Research Article

Reform and Practice of Public English Examination Mode in Colleges and Universities Using Big Data Analysis and Speech Recognition

Qianru Zhu

Chengdu College of Arts and Sciences, Chengdu 610100, China

Correspondence should be addressed to Qianru Zhu; zhuzhuviola2022@163.com

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In terms of the CPE (College Public English) test mode, it suffers from inefficiency and uniqueness. The test must be comprehensive and objective in order to serve as a standard for evaluating English proficiency. Promoting English examination reform and practice is extremely important for English teachers. In light of the current situation, the CPE test system is being researched and designed using BD (big data) analysis. To establish the index system and parameters for evaluating test questions, the test database maintenance module uses a method based on problem-solving theory. For pronunciation recognition, error judgment, and scoring of spoken English, speech recognition and HMM (hidden Markov model) scores are used, and the final spoken English score is obtained through percentile transformation. In intelligent scoring, the AdaBoost CT (adaptive enhancement classification) algorithm is introduced, and various algorithms are compared through extensive literature reading. The results show that when the parameter is set to 50, the AdaBoost CT algorithm has the highest accuracy, at 88.39%. The platform improves students’ learning efficiency and quality by diagnosing their learning problems and intervening in their learning in real time. The results are significantly better than those of other students.

1. Introduction

Public English is a large-scale, universal course with a large number of students that is usually required in vocational colleges. At the moment, college English is taught in a teacher-centered manner, with students listening to lectures, taking notes, and doing exercises. Today’s English education must deal with the complexities and contradictions of emerging globalization, social economy, culture, and historical changes in order to be perfect. Redesigning the English learning environment, rebuilding the English teaching model, striving for true multicultural communication and understanding, improving English listening and speaking ability, moving toward practical application of English, and improving English communication ability in the workplace are all attempts and innovations in the reform and implementation of the English learning plan [1]. The creation of a CPE (College Public English) test mode based on BD (big data) [2] can create a personalized learning environ-ment and personalized courses for each student, as well as an early warning mode to detect potential risks like landslides and even avoid boredom. It provides a challenging but not boring learning mode for students’ future learning through guided learning.

Large quantities, a variety of types, low value density, and real-time processing are all characteristics of BD. At the same time, valuable data can be gathered, processed, analyzed, and extracted quickly. The allure of DB is not in its size, but in the fact, that such vast amounts of data can generate ever-increasing value [3]. From an analysis of the problems that exist in CPE examination, Neumann and others discussed the necessity of CPE examination reform and practice and on this basis proposed CPE examination reform and practice [4]. Designed to address the issues of a convoluted workflow and low scoring accuracy in the English test scoring system, Li et al. developed an HMM-(hidden Markov model-) based English test scoring system, as well as a speech recognition module and scoring system.
2. Related Work

2.1. Research Status of Evaluation System. Cui evaluates the quality and writing style of articles based on the shallow text feature analysis method in statistical technology. As it happens, the system adopts the shallow text feature analysis technology, and it covers the content, organizational structure, and genre of the composition [10]. Feng et al. combined several analysis tools such as dictionary and semantic analysis with various resources in the system, which improved the performance of the system to a certain extent and avoided the problem of relying too much on the surface features of the composition [11]. Tabrizi et al. adopted the information retrieval technology, screened out the influential index items, and calculated the proportion of each index’s influence. Finally, 67 index items were extracted as independent variables, and a computer program for online evaluation of English composition scores was developed by linear regression with the artificial scores of dependent variables [12]. The comments made by Qia and Fgc include specific sentences pointing out grammatical errors, vocabulary usage, text structure, and whether Chinglish exists or not [13]. Zhang and Goh have built an automatic scoring statistical model for Chinese students’ English compositions, although the accuracy rate is higher than that of manual scoring [14], but to a certain extent, due to the neglect of the characteristics of text content and deep structure, the number of samples is too small, the source range is small, and it is not representative. Alkurd et al. used statistical analysis technology to analyze many factors affecting CPE and obtained the linear regression relationship between CPE performance and its influencing factors [15]. Od et al. designed an intelligent evaluation and feedback system for online examination based on data mining [16]. This system can intelligently collect, analyze, and provide deep-level teaching diagnosis for students’ examination data and information accumulated by teachers during marking.

