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A Study on the Teaching Application of AI Corpus-Assisted Expression Training in Business English Courses in Colleges and Universities

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SUMMARY: *In this paper, we first construct a corpus system that can automatically crawl, clean and categorize business texts from the Internet. Then, by introducing the HowNet lexical annotation algorithm and probabilistic sentence alignment model, the corpus is deeply semantically related and structurally aligned to Chinese and English, making it a structured bilingual teaching resource. Based on this, training strategies are designed for oral and written expressions, such as contextualized quiz, role-playing, imitation writing training, and mind mapping-assisted writing, etc., so as to transform the static corpus into an interactive teaching path. A semester-long comparative teaching of 124 students found that the experimental class with AI corpus-assisted instruction had significantly higher overall business English proficiency than the traditionally taught control class, with posttest mean scores of 88.52 and 81.10, and the mean speaking score of students in the experimental class increased from 12.17 to 17.43, far exceeding that of the control class, which was 14.62. The mean score for written expression jumped from 12.27 to 17.29, again significantly higher than the 14.71 of the control class. Statistical analysis of all p-values of 0.000 confirms the significance of the differences. The questionnaire survey shows that more than 80% of the students affirmed that the model is helpful in improving their speaking and writing skills, and more than 90% of the students think that this way of learning is more interesting and easy to learn.*

KEYWORDS: *AI corpus; oral expression; written expression; business English; word sense annotation*

1 Introduction

As China's trade volume continues to grow, the demand for bilingual trade talents continues to increase, in order to meet the needs of the times, major universities have opened Business English majors, with the intention of cultivating composite talents with both business skills, foreign language skills, translation skills, to meet the needs of China's international development, and to promote the further development of the country's business and trade [1, 2]. Business English expression, as a key content of business English course teaching, is directly related to the efficiency of business cooperation and professional image of students in their future work, so expression training is an important foundation for improving students' business English level [3, 4]. However, expression training is not a simple accumulation of vocabulary, but a comprehensive control of information, logic and scenarios, which is contrary to the current business English teaching in colleges and universities around the world. Most of the business English teaching in colleges and universities adopts the traditional lecture method, that is, the teaching method of "vocabulary + grammar + translation", through analyzing the

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grammatical phenomenon of sentences or comparing the meanings of words in the teaching method of sentence-by-sentence translation to complete the teaching of business English [5-7]; the one-way transmission of knowledge by the teacher as the main body of the teaching method ignores the initiative, positivity and independence of students' learning, and the students, once they have learned, will be able to learn the language in their own way. The teacher-oriented unidirectional transmission of knowledge ignores students' learning initiative, positivity and independence, and students rely on the textbook and the teacher, lack independent thinking ability, and cannot effectively improve students' business English expression ability [8-10].

With the development of Artificial Intelligence (AI), AI corpus plays a unique advantage in language education, and it is an inevitable choice to improve the quality of business English teaching by using AI corpus to transform the traditional business English teaching mode in order to assist the expression training [11, 12]. AI corpus refers to a collection of data in the form of text, speech, images, or other forms used for training AI algorithms and models [13, 14]. In business English expression training, AI corpus is firstly, the dialog coverage is wide, it can set the scene according to the students' needs so as to have a natural dialog [15]. Secondly, AI corpus is able to provide instant error correction and feedback for students' expression errors such as improper word usage, voice pronunciation, etc., explaining the reasons and giving ways to improve [16].

Regarding the expression training of AI technology in business English courses in colleges and universities and its application in related fields, literature [17] points out that with the increase of internationalization level, traditional foreign language training is difficult to meet the demand for composite talents in the business environment, for this reason, combining with AI technology, an intelligent English training dialogue model based on speech recognition and multi-feature parameters is proposed, which in terms of prediction accuracy, speech recognition rate and real-time response The model is excellent in prediction accuracy, speech recognition rate and real-time response, and can significantly improve learners' English application ability in business scenarios, providing a quantifiable intelligent training program for business foreign language teaching. Literature [18] highlights the current situation where globalization and the emergence of new technologies have led to more frequent business collaborations, where digitalization poses communication challenges, and where students need to be prepared accordingly, and, based on semi-structured interviews with 25 Economics students, explores how digital tools such as AI can impact on the development of communication skills of Business English students, with a particular focus on the potential for their application in core areas such as vocabulary learning, and the long-term effects of such tools. Literature [19] analyzed the application of AI technologies such as machine learning, deep learning and ChatGPT in the teaching of General English and Business English by combing through 32 pieces of literature during the period of 2021-2024, and found that they were significantly applied in the fields of speaking, writing and translation, but less in listening, and the research interest was highly concentrated in Asian, especially Chinese scholars, which provides a reference for language teaching in the era of AI innovation in the era of AI. Literature [20] proposes a deep neural network-based scoring method for business English oral training, which integrates the technologies of speech recognition, automatic error correction and deep learning, and utilizes the data of the machine test platform to train the intelligent scoring system, realizing the automatic scoring of the oral expression questions, and verifying its accuracy through the correlation with the teacher's manual scoring, which is a positive effect on the language training guidance. Literature [21] explored the development of students' soft skills in the age of AI, and found through an anonymous online survey that students use AI both for general motivations such as convenience and academic needs such as lack of knowledge and skills, in order to promote the development of students' soft skills and avoid the potential negative impact of AI, the study suggests integrating AI platforms into teaching and learning, for example, creating supportive environments and organizing discussions in communication courses, and in business writing courses encouraging teamwork and role-playing to keep classroom teaching relevant in the age of AI. Literature [22] developed a generative AI-based English speaking training system, which generates personalized conversation scenarios through ChatGPT and combines speech recognition and big language modeling to provide intelligent scoring and feedback, and also creates mouth-synchronized virtual characters using D-ID technology to enhance learners' oral fluency and confidence in a low-anxiety environment, which is proved to be effective in improving oral English proficiency in experiments The experiment proves that it can effectively improve the level of spoken English.

