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Retraction

Retracted: Analysis of English Education Quality Evaluation and Internationalization Integration Based on Deep Learning

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] Y. Song and G. Yang, "Analysis of English Education Quality Evaluation and Internationalization Integration Based on Deep Learning," *Security and Communication Networks*, vol. 2022, Article ID 9436538, 9 pages, 2022.

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Research Article

Analysis of English Education Quality Evaluation and Internationalization Integration Based on Deep Learning

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English education is one of the most active research directions in the field of natural language processing. With the gradual implementation of deep learning in various fields, more and more industries have begun to use deep learning to carry out more efficient work. In the field of education, it is also urgent to adopt a more intelligent set of algorithms to relieve the pressure of teachers to correct test papers, and also to increase the fairness of non-subjective evaluations in the process of scoring. Teachers conduct teaching evaluation when the concept of teaching evaluation is not clear; there are defects in learning evaluation goals; there are many problems in the relationship between ability evaluation and knowledge evaluation; in the process of English teaching evaluation, the phenomenon of using summative evaluation instead of procedural evaluation is very serious. Therefore, this subject uses deep learning to study the problem of text line positioning and recognition. At the same time, this subject also builds a text scoring network based on RNN and STLM as a quantitative evaluation index for text line detection and recognition algorithms. We will examine students later. Whether problem-based learning theory can be used to promote deep learning among students to determine whether students' systematic use of PBL in teaching can promote the use of deep learning in college English courses. Finally, comparing the effects of deep learning and shallow learning, it is concluded that the evaluation of deep English teaching can provide students with more learning opportunities, access to more learning-related materials, and questions are more transparent and are free, which is easy. It is speculated that the purpose of this problem is to facilitate the use of deep learning methods to find meaning types.

1. Introduction

We find that even Chinese provinces still rely more on goods from the rest of China than on international imports, implying greater discontinuity in the Chinese domestic market [1]. Traditional economic integration theories are notable for their failure to view the integration process itself as capitalism. In most cases, this theory implicitly assumes a framework of harmonious relations between capital and labor, thereby abstracting class relations in integration [2]. After decades of ups and downs in foreign language education in China, English regained its dominant position after 1949. In order to meet the challenges of the new century, we must fully understand the importance of foreign language design and pay attention to the problems in English teaching [3]. English is widely spoken around the world as an international language. In universities, bilingual teaching should be gradually introduced, focusing on students' communicative ability, focusing on speaking and writing, and network-based computer technology provides learners with an environment where they can actually communicate in English [4]. This article provides an overview of deep learning in neural networks, including popular architectural models and training algorithms. Deep learning is the part of machine learning that attempts to model high-level knowledge abstractions using multiple layers of neurons consisting of complex structures or nonlinear transformations [5]. Deep learning is capable of learning computer

models composed of multiple layers of processing from data representations at multiple levels of abstraction. These methods include visual object recognition, object and domain recognition [6]. Through extensive systematic experiments in this paper, we show how these traditional methods fail to explain why large neural networks generalize well in practice, and we confirm these experimental results with a theoretical structure that shows that as long as the number of parameters exceeds the data, the number of points, simple deep binary neural networks already have completely limited sample representation properties [7]. Factors associated with disadvantage expand as children enter the workforce through the education system. We document various forms of inequality in education, and we then review the available evidence in England on the impact of school-level policies on achievement and their potential to reduce the socioeconomic disparities [8]. This paper considers how English as a foreign language (EFL) can be taught more effectively in China by incorporating lessons from twentieth century English learning experiences. The main purpose is to learn more about how English was taught at different times. This information can be identified by identifying curriculum construction, successful and unsuccessful practices in teaching methods, and teaching materials to inform current and future practice [9]. Learning a language is very important in our globalized world, and this study aimed to investigate parental attitudes towards English education for kindergarten students, in which questionnaires were used as a data collection tool [10]. Extensive reading is a learning method that improves a learner's reading comprehension by reading many light-hearted books. We read extensively as part of the English education program at Shinshu University. In this study, we developed and operated an online extensive reading support system, and the results reveal how students feel about their progress and how to reduce the burden of extensive reading while staying motivated [11]. We conducted TOEIC-IP twice in three types of courses (1) general English + self-study listening CD-ROM, (2) WEB English learning system called Gyutoe, and (3) control class, the result was WEB learning system compared with the other two systems, it brings a significant score improvement. This result demonstrates the benefits of a WEB-based English learning system [12]. English education is often still seen as a purely instrumental effort. This article illustrates how English plays a role in an education system in a developing country that is rapidly becoming a rich base for alternative education research. This paper places English within the pragmatics of postcolonial mentality and the sociocultural expectations of stakeholders, and addresses the complexities of transitioning from policy to practice [13]. Improving vocational learning in general and vocational education and training programmes and qualifications has never been more important on the political agenda. This bias is dissected in the context of the most popular strategies for enhancing vocational learning and equal respect for programmes and qualifications in this field. It was concluded that changing terminology and modifying paths would not bring about the necessary shift in values needed to achieve the desired goals [14]. One of the underexplored areas of research in the language learning literature is investigating the role of various contextual factors influencing second/foreign language motivation. As foreign language teaching in Iran is relatively unique in terms of teaching and learning environments, this study examines the combined effects of these situational characteristics on changes in students' motivation after four years of English learning in high school. The study concluded that these changes in student motivation are due to the influence of traditional teaching environments and conservative policies for foreign language teaching. Clearly, in the context of this kind of English teaching, improving the motivation of learners requires scientific reforms within the education system [15].