2.2. Research Status of Personalized Learning. The establishment of a user model is crucial to BD analysis. We can only reasonably classify and analyze learning data and then provide targeted services for learners, if we establish an appropriate learner model. W. He et al. developed a distance learner model based on four factors, personal data, learning style, learning interest, and knowledge model, and proposed personalized teaching application ideas based on personalized resource push, personalized learning path, and remote supervision service [17]. Based on BD personalization and adaptation, Wójcik and Piekarczyk examined the learning process structure, learning process visualization, and learning effect demonstration, and the findings showed that data analysis of students’ learning behavior and knowledge mastery could recommend reasonable learning paths and learning resources with appropriate difficulty [18]. According to Z. Li et al., students’ mastery of objective and subjective questions is linked and compensated in different ways [19]. When it comes to objective questions, students can only master the test questions if they have mastered all of the test questions’ knowledge points. The more knowledge points students have mastered, the better their mastery of subjective questions is, and the higher their subjective question scores are. Students’ score matrix and knowledge point correlation matrix of test questions are used in the application of neural
network and educational cognitive diagnosis, and the knowledge point correlation matrix of test questions is modified by mining the text information of test questions through neural network. Yang devised a new recommendation system that took into account the preferences, background knowledge, and memory abilities of students to produce diversified personalized recommendations [20]. Gaye et al. proposed a massive open online course recommendation algorithm based on content and word2vec, which improved the performance of the traditional content-based recommendation algorithm [21]. It was based on the traditional content-based recommendation algorithm, combined with the word2vec model to model items and improve item similarity calculation. Hammou et al. used interest maps to model learners, studied the generation, evolution, and feedback methods of interest maps, and established personalized recommendation system in cloud environment based on in-depth analysis of user behavior data [22].

3. Methodology

3.1. CPE Test System Design. Various information management systems have appeared in schools as a result of the development of people's management ideas and computer software and hardware. The goal of this system’s development is to combine teaching detection and decision-making by scientifically managing large-scale student examination data, analyzing and forecasting, and determining the direction of each record. During the research and development of this system, the first half of the academic year’s examination information was saved, and the existing data were mined by association rules based on the characteristics of the data of each module in the system, realizing the function of CPE test system demand analysis. Data mining technology was used to analyze the examination situation of our college, and the quantitative analysis of all the staff was carried out.

The heavy work of sorting out the examination evaluation information has been freed up, manpower and material resources have been saved, and work efficiency has improved as a result of the actual operation of this system. This system analyzes the data of each teacher’s examination resources, understands the speculation or abnormal information displayed by the results, and completes the evaluation of the corresponding indexes of the examination evaluation in a standardized, scientific, and highly digital manner with the help of mining technology. The five modules of the CPE test system examined in this paper are user management, database management, analysis and evaluation of students’ scores, analysis and evaluation of test questions, and analysis and evaluation of teachers’ teaching quality. These five modules work together to provide a complete solution. Each module is relatively independent, even though they are mutually organized and restricted. The system uses data mining technology to complete the realization process of exam evaluation function as shown in Figure 1.

The index system of test questions is the description of the external characteristics and internal attributes of test questions, and it is the key to establish the system of generating test papers [2]. In this study, the three-parameter logistic model of item response theory is used, assuming that the guess coefficient is 0.25. Item response theory is determined according to the parameter estimation method in item response; that is, the difficulty of a test question is the natural logarithm of the ratio of the number of wrong answers to the number of correct answers.

Let \( R \) be the number of correct answers and \( W \) be the number of wrong answers. Test difficulty \( d \) is expressed as

\[
d = \ln \left( \frac{W}{R} \right) .
\]

The difficulty coefficient of the test paper, that is, the difficulty of the whole test paper, is an index to measure the difficulty level of the whole set of test questions. The calculation method is

\[
diff = \frac{\sum_{m=1}^{m_{\text{diff}}} \text{diff}_i \times S_i}{\sum_{i=1}^{m} \delta_i},
\]
where $S_i$ is the score of $i$ test questions and $m$ is the number of questions.

