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Article

An Algorithmic Study on Improving the Quality of English Writing Teaching to College Students in an Intelligent Environment

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Abstract: In response to the need to improve the quality of English writing instruction in higher education institutions in an intelligent environment, this paper proposes a writing diagnostic system based on Jieba word segmentation and the EVCM model. A teaching model framework oriented toward interactive instruction is constructed, and the Jieba word segmentation algorithm is optimized for text preprocessing. The EVCM model is designed to achieve lexical coherence diagnosis from three aspects: entity distribution, coreference resolution, and conjunction detection. The stability and diagnostic accuracy of the system under different network environments are verified through simulation experiments. Teaching practice activities were conducted, and T-tests and Pearson correlation analysis were used to explore the impact pathways of the system on improving the quality of English writing instruction. Teaching experiments showed that the pre-test mean score for the high-performance group was 8.95, which increased to 9.96 in the post-test. The mean score differences between the pre-test and post-test for the medium- and low-performance groups were both greater than 1.5 ($p < 0.001$). Students grouped by English writing performance exhibited significant differences in the overall use of the English writing diagnostic system and in four dimensions: self-motivation, monitoring and diagnosis, execution, and result generation. The use of the system not only directly affects students' writing proficiency but also indirectly promotes ability development by enhancing their writing motivation and beliefs.

Keywords: English writing diagnosis; Jieba word segmentation; EVCM model; Pearson correlation analysis; influence pathways

1. Introduction

English writing is a core skill through which learners integrate language knowledge and engage in cognitive reconstruction to produce meaningful output, and it is also a key component of the English language curriculum system [1]. As an important dimension of language proficiency, writing ability not only directly reflects learners' knowledge base and logical reasoning skills but also serves as the foundation for academic communication and cross-cultural expression [2-4]. Therefore, writing instruction has always been a central focus in the field of English education. However, current English basic writing instruction still faces significant challenges, primarily in terms of content and methodology. First, the instructional model remains entrenched in a “teacher-centered, one-way transmission” framework, manifested in a linear process of “lecture-practice-correction” [5-6]. Under this model, students passively receive knowledge input, lacking active exploration and critical reflection, leading to writing training becoming mechanical imitation and suppressing autonomy and creative thinking [7]. Second, textbook content lags behind contemporary demands, with material selection heavily reliant on traditional model essays, failing to incorporate diverse cultural contexts and real academic scenarios, thereby reducing learners' practical adaptability [8-10].

Currently, with rapid technological advancements, AI language models provide an intelligent environment that helps students improve their writing skills through features such as grammar correction and language expression suggestions. They can also provide personalized learning resources based on students' needs, enhancing their learning initiative [11-14]. Therefore, AI technology holds vast application potential in English writing instruction. Before the emergence of large language models like ChatGPT, research on English writing mainly focused on issues in writing and various methods for reforming English writing instruction [15]. For example, Liu, P used an optimized teaching and learning optimization algorithm (M-TLBO) to improve university English reading and writing instruction, and demonstrated the algorithm's effectiveness in enhancing students' writing abilities through practical testing [16]. Liu, M developed an automatic scoring algorithm using random sampling and Bayesian classification to construct a writing self-assessment assistance system aimed at reforming writing quality assessment methods in English writing instruction [17]. Wang, M proposed a step-by-step English writing teaching system based on cloud network technology to address issues of low user satisfaction and poor interaction accuracy, and demonstrated the improved effectiveness of English writing instruction through experimental results [18]. Li, M, and Ye, W investigated the application of a task processing system based on wireless sensor networks in an intelligent English writing assistance platform, focusing on corpus-based English writing and optimizing English writing instruction through features such as language error analysis and English broadcasting [19].

With the emergence of large language models such as ChatGPT and DeepSeek, more artificial intelligence technologies like large language models, intelligence, and the metaverse have begun to be applied in the new era, such as utilizing the latest developments in AIGC and the metaverse to develop new online university English writing teaching models [20-23]. Bonner, E., et al. pointed out that large language models have application potential in material development, classroom activities, and feedback in the field of language teaching, as they simplify teaching processes, allowing teachers to focus more on learners' needs [24]. Liu, Z. M., et al. integrated large language models into English teaching, and empirical research found that under this model, students achieved significant improvements in English writing performance, self-regulated learning strategies, and learning motivation [25]. Li, J., et al. explored the use of ChatGPT to enhance the English academic writing abilities of non-native English-speaking medical students, and the study found that students' writing quality improved significantly [26]. Tseng, Y. C., and Lin, Y. H. integrated ChatGPT-3.5 into university English as a foreign language courses and used the ADDIE and TPACK frameworks to address key issues in current teaching and improve students' English writing skills [27].

This paper first combines the connotation of interactive teaching models to clarify their specific application paths in English writing classrooms. Targeting the core characteristics of writing texts, natural language processing technology is introduced. A text preprocessing algorithm based on Jieba word segmentation and a writing vocabulary connection diagnosis model based on entity grids are designed to analyze students' writing texts. Through simulation experiments, the stability of the system under different network environments is verified. Compared with traditional systems, the superior performance of the system in diagnosis is examined. A teaching experiment is designed to explore the actual application effects of the system from three dimensions: improvement in learning outcomes, user satisfaction, and influence pathways.