Designing an automatic business English text categorization corpus building system, which automatically crawls relevant web pages from the Internet according to the set business topics and forms a corpus store after cleaning, parsing and categorizing. The system will also continuously expand the corpus size and quality through repeated iterations and core word extraction. A Chinese-English word sense annotation algorithm based on KnowNet is further introduced. HowNet, a bilingual knowledge base, is utilized to automatically determine the exact lexical meaning of a Chinese word in a specific business context and match the corresponding English expression. At the utterance level, a probability-based sentence alignment model is proposed, which pairs the original and translated sentences through statistical computation to ensure that the bilingual corpus used in teaching corresponds at the sentence level. Finally, bridging technology and teaching logic, we propose a strategy for business English oral and written expression training in colleges and universities, which transforms the aforementioned corpus resources into classroom activities. A multilevel training path from scenario simulation to writing conceptualization and from individual practice to collaborative output is designed.

2 Business English Expression Training Method System Based on AI Corpus

2.1 System design for automatic corpus building for business English text categorization

The study addresses the fact that the main source of business English corpus in colleges and universities is the Internet, and the method of collecting the corpus is to use a search engine, in which the greater the number of keywords entered, the more the results searched will meet the requirements of the corpus. Therefore, the overall idea is that the system automatically obtains relevant web pages on the Internet according to the initial input of category names and takes out the contents of these web pages that match the topics and saves them as the initial corpus. Then the core words of each category are calculated and analyzed according to the initial corpus. The core words with higher importance and category names are selected to continue to acquire relevant web pages on the Internet and take out the contents of these web pages that match the topics, and save them as the corpus. Finally, the corpus obtained repeatedly is coded and processed in a unified way to get the final corpus.

The overall idea of the large-scale automatic corpus building system based on business English text categorization in colleges and universities consists of the following steps.

(1) Data collection stage: Grab the topic-related HTML pages from the Internet and save them to the initial webpage library.

(2) Page cleaning phase: these HTML pages are cleaned and optimized. Since there are various encoded web pages on the Internet, the different page encodings are first converted into

a unified encoding method. Then these structurally unstandardized HTML pages are converted into structurally standardized XHTML pages, which are saved in the cleaning web page library.

(3) Page parsing process: these standardized pages are parsed by XML parser, and the information not related to the topic is removed from the pages to get the topic-related data, which is output to the corpus.

(4) Segmentation stage: the extracted data are subjected to Chinese segmentation, and the word frequency and document frequency are counted.

(5) Category core word acquisition stage: through the algorithm proposed in this paper, the core words of each category are calculated and the importance of these category core words are ranked.

(6) Scale control phase according to the acquired category core words, iterating the above process until the scale reaches the requirement.

Corpus validation phase validates the validity of the automatically machine-generated corpus by means of various classifiers and standardized test corpora.

According to the overall research idea of the system, the workflow of this automatic text corpus building system for business English texts in colleges and universities is shown in Figure 1.

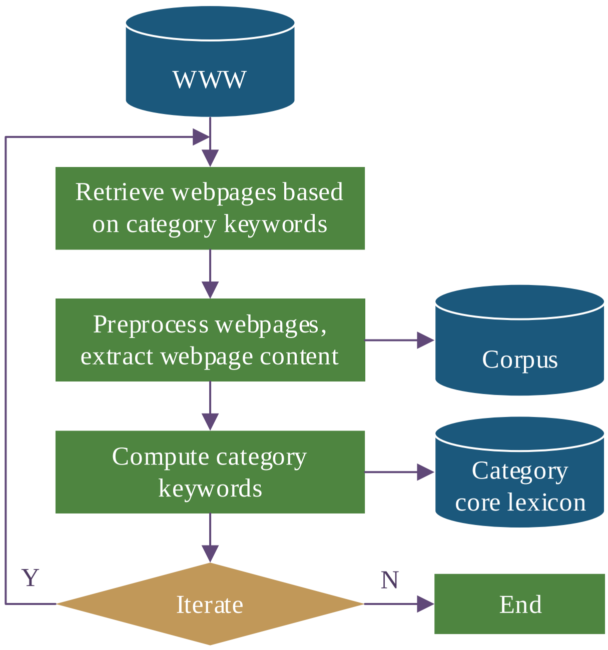


Figure 1: The process of establishing an automatic corpus system

2.2 Chinese-English Word Sense Annotation Algorithm Based on Zhi.com

After completing the automatic construction of the Business English text classification corpus, the Chinese-English lexical annotation algorithm based on HowNet is further introduced to realize the accurate semantic annotation of the bilingual corpus.

HowNet is a bilingual semantic resource, which contains a large number of Chinese lexical entries and English translations, and can be regarded as a bilingual dictionary with semantic categorization. If its bilingual feature can be fully utilized, it is not necessary to calculate the similarity on the set of statistical target language translations, but with the dictionary translations under a certain DEF in HowNet, which can be regarded as the correct translations, and thus it is expected to improve the accuracy of the annotation. In summary, the improved word sense annotation algorithm can be viewed as a bi-semantic lexicon based approach, according to which the word senses of two languages can be annotated by only performing the Chinese-English perspective, described as follows:

(1) With Chinese as the source language and English as the target language, the set of English translations $\{EW_i\}$ corresponding to the Chinese word CW is counted according to the word alignment information.

