Analysis of Diversification of Intelligent Teaching in English Literacy Integrated Classroom Empowered by Artificial Intelligence Technology in Colleges and Universities

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Abstract

In recent years, an increasing number of English teachers have recognized the importance of reading and writing skills. Traditional English teaching methods often overlook the essential link between these skills, which hinders the improvement of students’ overall English proficiency. This paper introduces an adaptive Huber growth curve model to represent cognitive abilities in English reading. It develops an English reading ability detection model using a function-based approach. The model involves word feature extraction, fine-grained learning, and establishing information channels. These processes collectively contribute to a sequence annotation model that not only identifies but also automatically corrects errors in English writing samples. This facilitates integrated intelligent teaching of reading and writing skills. Analysis of English reading and writing capabilities among students at various colleges and universities reveals that the most notable improvement is in students’ critical thinking abilities during English reading, with most scores ranging between 3.5 and 4 and a total of 52 students participating. The difference in writing scores of the subject classes was 1.4186, of which the T value was 3.7855, the DF value was 112.3, and the P value was 0.000, which was significant, and the magnitude of the English writing scores of the subject class A was greater than that of the class B, which indicated that the integration of literacy and writing effectively improved the overall writing skills of the students.

Keywords: Adaptive Huber; Feature extraction; Fine-grained learning; Sequence labeling model; English literacy integration.

AMS 2010 codes: 68T05
1 Introduction

The fundamental purpose of English teaching in colleges and universities is to cultivate students’ comprehensive reading and writing skills in English. However, at present, students’ actual mastery of the English language does not achieve the expected ideal results [1-2]. With the rapid development of Chinese society and the increasing international exchanges, proficiency in the English language has become particularly important, which brings significant challenges to English teaching in colleges and universities [3-5]. In today’s English teaching, traditional teaching methods can no longer meet the needs of contemporary society for comprehensive talent training [6]. In recent years, the rapid development of artificial intelligence technology has brought new opportunities for the modernization of English teaching, which provides new opportunities for the creation of an intelligent English teaching environment [7-9]. At present, the importance of artificial intelligence technology applied to the teaching system has been agreed upon, and it is of great practical significance to study the application of artificial intelligence technology in English teaching in colleges and universities, oriented by the integration of information technology and curriculum.

Scholars have studied and elaborated on the ways to deeply integrate AI technology with English language teaching from different perspectives. Literature [10] argues that AI has a positive impact on students’ state supervision, recognition ability, and personalized learning, in addition to the use of location methods based on improved deep belief networks to provide real-time location control and state recognition for students in online learning to help students improve their English skills. Literature [11] constructed a personalized English distance learning platform based on artificial intelligence, which uses collaborative filtering personalized recommendation algorithms to obtain the best course recommendation results and achieve the scheduling and management of course resources. Literature [12] based on artificial intelligence and particle swarm algorithm constructed a flipped classroom English teaching mode. Combining artificial intelligence and virtual reality technology can create a better language environment for students, which helps the development of English listening practice courses. Literature [13] constructed an online intelligent English teaching system based on artificial intelligence and deep learning to help students improve the efficiency of English teaching according to their knowledge mastery and personality, which not only optimizes the teaching environment but also enriches the learning mode of students, with noticeable results.

Literature [14] constructed a university English teaching model based on artificial intelligence and information technology. It made full use of technological means for resource sharing, data collection, intelligent analysis, and feedback evaluation in the teaching process, which enhanced classroom efficiency and nurturing effect through a student-centered integrated intelligent teaching model. Literature [15] constructed an integrated intelligent teaching mode of English reading and writing based on the combination of semantic Web technology and artificial intelligence technology, which constructed the system functional modules based on the actual needs of English reading and writing with a high degree of satisfaction. Literature [16] constructed an online intelligent English training system based on wireless communication (WC) and artificial intelligence (AI), which improves the efficiency of English learning by proposing personalized teaching strategies based on the assessment of student’s English knowledge cognitive level.

