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Article

A Path to Enhance the Effectiveness of Secondary School English Vocabulary Teaching Empowered by Natural Language Processing in the Era of Artificial Intelligence

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Abstract: With the rapid development of science and technology, artificial intelligence (AI) technology has been deeply integrated into the field of education, and the teaching of English at the secondary school level, as a key link in the cultivation of high-quality skilled talents, is in urgent need of innovative change. This paper firstly proposes a secondary school English vocabulary teaching model using natural language processing (NIP) technology, which integrates key technologies such as Wikipedia corpus, semantic similarity computation, Word2vec tool, etc., aiming at solving the dilemmas faced in the traditional English vocabulary teaching process. Finally, the teaching practice shows that the experimental group is significantly higher than the control group in learning motivation (affective experience, cognitive level and behavioral tendency) in relation to test scores ($p<0.05$). Therefore, the use of NIP technology has brought a positive impact on the reform of English vocabulary teaching in secondary schools.

Keywords: natural language processing; corpus; semantic similarity; Word2vec; English vocabulary teaching

1. Introduction

Vocabulary is the most basic unit of language and the building material of language. Without vocabulary, language loses its practical significance. It can be seen that vocabulary teaching occupies an important position in English teaching [1], but there are still a lot of problems in secondary school English vocabulary teaching, mainly in vocabulary comprehension difficulties, memorization difficulties and so on, and it has become an urgent and realistic problem in secondary school English education to adopt effective teaching strategies to improve the effect of vocabulary teaching.

Traditional vocabulary teaching methods, mainly to strengthen the memory time, repeated practice, dialogue practice, etc., not only low efficiency, lack of personalization, etc., but also waste a lot of time, which is not worth the loss. With the gradual penetration of artificial intelligence into the field of education, natural language processing (NLP) technology has made an important role in enhancing the effectiveness of English vocabulary teaching in secondary schools due to its powerful capabilities of text comprehension, speech analysis, and personalized interaction [2-4].

NLP is an interdisciplinary discipline involving computer science, artificial intelligence, and linguistics, aiming to enable computers to understand, interpret, and generate human language [5-6]. Among them, Natural Language Understanding (NLU) is an important branch in the field of NLP, whose goal is to enable computers to understand and interpret the meaning of human language [7-8]. In recent years, with the rapid development of deep learning technology, natural language processing technology has also made remarkable progress. In secondary school English vocabulary teaching, NLP has the advantages of intelligent extraction and classification of vocabulary, pronunciation assessment and adaptive learning path planning, which can realize the systematization of English vocabulary and precise empowerment, thus significantly improving the effect of English vocabulary teaching, strengthening students' intrinsic motivation to learn vocabulary, and promoting vocabulary teaching in the direction of intelligent and personalized development [9-12].

This article presents an English vocabulary teaching model that utilizes Wikipedia as the corpus and employs NIP technology to automatically assist in the rewriting of example sentence expressions for vocabulary teaching in middle school English. Through experiments and the presentation of experimental results, it has been verified that this innovative teaching model helps improve students' academic performance during the learning process. Through effective divergence and association, as well as the original context, it can better promote students' understanding, memory and application of vocabulary, and enhance their motivation for vocabulary learning.

2. Design of English Vocabulary Teaching Models Empowered by Natural Language Processing

2.1. NLP and English Vocabulary Teaching

Natural Language Processing (NLP) technology, as a branch of Artificial Intelligence technology, mainly solves various real-world problems by means of algorithms and data, where algorithms refer to the clear instructions that allow computers to solve problems.Algorithms in NLP technology can be divided into three types of algorithms, namely, linguistic rule-based, statistic-based and hybrid algorithms, where statistic-based algorithms reflect the integration of various interdisciplinary theories, such as the principle of statistics, machine learning and so forth. The data in NLP mainly refers to a variety of semantic resources, including (multilingual) dictionaries, semantic class knowledge graphs, and (parallel) corpora.

In the process of teaching English vocabulary, teachers often face a dilemma: when teaching a new point, they often need to associate and inspire what they have already learned, but they cannot think of multiple examples whose semantics and usage are highly similar to that of the new point at one time, and this dilemma is particularly common in vocabulary teaching and grammar teaching. Lack of accurate understanding of semantics is a common problem in vocabulary learning, so what we urgently need to do is to try to present vocabulary in context, to teach vocabulary in context, and to teach students to learn vocabulary in context. By effectively associating learned vocabulary knowledge and using context to establish connections between unlearned and learned vocabulary, it will help to understand, memorize and use vocabulary.