(2) For each of them, select all the English translations (i.e., the corresponding items) corresponding to each different lexical meaning (i.e., different DEF items) of CW in KnowledgeNet to form a number of sets. Let CW have j different DEF items, then the j selected sets are $HE_1, HE_2, \cdots, HE_j$. And these j sets have been semantically categorized according to the lexical meanings in KnowledgeNet. For each word EW_i in the target language translation set $\{EW_i\}$ corresponding to CW, we calculate the similarity with DEF, EW_i and the similarity with DEF is defined as the sum of the similarity of each word in EW_i and HE_j divided by the number of words in the DEF, and the similarity of word to word is defined as the maximum value of the similarity of the semantics of all the words, and after calculating the similarity with all the j DEFs, we choose the one with the maximum value of similarity as the category to be EW_i categorized, and this DEF has already been categorized according to the semantics of the words in KnowledgeNet. The DEF that has the largest similarity value is also the one that corresponds to the Chinese word CW of EW_i. At this time, we calculate the support degree of each English translation of each DEF for each word sense of EW_i, and choose the one with the largest value as the correct word sense of EW_i. In this way, the lexical meanings of Chinese words and English words in each $\left(CW, EW_i\right)$ word pair can be determined.

(3) Write the word sense annotation information back to the source file to complete the annotation.

The similarity between English words EW_1 and EW_2 is defined as:

$$Sim(EW_1, EW_2) = \max_{\substack{S1_i \in Synset(EW_1) \\ S2_j \in Synset(EW_2)}} Sim(S1, S2_j) \tag{1}$$

where Synset returns all the lexical meanings of the English word, based on which we define the similarity between the English word EW and a certain Chinese word DEF as:

$$Sim\left(EW, DEF\right) = \sum_{EW_i \in Words(DEF)} Sim\left(EW, EW_i\right) / \left|DEF\right| \tag{2}$$

where Words returns all English words under DEF, $\left|DEF\right|$ is the number of English words under DEF.

The framework of the word sense annotation algorithm for Chinese-English corpus based on Zhi.com (bi-semantic dictionary) is shown in Figure 2

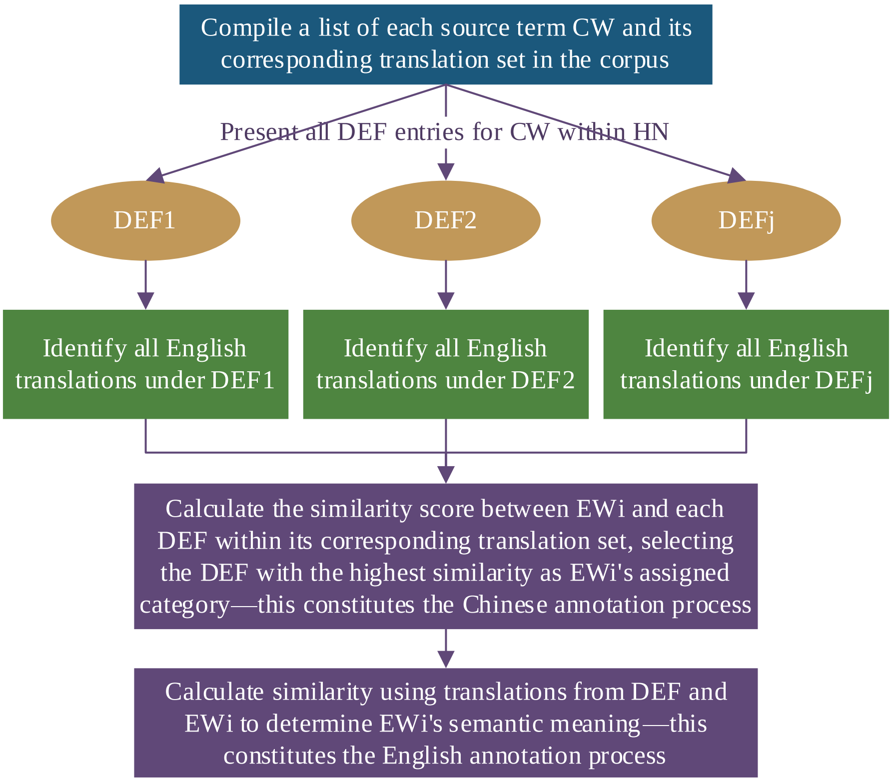


Figure 2: Based on the Chinese-English semantic annotation algorithm of "CNKI"

The word sense annotation algorithm in this paper mainly utilizes the bilingual lexicon feature of HowNet, and uses the similarity calculation tool on the English side to categorize the target translation EW_i corresponding to the Chinese word, and this categorization process is the lexical annotation process of the Chinese word, and after categorization, then the translation of ZhiNET under the DEF is used to calculate the similarity to EW_i, which is the process of annotating the English word, so as to The annotation of both Chinese and English can be accomplished just by conducting a perspective.

2.3 Probability-based sentence alignment models

Meanwhile, in order to guarantee the correspondence quality of the corpus at the sentence level, this section proposes a probability-based sentence alignment model to optimize the sentence matching of the bilingual corpus from a statistical perspective.

Definition 1: Suppose that the source text S and its corresponding translated text T have an alignment $A=\{A_1,A_2,A_3,\cdots,A_l\}$ of length l, $A_i=<A_{iS},A_{iT}>(i=1,2,\cdots,l)$. An A is called a sentence alignment of S, T if each A_{iS}, A_{iT} contains zero, one, or more sentences of the source or translated text, respectively. Each $|A_{iS}|$, $|A_{iT}|$ is called a matching pattern of sentences.

Similarly, a valid sentence alignment should satisfy the principle of "minimum fragment matching". In order to avoid the complexity of cross-dependency, we try to find a sentence alignment that satisfies the following ordering assumptions.

