWO algorithm needs about 30 iterations. In contrast, for the original BPNN network and the improved degree BPNN network, the improved BPNN network is generally better than the original BPNN network in terms of the effect of iterations, and the improved BPNN network yields better results with the same number of iterations. On the other hand, the improved BPNN network based on the GWO algorithm occupies relatively less system resources during iteration and requires less hardware computing power, which has more potential for portability to different platforms.

*4.3. Convergence and Utilization Analysis of Optimal Response Strategy.* Figure 7 shows that specific differences and changes in the effectiveness of the GWO algorithm-based optimized BPNN network and the original BPNN network in the English learning process were used. The four aspects of the learning process in the class, namely listening, speaking, reading, and writing, were assessed for their effectiveness. Assessments were conducted every two weeks, up to ten weeks in total. During these ten weeks, it can be seen that the learning model provided by the improved BPNN network has a significant improvement in learning effectiveness over the model provided by the original BPNN algorithm, especially in the area of writing, as shown in Figure 7. However, the overall learning efficiency in writing is still lower than the other three areas. The best learning efficiency is in listening, which can reach 90.83 after ten weeks of learning with the modified BPNN network, as shown in Figures 7(a) and 7(c). As for speaking, the overall improvement is relatively small, which may be caused by the lack of motivation of students to express themselves actively in the learning process influenced by their previous learning habits, as shown in Figures 7(b) and 7(d). This improvement was gradual, with a relatively small improvement in the first six weeks, while the change in learning effectiveness was more clearly demonstrated as time went on.

In order to test the optimization effect of ESP education influencing factors based on the BPNN network optimized