The total score of the test paper is the sum of the scores of all test questions $S$.

$$S = \sum_{i=1}^{m} S_i.$$  \hspace{1cm} (3)

Although the simple English test system can automatically generate test paper, it can reduce the time of generating test paper and marking paper compared with the traditional test and can assist teachers to complete the test process, but it often fails to consider the ability level of the subjects, which makes the test paper too difficult or too simple, the test effect is not good, and it does not have intelligence and adaptability [1]. In view of this weakness, this paper puts forward a calculation method of PGTPG_2F (personalized genetic test paper generation based on forcing factor) and establishes a test paper model, which can provide different test papers for different subjects.

PGTPG_2F algorithm introduces forgetting factor into personalized information (that is, user’s mastery) and regards it as a gene preference feature of chromosome genes. Finally, the generated test paper is a test paper that comprehensively considers the difficulty, discrimination, and user's personalized features. The test paper generating process of PGTPG_2F is shown in Figure 2.

The system uses the phoneme logarithm posterior probability scoring method based on HMM to give the examiners’ oral English test scores. The scoring process is shown in Figure 3.

The scoring process based on HMM trains the acoustic model through the standard English pronunciation recognizer Sphinx4, in which the standard pronunciation includes the standard pronunciation of English native language, non-native language pronunciation, and mixed pronunciation. The frequency domain analysis method of Mel cepstrum coefficient is used to extract the spoken English pronunciation feature sequence of examiners and the feature sequence of acoustic model, and then, the acquired spoken English pronunciation feature sequence is operated by the forced alignment method, and the time subscript of phonemes is identified, so that the matching reference model feature sequence can be obtained, and finally the scoring process is realized.

The scoring process can be regarded as a pattern recognition process based on HMM model. In a known state, the prior probability $p(q)$ of phoneme $q$ should be obtained before the posterior probability can be obtained. Based on the posterior probability, the final output of the logarithmic posterior probability pronunciation evaluation result is as follows:

$$p_t = \sum_{t=t_r}^{t_r+s_r-1} \log[p(q_t|O_t)],$$  \hspace{1cm} (4)
where $\tau_i$ is the starting time of phoneme $q_i$ and $t_i$ is the pronunciation duration of phoneme $q_i$.

The phoneme logarithm posterior probability scoring method based on HMM is the digital scoring result obtained by the system fusion recognition algorithm and scoring scheme, and it cannot directly describe the pronunciation level of examiners. Therefore, in this paper, the logarithmic posterior probability score of phonemes obtained by systematic operation is transformed into percentile system. By training the expert scoring model, the corresponding standard between its scoring standard and systematic scoring standard is analyzed, and the transformation relationship between logarithmic posterior probability score and percentile system score is obtained. The corresponding transformation formula is

$$
\text{Score}(P_{q_i}) = \frac{100}{1 + \exp(-\phi P_{q_i} + \lambda)},
$$

where $\phi, \lambda$ is obtained through training summary and $P_{q_i}$ is the posterior probability score of the $i$th phoneme.

Adaptive enhancement AdaBoost algorithm is more and more widely used. Adaboost_CT (centralized trend adaptive enhancement) algorithm proposed in this paper draws on the instability of expert group intelligence, excludes data deviating from centralized trend, and exerts its original advantages.

Concentration trend is a concept in statistics, which represents the degree to which a group of data is close to a certain central value and reflects the central position of a group of data [5]. This value can be determined by a value in the population or by a value in a part of positions. Adaboost_CT algorithm basically keeps the advantage of classic AdaBoost algorithm that there is no overfitting. At the same time, it concentrates the whole sample trend, eliminates bad data, and solves the superposition error trap of weak classifiers.

Error of improved Adaboost_CT algorithm:

$$
\epsilon_t = \text{Pr} \{h_t \neq y\}.
$$

(6)

Weight classification:

$$
\alpha_t = \frac{1}{2} \ln \left( \frac{1 - \epsilon_t}{\epsilon_t} \right).
$$

(7)

Update weight:

$$
D_{t+1}(i) = D_t(i) \exp \left( -\alpha_t y_i h_t(x_i) \right) / Z_t.
$$

(8)

$Z_t$ is a normalized constant.

The data set is an index system collection; sample set is index value $X$ and classification $Y; y_i \in Y = \{-1, +1\}$ corresponds to classification failure and success, respectively. When there is a superposition error, that is, when the number of errors is greater than 2, the data set is subjected to centralized trend mapping, and $D_t'$ is the mapping of $D_t$ to eliminate the superposition error.