Assumption 1: (Sequential Assumption) Let the source text S and the translation T have an alignment $A=\{A_1,A_2,A_3,\cdots,A_l\}$ of length l, $A_i=<A_{iS},A_{iT}>(i=1,2,\cdots,l)$. $Off(x,S)$, $Off(x,T)$ denote the byte offsets of byte x in the source text S and x in the translated text T, respectively, and any two elements of A, $<A_{iS}, A_{iT}>$, $<A_{jS}, A_{jT}> (1 \le i, j \le l)$, meet the following criteria :

(1) If both A_{iS} and A_{jS} are not empty and $i < j$, then there are

$$\max_{x \in A_{iS}} Off\left(x, S\right) < \min_{y \in A_{jS}} Off\left(y, S\right) \tag{3}$$

(2) If both A_{iT} and A_{jT} are not empty and $i < j$, then we have

$$\max_{x \in A_{iT}} Off\left(x, T\right) < \min_{y \in A_{jT}} Off\left(y, T\right) \tag{4}$$

where x, y are any bytes of A_{jS}, A_{jT} respectively.

In statistics, any event is assigned a certain probability so that the likelihood of its occurrence can be known by the magnitude of the probability value. Similarly, introducing the concept of statistics in the alignment of sentences (see Chapter 2 for the evaluation of alignment), there exists a certain probability that a certain sentence alignment A (which can be viewed as a certain event) of the source text S and the translated text T can be expressed as $\Pr ob\left(A \middle| S, T\right)$. Assuming that there is also a certain probability of the event of bilingual segments being translated into each other, it is clear that the value of the probability $\Pr ob\left(A \middle| S, T\right)$ is equal to the probability that each of the bilingual segments of A are translated into each other's segments.

Obviously, since the value of the probability $\Pr ob\left(A \middle| S, T\right)$ varies only with A for the same source text S and translation T. Thus, the process of seeking sentence alignment of S and T can be transformed into a process of finding the A that maximizes the value of the probability $\Pr ob\left(A \middle| S, T\right)$.

Formally, the probabilistic model of sentence alignment is as follows:

Probabilistic Model of Sentence Alignment Let A be a sentence alignment between the source text S and the translation T, and the probability of obtaining sentence alignment A is $\Pr ob\left(A \middle| S, T\right)$, then the best sentence alignment to be sought is:

$$\hat{A} = \arg\max_{A} \Pr ob\left(A \middle| S, T\right) \tag{5}$$

Under the above probabilistic model, the key to perform sentence alignment is to solve two problems: one is how to calculate the probability $\Pr ob\left(A \middle| S, T\right)$; the other is how to efficiently search for the largest probability value corresponding to the alignment in the huge search space. In order to calculate the value of probability $\Pr ob\left(A \middle| S, T\right)$, this paper puts forward the following hypotheses in turn:

Assumption 2: For $A = \{<A_{iS}, A_{iT}>\}$, $1 \le i \le l$, it is assumed that the events (denoted by double arrows) that each alignment slice A_{iS} is translated to each other with A_{iT} are independent of each other. According to this hypothesis there are:

$$\Pr ob\left(A\middle|S,T\right) \approx \prod_{i=1}^{l} \Pr ob\left(A_{iS} \Leftrightarrow A_{iT} \middle|S,T\right) \tag{6}$$

Under Assumption 2, the probabilistic solution of alignment A can be transformed into a process of solving the probability of intertranslation for each bilingual fragment in it.

Assumption 3: Suppose that in Assumption 2, the probability of each A_{iS} and A_{iT} intertranslated event does not depend on the context, but only on A_{iS} and A_{iT} themselves. According to this assumption, there are:

$$\Pr ob\left(A\middle|S,T\right) \approx \prod_{i=1}^{l} \Pr ob\left(A_{iS} \Leftrightarrow A_{iT} \middle|A_{iS}, A_{iT}\right) \tag{7}$$

Under Assumption 3, the solution of the inter-translation probability of each bilingual fragment is independent of the context and depends only on themselves, which greatly simplifies the process of calculation.

Assumption 4: Suppose that under Assumption 3, the probability of the event that A_{iS} and A_{iT} are intertranslated depends only on a finite number of their attributes $\lambda_1, \lambda_2, ..., \lambda_k$ take on values. Then there are:

$$\begin{aligned} &\Pr ob\left(A_{iS} \Leftrightarrow A_{iT} \middle|A_{iS}, A_{iT}\right) \\ &\approx \Pr ob\left(A_{iS} \Leftrightarrow A_{iT} \middle|\lambda_1\left(A_{iS}\right), \lambda_1\left(A_{iT}\right), \cdots, \lambda_k\left(A_{iS}\right), \lambda_k\left(A_{iT}\right)\right) \end{aligned} \tag{8}$$

Under Assumption 4, the probability solution of each bilingual fragment only depends on its own finite number of attributes, so how to seek these attributes becomes the key to solve the sentence alignment probability.

Thus, through the above assumptions, the computation of $\Pr ob\left(A\middle|S,T\right)$ can finally be reduced to the computation of the conditional probability of each bilingual fragment under a finite number of attributes.

2.4 Strategies for Training Oral and Written Business English in Colleges and Universities

Based on the corpus constructed in the previous section and its annotation system and sentence alignment, this section integrates this structured AI corpus resource into business English teaching practice in colleges and universities. From the two dimensions of speaking and writing, targeted expression training strategies are designed to promote the language use ability of college students in business English courses and realize the closed loop of teaching from corpus input to language output.

2.4.1 Strategies for Oral Expression

(1) Construct real contexts and carry out contextualized Q&A training

Using the AI corpus constructed above, we extract real business conversation materials and design progressive classroom Q&A. Initially, students are guided to open their mouths through simple questions, and then gradually transition to in-depth questions based on real conversation clips in the corpus to help students familiarize themselves with typical expressions and reaction patterns in business scenarios.

(2) Group work and role play

Group students together to design a drama task around a specific business topic (e.g., product promotion, negotiation simulation). Teachers can provide relevant dialogue templates and professional vocabulary lists in the AI corpus to guide students in script writing and rehearsal, so as to enhance language fluency and professionalism in interaction.