2. Design of an English Writing Diagnostic System for Interactive Teaching Models

As the process of educational informatization and intelligence accelerates, English writing instruction in higher education is undergoing a transformation from traditional one-way transmission to multi-dimensional interaction. Interactive teaching models, as student-centered pedagogical approaches, emphasize multi-directional communication among teachers and students, among students, and between students and texts to facilitate knowledge construction and the development of higher-order thinking skills. However, the effective implementation of such teaching models relies on precise diagnosis and dynamic feedback regarding students' writing processes. However, in traditional English writing instruction, teachers' diagnosis of core elements such as vocabulary coherence and logical consistency often relies on manual experience, resulting in issues such as low efficiency, strong subjectivity, and limited coverage dimensions, which fail to meet the demands of personalized instruction in an intelligent environment. Against this backdrop, this paper proposes an English writing diagnostic system tailored for interactive teaching models.

2.1. The Essence of Interactive Teaching Models

In the mid-to-late 20th century, the social term “interaction” was introduced into the field of education, and scholars began to conduct educational research on it. Based on this research, the theory and model of interactive teaching gradually took shape. The basic framework structure of the interactive teaching model is shown in Figure 1. Classroom instruction centers on the student as the primary participant, with teachers consciously planning, organizing, and guiding instructional activities around the curriculum content. Students, under the guidance of teachers, enter a state of learning, which may be a conscious process or an unconscious one. Students acquire knowledge through thinking, speaking, and hands-on activities. The essence of this teaching model lies in “activity.” Interactive classroom teaching involves teachers and students, as the main subjects of teaching, engaging in dialogue and interaction during the teaching process. Teachers and students collaborate to create an equal and comfortable teaching environment and atmosphere that meets the needs of both parties. In this teaching environment, students are the main subjects of teaching activities. Teachers base their teaching on students' learning and actively create and modify teaching activities in accordance with students' learning. Students also have the opportunity to adjust classroom communication and interaction activities based on their own development. Throughout the teaching process, the knowledge, emotions, and thoughts of both teachers and students are integrated and developed. The interactive teaching model is a teaching approach that, under the guidance of teachers and using appropriate teaching materials, enhances students' enthusiasm for learning, expands their thinking, and cultivates their ability to identify and solve problems. The interactive teaching model is a student-centered teaching model that advocates that students are the main participants in teaching. All activities in teaching must be student-centered, allowing students to fully develop themselves and enhance their higher-order thinking abilities in the classroom. However, it also emphasizes that the role of students as the main participants is realized under the guidance of teachers. Classroom teaching is a process of interaction between teachers and students. This interaction is not superficial or shallow but occurs in a free and relaxed teaching environment, where knowledge is transmitted, emotions are exchanged, and ideas are exchanged, achieving the fusion of teachers' and students' lives, the generation of wisdom, and the awakening of the spirit. The interactive teaching model is a dynamic, evolving, and developing teaching approach that permeates the entire teaching process. This is because the teaching elements—teachers, students, teaching content, and teaching methods—are constantly changing and developing, and the teaching environment is also continuously being updated and created. The various teaching elements, which are in constant motion and change, interact and influence one another, requiring teachers to engage in interactive activities throughout the teaching process and continuously facilitate communication between participants.

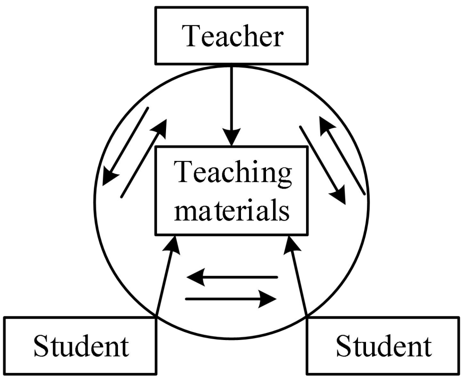


Figure 1. Interactive Teaching Model Diagram.

Based on the research focus of this study, the interactive teaching model is applied to college English writing classrooms. The interactive teaching model applied to college English writing classrooms is defined as follows: in writing classroom instruction, teachers center their teaching around interaction, creating a variety of interactive communication activities for students to engage in. These activities involve interactions between characters and situations, teachers and students, students and students, and students and texts, thereby fostering a collaborative and mutually supportive teaching environment. This environment facilitates exchanges and interactions between teachers and students, as well as among students themselves, on the levels of knowledge, emotion, and thinking.

2.2. Jieba Word Segmentation Algorithm and Process

(1) Perform a high-level word graph scan using a Trie tree structure. In mathematical sentences, for all Chinese characters that form words, a directed acyclic graph (DAG) is formed.

The Trie tree structure is similar to a tree structure. It counts, sorts, and stores strings based on their common prefixes.

Its properties are summarized as follows:

1) The root node does not contain any characters (or Chinese characters), but any node other than the root node can only contain one character (Chinese character).

2) Starting from the root node, the string formed by arranging the characters in all nodes along any path in a specific order is the corresponding string for that node.

3) For any node, the characters in all its child nodes are not identical.

The above three properties ensure that searching for any string (phrase) in the Trie tree minimizes the number of comparisons required, thereby achieving efficient retrieval of the corpus. A subtree of a Tire tree generated from the phrase set<ben, originally there was, originally, originally year, should not have been, originally not>. When starting from the root node 'ben' of the subtree, any path can form a Chinese vocabulary starting from 'ben'. But in practical situations, any node should be labeled with corresponding data attributes, such as word frequency, so that these attributes can be used to distinguish whether a string on a certain path is a true vocabulary. If the frequency of the word "life" in a node is -1, then "native life" does not constitute a phrase.