In addition, changing expressions and choosing appropriate expressions are also important skills that students need to master in the process of language teaching and learning, and if they can be accurately modeled in the teaching process, it will help them improve their language skills. It can be said that such practical needs of teaching require teachers not only to make a lot of preparations to do with what they have already learned and change the materials of expressions at the stage of lesson preparation, but also require them to expand, associate, explain in more depth, and answer students' questions at any time in the classroom according to the progress of the lesson and students' feedback. Therefore, no matter in the stage of lesson preparation or in the actual teaching process, there is a need for a tool to help teachers automatically associate and assist them in changing their expressions appropriately. This tool will greatly improve the efficiency of teachers' preparation and classroom efficiency, and can provide original and accurate example sentences. In addition, if students have a tool that can help them automatically associate and rewrite the expressions of the example sentences, it can also effectively help them to learn from the past and build a knowledge network, so as to achieve the effect of promoting the students' learning desire and improving the efficiency of their independent learning.

Therefore, this paper takes the rewriting of vocabulary expressions in example sentences in English vocabulary teaching as an example of an application scenario, provides an innovative English vocabulary teaching mode that utilizes natural language processing technology to automatically associate the rewriting of vocabulary expressions in example sentences, and then discusses the operability and practicability of this mode in the actual English vocabulary teaching process.

2.2. Relevant resources and technologies

2.2.1. Wikipedia

Wikipedia is an encyclopedia that is publicly available on the Internet and can be freely edited by anyone. With its rich semantic resources and semi-structured data form, Wikipedia has become the basis for building NLP corpora. The most obvious advantage of corpus-assisted language teaching is reflected in the vocabulary, and at the same time, corpus is also an essential tool for modern lexicography. In corpus searching, the search item is usually used as the entry point, and then a large number of search lines are obtained, and the actual use of the search item is observed through the context.

In corpus linguistics, the word list refers to the word frequency list, rather than a simple list of words, which is one of the important bases for the dictionary to collect the words and establish the purpose, and of course, there is the option of arranging them in alphabetical order. English teachers can make use of collocated word lists to optimize vocabulary teaching by first collocating high-frequency words in textbooks and dictionaries and presenting them to learners in priority. Corpus linguistics believes that the core of language is vocabulary, and the two central concepts of frequency and collocation should be emphasized. In addition, in English vocabulary teaching, teachers can deepen the data-driven learning method, screen the corpus according to the students' English level, interests and needs, and guide the students to master the basic terms of the corpus and the regular expressions needed for complex searches, in order to improve their utilization of the corpus and cultivate their self-learning ability. In order to deepen students' understanding of foreign languages and cultures, teachers can also guide students to query keywords that contain strong cultural information, observe the characteristics of their collocations, and explore the trends of mainstream ideas and socio-cultural patterns of discourse.

And in this study, a model that uses the body of Wikipedia as a corpus and is trained using NLP techniques such as deep learning and word vector representation is discussed to obtain a model that can be used to assist English teachers to make automatic associations in the rewriting of expressions in example sentences.

2.2.2. Semantic similarity calculation

To realize the automatic association of lexical expressions rewritten in example sentences, two main problems need to be solved:

One of them is to solve the problem of participle and morphosyntactic parsing of the words in the section;

The second is to have a technical means to be able to rewrite the specified object and find a lexical expression that can replace the specified object to form a new example sentence.

In 2013, Google Inc. launched the open source Word2vec tool, which references the basic idea of neural probabilistic language modeling, but is specifically used to train word vectors. The Word2vec word vector model obtained after large-scale corpus training is able to compute lexical semantic similarity.

Word2vec model is currently the mainstream word distributed representation model, Word2vec model contains two models, CBOW (Continuous Bag of Words) model and Skip-Gram (Continuous skip-gram) model, the structure of the model is shown in Fig. 1.The core idea of CBOW is to predict the center word through contextual words to predict center words, while Skip-Gram predicts context words from center words. Compared with the Skip-Gram model, the CBOW model is more suitable for processing large-scale text data. However, the Skip-Gram model performs better in terms of computational accuracy, especially in the representation of low-frequency words. Given the priority of computational accuracy, this paper chooses to use the Skip-Gram model.The Skip-gram model has three layers: input layer, hidden layer and output layer. The first input layer is a 01 vector, the length of which is the total number of words in the text base dictionary, which traverses the text content through a sliding window. During the traversal process, the neuron representing the position of the word is activated, the value of the activated neuron is 1 and the other positions are 0. The one-hot coded representation of the word is realized by this method.