Feedback in English composition is to provide real-time information feedback to improve students’ writing level, help students find problems, and guide students to improve their writing level. On the basis of intelligent marking, this paper adds specific feedback to students in time in the form of natural language. The comment generation model is shown in Figure 4.

This topic adopts a hierarchical index system, which is also conducted hierarchically when feedback the comment results of the composition. This model is helpful for students to know which specific indicators of their own level have not met the requirements, so as to guide the direction of their efforts.

3.2. Personalized Learning Analysis Model Based on BD. Individualized learning, which originates from the transformation of information-based education, is a new learning method actively advocated by modern educational concepts. It breaks the teacher-centered education model and emphasizes the students’ development needs as the center, which is a three-dimensional learning in time, space, content, and form. Use BD technology to track and record personalized education information, objectively analyze learning data, truly feedback data information, bid farewell to the education mode of “speaking with experience,” use data to find problems, evaluate learning process, warn learning situation and make decisions on teaching and learning, and help realize personalized learning.

The realization of personalized learning depends on the establishment of personalized learning analysis model. Personalized learning analysis requires not only available data but also data mining and maximizing the value of data. Therefore, from the perspectives of data, data mining, and

![Figure 4: Comment generation model.](image-url)
data value, this study builds a personalized learning analysis model based on BD, as shown in Figure 5.

The ideal scores of students can be reconstructed by students’ cognitive state \(\alpha\) and the relation vector \(q_j\) between test questions and knowledge points, which can support all kinds of ideal scores from 0 to full marks. The specific calculation formula is as follows:

\[
\eta_{ij} = \text{fix}\left(\alpha_i q_j q_j' \times m_j\right),
\]

where \(\alpha_i\) represents the cognitive state of student \(i\), \(q_j\) represents the knowledge vector investigated by test question \(j\), \(q_j'\) represents the transposition of \(q_j\), \(m_j\) represents the full score of test question \(j\), and \(\text{fix}(\cdot)\) represents the integer function.

Test error rate and guessing rate are introduced to model students’ answers. The formula is as follows:

\[
P(X_{ij} = 1 | \eta_{ij}, s_j, g_j) = (1 - s_j)^{\eta_{ij}} g_j^{(1-\eta_{ij})},
\]

where \(X_{ij}\) represents the score of student \(i\) on question \(j\), with a value of 0 or 1, and \(\eta_{ij} = 1\) represents that student \(i\) has mastered all the knowledge points investigated by question \(j\).

\(\eta_{ij} = 0\) means that student \(i\) has not mastered all the knowledge points investigated by test question \(j\); \(s_j\) is the error rate, which indicates the probability of mastering all the knowledge points investigated by test question \(j\) but making mistakes; \(g_j\) is the guessing rate, which indicates the probability of not mastering all the knowledge points examined in question \(g_j\) but doing it right by guessing.

The manager of the tutoring platform creates personalized learning and tutoring programs for learners based on the feedback results of visual data, which include knowledge tutoring for learners by tutors, private tutoring for learners by consultants, and opinions and suggestions for learners, parents, and teachers. In short, learners’ learning can be
more targeted, and their learning quality can be improved through personalized counseling.

After passing the personalized learning diagnosis, the learner will use the tutoring platform to practice in the future, and the tutoring platform will extract the learner’s weak knowledge points from the question bank to practice repeatedly, based on the analysis data. Simultaneously, determine the learners’ current level of learning and ask questions of similar difficulty. This diagnostic result relieves learners’ burdens and gives meaning to the questions they ask. Avoid asking easy questions more than once, wasting time, and avoiding difficult questions that are beyond your abilities.

4. Experiment and Results

Set the number of test papers to 10 questions, including 10 multiple choice questions, set the expected difficulty of the test papers to 0.6, and set the expected discrimination of the test papers to 0.5, and use the PGTPG_2F algorithm to compose the test papers. The change trend of objective function value with expected mastery degree is shown in Figure 6.

It can be seen that when the mastery degree is low, the fitness function value is relatively low, and when the mastery degree is 0.5, the fitness value is high, so the PGTPG_2F algorithm tends to choose the test questions that users have poor mastery.

According to the personalized characteristics of student S1, the comparison chart of the results of multiple test papers is shown in Figure 7. Among them, the master degree of student S1 is the average master degree of the generated test paper, and the master degree of student S2 is the master degree of student S2 on the same test paper.