View the code package for Jieba word segmentation, which includes a file named dict.txt containing a large dictionary with over 20,000 entries, along with the number of times each entry appears in the text and its part of speech. In the Trie tree word graph scanning step, these entries are placed into the Trie tree. The Trie tree is a commonly used prefix tree. For the first characters of a sentence, the prefixes are usually the same, so this paper uses the Trie tree for storage, which has the advantage of fast lookup.

For DAG, i.e., directed acyclic graph, first determine a Chinese sentence to be segmented, and then generate a directed acyclic graph for this sentence. The segmentation methods are as follows:

1) Construct a Trie tree based on dict.txt;

2) Generate a DAG for the sentence to be segmented. In simple terms, this involves querying the dictionary based on the existing vocabulary for the Chinese sentence, thereby forming several forms of sentence segmentation.

(2) Dynamic programming algorithm for identifying the maximum probability path

In natural language processing, the maximum probability method is an effective algorithm. The dynamic programming algorithm works in conjunction with the maximum probability method. The main process is as follows: for any Chinese sentence, first list all the word groups that exist in the dictionary according to the order of word group combinations in the sentence; treat any word in these word groups as a vertex, with the start vertex and end vertex, and draw a directed graph based on the original structure of the sentence; then assign reasonable weights to the directed paths between adjacent vertices in the directed graph, such as the path C->D, where the weight between C and D is the cost of D (if D is the end vertex, the weight is 0); the current task is to find the shortest path and use the dynamic programming algorithm to derive the final solution.

The phrase "stammering participle" is mainly used in the dictionary as follows: knot: a, stammering: b, ba: c, ba: d, p: e, participle: f, word: g. The above phrases are formed into a directed graph with weights, and the optimal solution of these paths from "Start" to "End" is the word segmentation result of the sentence "stuttering participle".

The purpose of the maximum probability method is to find the product of the maximum probability of some phrases in the dictionary. To illustrate this problem with the cost of the shortest path:

$$\text{Expenditure} = \log(\text{total word frequency}/\text{word frequency of a phrase}) \qquad (1)$$

Observing the above equation, we find that to find the “maximum” value, we can convert it to finding the “minimum” value, and the ‘product’ can be converted to “sum,” thereby solving the problem.

After applying the Trie tree algorithm to the dictionary as described above, the number of occurrences of each word in Chinese sentences is converted into frequency. The frequency value is always between 0 and 1, i.e., the number of occurrences divided by the total number of experiments. If a large number of experiments are conducted, the frequency result is approximately equal to the probability result, meaning that taking the limit of the frequency result equals the probability.

For dynamic programming research, first identify all fully segmented word groups in short sentences, then calculate the frequency of each word group by dividing the number of occurrences by the total number. If a word group does not exist, use the frequency of the word group with the smallest frequency in the dictionary as the frequency of that word. The calculation formula is as follows:

$$P(\text{A word}) = FREQ.get('\text{A word}', \min\_freq) \qquad (2)$$

Based on the dynamic programming algorithm, check the maximum probability path and calculate the maximum probability value of the Chinese sentence from back to front. The formula is (N represents the Nth node):

$$P(N) = 1 - 0 \tag{3}$$

$$P(N-1) = P(N) * Max(P(\text{The last word})) \tag{4}$$

Then, by analogy, we finally obtain the maximum probability path segmentation combination.

For the handling of unregistered words, Jieba word segmentation utilizes the HMM model concept and conducts research and calculations using the Viterbi algorithm.

The Viterbi algorithm process is as follows:

1) Initialization:

$$\delta_t(i) = \pi_i * b_i(O_1), 1 \le i \le N \tag{5}$$

$$\psi_t(i) = 0 \tag{6}$$

2) Inductive calculation:

$$\delta_t(i) = \delta_{t-1}(j) * a_{ji} * b_i(O_t), 2 \le t \le T; 1 \le i \le N; 1 \le j \le N \tag{7}$$

$$\psi_t(i) = \arg[\delta_{t-l}(j) * a_{ji} * b_i(O_t)] \tag{8}$$

3) Conclusion:

$$Q_T^{'} = arg[\delta_T(i)] \tag{9}$$

$$P^{'}(Q_T^{'}) = \max[\delta_T(i)] \tag{10}$$

4) Path backtracking:

$$q_t^{'} = \psi_{t+1} q_{t+1}^{'}, t = T-1, T-2-..1 \tag{11}$$

The explanation for unregistered words is “word groups not recorded in the dictionary dict.txt.” This paper conducted an experiment in which all words in dict.txt were deleted to test whether Jieba could still perform word segmentation. The experiment found that Jieba could still perform word segmentation, but most of the segmented word groups were two characters long.

HMM can be used to predict sentences for segmentation. Typically, Chinese prediction methods follow the BEMS four-state marking process. For example, Changchun can be marked as BE, i.e., Chang/B Chun/E, indicating that Chang is the starting position and Chun is the ending position. Jilin University can be marked as BMME, i.e., beginning, middle, middle, ending.