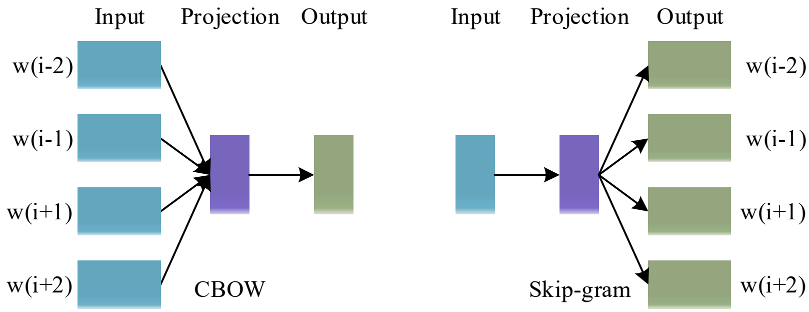

Figure 1. Word2Vec Model

The second layer of the model is the middle layer, which is a fully connected neuron layer. The neuron computation in the middle layer is independent of the vectorized encoding of the textual content, and is mainly responsible for activating the unactivated word encoding in the sliding window. Each time the sliding window moves, the middle layer is updated once. Due to the large number of words in the corpus, updating the parameters of the middle layer in full volume will increase the computational complexity, so the model randomly selects some neurons for updating, which effectively solves the dimension explosion problem. The final generated word vectors are represented by the middle layer weights, and after the training is completed, the words that activate the input layer will activate the corresponding middle layer weights to get the vectorized representation of the words.

The third layer of the model is the output layer, both the output layer and the input layer are essentially layers of neurons that are encoded by One-Hot to stand in for the words in the text, after the corresponding neurons in the input layer have been activated, it is necessary to go further in the output layer towards 1 for the nodes that correspond to the other words in the sliding window. Then, the deep learning model is trained by backpropagation. Although the third layer is the output layer, the word vectors are not generated in the output layer, the final word vectors needed are obtained in the intermediate layer, where multiple neurons are activated at the same time, which correspond to the neurons representing the other words in the sliding window.The cost function of the Skip-gram model is shown below:

$$\Gamma = \sum_{w \in C} \log p\left(context\left(w\right) \middle| w\right) \tag{1}$$

Where C stands for the entire corpus content, while w is the words in the corpus, $context\left(w\right)$ is the predicted word in the sliding window traversal, and $p\left(context\left(w\right) \middle| w\right)$ denotes the probability that the center word w is predicted $context\left(w\right)$ in the context.

In summary, in the Skip-gram model, the first step is to make a glossary of words in the corpus which contains all the words in the corpus, the input layer of the model is a neuron model with the length of the glossary N, and each neuron represents a word in the corpus, and through the intermediate layer, the words in the sliding window will be transmitted to the corresponding output layer, and the number of neural network layers is N, and the length is also N. The output layer is a neural network layer of length N, and the length is also N, and the number of neural network layers is N, and the length is also N. neural network layer of length N as well. The third layer is essentially a Softmax classifier, whose corresponding word is in a classifier node that produces a number between 0 and 1, and whose output value sums to 1 over all.

CBOW has the same principle as Skip-gram, but in in Skip-gram the center word is used to predict the surrounding words, whereas CBOW uses the surrounding words to predict the center word with the following cost function prediction formula:

$$\Gamma = \sum_{w \in C} \log p\left(w \middle| context\left(w\right)\right) \tag{2}$$

Where w denotes the center word and $context\left(w\right)$ denotes the prediction word, the input layer of the model is activating the nodes corresponding to the surrounding words in the sliding window, while the neurons activated in the output layer are those corresponding to the center word.

In this paper, Pearson correlation coefficient and Spearman correlation coefficient are used as evaluation metrics in the evaluation of semantic similarity computation.