2. Research Overview of Deep Learning

2.1. Overview of Foreign Deep Learning Research. Marto and Sajlo of the University of Gothenburg in Sweden first proposed slowing down "deep learning" study abroad. In 1976, he dealt with data processing in learning methods, and the ability to interpret shallow and layer-by-layer changes. When a student uses superficial learning methods, his or her response is only at a low level, and the learning process also seems to be mechanical memory learning. He excels at subject and text topics when he uses deep learning methods. Therefore, the two researchers introduced the concept of "deep learning," arguing that immersion is a process of knowledge transfer that can help learners improve their ability to improve problems and become scientifically minded.

2.2. Overview of Domestic Deep Learning Research. Deep learning plays an important and constructive role in promoting students' information processing, in-depth analysis, innovation, and development. If students gradually get rid of the superficial learning state, and achieve the state of understanding and applying words through simple word repetition and expansion, the learning effect will be improved. If teachers can wisely combine deep learning theory and design English vocabulary lesson plans suitable for students' learning, vocabulary teaching will also have good learning effects. Under the guidance of deep learning theory, students can lay a good vocabulary foundation and gradually implement in-depth learning of English vocabulary. At the same time, teaching under the guidance of deep learning theory can improve students' thinking level and increase their enthusiasm for learning English. At the same time, it can improve students' autonomous learning ability, problem-solving ability, transfer application ability, and knowledge innovation ability.

2.3. Overview of English Vocabulary Teaching Research. Vocabulary teaching methods have also changed. Starting from the vocabulary teaching methods, the context of vocabulary and the emphasis on thinking training in vocabulary teaching have changed, and the vocabulary teaching methods have also changed. It can be seen that in recent years, the vocabulary teaching mode has gradually

improved, and became more scientific and in-depth. On this basis, the vocabulary teaching guided by the deep learning theory is also in line with the new method of education supported by the education community, lifelong learning, critical thinking and advanced thinking training, and student-centered education. This paper integrates deep learning into high school English vocabulary teaching. Combining deep learning theory with vocabulary construction strategies can help teachers think about vocabulary teaching and bring new ideas for the development of English vocabulary teaching. Provides more comprehensive strategies for teachers who learn English vocabulary and teach English vocabulary. Vocabulary teaching guided by the construction of deep learning theory will conform to the development and trend of the times and is expected to become a reference for vocabulary teaching in the new era.

2.4. The Theoretical Basis of English Teaching. According to the definition of deep learning and most of the learning process, it can be clearly seen that teaching under the guidance of deep learning theory requires the active construction of students and the careful guidance of teachers. Teachers should use previously learned knowledge when teaching vocabulary information. Students do not master vocabulary until they learn vocabulary for a new unit. They already have a certain vocabulary and life experience to learn English vocabulary every day. NaMA knowledge and experience can support or prevent the learning of new words. Therefore, when teaching English words, in addition to normal guidance, teachers should also be fully involved in the information or experience that hinders the words, allowing students to learn meaningfully and helping students learn from ancient knowledge and experience. Based on current experience, help students to think deeply through meaning construction, change their knowledge, experience and values, promote students' ability to form words in speech, and promote effective and deep learning.