The Jieba word segmentation algorithm process is shown in Figure 2. The main process of Jieba word segmentation is to first load the dictionary and construct a Trie tree structure. Then, a sentence to be processed is listed, and natural language processing methods such as regular expressions are used to obtain continuous Chinese characters and English characters, which are then split into a list of phrases. For these phrases, use DAG and dynamic programming to derive the maximum probability path. For characters that exist in the DAG but not in the dictionary, merge them into a new phrase. Then use the HMM model for word segmentation to identify new words outside the dictionary. These words are collectively referred to as unregistered words in the following text. Finally, use the yield syntax in Python to construct a word generator and return each word sequentially.

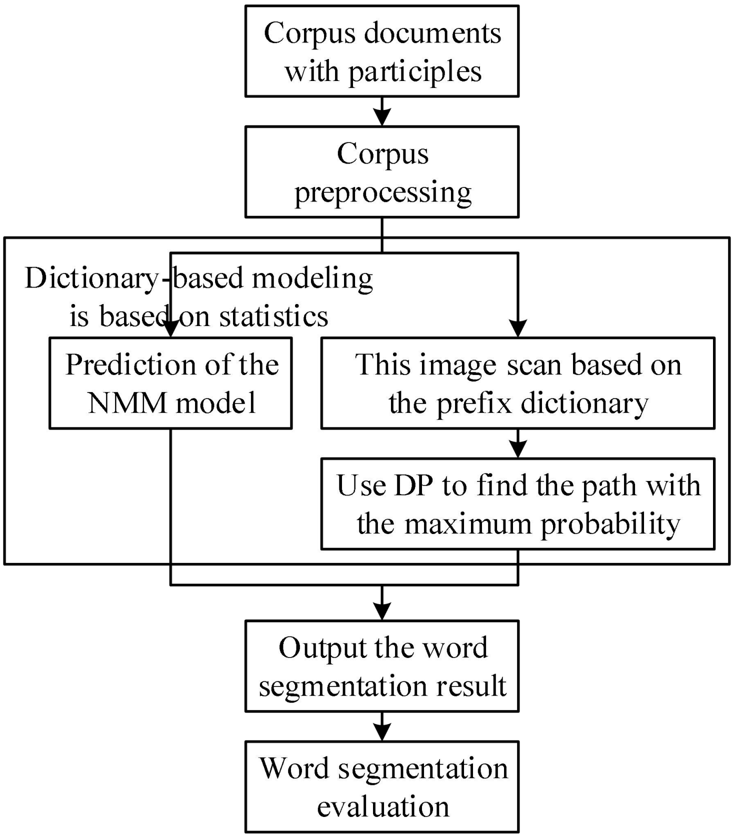


Figure 2. Flow of the Jieba word segmentation algorithm.

The development of Jieba word segmentation has been of great help to pure Python developers, but it is not yet fully mature. There are still some shortcomings and limitations in the word segmentation algorithm, which can be summarized as follows:

1) Poor handling of unusual words and unregistered words.

2) For proper nouns such as personal names and place names, Jieba's word segmentation results are not accurate.

3) During word segmentation, it is not possible to obtain the frequency of words appearing in a sentence, meaning that high-frequency words and their frequencies cannot be extracted, thereby preventing the extraction of keywords from the entire text.

4) The dictionary primarily serves to assist the HMM model. If the dictionary is missing, word segmentation can still be performed using the Viterbi algorithm of the HMM model alone.

5) HMM can undoubtedly recognize new words, but the final results are not satisfactory. For example, it can only recognize two-character words, while three-character new words result in errors. Therefore, in subsequent research, improvements can be made to algorithms such as BEMS sequence labeling, or the method for obtaining new words can be improved.

2.3. Writing vocabulary connection diagnosis model based on entity grid

Lexical coherence generally refers to the use of word repetition, synonyms, hypernyms/hyponyms, and cohesive words to achieve textual coherence. Based on the above concepts, the EVCM proposed in this paper is divided into three parts: entity grid, coreference resolution, and cohesive word detection. The entity grid component focuses on the distribution of entities, evaluating the coherence of entity distribution in the target English text by calculating the transition probabilities of entities in the text. detecting the repetition of vocabulary; the coreference resolution component merges different descriptions of the same entity, detecting synonyms and antonyms of vocabulary; the transition word detection component identifies transition words in English texts that enhance contextual coherence, evaluating the quality of transition word coherence in English texts.

1) Entity Grid and Coreference Resolution Components

The integration of entity grids and co-reference resolution can be defined as an entity chain grid model. The entity chain grid model proposed in this paper is based on a key assumption: the transfer patterns of the syntactic roles corresponding to entities in coherent English texts are always similar.

Before calculating the entity linking quality of English texts, we first briefly introduce an important concept of the entity chain grid: the syntactic role transfer sequence. A syntactic role transition sequence refers to the transformation of an entity's syntactic role across N consecutive sentences, where the range of N is as shown in Formula (12), and $Num_{sentences}$ denotes the total number of sentences in the English text.

$$1 < N \le Num_{sentences} \tag{12}$$

The entity chain grid model defines the entity linkage quality of English text as the joint probability distribution of sentences and entities, where E denotes the English text to be diagnosed, $S_1 \cdots S_n$ denotes the sentences in the English text, and $e_1 \cdots e_m$ denotes entity words or entity phrases. The joint probability distribution formula for the entity linkage quality of English text is shown in (13).

$$P_{coherence}(E) = P(e_1 \cdots e_m, S_1 \cdots S_n) \tag{13}$$

Assuming that each entity word or entity phrase is relatively independent of other entity words and entity phrases, we can obtain formula (14).