Pearson correlation coefficient is usually used to measure the degree of correlation. Its measurement is less than 1 and greater than -1. The intuitive explanation of this linear relationship is that one variable increases or decreases as the other increases or decreases. The Pearson correlation coefficient is 1 or -1 when the two variables are distributed on the same straight line. The distance between two variables that are almost unrelated is 0. The mathematical formula is defined as:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \cdot \sum (y_i - \bar{y})^2}} \tag{3}$$

where $\bar{x}$ and $\bar{y}$ are the means of variables x and y, respectively.

The Spearman correlation coefficient is a nonparametric statistical method for measuring the monotonic relationship between two variables (i.e., the tendency of one variable to increase or decrease with the other, whether linear or not). The central idea is to assess correlation by comparing the ranked consistency (rather than specific values) of the variables. Mathematically, the Spearman coefficient is equivalent to the Pearson correlation coefficient computed by performing a rank transformation on each of the two variables. Its formula is:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2 - 1)} \tag{4}$$

2.3. Instructional model design

Taking English vocabulary teaching in secondary schools as an example, this study proposes a way to utilize NIP technology and Wikipedia to solve the dilemmas faced in the process of English vocabulary teaching.The design flow of the English vocabulary teaching model empowered by NIP is shown in Fig. 2, as well as the main steps are as follows:

(1) Clean and process the Wikipedia entries into a corpus;

(2) Perform participle or morphosyntactic parsing on the texts in the Wikipedia corpus;

(3) Train the Wikipedia corpus with the help of external tool Word2vec to generate models;

(4) When the computer receives input from the user (i.e., English teachers or students), it performs participle or morphogenetic parsing. The object vocabulary for taking out the automatic associations (which can be obtained based on lexical properties such as nouns, verbs, etc., or user-specified vocabulary) is set in advance according to the requirements. The Word2vec model is invoked, and the words with higher similarity and matching with the lexical properties of the object of automatic association are taken as alternates. Finally, the alternates are visualized and displayed to the user after combining them with example sentences and the automatically associated object lexicon.

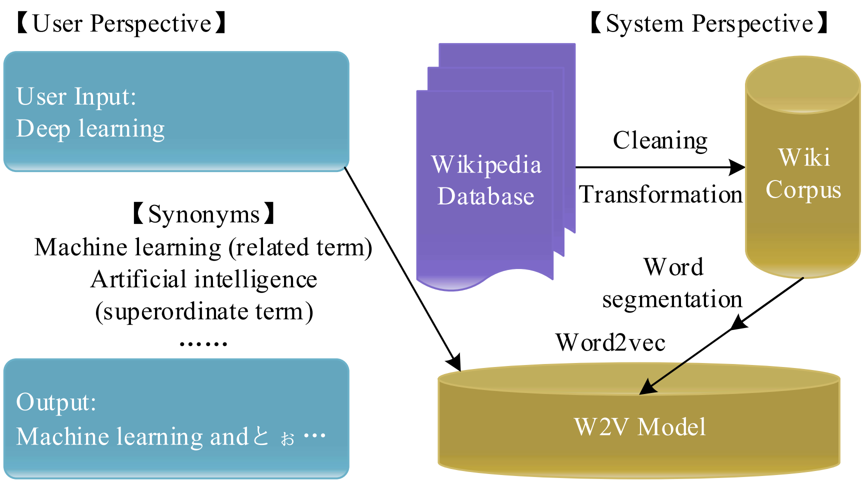

Figure 2. The English vocabulary teaching model empowered by NIP

3. Study design

3.1. Subjects of study

This study was conducted on two classes of equal level in a city G secondary school with a total of 93 students. Among them, (1) class was 47 students and (2) class was 46 students. The author randomly grouped the two classes and named them as experimental and control classes. Among them, class (1) is the experimental group and class (2) is the control group. The length of this experiment was four months, and the students in both classes were taught by the same English teacher, and the textbook used was “The New Humanistic Version of High School English Compulsory Book III”, and the teaching content and teaching schedule of the two classes basically remained the same. Influenced by objective factors such as actual teaching and exam-oriented education, the PPP (Presentation -Practice -Production) teaching mode has always been the classic mode of English teaching at the secondary school level in China. Therefore, in the experimental process, the control group mainly adopts the traditional PPP vocabulary teaching mode, while the experimental class incorporates the English vocabulary teaching mode under the NIP empowerment proposed in the previous article on the basis of the traditional PPP vocabulary teaching.