In this paper, based on the growth curve model, the Huber loss function growth curve model is established, and the penalty function estimation is introduced in the high-dimensional space to optimize the inference ability of this model in the English reading cognitive ability model. The matrix straightening technique is used to express the English reading cognitive ability model as a function. The recurrent neural network algorithm is used for English reading annotation, which involves word feature extraction, fine-grained learning, and information channel establishment. This model detects and corrects grammatical errors in English writing samples, which enhances self-checking ability.
when writing in English. On the basis of the above, an integrated integration strategy for English reading and writing is proposed, in which the two models are jointly used in the intelligent teaching of English reading and writing classrooms in colleges and universities. The method before and after tests and relevance tests are used respectively to verify the quality of college students’ English reading thinking and the relevance of English reading. The relevant indexes of English writing performance are established to test college students’ English writing statically and dynamically, respectively, and to get the results of the improvement of writing ability.

2 English reading proficiency test model

In this paper, the intelligent teaching model is created by combining reading and writing ability. First, the reading ability test model. The construction process is as follows:

2.1 Growth curve model

Initially, the concept of a growth curve was considered as a generalized multivariate analysis of the variance model. Subsequently, many statisticians have studied methods of parameter estimation for this model under different conditions. In the fields of education, psychology, medicine, agriculture, and biological sciences, researchers often use the growth curve model to study the developmental process of things. For example, in the field of pedagogy, one can study the change in students’ learning ability with the increase in the length of education by defining the general growth curve model as:

\[
\begin{align*}
Y_{np} &= X_{nm} \theta_{mr} Z_{rp} + E_{np} \\
E_{np} &\sim N_{np}(0, \sum_i j_p)
\end{align*}
\]  

(1)

In the above equation (1), \(Y\) is the observation matrix of \(n \times p\), \(X\) and \(Z\) are the known design matrices of order \(n \times m\) and \(r \times p\), respectively, and \(\text{Rank}(X) = m < n\), \(\text{Rank}(Z) = r < p\), and \(\theta\) are the unknown parameter matrices of order \(m \times r\), and \(E\) is the random error matrix of order \(n \times p\), whose column vectors are uncorrelated with each other and are all random vectors with mean 0 and covariance array \(\sum > 0\), which, in general, obey the multivariate normal distribution.

2.2 Adaptive Huber growth curve modeling

2.2.1 English Reading Cognitive Ability Model Construction

In this paper, we consider the growth curve model:

\[
\begin{align*}
Y &= X \theta Z + E \\
E(E_i) &= 0, \text{Cov}(E_i) = \Sigma, i = 1, 2, \ldots, n
\end{align*}
\]  

(2)

In the above equation (2), \(Y = (y_1, \ldots, y_n)^T \in \mathbb{R}^{n \times p}\) is the observation matrix, \(X = (x_1, \ldots, x_m)^T = (X_1, \ldots, X_m) \in \mathbb{R}^{n \times m}\) and \(Z = (z_1, \ldots, z_r)^T \in \mathbb{R}^{r \times p}\) are known design matrices and have \(\text{rank}(X) = m\), \(\text{rank}(Z) = r\); in addition, \(\theta = (\beta_1, \ldots, \beta_m)^T \in \mathbb{R}^{m \times r}\) is the unknown parameter matrix and \(E = (e_1, \ldots, e_n)^T \in \mathbb{R}^{n \times p}\) is the random error matrix.
The growth curve model is an important method to analyze longitudinal data. In practical applications, many data have thick tails or contain outlier problems. At this time, the use of a growth curve model for data analysis is no longer appropriate. A robust method is needed. In this paper, we will establish a growth curve model based on the Huber loss function, for the growth curve model (2) can be defined as the multivariate Huber loss function:

\[
L_\tau(\theta) = \frac{1}{n} \sum_{i=1}^{n} l_i(Y - X \theta Z)
\]

The Huber loss function is a combination of a quadratic function and an absolute value function, where \( \tau > 0 \) is any given constant, minimizing the loss function \( L_\tau(\theta) \), which for the coefficient matrix \( \theta \) is estimated as:

\[
\hat{\theta}_\tau = \arg \min_{\theta \in \mathbb{R}^{m \times r}} L_\tau(\theta)
\]

