Research Article

Evaluation of College Students’ Classroom Learning Effect Based on the Neural Network Algorithm

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With the advent of the digital society, the amount of information we face will increase exponentially, which will challenge our level of educational knowledge, so we begin to pay attention to the effect of education and teaching in the context of digitalization. The purpose of this paper is to study the evaluation of students’ classroom learning effect based on the neural network algorithm and scientific objectivity. Assessment and other principles are to create an assessment system for students’ learning outcomes in the classroom. The system includes three first-level indicators, including first-level indicators and their weights. By selecting a university to test the system, the results show that the system can quantitatively evaluate the learning outcomes, and the corresponding scores and grades can be obtained through the formula. After adjusting the parameters of the hidden layer nodes, the BP elastic gradient algorithm is used to complete the evaluation model generation. The training error results show that the target curve and the output curve almost coincide, and the error curve is also between −0.2 and 0.5. Therefore, the learning outcome score obtained by the BP neural network based on the principal component factor data is basically consistent with the given learning outcome score.

1. Introduction

With the rapid rise of MOOCs in the world, the reform of online learning in the field of higher education has also become a hot topic of educational research at home and abroad. Although online learning has entered the campus with the characteristics of openness and flexibility and emerged, the traditional offline teaching is still more in line with the thinking inertia and ideological expectations of teachers and students. At the same time, there are still many problems in online learning, such as lack of teacher-student interaction, limited learning support, and academic integrity, especially the discussion about its learning quality and effect, which has always existed [1]. Therefore, it is necessary to find out the learning effects of the two learning styles [2].

At home and abroad, there are in-depth studies on the theory of classroom learning outcome evaluation, the improvement of related technologies, practical application, and evaluation. Omare employed a mixed method design, combining Solomon’s four-group experimental design with in-depth interviews. The study used a random sampling procedure of 3 students from 23 public high schools and 1,397 students from 49 English teachers, and 283 of the 3
students participated in the study. Four groups of participants were randomly divided into experimental and control groups. Twelve (12) English teachers were recruited using purposeful sampling techniques. Data were collected by triangulation, using pre/post-test scores, focus group discussions, in-depth interviews, and a metacognitive learning strategies’ questionnaire. The results of multiple regression analysis showed that self-efficacy explained 6.4% of the difference in English academic performance [3]. Dhamodharavadhan and Rathipriya developed a COVID-19 mortality prediction (MRP) model for India using statistical neural networks and generalized recurrent networks and Gaussian process regression (GPR). Hyperparameter optimization or tuning is used in these regression models, which is the process of determining the best set of hyperparameters with minimal error [4]. Therefore, further research and innovation are needed on the evaluation of college students’ classroom learning effect.

For the first time, this paper focuses on the comparative study of the learning effects of online learning and blended learning on noncommon language learning, hoping to help course learners improve their learning effects through strategies and suggestions and provide references for later resource construction and platform function development. Through the review and analysis of existing research and related literature, understand the interpretation of online learning and blended learning at home and abroad, clarify the main trends of the current online learning effect and blended learning effect research, and evaluate the effect of the two learning methods. This paper sorts out the research status of learning effects at home and abroad, excavates the evaluation framework suitable for this research, and clarifies the value and significance of learning effect evaluation to improve teaching quality. Summarize the current learners’ problems in course learning and lay a theoretical foundation for putting forward strategies to improve the learning effect. After studying the relevant literature, it is found that there is very little research on the learning effect of nonlingua franca at home and abroad, and the research will make up for the shortcomings of the current research to a considerable extent.

2. Research on the Evaluation of the Classroom Learning Effect Based on the Neural Network Algorithm

2.1. BP Neural Network Algorithm. The BP neural network is used as a neural network for error correction algorithms. The mean is less than the specified error, saving the weights and margins of the network. The structure of the BP neural network is similar to RBF, which is a multilayer network structure. The same layer is not connected. Similar to RBF, the BP neural network has a good mapping ability, so it has been widely recognized in various fields and has achieved satisfactory results [5, 6].