3. Text Recognition Algorithms Based on Deep Learning

3.1. Recurrent Neural Network RNN. RNN (recurrent neural network) is mainly used to deal with timing problems. There is a connection between each neuron state in the hidden layer of RNN. The input in the neuron state not only includes the input of the input layer, but also includes the output of the previous neuron state. The semantic information before and after the text sequence is very important for the recognition accuracy of the current sequence, so RNNs are mostly used in text recognition, speech recognition and other tasks.

3.2. Long Short-Term Memory Network LSTM. The difference between LSTM and ordinary recurrent neural network is that it has three gating units to retain the information of the previous neuron, thereby reducing the loss of information in the transmission of neurons. At the same time, LSTM can also solve the problem of gradient descent. The "gate" structure in LSTM allows it to selectively retain or discard information, and the gate structure is the sigmoid function multiplied point by point. The output of the sigmoid function is between 0 and 1. This output value represents the amount of information retained, that is, when the value is 1, all information flows to the next network structure; when the value is 0, the gate structure is closed, and all information does not pass through the gate control unit. LSTM determines the information discarded in the network through the "forgetting gate," and the decision rule is determined by the current input and the state of the previous hidden layer h_{t-1}. The "forget gate" is essentially a sigmoid function layer, which is used to forget the useless prediction information that may lead to errors. The expression of "forgetting gate" defined by LSTM is as formula (1): where x_t is the input at the current moment, h_{t-1} is the state of the previous hidden layer, and the judgment result f is also a vector with a dimension of n ranging from 0 to 1. Because any dimension in the f vector has a range of values between 0 and 1, dimensions with values close to 0 will be discarded by the forget gate, and dimensions with values close to 1 will be retained.

$$f_t = sigmoid\left(W\left[h_{t-1}, x_t\right] + b_f\right). \tag{1}$$

LSTM will discard the wrong information after passing the "forgetting gate," and the current valid input information needs to be stored in the neuron state to supplement the new information of the network, so the function of the "input gate" is to store the new valid information in the LSTM. The "input gate" mainly consists of two parts. First, the tanh function layer generates a vector that can be stored in the neural network, and then, the sigmoid function layer outputs a value ranging from 0 to 1. The "input gate" expressions defined by LSTM are such as equations (2) and (3): where x, is the input at the current moment, and h_{t-1} is the state of the previous hidden layer. If the LSTM needs to update the current information, the information to be stored is combined with the previous neuron state Cq-: through the update gate to generate a new neuron state Gq. Update state expressions such as (4)

$$z_t = \tanh\left(W_z\left[h_{t-1}, x_t\right] + b_z\right., \tag{2}$$

$$i_t = sigmoid\left(W_i\left[h_{t-1}, x_t\right] + b_i\right), \tag{3}$$

$$c_t = f_t * c_{t-1} + i_t * z_i. \tag{4}$$

Tanh is one of the hyperbolic functions, which is widely used as the activation function of neurons in neural networks in the field of deep learning. Finally, the "output gate" determines the output h_t, h_t of the LSTM. It is jointly determined by the updated neuron state c, the output h_t of the previous hidden layer, and the input x_t of the current neuron. First, the sigmoid function layer determines the neuron state o_t to be output, and then sends the updated neuron state c to the tan$h$ function layer, and multiplies the

output result of the sigmoid function layer, so that the LSTM only outputs the part that needs to be output. The expression of "output gate" defined by LSTM is as formulas (5) and (6):

$$o_t = sigmoid\left(W_o\left[h_{t-1}, x_t\right] + b_o,\right. \tag{5}$$

$$h_t = o_t{}^* \tanh\left(c_t\right). \tag{6}$$

The sigmoid function is a common function in biology, also known as the growth curve. In information science, the function is often used as the activation function of neural networks to map variables between 0 and 1.