For more convenient inference in higher dimensional spaces, the Huber loss function can be improved to use M estimation with penalty. The objective function can be denoted as \( F(\beta) = L_\tau(\theta) + R(\beta) \), where \( L(\cdot) \) is the loss function and \( R(\cdot) \) is the penalty function with regularization parameter \( \lambda \), which in this paper will be taken to be \( \lambda \| \theta \|_1 \). The \( \theta \) estimation of the then has when different parameters \( \tau \) and \( \lambda \) are chosen:

\[
\hat{\theta}_\tau = \arg \min_{\theta \in \mathbb{R}^{m \times r}} (L_\tau(\theta) + \lambda \| \theta \|_1)
\]

### 2.2.2 Expression of Cognitive Ability Functions for English Reading

In order to facilitate the calculation, this paper uses a use of matrix straightening way to design the algorithm, which can be transformed into a function of (5) \( L(\beta) = \frac{1}{n} \sum_{i=1}^{n} \left( y_i - \langle x_i, \beta \rangle \right) \), by the local adaptive optimization minimization algorithm can be known, according to the objective function \( F(\beta) \) can be considered to construct the function \( G(\beta) \) at \( \beta^{(k)} \), and \( G(\beta^{(k)}) \) to meet the \( G(\beta^{(k)}) \geq F(\beta) \) and \( G(\beta^{(k)}) = F(\beta^{(k)}) \). In order to minimize the objective function \( F(\beta) \), will be \( \beta^{(0)} \) initialized in the iterative computation process there are \( \beta^{(k+1)} = \arg \min_{\beta \in \mathbb{R}^d} G(\beta|\beta^{(k)}) \), \( k = 0, 1, \ldots \), so that the algorithm’s objective value is gradually decreasing. Then there are:

\[
F(\beta^{(k+1)}) \leq G(\beta^{(k+1)}|\beta^{(k)}) \leq G(\beta^{(k)}|\beta^{(k)}) = F(\beta^{(k)})
\]

Moreover, the functional equation of \( G(\beta|\beta^{(k)}) \) at \( \beta^{(k)} \) is:

\[
G(\beta|\beta^{(k)}) = L(\beta^{(k)}) + <\nabla L(\beta^{(k)}), \beta - \beta^{(k)}> + \frac{\lambda}{2} \| \beta - \beta^{(k)} \|_2^2
\]
Where \( \phi_k \) is a quadratic parameter that makes condition \( G(\beta^{(k+1)}|\beta^{(k)}) \geq L(\beta^{(k+1)}) \). At this point, the optimization problem for the objective function \( F(\beta) \) is transformed into:

\[
\min_{\beta \in \mathbb{R}^p} \left\{ L_\tau(\beta^{(k)}) + <\nabla L_\tau(\beta^{(k)}), \beta - \beta^{(k)} > + \frac{\phi_k}{2} \| \beta - \beta^{(k)} \|_2^2 + \lambda \| \beta \|_1 \right\}
\]

(8)

The corresponding solution can be expressed as:

\[
\beta^{(k+1)} = T_{x, \phi_k}(\beta^{(k)}) = S(\beta^{(k)} - \phi_k^{-1} \nabla L_\tau(\beta^{(k)}), \phi_k^{-1} \lambda)
\]

(9)

Where \( S(x, \lambda) \) is defined as \( S(x, \lambda) = \text{sign}(x) \cdot \max(|x| - \lambda, 0) \). Therefore, in this paper, the original problem is transformed into an unconstrained optimization problem with an objective function. According to the LAMM algorithm, the obtained \( \beta^{(k+1)} \) can be iterated to generate the following solution until the sequence of solutions \( \{\beta^{(k)}\}_{k=1}^{\infty} \) converges, the convergence criterion is set to \( \| \beta^{(k+1)} - \beta^{(k)} \|_2 \leq \varepsilon \), \( \varepsilon \) is a minimal value similar to \( 10^{-4} \). The series \( \beta^{(k)} \), \( k = 1, \ldots, n \) can be obtained by the I-LAMM algorithm.

3 English Writing Error Detection and Correction Modeling

3.1 Sequence labeling based on recurrent neural networks

In the second section, this paper presents a model for improving English reading ability, and next, the third subsection will construct an auxiliary model for improving English writing ability.