(3) Expand extracurricular training pathways

Organize activities such as English speeches and business debates, and encourage students to use the AI corpus to prepare their own speeches. The corpus can provide high-frequency expressions and sentence structures of different business topics to help students standardize their language output and enhance their confidence in expression.

(4) Enhance speech and vocabulary training

Combining the business vocabulary and common word blocks in the corpus, students can focus on reading aloud and intonation training, and the AI voice recognition tool can assist in correcting the pronunciation to improve the accuracy and naturalness of oral expression.

2.4.2 Strategies for training in written expression

(1) Accumulate professional expressions with the help of AI corpus

Students are guided to regularly read and analyze business texts in the corpus, such as emails, reports, contract terms, etc., to summarize commonly used sentence patterns, articulations and terminology, and to build up a personal writing material base.

(2) Imitation and Sentence Training

Select typical business texts in the corpus for imitation practice. Teachers can design targeted tasks that require students to use specified sentence patterns or structures to complete the writing and strengthen the transition from imitation to application.

(3) Thinking Maps to Assist Writing Ideas

Before writing, students are encouraged to use mind maps to organize their ideas and vocabulary, and the AI corpus can provide keywords and expression references for related topics to help students build a content framework and improve their logical organization skills.

(4) Strengthen the guidance and evaluation of the writing process

Teachers focus on the weak points in students' writing and compare and contrast them with the correct examples in the corpus; AI writing aids can provide initial feedback on grammar and diction, and teachers can then make in-depth comments on stylistic, logical, and business decency levels.

(5) Promote the combination of reading and writing to promote writing.

Focusing on the business articles in the textbook or corpus, students are guided to analyze the text structure and language features, and are assigned writing tasks on related topics, which require the use of learned sentences and vocabulary, realizing the effective transformation from input to output.

3 Empirical research design of AI corpus-based instructional models

An empirical study of the teaching model based on AI corpus is conducted. A semester-long teaching experiment was conducted in a business English course in a university to assess the effectiveness of the teaching model in terms of both objective achievement and subjective perception.

3.1 Subjects and methodology of the study

The empirical study of AI corpus-assisted expression training in business English courses in colleges and universities was conducted by a combination of practical teaching experiments and questionnaires, through which it was confirmed whether the AI-based corpus affects students' business English proficiency, focusing on their oral and written expressions, and at the same time exploring whether it can improve students' learning initiative and learning interest.

The study was conducted in two parallel classes of the 2023 sophomore class of Business English majors in a university, with 62 students in each class and a total of 124 students, and the empirical research cycle lasted for 1 semester. The business English course in the experimental class was taught using AI corpus-assisted instruction, while the control class continued to follow traditional classroom instruction. A business English proficiency test was conducted simultaneously in both classes before the study began and at the end of the study. The focus of the test was on their oral and written expressions.

An anonymous questionnaire survey was conducted through the mobile app "Questionnaire Star". The questionnaire was adapted from Gardner's Attitude/Motivation Scale and was scored using the 5-point Likert scale. Each questionnaire contained 25 questions, with each question having 5 options, labeled as 5, 4, 3, 2, and 1 points respectively ("very much in line", "in line", "uncertain", "not in line", "very not in line"). Additionally, the experimental group tested the reliability of the scale, and the results showed that the Cronbach's α of each dimension of the scale ranged from 0.781 to 0.885, indicating good internal consistency and high reliability of the scale.

3.2 Comparative analysis based on business English proficiency tests

3.2.1 Comparison of overall performance

Firstly, based on the Business English Proficiency Test, the overall test scores of the students in the two classes, the experimental class and the control class, before and after the experiment are compared and analyzed.

(1) Comparison between the control group and the experimental group in pre-test scores

The overall pretest scores of the control and experimental groups are shown in Figure 3. The data points on the left side of the achievement grouping are for the experimental class. The data points on the right side are distributed for the control class (the same below).

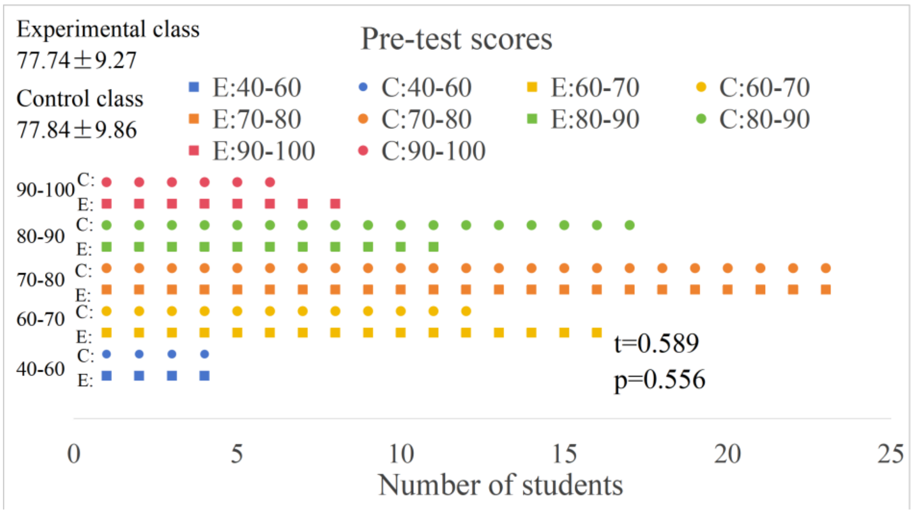


Figure 3: The overall pre-test scores of the control group and the experimental group

The pre-test scores of the experimental and control classes before the experiment were 77.94±9.27 and 77.84±9.86, respectively, and the scores of the students' business English proficiency in the two classes were mainly concentrated in the middle range of 60-89. In the independent samples t-test, a positive value of t=0.589 was obtained, indicating that the pre-test scores of the control group were higher. In addition, the p-value is 0.556>0.05, indicating that there is no significant difference between the pretest scores of the control group and the experimental group, and the pretest levels of the students in the two classes are relatively consistent, which is conducive to the follow-up study.