$$P_{coherence}(E) = \prod_{j=1}^{m} P(e_j; S_1 \cdots S_n) \tag{14}$$

Among them, $P(e_j; S_1 \cdots S_n)$ represents the probability distribution of the transition sequence of the entity word or entity phrase e_j in n sentences, that is, the probability distribution of the syntactic role transition sequence of e_j in n sentences. For ease of observation, we use $P_{transition}(e_j)$ to denote the probability distribution of the syntactic role transition sequence of e_j across n sentences, and $r_{i,j}$ denotes the syntactic role information of e_j in sentence i. The calculation formula is shown in (15).

$$P(e_j; S_1 \cdots S_n) = P_{mansition}(e_j) = P(r_{1,j} \cdots r_{n,j}) \tag{15}$$

Based on the independence assumption of the standard Markov model, we can derive further formulas for the probability distribution of the sequence of syntactic role transitions of entity words or entity phrases e_j in n sentences, where h denotes the length of the historical dependency pattern. The formula is shown in (16).

$$P_{transition}(e_j) = P(r_{1,j} \cdots r_{n,j}) = \prod_{j=1}^{m} P(r_{i,j} \mid r_{(i-h),j} \cdots r_{(i-1),j}) \tag{16}$$

Finally, by combining the above formulas and normalizing them according to the number of entities m and the number of sentences n in the English text, we can obtain the entity connection quality of the English text. The calculation formula is shown in (17), where $Score_e$ represents the entity distribution score of the English text.

$$Score_e = P_{coherence}(E) \approx \frac{1}{m \times n} \sum_{j=1}^{m} \sum_{i=1}^{n} \log P(r_{i,j} \mid r_{(i-h),j} \cdots r_{(i-1),j}) \tag{17}$$

After being trained on a large corpus of coherent English text, the entity chain grid model can be used to evaluate the entity distribution scores of English text. Specifically, in the entity chain grid model proposed in this paper, the entity connection features of English text are reflected in the distribution differences of the syntactic role transition patterns corresponding to entities, i.e., the distribution differences of syntactic role transition sequences. Coherent English text and incoherent English text often exhibit different distribution trends in syntactic role transition sequences. Therefore, this paper diagnoses the entity linkage quality of English texts by capturing the distribution differences of syntactic role transition sequences. Specifically, this paper selects English texts with high coherence as the training set for the entity chain grid model, then generates syntactic role transition sequence distribution features with high coherence quality. Subsequently, the syntactic role transition sequences corresponding to entities in the English text to be diagnosed are statistically analyzed and matched with the trained syntactic role transition sequence distribution features. Finally, the entity connection quality score of the English text is calculated. It should be noted that in this chapter, EVCM uses grammatical role transition sequences of length 2 to analyze the entity connection quality of English texts.

2) Connection word detection section

In the conjunction detection section, this paper adopts the "English Common Conjunction Dictionary with Examples," which categorizes common conjunctions into the following 22 types: evaluation; comparison; opposition; expansion; enumeration; assumption; apposition; negation; clarification; concession; confirmation; trust; result; continuation; topic change; euphemism; transition; warning; summary; suggestion; citation; and contraction. By comparing the English text to be diagnosed with the dictionary, all conjunctions in the text can be detected, and the conjunction score of the English text can be calculated using formula (18).

$$Score_c = MaxMin(\frac{Num_{co-words}}{Num_{sentences}}) \tag{18}$$

Among these, $Num_{co-wonds}$ denotes the number of conjunctive words in the English text, $Num_{sentemes}$ denotes the total number of sentences in the English text, $MaxMin(n)$ denotes the maximum-minimum normalization operation on n, converting n to a value between 0 and 1, and $Score_c$ denotes the conjunctive word score of the English text.

Finally, the entity distribution score $Score_e$ and the conjunction word score $Score_e$ are weighted and fused to obtain the vocabulary conjunction score $Score_w$. S denotes the full score for the English text, α denotes the weight coefficient, and $\alpha \in [0,1]$. When α approaches 1, it indicates that the entity distribution score has a larger proportion. The calculation formula is shown in (19).

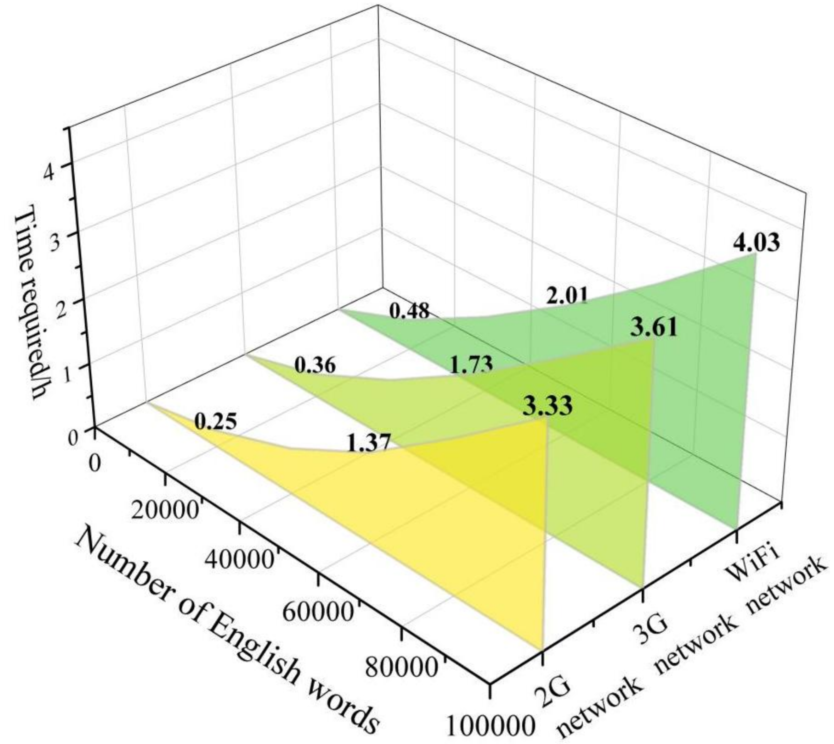
$$Score_w = S \times [\alpha \times Score_e + (1-\alpha) \times Score_c] \tag{19}$$