3.1.1 Word feature extraction

In this paper, we design a convolutional recurrent neural network to vectorize words from the character level. Because character is the smallest unit to make up a word, and the total number of characters is a finite set, representing words from the character level can solve the problem of unregistered words fundamentally. Firstly, the word is decomposed according to the characters, and each character is mapped as a vector. Then, the vectors of each character are collocated together to get the First characters to decompose the words, and each character is mapped into a vector. Each character vector is collapsed to get the matrix representation of the word. Finally, the final CRNN word vector is obtained after the process of convolution, pooling, and recurrent neural network feature extraction.

Modeling sequence data often requires taking into account the contextual features of the sequence data. Compared with simple feed-forward networks, the critical advantage of recurrent neural networks is that when mapping the input sequence to the output sequence, the information of the previous context can be retained and have an impact on the current output:

\[
s_t = \sigma(W_{s,t-1} + U_{s,t})
\]

(10)
Where $W$ and $U$ are the parameters between hidden layers and between hidden layer and input layer, respectively, $x_t$ is the input at moment $t$, and $s_{t-1}$ is the hidden layer output at moment $t-1$.

To perform gradient backward conduction, the BPTT algorithm is used as shown in equation (11):

$$\frac{\partial L}{\partial W} = \sum_k \frac{\partial L_k}{\partial s_t} \frac{\partial s_t}{\partial s_k} \frac{\partial s_k}{\partial W}$$

(11)

Among them:

$$\frac{\partial s_t}{\partial s_k} = \prod_{i=1}^t \frac{\partial s_i}{\partial s_{i-1}} = \prod_{i=1}^t W^T \text{diag} \left( \sigma' \left( x^{i-1} \right) \right)$$

(12)

Where $L_t$ is the loss function accumulated to the moment $t$, and $W$ is the parameter the common between the hidden layers.

However, when the traditional recurrent neural network is dealing with sequence data, the length of the sequence is often limited. The reason is that when the length of the sequence becomes very long, phenomena such as gradient disappearance or gradient explosion will occur, and the network becomes difficult to train. The traditional recurrent neural network model, in the weight update, i.e., in the process of calculating the gradient, is more inclined to follow the end of the sequence in the direction of the weight correction to update, that is, the more “far” the sequence input on the weight correction of the less “influence.” Hence, the network is less likely to have a long memory. The network is unlikely to have an extended memory function.

As shown in equation (12), when the sequence is too long, the problem of gradient explosion may occur if the maximum value of the matrix eigenvalue of $W$ is $\rho > 0$, while the problem of gradient vanishing may occur if the maximum value of the matrix eigenvalue of $W$ is $\rho < 0$ when conduction is done in the reverse direction.

### 3.1.2 Coarse-grained learning

From the deep learning perspective, the underlying a priori knowledge factors that can explain changes in the data are often shared across two or more tasks. Meanwhile, because of parameter sharing, the statistical strength of the parameters can be significantly improved, and the generalization problem can be ameliorated. The sequence annotation model in this paper divides the process of annotation into a multi-task learning process from shallow to deep, i.e., Firstly, the sequence data is annotated roughly, and then the annotations of the same broad category are further divided. Such a division can effectively annotate the lexical information of corpora, such as English compositions written by Chinese students.

### 3.1.3 Information Channel Establishment

In this paper, the model divides the sequence labeling into two parts, firstly, the rough labeling is carried out. Then, the fine-grained labeling is carried out using the information from the rough labeling. At the same time, in fine-grained labeling, the original input information is extracted and filtered, and some of the features are not used in the final fine-grained labeling. As the network’s depth increases, the training process becomes more difficult.
In deep learning models, the more layers of the neural network, the richer the features that can be extracted at different levels. Moreover, the deeper the network, the more abstract the features extracted and the more semantic information extracted. As the network’s depth increases, so does the difficulty of training it. At the same time, due to the increase in the depth of the network, when calculating the gradient, it will cause gradient dispersion or gradient explosion. In addition to this, if the effect of the shallow network is saturated, simply increasing the depth of the network may cause the network to degrade, i.e., The newly added part of the network learns a constant mapping, at which point the deep network degrades to a shallow network.

In 2016, some scholars used residual networks to model deep neural networks between partially hidden layers, creating information pathways that allow information to pass across the hidden layers of the network. It is assumed that the computation between the original network layers is shown in equation (13):

\[ F = W_2f_1(W_1x) \]  

With the introduction of the residual network, this part of the calculation is shown in equation (14):

\[ F = W_2f_1(W_1x) + x \]  

Where \( W_2 \) is the parameter of the second hidden layer, \( W_1 \) is the parameter of the first hidden layer, \( x \) is the input data, \( f_1 \) is the activation function of the first layer, and \( F \) is the output of the second layer.