3.2. Research tools

In order to have a more comprehensive understanding of how the English vocabulary teaching mode under NIP empowerment affects secondary school students' English vocabulary learning motivation and English vocabulary learning achievement, this study chose the English Vocabulary Learning Motivation Questionnaire (reliability coefficient of 0.934 and validity KMO value of 0.781, with good reliability and validity), English vocabulary test paper and Wikipedia Corpus as the research tools to carry out the teaching practice for four months. Among them, the English Vocabulary Learning Motivation Questionnaire was designed to investigate the changes in English vocabulary learning motivation of the students in the experimental and control classes. The English Vocabulary Test Paper was designed to measure the changes in the English vocabulary scores of the students in the two classes before and after the experiment, which was mainly in the form of writing, and its scoring standard was taken from the Instructions for the English Test of the National Unified Examination for Enrollment in the General Higher Education Institutions. The experimental group was tested simultaneously with the control group to avoid the experimental results being affected by other external factors. The pre-test English vocabulary test paper is designed to determine whether there is a difference in the level of English vocabulary knowledge between the two classes, to ensure the scientific nature of the experimental conclusions and to provide data reference for the subsequent analysis. The post-test English vocabulary test paper aims to analyze the effect of the English vocabulary teaching model under NIP empowerment on students' English vocabulary learning performance. The Wikipedia corpus was used as an auxiliary teaching aid in the experiment to help students understand the use of the target words in terms of lexical properties, contexts of use and related collocations.

3.3. Data collection and organization

At the end of the experiment, the author collected the data obtained before and after the experiment and analyzed them with SPSS 26.0 software. The purpose is to test the effect of NIP empowering English vocabulary teaching on secondary school students' English vocabulary learning motivation and English vocabulary learning achievement.

In order to understand the changes in the English vocabulary learning motivation of the students in the two classes, the author distributed questionnaires on English vocabulary learning motivation to the control group and the experimental group before the experiment and after the experiment, and collected the relevant data. Both questionnaire filling were distributed on the same day, and a total of 186 questionnaires were distributed and 186 questionnaires were returned on both occasions. Among them, 93 in the pre-test phase and 93 in the post-test phase of the experiment, with a recovery rate of 100%, and the data obtained were tested and analyzed using SPSS 26.0 software.

In order to test the effect of NIP-enabled vocabulary learning on students' English vocabulary learning achievement, the author distributed English vocabulary test papers to two classes of students before and after the experiment. In this experiment, students' English vocabulary knowledge was tested in the form of English vocabulary test papers, and the data obtained were analyzed using SPSS26.0 software. In particular, the English vocabulary learning achievement of the two classes was analyzed using SPSS26.0 software, and the independent samples t-test was used to test that there was no significant difference between the English vocabulary achievement of the two classes of students before the experiment and to elaborate on the specifics of the English vocabulary learning achievement of the students in the two classes. Paired samples t-test was used to describe the specific changes in the English vocabulary learning achievement of the two classes before and after the experiment and to determine whether there was a significant change in the changes. The test papers of the two exams were selected from the previous years' questions of the National Unified Examination for Admission to Ordinary Colleges and Universities (NUAOCE) in English, and for the two exams, a total of 186 vocabulary test papers were distributed, and there were a total of 186 valid test papers with a recovery rate of 100%.

4. Analysis of the results of the study

4.1. Analysis of the results of vocabulary learning motivation

This study investigates the impact of the NIP Empowering English Vocabulary Teaching Model on students' vocabulary learning motivation through the research method of questionnaire. The researcher systematically analyzed the multidimensional effects of this teaching method on students' vocabulary learning motivation from three dimensions: affective dimension, cognitive dimension and behavioral intention. In order to control the experimental variables, the researcher conducted a pre-questionnaire survey on the students in the experimental group (EG) and the control group (CG) at the early stage of the experiment and analyzed the results with the help of SPSS27.0, and the results of the processing are shown in Table 1.The data show that the mean scores of the affective experience dimension in the initial motivation to learn in the experimental group and the control group are 13.287 and 13.525, respectively, and the standard deviations are 5.234 and 4.709.In the dimension of cognitive level, the mean values of the subjects' pre-experimental test scores in the two classes were 11.056 and 10.837 respectively, and the standard deviations of the experimental group and the control group were 3.535 and 4.012 respectively.In the dimension of behavioral tendency, the mean values of the experimental group and the control group were 33.526 and 32.299 respectively.It can be seen that the two classes of students' English vocabulary learning motivation had no significant difference before the experiment.