3.3. Text Line Detection Model Based on CTPN. The y-axis coordinate of the returned text area height vh is shown in formula (7), and the y-axis coordinate of the center Vc of the bounding box is shown in formula (8). The representation of $*$ is GroundTruth, and the representation is the anchor point. Finally, multiple dense fine-grained candidate boxes are merged into text lines through a text line construction algorithm.

$$\begin{aligned} v_h &= \log\left(\frac{h}{h^a}\right), \\ v^*{}_h &= \log\left(\frac{h^*}{h^a}\right), \end{aligned} \tag{7}$$

$$\begin{aligned} v_c &\frac{\left(c_y - c_y^a\right)}{h^a}, \\ v_c^* &\frac{\left(c_y^* - c_y^a\right)}{h^a}. \end{aligned} \tag{8}$$

3.4. Improved MLC-CRNN Feature Extraction Layer Based on Multi-Feature Fusion. In the handwriting recognition task of this topic, the letters written by students can be regarded as small objects, and multi-feature fusion can prevent the recognition accuracy of small objects from decreasing. The idea of feature extraction of multi-feature fusion module is shown in equations (9)–(11). The convolutional layer with multiple feature extraction units fuses features of different depths to improve the ability to describe the features of the image itself. By fusing a smaller convolutional layer and a larger convolutional layer on two branches, both low-level features (such as letters) and high-level features (such as words) of the handwritten text can be learned well. This subject named this multi-feature fusion module as MLC module (Multi-LayerConvolutionsBlock).

$$\begin{aligned} y_n^1 &= W_n^1 \cdot h_{n-1} + b_n^1, \\ y_n^2 &= W_n^2 \cdot h_{n-1} + b_n^2, \\ y_n^3 &= W_n^3 \cdot h_{n-1} + b_n^3, \end{aligned} \tag{9}$$

$$h_n = sigmoid\left(y_n^1 + y_n^1 + y_n^1\right), \tag{10}$$

$$\begin{aligned} y_{n+1} &= W_{n+1} \cdot \left(h_n + bn + 1\right) \\ &= W_{n+1} \cdot \tanh y_n + b_{n+1}. \end{aligned} \tag{11}$$

3.5. CRNN Feature Sequence Prediction Layer Based on Bi-directional LSTM. Therefore, this topic adopts Bi-LSTM to learn the sequence features of in-line context of a long text. The experiments combine a forward pass and a backward pass LSTM into a bidirectional LSTM (Bi-LSTM), which generates a deep Bi-LSTM by stacking multiple Bi-LSTMs. Among them, for the forward pass, when the input feature sequence $x = x_{1,}x_{2,} \ldots x_{t,}$ is passed into the forward LSTM, a set of neuron states $u = u_1, u_2, \ldots u_t$ will be obtained, as shown in equation (12); for the backward pass, the input sequence of the feature sequence is the same as $x = x_{1,}x_{2,} \ldots x_t$, which is passed into the backward LSTM, and another group of neuron states $z = z_1, z_2, \ldots z_t$ will be obtained, as shown in equation (13). Finally, through the SoftMax function operation, the column vector $y = y_1, y_2, \ldots y_t$ output by the sequence prediction unit represents the prediction probability of the corresponding text, as shown in formula (14).

$$u_t = Wh_t + b, \tag{12}$$

$$z_t = W' h_t + b', \tag{13}$$

$$\begin{aligned} y_{ut} &= \frac{e^{u_i^t}}{\sum_{k=1}^k e^{u_t^k}}, \\ y_{zt} &= \frac{e^{z_i^t}}{\sum_{k=1}^k e^{z_t^k}}. \end{aligned} \tag{14}$$

LSTM mode is a type of RNN, consisting of forward LSTM and backward LSTM, which are commonly used to model contextual information in natural language processing tasks. Using LSTM models can better capture long-range dependencies, while Bi-LSTM can better capture bi-directional semantics.

3.6. CRNN Sequence Transcription Layer Based on CYC Mechanism. CTC introduced a blank insertion mechanism, which uses the "_" symbol to represent blank labels. That is, the label "aaaaattt" is mapped to "aab" under the CTC mechanism, and "aaaaattt" is mapped to "at." But at the same time, time series composed of multiple different characters such as "aa-aaaattt" and "aa-aaaaatt" will be mapped to the same output word "aat" at the same time | that is, there is one or more mapping paths for the same label. For example, in the experiment of this subject, the high-frequency word "write" that appears in the English composition of primary and secondary schools has many different paths, such as equations (15) to (18), and the mapping result is "write":

$$B\left(\pi_1\right) = B\left(wwr - ii - t - - - e\right) = \text{"write"}, \tag{15}$$

$$B\left(\pi_2\right) = B\left(- - \text{wrri} - t - - - e\right) = \text{"write"}, \tag{16}$$