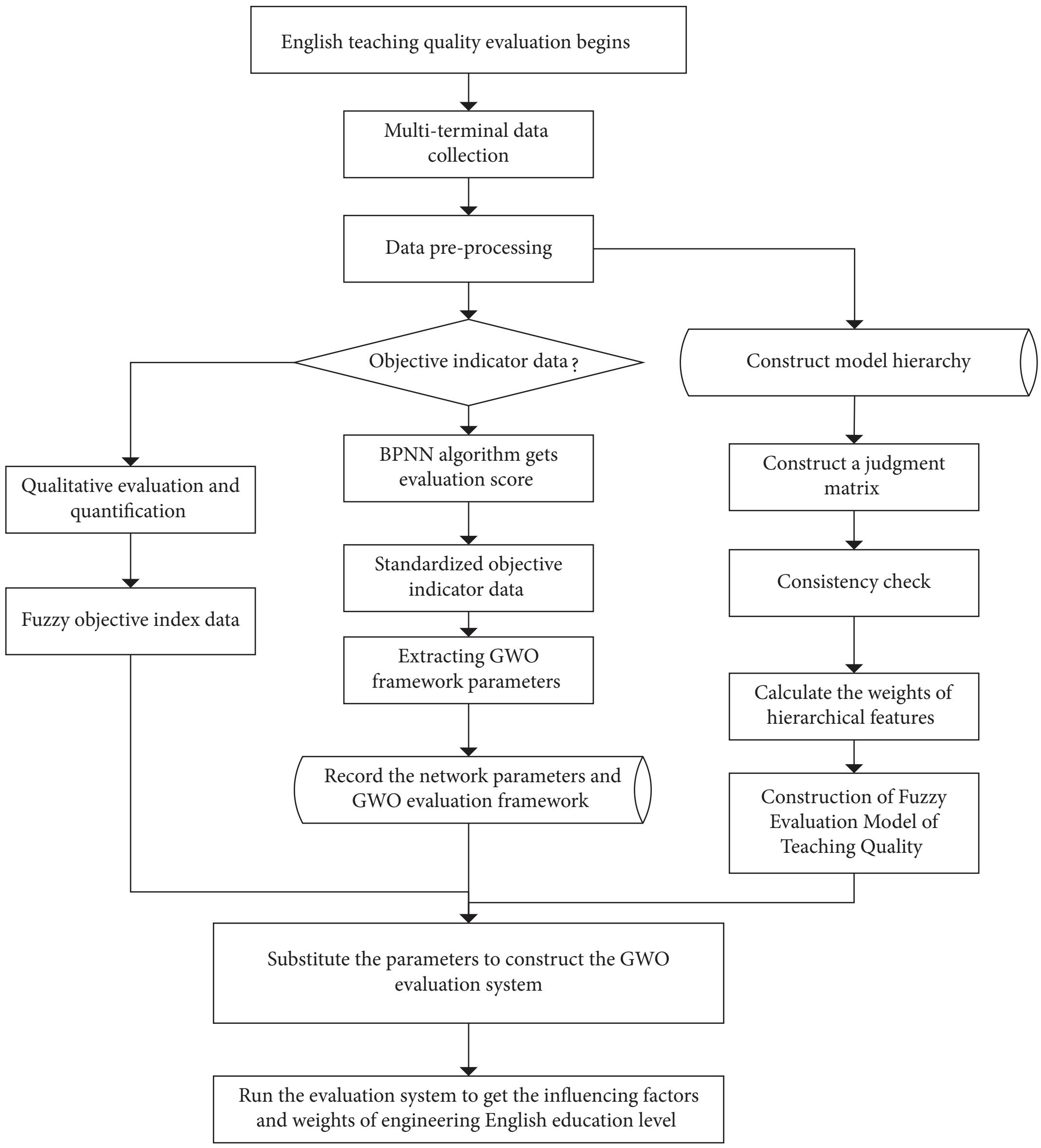


Figure 4: An evaluation framework for English language teaching based on improved BPNN.

by the GWO algorithm, a questionnaire was conducted anonymously, asking 18 independent English pedagogical experts to objectively and impartially rate the comprehensive English teaching process involving students' listening, speaking, reading, writing, and independent learning skills, thus providing a comprehensive response to the actual effect of the teaching framework designed in this paper. The weighted average was then converted to an exact value between (0, 1). As shown in Figure 8, the optimization effect of the improved BPNN network will keep improving as the

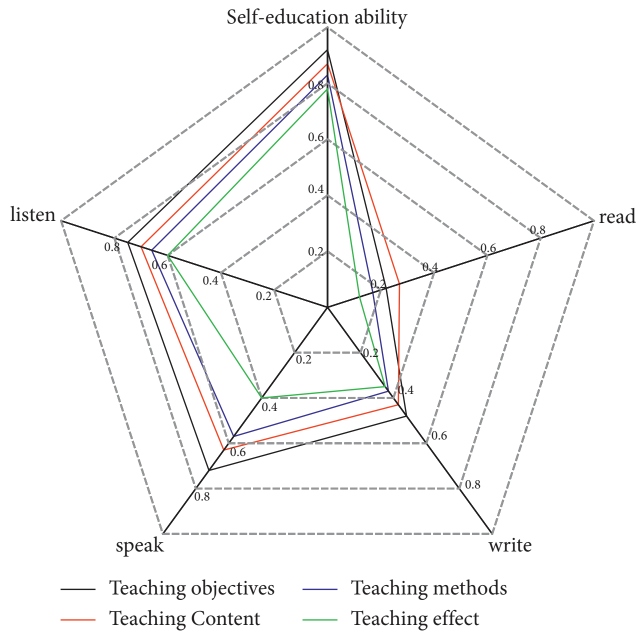


Figure 5: Criterion level indicator affiliation.