(2) Comparison between the control group and the experimental group in posttest scores

After a semester of comparative experiments under different teaching methods, the posttest scores of the control group and the experimental group are shown in Figure 4.

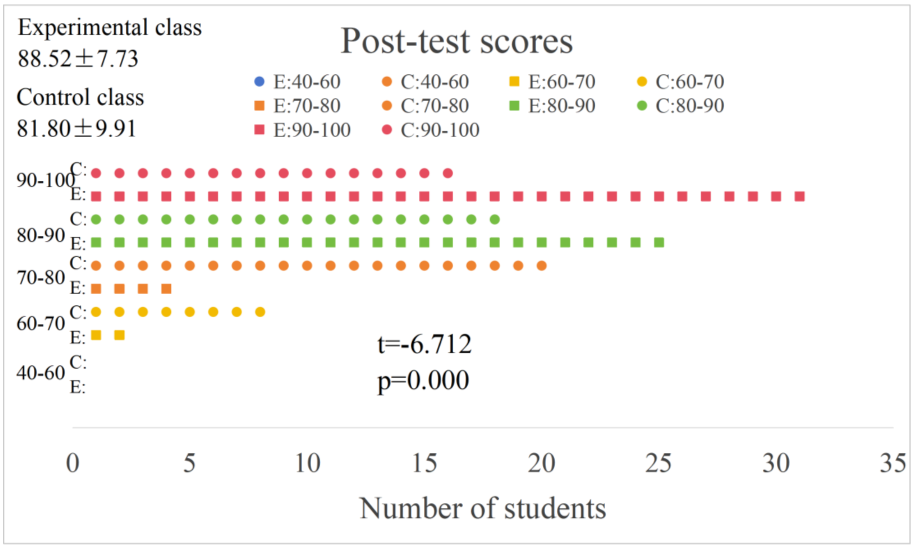


Figure 4: The overall post-test scores of the control group and the experimental group

After one semester of teaching practice in different modes, the experimental class and the control class showed obvious differentiation in the comprehensive ability of business English. The overall average scores of the two classes were 81.10±9.91 and 88.52±7.73, respectively, which opened up a gap of more than 7 points. There were no failing students below 60 points in either class, and half of the students in the experimental class scored in the high 90-100 range, with the overall level shifting upward, while there were only 16 students in the control class in the high range, with a higher concentration in the 70-89 subsection. Statistically, t=-6.712, p=0.000, indicating that AI corpus-assisted instruction in does produce a significant improvement in students' overall business English level.

3.2.2 Comparison of oral scores

Focusing again on the comparison between the two classes of students before and after the experiment on their oral scores, which totaled 20 points.

(1) Comparison between the control group and the experimental group in the pre-test speaking scores

Figure 5 shows the speaking scores of the experimental and control groups on the pre-test of the experiment.

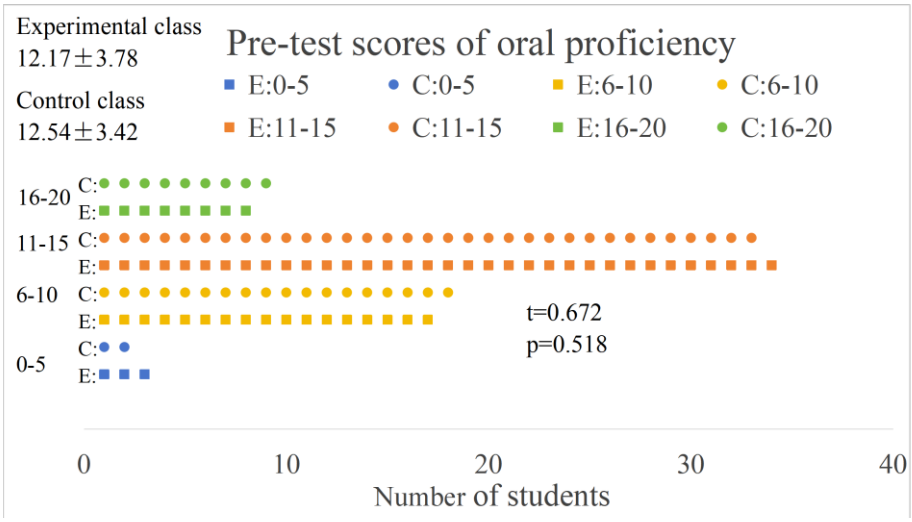


Figure 5: Pre-test scores of oral language in control group and experimental group

Before the experiment, the average speaking scores of the two classes were almost equal, and the performance of the experimental class and the control class in speaking scores was 12.17±3.78 and 12.54±3.42 respectively, with the majority of the students being in the middle of the range of 11-15 points, and again the performance of the control class was slightly higher than that of the experimental class, but the two t=0.672, p=0.518>0.005, which did not constitute a statistically significant difference.

(2) Comparison of the control and experimental groups in post-test speaking scores

Figure 6 shows the speaking scores of the experimental group and the control group on the posttest under different teaching modes in one semester.