In the model of this paper, the word vector information at the character level is first extracted for coarse-grained supervision. At this time, the word vector information at the word level is passed across the coarse-grained learning layer to the fine-grained annotation layer. Meanwhile, the word vector information at the character level is passed across the coarse-grained learning layer to the fine-grained annotation layer. Then, the word-level vector information and the coarse-grained learning results are used for fine-grained annotation.

### 3.2 Detecting and Correcting English Grammatical Errors Based on Sequence Annotation

#### 3.2.1 Target detection lexical labeling

Sequence annotation-based English grammatical error detection and correction model needs to process the corpus when correcting English grammatical errors fixed in the confusing set of articles and prepositions, taking the preposition to use error as an example: replace the preposition with a particular marker “or,” and swap the lexical annotation position with the position of the preposition. All the places in the sentence where the preposition occurs are replaced with “ro,” and its corresponding lexical properties are modified to the preposition that should occur here. Based on the given sentence, we judge where the preposition may be misused, lexically annotate the sentence, and then identify all the lexical properties that have been annotated as specific prepositions.

#### 3.2.2 Post-labeling

Sequential annotation is used to detect and correct English grammatical errors. The detection and correction results are obtained by swapping the specially labeled words in the annotated original corpus with the final labeled tokens after annotation.
4 Integration Strategies for Integrating English Reading and Writing in Colleges and Universities

In this paper, the auxiliary models of English reading and writing ability of college students are proposed in Chapter 2 and Chapter 3, respectively. Next, the model integration strategy is proposed to realize the integration of English reading and writing in colleges and universities.

4.1 Expanding reading materials with students in mind

1) Mining the writing text and summarizing the writing “ingenuity.”

With the reform of the new English curriculum, the content not only includes the output of basic knowledge but also includes the exploration of writing skills and writing methods. In daily teaching activities, teachers should start from the main idea of the text and guide students to understand the structure and tone of the article. At the same time, teachers should summarize the vocabulary and expressions in the text and let students analyze the “ingenuity.”

2) Expanding reading materials to strengthen the ability to input reading knowledge

It should be noted that in order to strengthen students’ knowledge accumulation, teachers should do an excellent job of collecting information, taking into account curriculum standards and students’ natural interests. The introduction of extracurricular resources should be based on the characteristics of students’ learning situations and teaching content. Students can acquire a significant amount of knowledge points driven by their interests by combining textbook content and extracurricular resources.

4.2 Focus on writing details and will correct errors in a timely manner

As a language, English was created in a specific cultural context. Therefore, students often have the following two kinds of problems in the process of writing: first, logical problems, i.e., Lack of logical thinking in English. There are differences in grammar and syntax between English and Chinese, so how to make students realize the differences, try to share what they think in English, and find and correct mistakes in time for problems. Second, improving writing ability is a systematic process. In previous writing training, students often hesitate to complete writing tasks. Teachers should pay attention to writing training and optimize the mode of writing training in light of the two situations above.

5 Analysis of the Integration of English Reading and Writing in Colleges and Universities

Based on the theory of intelligent teaching in the literacy-integrated classroom, this study applies the literacy-integrated teaching strategies proposed in this paper to the subject colleges and universities so as to cultivate students’ literacy-integrated abilities.

In this paper, 120 reading comprehension as well as essay topics of 2013-2022 National Grade 4 and 6 English, Class A and B of I college, 152 students each (Class A is the class that received this paper’s reading-writing integration teaching, and Class B is the traditional English teaching class) are taken as the research subjects. The research period is from September 2023 to December 2023 for the whole semester.
5.1 Evaluation of English Reading Ability of Students in Colleges and Universities

5.1.1 Quality of students’ reading thinking improves

The results of the pre-and post-test comparison of reading thinking quality among students in Class A are shown in Figure 1. Logicality: in the post-test, the mean value of the scores was concentrated in the range of 2.5-3, while the pre-test scores were concentrated in the range of 2-2.5, which indicates that the reading logic of the students in Class A has been significantly upgraded by one notch after receiving the intelligent education of literacy integration program. The band 3.5-4 was marked by students for creativity, with a score of 3.516, which was significantly higher than the pre-test. For Criticality, 52 students in Class A were concentrated in sub-segment 3.5-4 for critical reading skills, 29 more than in Class B.