In summary, this paper introduces the Entity-based Vocabulary Coherence Model (EVCM) for writing. The model first preprocesses English text, then identifies entity words in the text based on the preprocessing results. It then constructs entity chains through coreference resolution, calculates the transition probabilities of entities, and derives entity distribution scores. These scores are subsequently weighted and fused with cohesion word scores to obtain the final lexical cohesion score, which is used to evaluate the lexical cohesion of the English text.

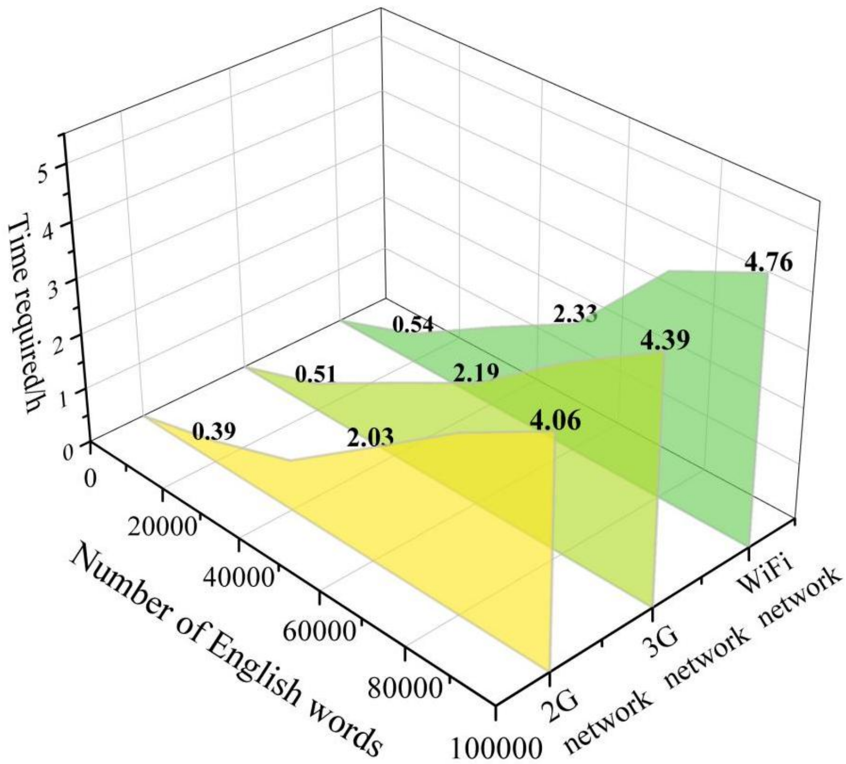
3. Research on the Effectiveness of English Writing Diagnosis Systems

3.1. Simulation Experiment Analysis

To validate the stability of the English writing diagnostic system designed in this paper during diagnosis, tests were conducted using the system to perform vocabulary word diagnosis and comprehensive diagnosis of English writing under different network environments. The comparison of the time required for different forms of English writing vocabulary diagnosis is shown in Figure 3 (a–b). Under different network environments, the curve comparison of the results of the system's rapid diagnosis and comprehensive diagnosis of English writing words showed little variation, generally exhibiting linear growth. When the number of English vocabulary words is 100,000, the average time required for rapid diagnosis and comprehensive diagnosis is 3.66 hours and 4.40 hours, respectively, indicating that the system can perform English writing vocabulary diagnosis at a consistent rate across different environments. The experiments demonstrate that the system possesses excellent stability.



(a) Rapid diagnosis



(b) Comprehensive diagnosis

Figure 3. Comparison of diagnosis time consumption.

Ability represents the diagnostic comparison results of English writing errors for the tested subjects, while Score represents the test results of English writing errors for the tested subjects. The scatter plot distribution of English writing error diagnosis results and vocabulary ability is shown in Figure 4. The test subjects' English writing error test results and English writing vocabulary ability exhibit a roughly linear positive correlation relationship from an intuitive perspective. That is, the vocabulary ability of the test subjects diagnosed by the diagnostic system designed in this paper and the English writing error diagnosis results exhibit a certain degree of consistency and correlation.