Table 1. Descriptive Statistics of Pre-test scores for Learning motivation

Dimension	Class	N	Mean	SD	Average standard error
Emotional experience	EG	47	13.287	5.234	0.592
	CG	46	13.525	4.709	0.438
Cognitive level	EG	47	11.056	3.535	0.472
	CG	46	10.837	4.012	0.463
Behavioral tendency	EG	47	33.526	12.375	1.587
	CG	46	32.299	10.097	1.449

The independent samples t test was conducted on the two sets of data, and the results are shown in Table 2. As can be seen from the data in the table, in terms of the dimension of affective experience, the t values of the two classes were -1.158, df = 91, and Sig. = 0.182 (>0.05), which indicated that the affective experience of the students of the two classes was at the same level before the experiment. In addition, in the cognitive level dimension, the t values of the pre-test scores of the subjects in the two classes were -0.943, df = 91, and Sig. = 0.328, and the data showed that there was not much difference between the students of the two classes in the cognitive level dimension. Meanwhile, in the dimension of behavioral tendency, the value of score t is -0.231, df = 91, and Sig. = 0.844. Based on the test data, it can be concluded that there is no significant difference in the motivation of English vocabulary learning of the students of the two classes, which ensures the practicability of the subsequent experiment and the validity of the final results.

Table 2. Independent sample *t*-test of learning motivation (Pre-test)

Learning motivation		Levin variance equivalence test		Mean equivalence t-test					95% CI of difference	
		F	Sig.	*t*	df	Sig (2-tailed)	Mean difference	Standard error difference	Lower limit	Upper limit
Emotional experience	Assumed variance	7.051	0.008	-1.158	91	0.182	-1.215	0.789	-2.835	0.372
	Equal variance not assumed			-1.152	84.2	0.180	-1.215	0.786	-2.831	0.368

Cognitive level	Assumed variance	0.486	0.527	-0.943	91	0.328	-0.680	0.692	-1.886	0.703
	Equal variance not assumed			-0.943	87.6	0.328	-0.680	0.691	-1.887	0.704
Behavioral tendency	Assumed variance	0.121	0.748	-0.231	91	0.844	-0.458	2.202	-4.389	3.205
	Equal variance not assumed			-0.230	89.2	0.844	-0.458	2.202	-4.389	3.206

After a four-month teaching experiment, the researcher conducted a second questionnaire survey on the subjects in the experimental group and the control group, and the results of the post-test questionnaire and its analysis are shown in Table 3.On the dimension of emotional experience, the mean scores of the two groups were 16.031 and 12.218, with a standard deviation of 4.232 and 5.051, respectively.On the cognitive level, the mean scores of the two groups of students were 13.352 and 10.631, and data analysis showed that the mean values of the experimental group students were significantly better than those of the control group students in the test, while the degree of dispersion in the distribution of their scores was relatively small. In addition, in terms of behavioral tendencies, the mean values of the posttest scores of the students in the two classes were 40.083 and 31.056, respectively, and the standard deviation of the students in the experimental group (6.837) was lower than that of the control class (10.399). The data show that the experimental group students' motivation to learn vocabulary changed significantly after the intervention of NIP's empowering English vocabulary teaching model.

Table 3. Descriptive statistics of post-test scores for learning motivation

Dimension	Class	N	Mean	SD	Average standard error
Emotional experience	EG	47	16.031	4.232	0.555
	CG	46	12.218	5.051	0.703
Cognitive level	EG	47	13.352	3.187	0.322
	CG	46	10.631	3.204	0.358
Behavioral tendency	EG	47	40.083	6.837	0.731
	CG	46	31.056	10.399	1.384

Independent samples t test was conducted on the scores of the vocabulary learning attitude posttest, and the specific results are shown in Table 4. The t value of the experimental group and the control group in the affective experience dimension was 4.835, df = 91, and the mean scores differed significantly, Sig. < 0.001. Meanwhile, in the cognitive level, the t value of the posttest scores was 8.267, df = 91, Sig. < 0.001. In the dimension of behavioral tendency, the t value of the post-test scores of the students in the two classes is 9.935, df = 91, Sig.<0.001. From the test data, it can be concluded that there is a significant difference in the attitudes of English vocabulary learning of the students in the two classes after a period of time of the experiment.