In summary, it can be seen that compared to the pre-test, the post-test results of logical, critical, and innovative English reading thinking qualities have been significantly improved, with the most significant improvement in innovative thinking with 0.83 points, followed by logical thinking with 0.68 points, and lastly, critical thinking with 0.61 points.

![Figure 1](image)

**Figure 1.** Class students read the results of the comparison

5.1.2 English Reading Correlation Analysis

Table 1 shows the correlation analysis between the intelligent teaching model of reading and writing in the classroom and the attitude toward English reading motivation and ability in Class A. The process of correlation analysis involves studying the relationship and interaction between two or more variables. The correlation coefficient with an * in the upper right corner indicates that the value of significance has not exceeded 0.05, which means that there is a relationship between the two and vice versa. A correlation coefficient value less than 0 means that there is a negative relationship between the two and vice versa. The values of the correlation coefficient and significance level of the variables of intelligent teaching mode of reading and writing integrated classroom and English reading motivation and attitude are 0.3544 and 0.05, respectively, thus indicating that there is a significant positive correlation between intelligent teaching mode of reading and writing integrated classroom and English reading motivation and attitude. The correlation coefficient value between the intelligent teaching mode of reading and writing integrated classroom and English reading learning ability is 0.6448. It shows a significance level of 0.01, thus indicating that there is a significant positive correlation between the teaching mode of this paper and English reading learning ability.
Table 1. Correlation analysis

<table>
<thead>
<tr>
<th></th>
<th>Read and write the teaching mode of integration</th>
<th>English reading motivation and attitude</th>
<th>English reading ability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Correlation</td>
<td>1</td>
<td>0.3544*</td>
<td>0.6448**</td>
</tr>
<tr>
<td>Significance</td>
<td></td>
<td>0.0345</td>
<td>0</td>
</tr>
<tr>
<td>Case number</td>
<td>152</td>
<td>52</td>
<td>52</td>
</tr>
</tbody>
</table>

|                         | English reading motivation and attitude        |                                         |                         |
| Correlation             | 0.3544*                                       | 1                                       | 0.3468*                 |
| Significance            | 0.0345                                        | -                                       | 0.0384                  |
| Case number             | 152                                           | 52                                     | 52                      |

|                         | English reading ability                       |                                         |                         |
| Correlation             | 0.6448**                                      | 0.3468*                                | 1                       |
| Significance            | 0                                             | 0.0384                                 | -                       |
| Case number             | 152                                           | 152                                    | 152                     |

Note: *At the 0.05 level (double tail), the correlation is significant. **At 0.01 level (double tail), the correlation is significant.

5.2 Improvement of English Writing Skills of Students in Colleges and Universities

5.2.1 Analysis of Writing Indicators

In order to better understand what aspects of the “reading and writing integration” method have an impact on the students’ writing performance, before the implementation of the experiment, the pre-test compositions of students in classes A and B were scored in terms of vocabulary (3 points), content richness (3 points), grammar (4 points), language expression (3 points) and writing (2 points). Data were uniformly collected and analyzed with reference to the scoring standards of English compositions of I colleges and universities. Two points were assigned on five levels, and the data were collected and analyzed uniformly.

After the teaching experiment, the two classes’ writing texts and scores were analyzed again using the five specific levels. Figure 2 shows the analysis of the five dimensions of English writing in the posttest. The p-values of vocabulary, grammar, language expression, and content richness are all 0.000, which are all less than 0.05, which indicates that the differences between the experimental class and the control class after the experiment are significant in terms of the scores of vocabulary, content richness, grammar and language expression, and class A is significantly higher than class B. The results are shown in Figure 2. It can be seen that after one semester of the “reading and writing integration” teaching experiment in class A, the writing scores of the students in this class have increased more than those of the control class in these four dimensions. In contrast, the difference between the two classes is not significant in terms of paper writing, with a t-value of 4.154 and a P-value of >0.05, which means that The effectiveness of the “reading and writing integration” method is not very clear in terms of whether it can improve students’ performance in paper writing.
5.2.2 Analysis of Writing Performance