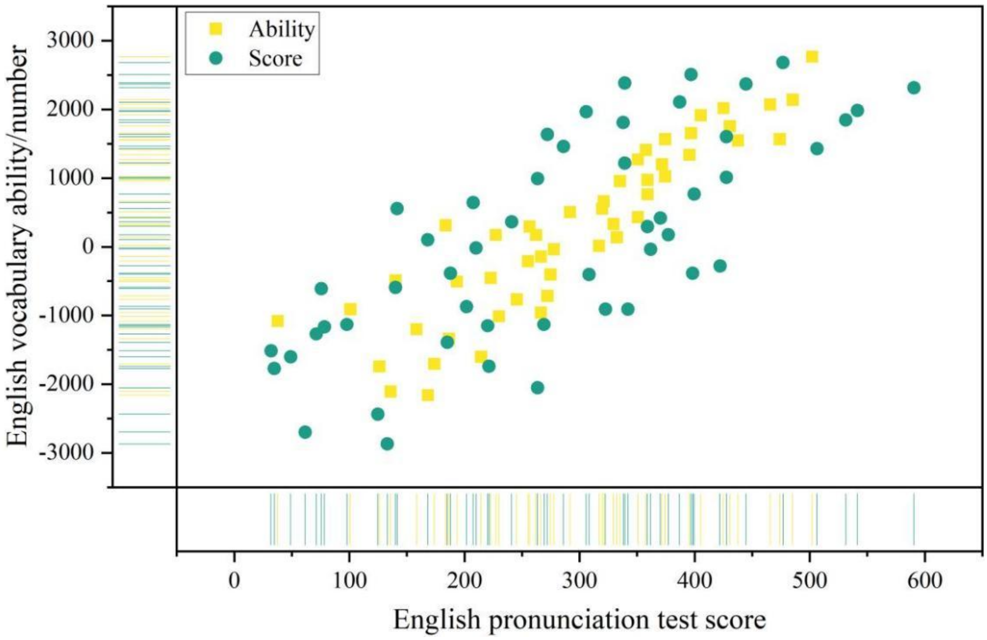


Figure 4. Scatter distribution of error diagnosis results and vocabulary ability.

Further quantitative validation of the correlation. This paper statistically analyzed 10 sets of data, and the comparison of the success rates of error diagnosis results tracking between the proposed system and the traditional system is shown in Table 1. From the statistical data in Table 1, it can be analyzed that the proposed system design has a significant advantage in terms of the success rate of error diagnosis results tracking, with an average improvement of 10.89% compared to the traditional system.

Table 1. Comparison of tracking success rates of error diagnosis results.

Experimental data	Tracking success rate of English writing error diagnosis results	
	Traditional system	The proposed
1	0.867	0.973
2	0.902	0.955
3	0.895	0.968
4	0.843	0.971
5	0.866	0.982
6	0.871	0.979
7	0.883	0.964
8	0.829	0.988
9	0.845	0.975
10	0.834	0.969

3.2. Application Effect Analysis

To comprehensively assess the practical application value of the English writing diagnostic system, this study analyzes three dimensions: improvement in learning outcomes, user satisfaction, and influence pathways. The data is derived from a teaching experiment involving 50 undergraduate students majoring in English from the Class of 202X at a certain university. The experimental subjects were divided into three groups based on their English writing standardized test scores at the time of enrollment (pre-test): high (n=10), medium (n=26), and low (n=14). The post-test scores were derived from the final exam, with a maximum score of 15 points for all groups. Satisfaction surveys used a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). Writing motivation beliefs were measured using a self-designed scale, which underwent pre-experimental reliability and validity testing with a Cronbach's α of 0.895.

3.2.1. Effect

The results of the paired sample t-test for pre-test and post-test writing scores of students with different English proficiency levels are shown in Table 2. The mean pre-test score for the high-scoring group was 8.95, and the mean post-test score increased to 9.96, although it did not reach a significant level but showed a positive trend. The mean pre-test score for the medium-scoring group was 7.18, and the mean post-test score was 8.83 ($p<0.001$). The low-scoring group had a pre-test mean of 4.96 and a post-test mean of 7.95 ($p < 0.001$). This indicates that the system significantly promotes improvements in writing performance for students with medium to low proficiency levels, which is likely due to their weaker foundational skills and greater need for diagnostic feedback. In contrast, high-proficiency students, who already possess stronger abilities, have relatively limited room for improvement, resulting in effects that did not reach statistical significance.

Table 2. Paired sample *t*-test of students with different English proficiency

		Mean value	N	Mean difference	t	df	Sig.(Bilateral)
High grouping	Pre-test	8.95	10	-1.01	-2.054	9	.077
	Post-test	9.96	10				
Medium grouping	Pre-test	7.18	26	-1.65	-13.586	17	.000
	Post-test	8.83	26				
Low grouping	Pre-test	4.96	14	-2.99	-14.037	9	.000
	Post-test	7.95	14				

3.2.2. Satisfaction

The results of the paired-sample t-test for the pre- and post-test questionnaires on students' attitudes toward the English writing diagnostic system as an auxiliary learning tool are shown in Table 3. Significant positive changes were observed across all dimensions, with the most notable improvement in the practicality dimension. The pre-test mean was 3.18, and the post-test mean increased to 3.95, indicating that students highly recognized the accuracy of the system's diagnostic functions and the practicality of its suggestions. The significance of the experience dimension ($p=0.042$) suggests that while the system's operational convenience is generally good, there is still room for improvement.

Table 3. Results of the paired sample t-test for the attitudes.