2.2. Learning Evaluation. This paper believes that the so-called learning evaluation is under the guidance of the national education policy, under the guidance of the education policy, based on the implementation requirements of specific teaching objectives, applying the theories and methods of systematic science and responding to the realization of the teaching objectives in various teaching and learning processes. To establish an objective evaluation standard system, measure the relevant data and data collection, display, and inspection and make a relatively objective value judgment [7, 8]. Learning evaluation is a systematic investigation of teaching effects or all aspects of student development according to certain standards and value analysis and judgment based on the acquisition of sufficient data. The learning evaluation index system is a series of variables that reflect the quantitative characteristics of the entire learning process. In blended learning, learning evaluation is more important to monitor the entire learning process, and students and teachers are both the object of evaluation and the evaluator [9, 10].

2.3. Principles of Learning Effect Evaluation

(1) Feasibility. The way and content of evaluation can be different, but there is a condition here, that is, no matter how the form and method of evaluation change, it must be ensured that all evaluation work can be carried out smoothly and can play a role [11, 12].

(2) Subjectivity. As an important participant in learning activities, students are both the object of evaluation and the object to be evaluated. Therefore, it is necessary to improve students’ participation in the evaluation process so that students can fully understand their own learning situation and adjust their learning strategies in time [13, 14].

(3) Differences. It is well known that there are individual differences among students. This difference complicates the subject of education and brings great difficulties to teaching activities. However, in the evaluation process, especially when evaluating students’ learning, more attention should be paid to this difference to ensure the accuracy of the evaluation results [15, 16].

(4) Guiding. The purpose of assessment is not just to check the number of educational activities but to give people an idea of how well students are learning so that they can see the deficiencies and develop better. Therefore, evaluation activities must play a guiding role in the progress of students and teaching activities, in order to play a role in guiding and promoting education [17, 18].

3. Model and Research on the Evaluation of College Students’ Classroom Learning Effect Based on the Neural Network Algorithm

3.1. Determination of the Evaluation System. By summarizing and sorting out relevant literature, the learning effect of the blended physical education course in higher
vocational colleges is defined as the three time nodes (i.e., before class, during class, and after class) of students in higher vocational colleges on the knowledge and the learning effect of emotional attitude values. In order to further define the structure and content of blended learning and learning effect evaluation more clearly and accurately, the researchers conducted interviews with experts in physical education and blended teaching, obtained valuable suggestions and information, and referring to the existing theories based on blended learning and learning effect evaluation, combined with the characteristics of students in higher vocational colleges and related literature; the evaluation indicators of blended physical education courses in higher vocational colleges have been preliminarily established.

As shown in Figure 1, the three time nodes in the mixed physical education course, namely before class, during class, and after class, are the first-level indicators, and the preclass includes three second-level indicators: watching video time, online learning, and discussion. There are participation times, online answering scores, and three secondary indicators in the class as follows: learning attitude, mental health level, and progress; after class, there are two secondary indicators which are as follows: the quality of online homework and after-class practice feedback. Among them, the three-level indicators included in the active learning situation include three indicators: the number of questions asked, the number of questions answered, and the independent preview video; the three-level indicators included in the learning attitude include three indicators: physical education class attendance, classroom performance, and love of sports; psychological: the three-level indicators included in the health level include cooperative communication ability, environmental adaptability, and self-regulation ability; the three-level indicators included in sports healthcare knowledge are the prevention and treatment of common sports injuries and the prevention and rehabilitation of professional-related occupational diseases. There are two indicators; the three-level indicators included in the progress range are the progress of health knowledge, the progress of motor skills, and the improvement of physical fitness; the three-level indicators included in the ideological and moral quality are enterprise consciousness and rule awareness. Indicators: the three-level indicators included in the quality of online homework are the time of submitting homework and the quality of the homework; the three-level indicators included in the after-school practice feedback are after-class practice time and after-class practice quality.

3.2. Neural Network Model. Under normal circumstances, the number of input nodes and input vectors are in one-to-one correspondence, so we simplify the model structure.
proposed in and obtain the mathematical model of the
neural network that we commonly use as follows:
\[
\begin{align*}
  o_k &= f_2(\text{net}_k), \\
  \text{net}_k &= \sum_{i=0}^{k} w_{ik} y_j.
\end{align*}
\]

Among them, \( k \) is the number of nodes of the evaluation
model of college students’ classroom learning effect, and \( w \) is
the input vector of the evaluation model of college students’
classroom learning effect.