It can be seen from the Figure 7 that when the target difficulty is 0.6, the target discrimination is 0.5 and the target mastery is 0.2; if the personalized information of student 1 is used for generating the test paper, the final mastery of the test paper roughly meets the requirement of 0.2 set for generating the test paper. Taking the sentence “chestnuts are starchy” in the standard corpus as the detection object, this system is used to obtain the phoneme score of the spoken sentence, the standard score of the standard pronunciation, and the average pronunciation level of the phoneme sequence. The results are shown in Figure 8.

According to the analysis of Figure 8, the pronunciation scores of phonemes N, T, AA, and R are higher than the average pronunciation level, or misjudgment is easy to occur between the average pronunciation level and the standard pronunciation level. In this case, the system uses the average pronunciation level and the standard pronunciation level to coordinate and compare and judges whether the examiners’ pronunciation is wrong according to the statistical threshold of phonemes. Only the most mispronounced phonemes and the least mispronounced phonemes were collected in the experiment, and the accuracy and misjudgment rate of phoneme judgment by traditional scoring system and this system were tested (see Table 1).

From the analysis of Table 1, we can see that for nonnative speakers, the mispronunciation rate is high when they pronounce "R" and "ER" retroflex. The corpus used in the traditional scoring system is trained by American English pronunciation, and for Chinese people, there is a high mispronunciation rate when they pronounce words with retroflex.

![Figure 8: Comparison between score and average pronunciation level.](image1)

![Table 1: Performance comparison.](table1)

<table>
<thead>
<tr>
<th>Wrong pronunciation</th>
<th>Traditional scoring system</th>
<th>This paper system</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Correct rate (%)</td>
<td>Misjudgment rate (%)</td>
</tr>
<tr>
<td>T</td>
<td>80.23</td>
<td>30.04</td>
</tr>
<tr>
<td>K</td>
<td>80.14</td>
<td>41.27</td>
</tr>
<tr>
<td>S</td>
<td>74.63</td>
<td>8.03</td>
</tr>
<tr>
<td>IY</td>
<td>66.58</td>
<td>9.91</td>
</tr>
<tr>
<td>CH</td>
<td>40.12</td>
<td>6.63</td>
</tr>
<tr>
<td>ER</td>
<td>36.92</td>
<td>2.08</td>
</tr>
<tr>
<td>R</td>
<td>32.38</td>
<td>1.39</td>
</tr>
<tr>
<td>SH</td>
<td>28.09</td>
<td>0.68</td>
</tr>
</tbody>
</table>

![Figure 9: Comparison of classification results under different parameters.](image2)
improving the accuracy and stability of the system thus completing the judgment of wrong pronunciation and in the threshold based on the average level of phonemes, In this case, the system analyzes whether there is a change with the average level when pronouncing these phonetics. "88.39%. The method used in this paper is similar to the AdaBoost in accuracy. When the parameter is 50, AdaBoost_CT not only solve the interference caused by singular values compared with AdaBoost, the improved Adaboost_CT can be achieved. The results are shown in Figure 9.

Table 2: Comparison of learner’s achievement.

<table>
<thead>
<tr>
<th>Fractional interval</th>
<th>Experimental group</th>
<th>Control group</th>
</tr>
</thead>
<tbody>
<tr>
<td>Below 70</td>
<td>3</td>
<td>7</td>
</tr>
<tr>
<td>70–80</td>
<td>8</td>
<td>14</td>
</tr>
<tr>
<td>80–90</td>
<td>10</td>
<td>18</td>
</tr>
<tr>
<td>90–100</td>
<td>4</td>
<td>11</td>
</tr>
</tbody>
</table>

According to the standard phonetics of phonemes T, K, S, and Y in Table 1, the examiners have a high difference with the average level when pronouncing these phonetics. In this case, the system analyzes whether there is a change in the threshold based on the average level of phonemes, thus completing the judgment of wrong pronunciation and improving the accuracy and stability of the system’s wrong judgment. By using Adaboost_CT algorithm to classify hierarchically, we get two kinds of accuracy, precise accuracy and adjacency accuracy. Accuracy refers to the accuracy that the score of algorithm evaluation is consistent with the score of manual evaluation. Adjacency accuracy refers to the score that is close to or consistent with the score of manual evaluation. The results are shown in Figure 9.