$$B(\pi_3) = B(wwr - \text{iii} - \text{tee}-) = \text{“write”}, \tag{17}$$

$$B(\pi_4) = B(- - \text{wrrii} - \text{tee}-) = \text{“write”}, \tag{18}$$

Since the last RNN output is the probability matrix of the sequence, then, for $B(\pi 1)$, the mapping probability is shown in equations:

$$p(\pi = (wwr - ii - t - -e)|x, S) = \sum_t y_{\pi t}^t, \tag{19}$$

$$\sum_t y_{\pi t}^t = \left(y_w^1\right) \times \left(y_w^2\right) \times \left(y_w^3\right) \times \left(y_r^4\right) \times \left(y_w^5\right) \times \left(y_-^6\right) \times \left(y_t^7\right) \times \left(y_i^8\right) \times \left(y_w^9\right) \times \left(y_-^{10}\right) \times \left(y_e^{11}\right) \times \left(y_w^{12}\right). \tag{20}$$

Input a text image into the network, the input space is a set X composed of text sequences $x = x_1, x_2, \ldots x_t$, the input text sequence, the result space is a set L composed of output label sequences, T is the length, B is the text sequence to label sequence mapping function. The experiment should maximize the probability that the output is the result space L. Since the mapping paths are mutually exclusive, the sum of all probabilities mapped to L based on the mapping function X is the conditional probability equation:

$$p(l \mid x) = \sum_{\pi \in B^{-1}(l)} p(\pi \mid x). \tag{21}$$

CTC trains and decodes all labels, performs many-to-one alignment output, sums all paths, and calculates the maximum value of the above conditional probability formula (21). The output of the final time series classifier equation (22) is the most likely sequence label of the input text sequence.

$$h(x) = \text{argmax} p(l \mid x). \tag{22}$$

3.7. Experimental Details and Verification Effects. In order to prove the effectiveness of the scoring network, this subject conducts experiments on CNN + LSTM network and CNN alone with LSTM using 12948 passages in the dataset. The experiment uses the RMSProp optimizer to minimize the mean square error (MSE). The loss function of MSE is shown in equation (23), where s represents the text prediction score s_i represents the gold-score of the text label:

$$MSE(s, s^*) = \frac{1}{N} \sum_{i=1}^{N} \left(s_i - s_t^*\right)^2. \tag{23}$$

The experiment uses the averaged quadratic weighted Kappa coefficient (average QWK coefficient) as the evaluation index to measure the performance of the scoring module. The calculation formula of the average QWK coefficient is as equations (24) and (25), which represents the agreement between the predicted value (i) and the true value label (j)

$$k = 1 - \frac{\sum_i \text{jwi, joi, } j}{\sum_i \text{jwi, jEi, } j}, \tag{24}$$

where, w_i represents the quantified score of the difference between the predicted value and the true value

$$w_{i,j} = \frac{(i - j)^2}{(N - 1)^2}. \tag{25}$$

4. Research Findings and Discussion

4.1. Experimental Data Collection. The questionnaires of the two classes were collected and uploaded through the Questionnaire Star platform, and the test scores were obtained from the blackboard. In the pre-pilot stage, 33 students completed the two questionnaires before and after, we received 33 valid questionnaire responses. Students in both classes passed the exam, which consisted of an English proficiency test, an objective test based on textual content, and an essay. The questionnaire data and test data were analyzed by EXCEL and SPSS22, and the interview data were mainly analyzed and compressed by three-level coding. It describes the results of a survey of 33 students in the whole class before problem-oriented learning, and 33 valid questionnaires. Among them, the lowest score of the deep learning subscale of this survey was 15, the maximum value was 42, and the theoretical score of this subscale was 10–50. It can be seen that the students in this class vary greatly in the use of deep learning methods among individuals, and the use of shallow learning methods is the same. Furthermore, deep learning scores were higher than superficial learning, so it is prudent to conclude that students are more likely to use deep learning methods in English classes. 4.2 statistics and analysis of questionnaire results. Table 1 describes the data of the problem-oriented learning course. The results are that a questionnaire survey was conducted on 33 students in the whole class before the start of the course, and 33 valid questionnaire responses were obtained. Among them, the deep learning subscale of the questionnaire has a minimum score of 15 points and a maximum score of 42 points. The theoretical score range of this subscale was 10 to 50 points. Obviously, the use of deep learning methods by students in this class varies from strong to individual, and the use of superficial learning methods is the same. In addition, the scoring metrics for deep learning were higher than those for surface learning. It can be concluded that students were more inclined to use deep learning methods in natural English courses.