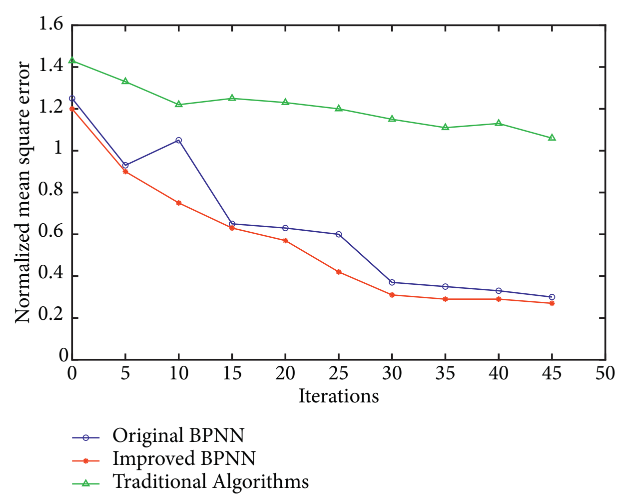


Figure 6: Mean square error curve of the model.

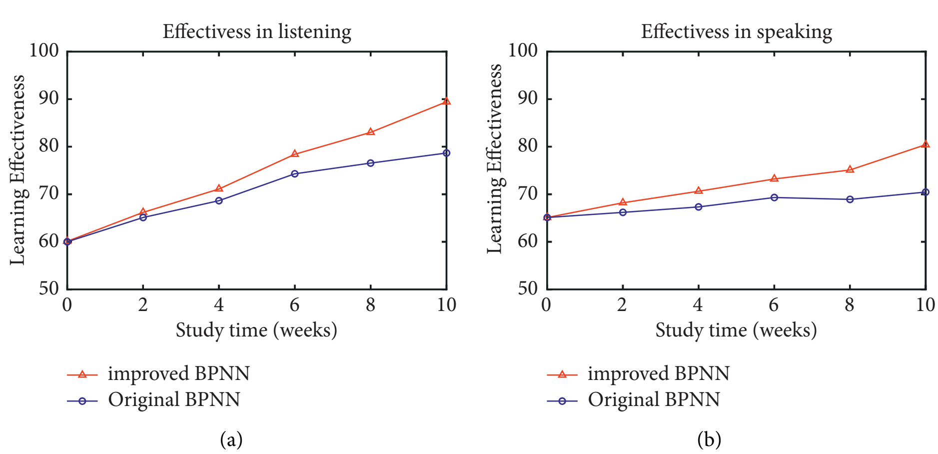


Figure 7: Continued.

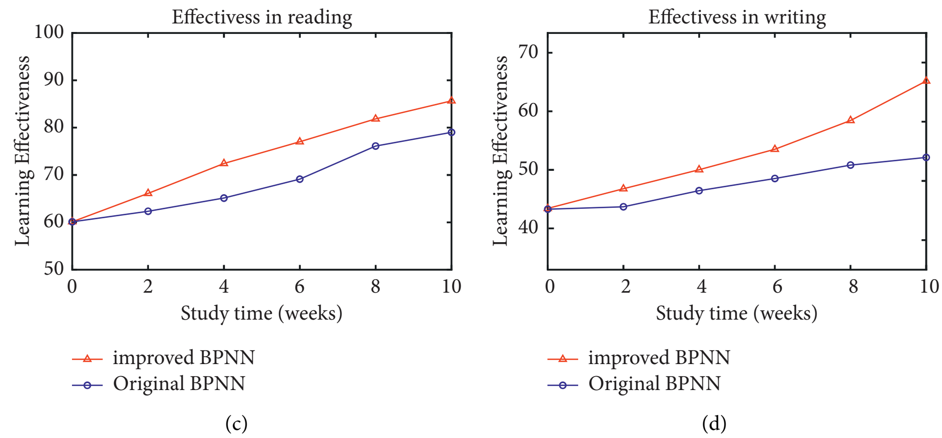


Figure 7: Evaluation accuracy curve of the model.