For the hidden layer, we have
\[
\begin{align*}
  y_j &= f_1(\text{net}_j), \\
  \text{net}_j &= \sum_{i=0}^{m} w_{ij} x_i.
\end{align*}
\]  

The above equation constitutes the mathematical model
of the three-layer neural network. Among them, \( k \) is
the number of nodes in the evaluation model of college students’
classroom learning effect, and \( w \) is the input vector of the
evaluation model of college students’ classroom learning effect. Among them, \( i \) is the number of nodes of the
evaluation model of college students’ classroom learning effect, and \( j \) is the input vector of the evaluation model of college students’ classroom learning effect.

3.3. Determination of the Number of Hidden Layers and the
Number of Nodes. For the learning effect evaluation of
mobile situational learning, the evaluation factor has only 4
inputs after optimization, and the relationship between the
information represented by the principal component factor
and the learning effect score is relatively simple to map. The
hidden layer is enough, and there is no need to select too
many hidden layers to provide the computational efficiency
of the model. Considering that the principal component
factors of the evaluation model are few, there is also a hidden
layer parameter in the mobile scene learning effect evaluation
model that must be determined in advance, that is, the
number of hidden layer nodes.

In the BP neural network model, the number of nodes in
the hidden layer generally does not have a fixed reference
and needs to be adjusted according to the data in practical
applications. From the overview of BP neural network
technology, it can be seen that for a single hidden layer, the
number of nodes between the number of input nodes and
the number of output nodes is optimal. In order to deter-
mine the approximate size of the number of nodes, the result
of the optimal number of nodes \( N \) in the range of \([2, 4]\) is
calculated by the formula.

After the input and output nodes are determined and the
relevant parameters of the hidden layer are selected, the
network topology of the entire evaluation model is basically
determined. The model structure diagram is shown in
Figure 2. The entire network model consists of three layers of
neurons, the input neuron is the evaluation factor, and the
output neuron is the learning effect score.

3.4. AHP. The method is generally divided into the target
layer, distribution layer, and index layer according to the
dicators related to decision-making, and then qualitative
analysis and quantitative analysis are carried out to provide
more rational analysis and decision-making. According to
the evaluation indicators obtained from the questionnaire,
we determine the target level, hierarchical level, and index
level of AHP and calculate the weight of the first-level indi-
cators according to the expert scores on the judgment
table. We calculate the three-level indicators and check the
consistency of each matrix and finally use the normalization
function to set the sum of the weights of all the level indi-
cators to 1.

CI can be derived from the following formula:
\[
CI = \frac{\lambda_{\text{max}} - n}{n - 1}.
\]

Among them, \( \lambda \) is the characteristic root, and \( n \) is the
number of variables in the evaluation system of college
students’ classroom learning effect.

Calculate the maximum eigenroot \( \lambda_{\text{max}} \) of the matrix
according to the following formula:
\[
\lambda_{\text{max}} = \frac{\sum(BW)_i/W_j}{n}.
\]

Among them, \( \lambda \) is the characteristic root, and \( n \) is the
number of variables in the evaluation system of college
students’ classroom learning effect.

3.5. Evaluation of the Learning Effect. Learning effect evalua-
tion is a diversified system. In evaluation, various aspects
of information are collected, analyzed, and then fed back to
teachers and school-related personnel. The overall structure
of teaching evaluation is shown in the following figure.

According to the analysis of the evaluation stage and the
overall structure diagram above, it can be obtained that the
evaluation system mainly has three function points: data
preparation, evaluation information collection, and evalua-
tion result analysis and feedback.

Data preparation: it mainly prepares the basic data for
evaluation, such as departments, majors, semesters, and
other basic information.

Evaluation information collection: the content of the
collection is determined according to the index system, and
the information is collected by the system.