4.2. Statistics and Analysis of Questionnaire Results. Table 1 describes the data of the problem-oriented learning course. The results are that a questionnaire survey was conducted on 33 students in the whole class before the start of the course, and 33 valid questionnaire responses were obtained. Among them, the deep learning subscale of the questionnaire had a minimum score of 15 points and a maximum score of 42 points. The theoretical score range of this subscale was 10 to 50 points. Obviously, the use of deep

Table 1: Questionnaire results of students' learning methods before the course starts.

Category	N	Minimum	Maximum value	Average	Standard deviation
Deep learning (DA1)	32	16	46	32.35	8.13
Shallow learning (SA1)	32	14	36	28.36	7.35
Effective N (listwise)	32	12	43	25.55	31.33

learning methods by students in this class varies from strong to individual, and the use of superficial learning methods was the same. In addition, the scoring metrics for deep learning were higher than those for surface learning. It can be concluded that students were more inclined to use deep learning methods in natural English courses.

Table 2 from the average scores of deep learning and superficial learning, it can be seen that to a certain extent, students were more inclined to use deep learning methods after completing the course, while there were superficial learning methods in the course.

As shown in Table 2, a paired sample t-test was performed on the scores of the deep learning subscales before and after the tested students. ($T = -1.941$, $df = 32$, $p = 0.061 > 0.05$). $T(30)$ in Figure 1 indicates that the number of samples is 30, and MD indicates the information data of students' shallow learning. A paired sample t-test was performed on the scores of the tested students before and after the superficial learning subscale. The results are shown in Figure 1. The scores for the second subscale of shallow learning were not significantly different from those for the first ($T = 1.894$, $df = 32$, $p = 0.067 > 0.05$).

As shown in the survey, there were two parameter tables for shallow learning, and the collected data were descriptively analyzed, as shown in Table 3. Show:

Since the difference between the lowest and the highest scores of undergraduates was 32, and the standard deviation SD1 = 5,734, it can be observed that the density of students who choose the undergraduate method before taking the English intensive program varies widely; the frequency of choosing the low study method also varies widely big. In addition, according to the scores of the two subscales (10–50), the average score of the students' deep learning scale is 33.40, which is greater than 3, while the average score of the shallow learning scale is 26, 78, which is less than 30 people. So far, it can be concluded that a group of students is before the start of the course. You may want to use deep learning methods in your English classes. After the course, the same questionnaires were distributed to the tested students again, and a total of 53 valid questionnaires were collected for descriptive analysis, as shown in Figure 2. Standard deviation is a statistical term. The smaller the standard deviation, the less the value deviates from the mean, and vice versa. The size of the standard deviation can be measured by the ratio of the standard deviation to the mean.

The data results in Figure 2 show that the maximum value of deep learning was higher than that of shallow learning, the fluctuation of deep learning was larger, and the variation of shallow learning was small. Through the comparison of Table 3 and Figure 2, it is worth noting that it is not possible to infer from the descriptive material whether there is a significant difference in the use of deep learning and shallow learning by students before and after the course, so further analysis is required. The list of students with valid data from the first and the second surveys screened a total of 47 students who participated in the two surveys, and performed a paired t-test on the data from the deep learning and surface learning scales, and the results are shown in Figure 3.

Through the data in Figures 3 and 4, the differences between the two samples before and after deep learning and shallow learning can be compared, as shown in Figure 5.

$T(30)$ represents the number of samples 30, and MD represents the information data of deep learning and shallow learning. The graph above shows that the scores on the two deep scales were not significantly different from those on the two low scales in subjects before and after the course (sample $T = -1.091$, $df = 46$, $p = 0.281 > 0.05$). The scores were also not significantly different ($T = -1.934$, $df = 46$, $p = 0.059 > 0.05$). df stands for degrees of freedom and is the number of variables with infinite values when computing a statistic. p value is a parameter used to determine the outcome of a hypothesis test. The smaller the p value, the more significant the result. As can be seen, based on the results of the dual L-learning process survey, it cannot be concluded that the PBL curriculum developed in the study will have a significant impact on student learning and the use of superficial learning methods. However, since the survey data is one or two online surveys filled out using the Questionnaire Star platform, some students repeatedly completed and submitted the survey, and the researchers first adopted the data, these situations may cause the survey data to not reflect the overall situation, so in the research on student learning, it is necessary to combine student performance analysis and homework to continuously draw student learning conclusions that are closer to the real situation.