To conduct a comparative analysis, the posttest writing scores of classes A and B were collected at the conclusion of the experiment. Table 2 shows the statistics of English composition post-test scores and the results of independent samples t-test. The mean value of posttest writing scores of class A is 9.7855, the mean value of the control class is 8.3669, and the difference in the mean value of writing scores of the two classes is 1.4186, and the independent samples t-test shows that the variance has chi-square. The T-value is 3.7855, the DF-value is 112.3, and the P-value is 0.000, which is less than 0.05. The difference in English post-test scores between the two classes is significant. It is concluded that the students in class A improved their English writing scores more than those in class B after being taught by the “reading and writing integration” method, which indicates that this teaching method can effectively improve the overall English writing scores of the students.

<table>
<thead>
<tr>
<th>Class</th>
<th>N</th>
<th>M</th>
<th>SD</th>
<th>SD(Mean)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>152</td>
<td>9.785</td>
<td>1.4685</td>
<td>0.2685</td>
</tr>
<tr>
<td>B</td>
<td>152</td>
<td>8.3669</td>
<td>2.3658</td>
<td>0.3493</td>
</tr>
</tbody>
</table>

Table 2. Test of the English composition scores and the independent sample T

5.2.3 Dynamic testing of writing performance

Figure 3 shows the dynamic changes in the achievement of English learners. Achievement analysis to test the effect of dynamic assessment on the magnitude of improvement in different aspects of learners’ writing achievement, based on the posttest results in Table 2, the students were divided into two subgroups of high, medium, and low. In the Figure 1 and Figure 4 are the low subgroups, 2 and 5 are the medium subgroups, and 3 and 6 are the high subgroups. The results of six times of the three groups of students’ writing collected after classroom instruction were compared, and the scores of the three groups were analyzed separately in each of the subcategories of vocabulary, grammar, language expression, content richness, and writing on the paper. According to Figure 3, in general, students’ scores in language expression fluctuated wildly. The total improvement of the three groups was
2.1482. The improvement of the middle and low groups in language expression was more prominent, indicating that the students in the low group had apparent progress. In terms of vocabulary, the improvement of the scores of the students in the high group was 0.4803, which indicated that the vocabulary level of the high-level students had continued to improve. Generally speaking, the student’s vocabulary level was improving, and the students’ vocabulary level had improved. In general, the intelligent teaching mode of integrated classrooms affects students’ writing performance.

![Figure 3. English learners’ dynamic performance changes](image)

6 Conclusion

In this paper, using the self-use Huber growth curve model and the method of sequence annotation, respectively, we constructed an automatic annotation model for the detection of English reading cognitive ability of students in colleges and universities, as well as the detection of grammatical errors in English writing. We constructed an integrated strategy for the integration of English reading and writing to realize the teaching mode of the integrated classroom intelligence of English reading and writing in colleges and universities. The following are the results of the practice of the English reading and writing integration teaching model in this paper:

1) After reading and writing integration education, the quality of students’ reading thinking has been improved in all aspects, especially in the critical aspect. The effect of improvement is the most obvious, after the teaching of students concentrated in 3.5-4 segments, the number of 52 people. There is a well-known correlation between reading and writing integration and English reading motivation, attitude, and reading learning ability, the values are 0.3544 and 0.6448, respectively, showing significant positive correlation at 0.05 as well as 0.01 levels.

2) English writing shows significant improvement in four indicators: vocabulary, grammar, language expression, and content richness, and the p-value is 0, which is less than 0.05. However, the difference between the classes in terms of writing is not significant; the scores are the same, and the p-value is >0.05. In terms of the dynamics of English writing performance, the language expression ability of the students of the high, middle, and low levels has the highest improvement in their scores. The total of the three groups is 2.1482, and the student’s writing ability is the most important one. The students’ writing proficiency is more evident at 2.1482.
Funding:
1. Project Name: 2022 Guangdong Province Continuing Education Quality Improvement Engineering Construction Project (Project No. JXJYGC2022DS129) Reform and Practice of Ideological and Political “Four-chain” Teaching in English Courses of Continuing Education for Industrial Workers Based on POA.


References