Table 4. Independent sample *t*-test of learning motivation (Post-test)

Learning motivation		**Levin variance equivalence test**		**Mean equivalence t-test**						
		F	**Sig.**	***t***	**df**	**Sig (2-tailed)**	**Mean difference**	**Standard error difference**	**95% CI of difference Lower limit**	**95% CI of difference Upper limit**
Emotional experience	Assumed variance	4.835	0.031	4.251	91	<0.001	3.518	0.834	1.941	5.442
	Equal variance not assumed			4.251	82.5	<0.001	3.518	0.836	1.935	5.448
Cognitive level	Assumed variance	8.267	0.004	4.381	91	<0.001	2.438	0.578	1.311	3.285
	Equal variance not assumed			4.375	86.3	<0.001	2.436	0.577	1.310	3.288
Behavioral	Assumed variance	9.935	0.001	5.371	91	<0.001	8.334	1.156	5.835	11.206

tendency	Equal variance not assumed			5.358	71.2	<0.001	8.334	1.121	5.905	11.328

In summary, the vocabulary learning motivation of the students in the experimental group changed significantly (Sig. < 0.001) after the implementation of the teaching intervention of the NIP empowering English vocabulary teaching model. Meanwhile, the affective experience, awareness level and behavioral tendency scores of the students in the control group were significantly lower than those of the experimental group. Therefore, the researcher can conclude that the traditional PPP vocabulary teaching method has a limited effect in influencing students' motivation to learn English vocabulary. Whereas, the NIP empowered English vocabulary teaching model, applied to English vocabulary teaching in secondary schools, can significantly influence students' motivation to learn English vocabulary.

4.2. Analysis of results for vocabulary scores

Based on the longitudinal comparison data between the experimental group and the control group in the English vocabulary test paper, this section focuses on the efficacy of the English vocabulary teaching model under NIP empowerment on students' vocabulary proficiency. By comparing the two tests before and after, the section aims to systematically respond to the second core topic proposed in this study, i.e., the effectiveness of the English vocabulary teaching model under the empowerment of Natural Language Processing in practice on the dimension of vocabulary achievement.

The descriptive statistics of the English vocabulary test scores of the two groups before the experiment are shown in Table 5, and the independent samples t test was conducted on the data of the two groups, and the results are shown in Table 6.According to the data in the table, it can be seen that the mean of the vocabulary test scores of the students of the experimental group and the control group are 63.251 and 62.481, respectively, and the difference of the two initial scores of the two groups is only 0.77 points. The independent samples t-test conducted by SPSS26.0 shows that Levine's chi-square test Sig. = 0.543>0.05, which satisfies the assumption of chi-square t =0.601. The statistical results show that the experimental group and the control group do not present a statistically significant difference in their English vocabulary test scores (p>0.05), which confirms that the two groups of subjects, before the implementation of the pedagogical intervention experimental vocabulary proficiency level, which has a homogeneous basis.

Table 5. Descriptive statistics of English vocabulary scores (Pre-test)

Dimension	Class	N	Mean	SD	Average standard error
Vocabulary test score	EG	47	63.251	19.203	2.505
	CG	46	62.481	22.438	2.837

Table 6. Independent sample T-test for English Vocabulary Scores (Pre-test)

Vocabulary test score		Levin variance equivalence test		Mean equivalence t-test						
		F	Sig.	*t*	df	Sig (2-tailed)	Mean difference	Standard error difference	95% CI of difference Lower limit	Upper limit
Emotional experience	Assumed variance	0.534	0.117	0.601	91	0.543	-1.081	0.831	-1.063	0.491
	Equal variance not assumed			-0.601	81.5	0.543	-1.080	0.835	-1.061	0.493

After a four-month teaching experiment, the descriptive statistics of the English vocabulary test scores of the two groups are shown in Table 7, and the results of their independent samples t tests are shown in Table 8.According to the measurements in the table, it was found that the mean values of the posttest vocabulary test scores of the students in the experimental group and in the control group were 75.081 and 66.304, respectively, and that there existed a difference in the score between the two groups of 8.777 points. In order to confirm the statistical significance of the difference, the independent samples t test was used to analyze the difference in the posttest data. The data showed that the test of chi-square of English vocabulary posttest scores showed F=0.122, which satisfied the condition of chi-square. The independent samples t test showed that the experimental group's posttest scores, were significantly better than the control group's (t =2.118, Sig.=0.029>0.05. This statistical evidence showed that the experimental group's posttest scores, were statistically different from the control group's ($p<0.05$). This verifies that the English vocabulary teaching model teaching intervention under NIP empowerment can effectively promote the English vocabulary proficiency level of secondary school students.