4.3. Analysis and Evaluation of PBL. English homework results there are also independent studies before and after PBL courses. In the past, the main goal of self-study was to complete learning tasks to obtain better grades. People tend to choose a "conservative action plan," that is, to try to achieve the learning goals set by teachers as little as possible. Possibly, in PBL learning, self-learning goals are influenced by personal interests and peer inspiration. In addition to achieving good grades, they also focus on individualized and comprehensive learning, and their learning input and learning effect have greatly improved. Of course, some people have reservations about cooperative learning. They found that cooperative learning was time-consuming and labor-intensive, preventing them from orienting their studies and completing tasks. This may be related to

Table 2: Results of the student learning methods questionnaire after the start of the course.

Category	*N*	Minimum	Maximum value	Average	Standard deviation
Deep learning (DA1)	34	17	47	36.5	8.35
Shallow learning (SA1)	34	13	35	275	7.65
Effective *N* (listwise)	34	13	42	26.7	32.67

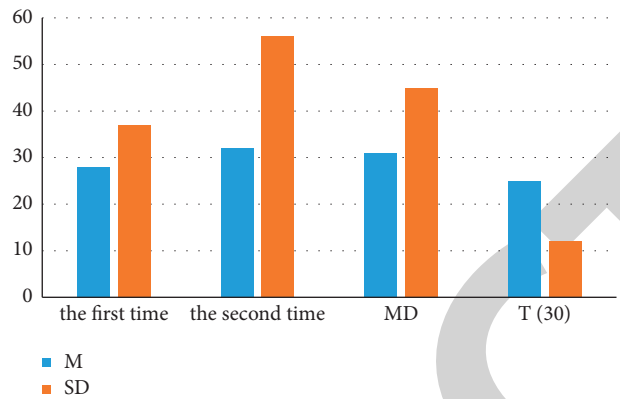

Figure 1: Differences in the subscale scores of the two shallow learning subscales.

Table 3: Descriptive statistics of the first test results.

Category	*N*	Minimum	Maximum value	Average	Standard deviation
Deep learning (DA1)	56	21	65	56	36
Shallow learning (SA1)	56	16	38	36	28
Effective *N* (listwise)	56	18	52	45	48

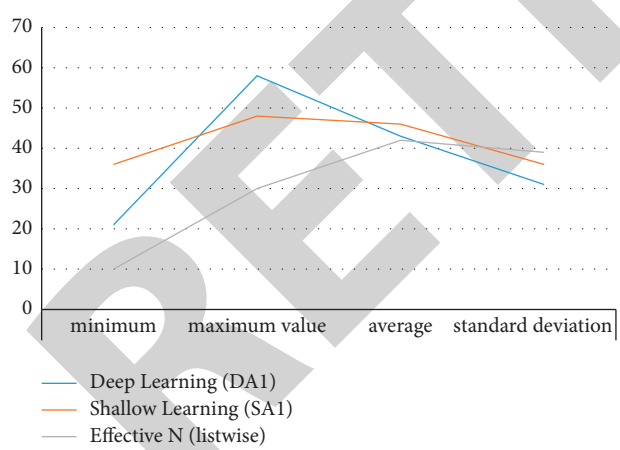

Figure 2: Descriptive statistics of the results of the second questionnaire test.

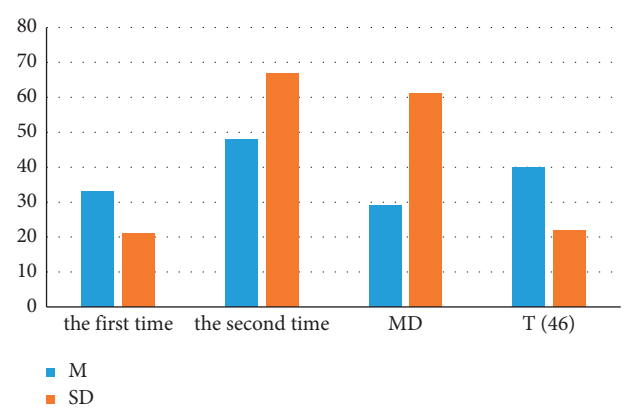

Figure 3: Deep learning paired sample test.