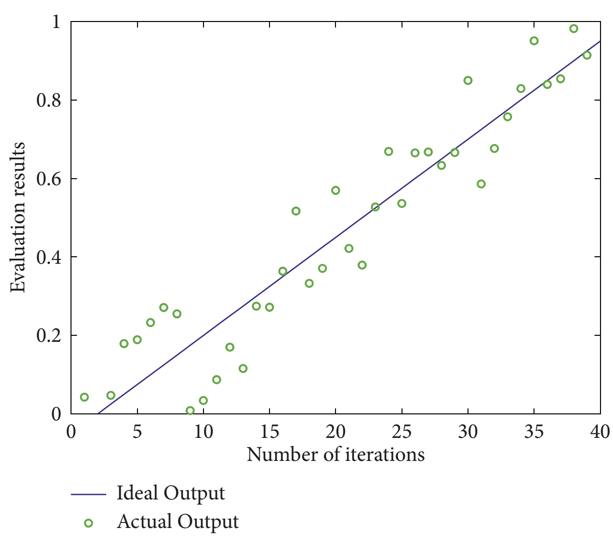


Figure 8: Theoretical expectations and expert evaluation of the effectiveness of ESP teaching based on an improved BPNN network.

number of iterations keeps increasing, and it shifts roughly above and below the theoretical curve, which can indicate that the actual measured changes in the teaching level match the theoretically predicted output results of the teaching level.

## 5. Conclusion

Artificial intelligence oriented real-world problem solving. In this paper, we propose a BPNN network approach based on the improved GWO algorithm, and its utilization in the ESP teaching process can effectively help veteran teachers to discover potential problems identified by students during the teaching process. At the same time, the mechanism of interaction between teachers and students is combined with the inclusion of an AI resource library, which allows teachers to make timely additions after discovering potential blind spots in students' knowledge. Then this paper organized teachers and students to conduct experiments according to the teaching framework proposed in this paper, and found that the teaching objectives, teaching content, teaching methods, and teaching effect of the output of the mathematical model established using the improved BPNN network have a greater impact on the teaching process, while the error between the recognition value and the true value obtained by the improved BPNN method based on the GWO algorithm is very small, which can evaluate teachers' teaching quality and effect more scientifically and accurately and provide useful reference values for further improving the ESP teaching level. In the process of modeling, we find that the GWO algorithm can achieve global optimization, but its convergence speed is slow in the later stage. Considering the influence of other factors, we will further improve the network model in the future research.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The author declares no conflicts of interest.

## Acknowledgments

This work was supported by the College of Foreign Languages, Jilin Agricultural University.

## References


[1] Y. Zou and H. Zhou, "Effect evaluation of small claim procedure based on fuzzy comprehensive evaluation," *Journal of Interdisciplinary Mathematics*, vol. 21, no. 4, pp. 837–848, 2018.

[2] A. Abu Saa, M. Al-Emran, and K. Shaalan, "Factors affecting students' performance in higher education: a systematic review of predictive data mining techniques," *Technology, Knowledge and Learning*, vol. 24, no. 4, pp. 567–598, 2019.

[3] S. Chatterjee and K. K. Bhattacharjee, "Adoption of artificial intelligence in higher education: a quantitative analysis using

structural equation modelling," *Education and Information Technologies*, vol. 25, no. 5, pp. 3443–3463, 2020.

[4] S. L. Wamba-Taguimdje, S. Fosso Wamba, J. R. Kala Kamdjoug, and C. E. Tchatchouang Wanko, "Influence of artificial intelligence (AI) on firm performance: the business value of AI-based transformation projects," *Business Process Management Journal*, vol. 26, no. 7, pp. 1893–1924, 2020.

[5] W. Fan, J. Liu, S. Zhu, and P. M. Pardalos, "Investigating the impacting factors for the healthcare professionals to adopt artificial intelligence-based medical diagnosis support system (AIMDSS)," *Annals of Operations Research*, vol. 294, no. 1-2, pp. 567–592, 2020.