Analysis and feedback of evaluation results: relevant
personnel of the school, let teachers find deficiencies and
adjust them in time; let managers grasp the overall situation
of teaching in a timely manner and formulate policies
accordingly.

4. Analysis and Research on the Evaluation of
College Students’ Classroom Learning Effect
Based on the Neural Network Algorithm

4.1. Determination of Indicator Weights. Consistency checks
are performed on the expert’s comparison matrix according
to the formula. As shown in Table 1, finally, the average is
calculated as the weight coefficient of the indicator through the scores of 9 experts.

According to Figure 3, the first-level indicators and their weights are 0.24 for online self-study before class, 0.56 for in-

<table>
<thead>
<tr>
<th>Experiment number</th>
<th>Expert rating results</th>
<th>Model output</th>
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</thead>
<tbody>
<tr>
<td>1</td>
<td>3</td>
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</tr>
<tr>
<td>2</td>
<td>2</td>
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<td>4.3</td>
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</table>

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According to Figure 3, the first-level indicators and their weights are 0.24 for online self-study before class, 0.56 for in-

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<tr>
<th>Expert serial number</th>
<th>Online self-study before class</th>
<th>Learning inquiry in class</th>
<th>C review and consolidate after the class</th>
<th>CI</th>
<th>RI</th>
<th>CR</th>
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<tr>
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<td>0.04</td>
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<tr>
<td>3</td>
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<td>4</td>
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<td>0.26</td>
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<td>5</td>
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<td>0.56</td>
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<td>0.04</td>
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<tr>
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<td>0.02</td>
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Table 1: Index weight coefficient and consistency test result table.

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<tr>
<td>10</td>
<td>4</td>
<td>4.3</td>
</tr>
</tbody>
</table>

Table 2: Evaluation results are given by experts and model output results.
class learning and exploration, and 0.2 for after-class review and consolidation.

4.2. Simulation of the Evaluation Model. After adjusting the hidden layer node parameters, the elastic gradient BP algorithm is used in this paper to complete the establishment of the evaluation model. The training error diagram is shown in Table 2.

It can be found from Figure 4 that the target curve and the output curve almost coincide, and the error curve also fluctuates between −0.2 and 0.5.

4.3. Comparison of Model Calculation Results. In order to compare the evaluation model established in this paper with the comprehensive scoring model of principal component analysis, the scoring results of three evaluation methods can be obtained according to the experiment, as shown in Figure 5.

From the scoring results in Figure 5, the evaluation results of the combination of the principal component analysis and the BP neural network model are closer to the expert opinion than the results calculated by the comprehensive scoring model of the principal component analysis.
4.4. Comparison of Learning Effects. In order to ensure the fair evaluation of online learning results and hybrid learning results, the BP neural network evaluates these two learning methods.

Table 3 is a descriptive statistical comparison of the test unit assessment scores of blended learners and online learners that are compared longitudinally. The maximum test scores of the two test units are 98 and 95, respectively, with little difference. The average score of blended learners (M = 90.32) is higher than that of online learners (M = 87.56), which is about 3 points higher, which means that the average level of blended learners exceeds that of online learners to a certain extent. The standard deviations of the test unit assessment scores for blended learners and online learners are 5.04 and 6.35, respectively. The standard deviation of the blended learners’ test scores is lower than that of online learners, indicating that the individual differences among blended learners are small.

5. Conclusions

Through preliminary empirical research, this paper understands the current situation of noncommon language teaching in the College of International Chinese Education and the overall situation of students’ learning effects, finds problems in language teaching and analyzes the reasons, and explores the advantages of online learning and blended learning. The practice path for reference is used to solve the related problems and offline classroom teaching. According to the survey results, the research intends to compare and analyze the learning effects of learners in different dimensions through the questionnaire survey method and interview method, combined with the learning data provided by the platform, and explores the current learning effects from the differences and correlations between the two learning methods. The problems in learning are expected to guide teaching practice through strategies and suggestions for problems, so the practical significance of the research is to provide reference suggestions for online learning resources and curriculum construction, as well as online learning and blended learning-teaching activities.

Data Availability

The data underlying the results presented in the study are available within the manuscript.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

References