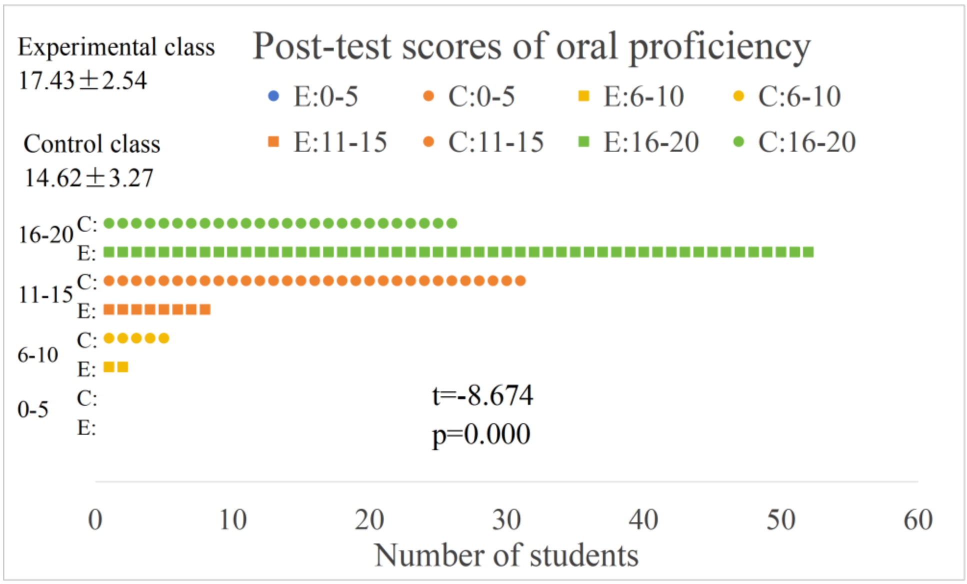


Figure 6: Post-test scores of oral language in control group and experimental group

The average oral score of the experimental class increased to 17.43, while the control class scored only 14.62. Fifty-two students (more than 80% of the total) in the experimental class entered the high 16-20 division, compared with only 26 in the control class. t-test results t = -8.674, p = 0.000 indicate that under the control of the teaching teacher and the consistency of the teaching content, the situational and interactive speaking training based on the AI corpus can really help students break through the trap of low or middle scores effectively, and achieve a breakthrough in oral expression fluency and accuracy to realize a breakthrough and reach high scores.

3.2.3 Comparison of performance in written expression

Focusing again on the comparison between the two classes of students' written expression scores before and after the experiment, the total score of writing is 20 points.

(1) Comparison between the control group and the experimental group in terms of written expression scores in the pre-test

Figure 7 shows the written expression scores of the experimental and control groups on the pre-test of the experiment.

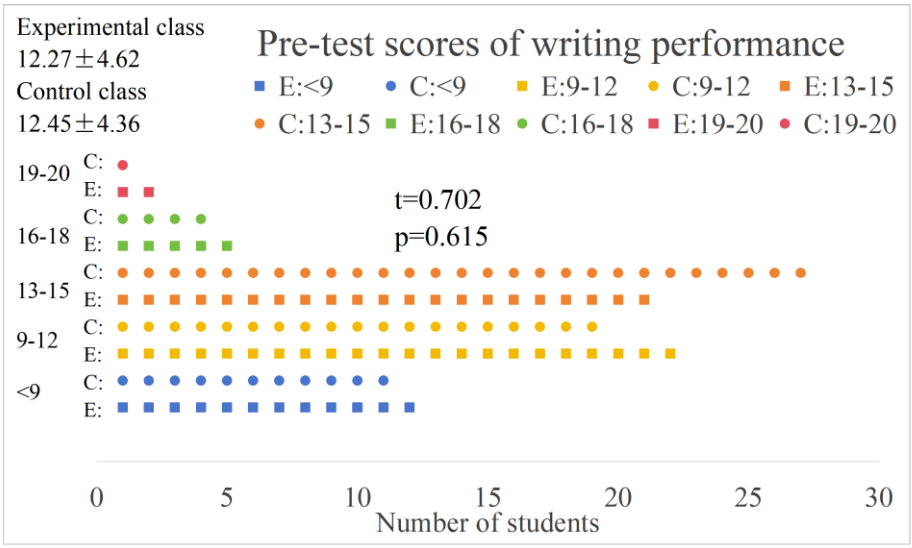


Figure 7: Pre-test scores of writing in control group and experimental group

Before the experiment, the average scores of writing in the two classes were similar, being 12.27 ± 12.27 and 12.45 ± 5.36 respectively. There were also a considerable number of students with scores lower than 9 points in both classes (12 students in the experimental class and 11 students in the control class). There were very few students who achieved a score of 16 or above in writing (7 students in the experimental class and 5 students in the control class). The paired sample t-test of the pre-experiment scores of writing for the two classes showed t = 0.702, p = 0.615, indicating no significant difference.

(2) Comparison of the control and experimental groups in terms of written expression scores in the posttest

Figure 8 shows the written expression scores of the experimental and control groups on the pre-test of the experiment.