Table 7. Descriptive statistics of English vocabulary scores (Post-test)

Dimension	Class	N	Mean	SD	Average standard error
Vocabulary test score	EG	47	75.081	19.183	2.381
	CG	46	66.304	23.556	2.733

Table 8. Independent sample T-test for English Vocabulary Scores (Post-test)

Vocabulary test score		Levin variance equivalence test		Mean equivalence t-test						
		F	Sig.	*t*	df	Sig (2-tailed)	Mean difference	Standard error difference	95% CI of difference Lower limit	Upper limit
Emotional experience	Assumed variance	0.122	0.731	2.118	91	0.029	4.828	0.429	1.783	5.448
	Equal variance not assumed			2.118	83.6	0.029	4.825	0.431	1.781	4.552

5. Conclusion

NIP technology provides new ideas and methods for secondary school English vocabulary teaching, which can effectively solve the pain points of traditional vocabulary teaching and improve students' vocabulary learning performance and motivation through automatic association, rewriting of example sentences, reinforcement of memorization, accurate feedback and extension. However, technology is not omnipotent, teachers need to adhere to the principle of “students as the root”, and in the AI era, through the deep integration of technology and teaching objectives and students' cognitive characteristics, in order to truly play the role of technological empowerment, and to promote the transformation of secondary school English vocabulary teaching to “accurate, personalized, living”, and to provide students with a better vocabulary learning experience. Only through the deep integration of technology and students' cognitive characteristics in the AI era can we truly play the role of technology empowerment, promote the transformation of secondary English vocabulary teaching to “precision, personalization and living”, and lay a solid foundation for students' English learning.

References

1. Susanto, A. (2017). The teaching of vocabulary: A perspective. Jurnal kata, 1(2), 183.
2. Basha, M. J., Vijayakumar, S., Jayashankari, J., Alawadi, A. H., & Durdona, P. (2023). Advancements in natural language processing for text understanding. In E3S web of conferences (Vol. 399, p. 04031). EDP Sciences.
3. Beltrami, D., Gagliardi, G., Rossini Favretti, R., Ghidoni, E., Tamburini, F., & Calzà, L. (2018). Speech analysis by natural language processing techniques: a possible tool for very early detection of cognitive decline?. Frontiers in aging neuroscience, 10, 369.
4. Sumon, R. I., Uddin, S. M. I., Akter, S., Mozumder, M. A. I., Khan, M. O., & Kim, H. C. (2024). Natural language processing influence on digital socialization and linguistic interactions in the integration of the metaverse in regular social life. Electronics, 13(7), 1331.
5. Joseph, S. R., Hlomani, H., Letsholo, K., Kaniwa, F., & Sedimo, K. (2016). Natural language processing: A review. International Journal of Research in Engineering and Applied Sciences, 6(3), 207-210.
6. Kazakova, M. A., & Sultanova, A. P. (2022). Analysis of natural language processing technology: modern problems and approaches. Advanced Engineering Research (Rostov-on-Don), 22(2), 169-176.
7. Yan, H., Xiao, J., Zhang, B., Yang, L., & Qu, P. (2024). The application of natural language processing technology in the era of big data. Journal of Industrial Engineering and Applied Science, 2(3), 20-27.

8. Kang, Y., Cai, Z., Tan, C. W., Huang, Q., & Liu, H. (2020). Natural language processing (NLP) in management research: A literature review. Journal of Management Analytics, 7(2), 139-172.
9. Jang, H., Jeong, Y., & Yoon, B. (2021). TechWord: Development of a technology lexical database for structuring textual technology information based on natural language processing. Expert Systems with Applications, 164, 114042.
10. Allen, L. K., & McNamara, D. S. (2015). You Are Your Words: Modeling Students' Vocabulary Knowledge with Natural Language Processing Tools. International Educational Data Mining Society.
11. Oraif, I. (2024). Natural language processing (NLP) and EFL learning: A case study based on deep learning. Journal of Language Teaching and Research, 15(1), 201-208.
12. Longjiang, D. (2021). Test of English vocabulary recognition based on natural language processing and corpus system. Journal of Intelligent & Fuzzy Systems, 40(4), 7073-7084.