[6] A. Chavoshi and H. Hamidi, "Social, individual, technological and pedagogical factors influencing mobile learning acceptance in higher education: a case from Iran," *Telematics and Informatics*, vol. 38, pp. 133–165, 2019.

[7] R. Nishant, M. Kennedy, and J. Corbett, "Artificial intelligence for sustainability: c," *International Journal of Information Management*, vol. 53, Article ID 102104, 2020.

[8] E. Fianu, C. Blewett, G. O. A. Ampong, and K Ofori, "Factors affecting MOOC usage by students in selected Ghanaian universities," *Education Sciences*, vol. 8, no. 2, p. 70, 2018.

[9] R. Baboota and H. Kaur, "Predictive analysis and modelling football results using machine learning approach for English Premier League," *International Journal of Forecasting*, vol. 35, no. 2, pp. 741–755, 2019.

[10] D. Schönberger, "Artificial intelligence in healthcare: a critical analysis of the legal and ethical implications," *International Journal of Law and Info Technology*, vol. 27, no. 2, pp. 171–203, 2019.

[11] A. M. Abubakar, E. Behravesh, H. Rezapouraghdam, and S. B. Yildiz, "Applying artificial intelligence technique to predict knowledge hiding behavior," *International Journal of Information Management*, vol. 49, pp. 45–57, 2019.

[12] O. Shatunova, T. Anisimova, F. Sabirova, and O. Kalimullina, "STEAM as an innovative educational technology," *Journal of Social Studies Education Research*, vol. 10, no. 2, pp. 131–144, 2019.

[13] N. Zeng, H. Li, Z. Wang et al., "Deep-reinforcement-learning-based images segmentation for quantitative analysis of gold immunochromatographic strip," *Neurocomputing*, vol. 425, pp. 173–180, 2021.

[14] Y. Riahi, T. Saikouk, A. Gunasekaran, and I. Badraoui, "Artificial intelligence applications in supply chain: a descriptive bibliometric analysis and future research directions," *Expert Systems with Applications*, vol. 173, Article ID 114702, 2021.

[15] S. L. Zubaidi, I. H. Abdulkareem, K. S. Hashim et al., "Hybridised artificial neural network model with slime mould algorithm: a novel methodology for prediction of urban stochastic water demand," *Water*, vol. 12, no. 10, p. 2692, 2020.

[16] J. Duan, P. G. Asteris, H. Nguyen, X. N. Bui, and H. Moayedi, "A novel artificial intelligence technique to predict compressive strength of recycled aggregate concrete using ICA-XGBoost model," *Engineering with Computers*, vol. 37, no. 4, pp. 3329–3346, 2021.

[17] Z. E. Abou Elassad, H. Mousannif, H. Al Moatassime, and A. Karkouch, "The application of machine learning techniques for driving behavior analysis: a conceptual framework and a systematic literature review," *Engineering Applications of Artificial Intelligence*, vol. 87, Article ID 103312, 2020.

[18] Y. Zhang and D. Wang, "Integration model of English teaching resources based on artificial intelligence," *International Journal of Continuing Engineering Education and Life Long Learning*, vol. 30, no. 4, pp. 398–414, 2020.

[19] D. A. Hashimoto, E. Witkowski, L. Gao, O. Meireles, and G. Rosman, "Artificial intelligence in anesthesiology: current techniques, clinical applications, and limitations[J]," *Anesthesiology*, vol. 132, no. 2, pp. 379–394, 2020.

[20] D. Juan and Y. Hong Wei, "Particle swarm optimization neural network for research on artificial intelligence college English classroom teaching framework," *Journal of Intelligent and Fuzzy Systems*, vol. 40, no. 2, pp. 3655–3667, 2021.

[21] X. Li, "The construction of intelligent English teaching model based on artificial intelligence," *International Journal of Emerging Technologies in Learning (iJET)*, vol. 12, no. 12, pp. 35–44, 2017.