From the performance point of view of the algorithm, compared with AdaBoost, the improved Adaboost_CT can not only solve the interference caused by singular values but also prove that Adaboost_CT algorithm has the highest accuracy, which is 88.39%. The method used in this paper is similar to the “threshold-based iterative method.” The basic learner selects the simplest BD as the base learner. The simple classifier has better effect and low computational complexity and insensitivity to the missing of intermediate values and can be used in discontinuous data sets. The indexes selected for each layer (coarse score, middle score, and subdivision) are selected after several rounds of screening to find out the most suitable threshold and then selected one by one through the linear fitting rate.

In the middle stage, it is divided into two small parts through the first layer of hard indicators. In this stage, instead of using the same set of indicators system, two sets of indicators suitable for high and low quality categories are used. The results show that the improved Adaboost_CT algorithm is still satisfactory. In the subdivision stage, specific scores have been assigned, and the accuracy rate is lower than that of rough scores and middle scores. Generally speaking, there is no fixed correct answer to subjective questions, and it is not a mistake in the strict sense to add or subtract one point.

The intelligent marking proposed by the subject is not only to grade the composition but also to grade the composition on the basis of analyzing the test paper, then give comments in natural language form according to specific conditions, and then give feedback to students’ personal learning suggestions in natural language form with comments as guidance, so as to guide students’ efforts concretely, so as to achieve the real teaching goal of “promoting learning by evaluation.” The improved Adaboost_CT algorithm is used to reevaluate the 300 papers collected and preprocessed to ensure the reliability of the scores, and experts are asked to reevaluate the papers with dissenting scores and get reliable scores. The differences between high and low score segments at different comment levels are shown in Figure 10.

The results show that the quality of students with high grades is better than that of students with low grades in three aspects. High-grade students have a firm grasp of vocabulary, and only 10.3% of them need to improve their vocabulary, which also shows that vocabulary is indeed an important factor that affects their writing performance. The number of students with low segmentation needs to be revised in syntax is the largest, accounting for more than half of the total (54.7%), which requires students with low segmentation to study deeply in syntax.

The number of students who need to improve their writing level in the area of text is about the same, indicating that students in any grade should make corresponding efforts in the area of text to improve their writing level. The experimental group and the control group were established using the CPE test system developed by the project team as the research platform and two university classes with 40 students in each. There was no significant difference in the initial cognitive ability of the two groups of learners, nor in their learning levels. The tutoring platform will test all students in the class after two months of experiments and compare the experimental results. The experimental group and the control group were tested on the same test paper in the following period, with a full score of 100, based on the tracking and recording of the learners in the control group for one semester. The control group had significantly better academic performance than the control group. The academic performance of the two groups is contrasted in Table 2.

Table 2 divides learners’ scores into four score segments: 90–100, 80–90, 70–80, and below 70. It can be seen from the data chart that the number of learners in the control group is significantly higher than that in the experimental group in the two score segments of 90–100 and 80–90 and the number of learners in the experimental group is higher than that in the low score segments of 70–80 and below 70. It can be seen that the final academic achievement of the control group is significantly higher than that of the experimental group.

Figure 10: Differences between high and low score segments at different comment levels.
Through case analysis, the diagnostic function of the tutoring platform for learning problems is further verified, which can improve learners’ learning efficiency and improve their academic performance quickly.

5. Conclusions

The trend of reforming CPE testing has become unavoidable. The development of education is being led by the new talent concept, and improving college students’ overall English ability has become a focus of reform practice. The use of BD in a CPE test system is designed and implemented, as well as a simple and efficient test and evaluation method. In practice, the AdaBoost algorithm has been improved, and the algorithm has shifted from rule-based to statistics-based. It can be used not only for pure theoretical calculations but also to help the algorithm avoid singular values and improve intelligent scoring accuracy. When the parameter is set to 50, the AdaBoost CT algorithm’s accuracy is at its highest, at 88.39 percent. Experiments show that the algorithm can select test questions with a high forgetting rate or a low accuracy rate, generate test papers for students based on their mastery of the test questions, and assist students in consolidating and deepening their memory, all while having a short running time and a high applicability and efficiency.

Data Availability

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

Conflicts of Interest

The author does not have any possible conflicts of interest.

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