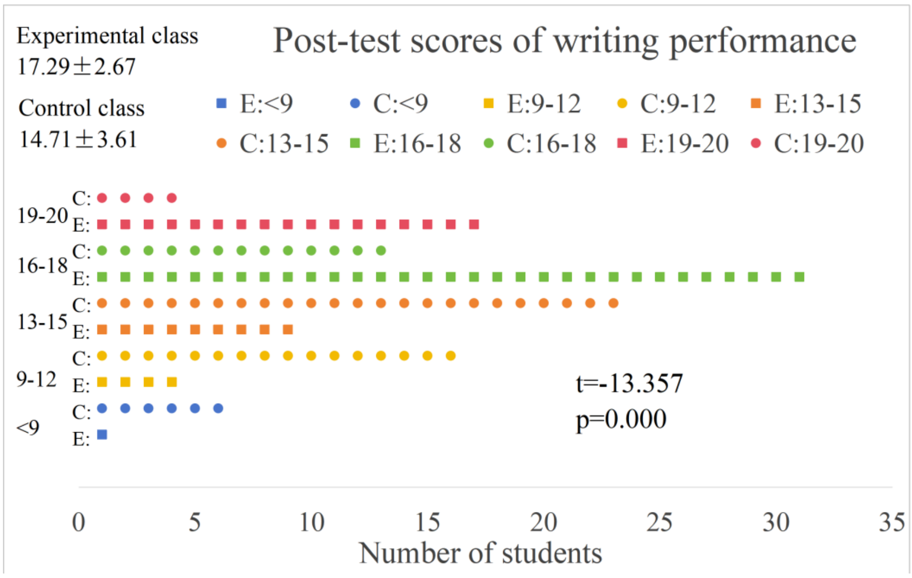
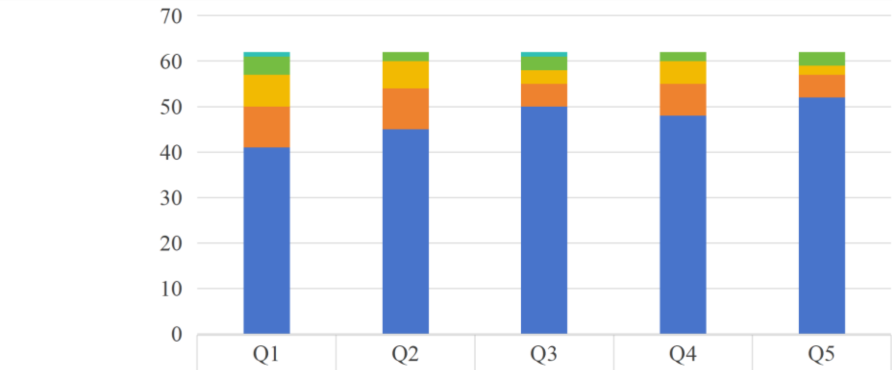


Figure 8: Post-test scores of writing in control group and experimental group

After a semester of systematic study and training, the average writing score of the experimental class soared to 17.29±2.07, with 48 students scoring 16 or more in writing, of which 17 received high scores of 19-20, and only 1 was still below 9. In contrast, the average score of the control class was only 14.71±3.61, and there were only 17 students in the high score band of 16-20, which was about 1/3 of the experimental class, and there were still 6 students in the lower range of below 9 points. Originally, the experimental and control classes with comparable English writing scores produce a significant difference in English writing scores after the experiment, t=-13.357, which fully reflects the effectiveness of the AI corpus written expression training strategy in the teaching experiment. As the AI corpus-based written expression training strategy proposed in Section 2.4.2, the AI corpus plays a key role in providing professional expression models, assisting in writing conceptualization and revising feedback, which strengthens students' standardization, logic and business decency in their written output, and elevates their business English writing scores.

3.3 Analysis of the results of the questionnaire survey based on the AI corpus-assisted expression teaching model

After conducting an experiment with 62 students in the experimental class who received training with the assistance of an AI corpus for expression, a questionnaire was distributed to them after the one-semester business English course was completed. The survey focused on five aspects: Q1 "The AI corpus has greatly helped improve English oral expression", Q2 "The AI corpus has greatly helped improve English writing", Q3 "The use of the AI corpus in expression training makes English oral learning easier", Q4 "The use of the AI corpus in expression training makes English writing learning easier", and Q5 "The use of the AI corpus in expression training is more interesting than traditional teaching methods". The results are shown in Figure 9.



	Q1	Q2	Q3	Q4	Q5
Strongly disagree	1	0	1	0	0
Disagree	4	2	3	2	3
Generally	7	6	3	5	2
Agree	9	9	5	7	5
Completely agree	41	45	50	48	52

Figure 9: Questionnaire survey based on the AI-assisted expression teaching model

The questionnaire clearly reflects the students' positive feedback on the AI corpus-assisted teaching model. 82% of the students (41 "strongly agree" + 10 "agree") believe that the AI corpus has greatly helped their oral language improvement, confirming the effectiveness of the oral language strategies such as "creating real contexts and conducting situational question-and-answer training" discussed in this article. In terms of Q2 writing improvement, the proportion is even higher, with 84% believing that it has greatly helped their writing ability. Similarly, thanks to the design of the article, the accumulation of professional expressions and imitation and sentence structure training through the AI corpus as written training strategies were also benefited. Students also gave positive feedback on their learning experience. 55 students each believed that this model made oral language learning and writing classes easier, and as many as 92% of the students (52 "strongly agree" + 5 "agree") expressed that this training method was more interesting than traditional teaching methods. The questionnaire survey once again demonstrates the significant effect of the AI corpus-assisted expression method in reducing the psychological threshold of learning and enhancing students' learning motivation.

4 Conclusion

With the AI corpus as the core, supplemented by word meaning annotation and sentence-to-sentence expression of its bilingual resources, and the situationalized, output-oriented training mode, it can significantly improve college students' oral and written expression ability in the field of business English, with the overall scores of 75.65→88.52, oral expression 12.17→17.43, and written expression 12.27→17.29. Compared with the control Compared with the control class under the traditional teaching mode, the overall score was 6.72 points higher, and the improvement in speaking and writing was 2.81 and 2.58 points respectively. The differences were statistically highly significant, $p=0.000$, confirming the effectiveness of the teaching intervention. In terms of subjective learning experience, the model also significantly improved students' motivation and engagement, and reduced students' learning anxiety. 82% and 84% of students each explicitly recognized that the AI corpus helped them improve their speaking and writing skills; moreover, 89% and 92% of students found this learning approach more interesting and easier to follow.

About the Author

Guofang Kou received her M.S. degree in Economy from Tianjin University in Tianjin, China. Her research interest is mainly in the area of International trade and Cross-border e-commerce. She has published several research papers in scholarly journals in the above research areas and has participated in several conferences.

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