students' learning motivation and learning style, and students who adhere to this view, learning participation and learning outcomes may be less affected by PBL courses. In terms of teaching, students' suggestions reflect the consistency of PBL learning characteristics and students' learning needs, including keeping pace with the times, strengthening the connection with current hotspots and students' future development, and focusing on the cultivation of English skills, enriching personal statements and evaluation methods, etc., However, through the content of the interviews, the students suggested that more emphasis should be placed on the teacher's guidance and explanation, that is, the English skills to improve the skills are explained separately in the course. And think that improving English is difficult. Learning efficiency is only through self-study. The explanation is divided into two parts before and after PBL learning, which can make better use of the benefits of teacher education and students' cooperative learning and self-

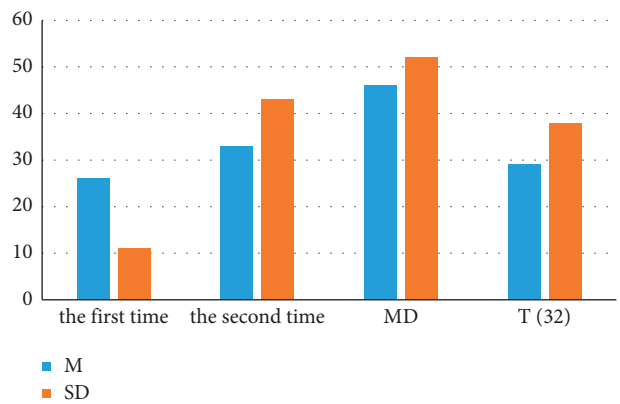

Figure 4: Shallow learning paired sample test.

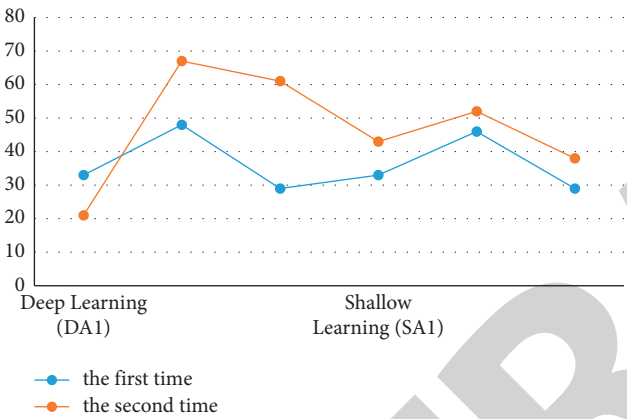

Figure 5: Comparison of samples before and after deep learning and shallow learning.

directed learning. Combining the results of PBL assignment analysis and student interviews, it can be concluded that while students may not be able to guide themselves in deep learning through metacognitive strategies when learning English, PBL students may be trained to use it. Deep learning methods help students perform deep learning to solve poorly structured real-world problems. In addition, according to the interview results, PBL questions may respond more to the learning needs of retirees in addition to language learning, but more factors will affect students' learning outcomes and final learning outcomes in PBL learning. Factors such as motivation, specific study schedules, and targeted learning tools. Therefore, students' learning influence is mainly manifested in cognitive level awareness, reading strategy skills, collaborative learning, deep learning, and so on. Numbers and deep learning are unclear and require further analysis.

5. Conclusion

By analyzing questionnaires, interviewing English teachers and analyzing classroom observation records, this study found the main problems affecting the deep learning of English reading courses and the cultivation of core English literacy. The correct understanding of core literacy training awareness and the role of deep learning and the function of English courses need to be strengthened. Reading class needs to be improved in terms of improving the comprehensive ability of language use and cultivating core qualities such as learning ability, emotional experience, thinking quality and cultural character. Secondly, teachers and students are utilitarian in English reading teaching goals, shallow in goals, test-oriented in content, solidified in teaching methods, outdated in programs, and simplified in evaluation, which hinders the development of deep learning and the realization of core literacy goals. Thirdly, using information technology to optimize teaching content, highlighting students' main body to optimize teaching process, and reforming standards and perspectives to optimize teaching evaluation are effective ways to promote in-depth learning of English reading courses and the development of students' core literacy. But how much of an impact it will have, we have not discussed any further, and we do not have enough data to prove it. If time permits, we can further improve the positioning of this paper from the following aspects: first, conduct experimental research to verify the feasibility of different evaluation methods; and second is to study the evaluation of "students with disabilities."

Data Availability

The experimental data used to support the findings of this study can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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