		Mean value	N	Mean difference	t	df	Sig.(Bilateral)
Practicality	Pre-test	3.18	50	-0.77	-8.038	45	.000
	Post-test	3.95					
Experience	Pre-test	3.24	50	-0.54	-2.117	45	.042
	Post-test	3.78					
Effect	Pre-test	3.55	50	-0.51	-2.568	45	.018
	Post-test	4.06					

3.2.3. Impact Pathways

The results of the independent samples t-test for differences in the use of the English writing diagnostic system among high, medium, and low-scoring groups in English writing proficiency are shown in Table 4. Significant differences were found across all dimensions between the groups ($p < 0.001$). Under the English writing performance grouping, the Sig. values for the Levene's test of equality of variances were 0.837 for overall usage of the English writing diagnostic system, 0.702 for self-driven, 0.403 for monitoring and diagnosis, 0.628 for execution, and 0.735 for result generation, all of which were greater than 0.05. This indicates that the groups with different English writing scores had homogeneity of variances in terms of overall usage and the four dimensions, thus confirming the assumption of homogeneity of variances. As a result, the Sig. (two-tailed) values for the overall situation of the English writing diagnostic system, self-driven, monitoring and diagnosis, execution, and result generation are all 0.000, and the 95% confidence intervals for the differences do not include 0. This indicates that students in the English writing performance groups exhibit significant differences in both the overall situation of the English writing diagnostic system and the sub-dimensions.

Table 4. Independent sample t-test for differences in system usage.

		Levin variance equivalence test		t	df	Average value equivalence T-test				
		F	Sig.			Sig. (Bilateral)	MD	SD	The difference is 95% confidence interval	
									Lower limit	Upper limit
Overall	Assume equal variance	30.694	0.837	7.184	178	.000	0.601	0.189	0.401	0.642
	Not assumed			7.339	172.584	.000	0.601	0.189	0.382	0.663
Self driven	Assume equal variance	12.575	0.702	7.297	178	.000	0.711	0.194	0.422	0.978
	Not assumed			7.368	174.747	.000	0.711	0.196	0.413	0.980
Monitoring and diagnosis	Assume equal variance	14.084	0.403	9.038	178	.000	0.596	0.166	0.412	0.694
	Not			9.021	173.57	.000	0.59	0.16	0.387	0.728

	assumed				4		6	6		
Execute	Assume equal variance	20.049	0.628	7.743	178	.000	0.728	0.144	0.656	0.845
	Not assumed			7.725	170.049	.000	0.728	0.144	0.602	0.891
Result generation	Assume equal variance	35.118	0.735	7.896	178	.000	0.669	0.175	0.441	0.733
	Not assumed			7.927	174.675	.000	0.669	0.172	0.434	0.801

To investigate the correlation among the application of an English writing diagnostic system, writing motivation beliefs, and writing proficiency, Pearson correlation analysis was employed. The results of the correlation analysis are presented in Table 5. The application of the system was significantly positively correlated with both writing motivation beliefs ($r = 0.803$, $p < 0.01$) and writing proficiency ($r = 0.718$, $p < 0.01$); writing motivation beliefs were also significantly correlated with writing proficiency ($r = 0.511$, $p < 0.01$). This indicates that the use of the system not only directly influences students' writing proficiency but also indirectly promotes skill development by enhancing their writing motivation beliefs.

Table 5. Pearson Correlation Analysis Results.

		System application	Writing motivation belief	Writing proficiency
System application	Pearson correlation	1	.803**	.718**
	Sig.(Bilateral)		.000	.000
	N	50	50	50
Writing motivation belief	Pearson correlation	.803**	1	.511**
	Sig.(Bilateral)	.000	.000	.000
	N	50	50	50
Writing proficiency	Pearson correlation	.718**	.511**	1
	Sig.(Bilateral)	.000	.000	.000
	N	50	50	50

4. Conclusion

This study focuses on improving the quality of English writing instruction in higher education institutions under intelligent environments. By integrating natural language processing technology, an English writing diagnostic system tailored for interactive teaching models has been designed.

Simulation experiments indicate that, across different network environments, the curves comparing the results of rapid and comprehensive English writing word diagnostics conducted by this system exhibit minimal variation, generally showing linear growth. When the English vocabulary size is 100,000 words, the average time required for rapid diagnosis and comprehensive diagnosis is 3.66 hours and 4.40 hours, respectively. The test results of English writing errors and English vocabulary proficiency show a roughly linear positive correlation. The proposed system demonstrates a significant advantage in the success rate of tracking English writing error diagnosis results, with an average improvement of 10.89% compared to traditional systems.

When using the proposed English writing diagnostic system to assist teaching, the pre-test mean score for the high-scoring group was 8.95, and the post-test mean score increased to 9.96, although it did not reach a significant level but showed a positive trend. The pre-test mean score for the medium-scoring group was 7.18, and the post-test mean score was 8.83 ($p < 0.001$). The low-scoring group had a pre-test mean of 4.96 and a post-test mean of 7.95 ($p < 0.001$). Students' attitudes showed significant positive changes across all dimensions, with the most notable improvement in the practicality dimension, which increased from a pre-test mean of 3.18 to a post-test mean of 3.95. Students in the English writing performance groups demonstrated significant differences in the overall use of the English writing diagnostic system and in the four dimensions of self-motivation, monitoring and diagnosis, execution, result generation. Pearson correlation analysis showed that system usage not only directly influenced students' writing proficiency but also indirectly promoted ability development by enhancing their writing motivation beliefs.

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