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Article

A Study on the Synergistic Development of Declarative Lexical Knowledge Representation and Cognitive Abilities in Adult EFL Learners Empowered by Word Embedding Models in the Era of Data Intelligence

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Abstract: In recent years, artificial intelligence technology has made significant strides in the field of education. Word embedding models, as a type of language generation model based on natural language processing, possess the ability to engage in real-time dialogue with students, offering a new form of support for vocabulary learning among English learners. Using the PyTorch deep learning framework, we constructed a word embedding model based on neural networks to design a word association memory system environment and conducted a 12-week experimental study involving 60 adult EFL learners. The results show that the average total scores for the participants' declarative vocabulary knowledge breadth and depth tests were 92.11 and 105.19, respectively, and that the word embedding model was able to enhance the development of cognitive abilities. Furthermore, at the macro level, the scale of the second-language vocabulary semantic network expanded, its diameter increased, and its small-world characteristics were enhanced, while the network's density and centrality decreased. At the macro level, the network's modularity increased, and semantic partitioning became clearer. At the micro level, central words remained relatively stable, but the specific positions of most words within the network fluctuated significantly; English proficiency did not affect vocabulary connections. Strategic awareness can be strengthened, learning interest stimulated, language input increased, vocabulary strategies optimized, language output emphasized, and cooperative learning encouraged.

Keywords: word embedding model; word association memory; declarative vocabulary knowledge representation; cognitive synergy; adult English learners

1. Introduction

Current approaches to adult English learning emphasize the development of practical language skills, with reform efforts focused on cultivating listening and speaking abilities—an approach that is indeed feasible and effective for general learners [1-2]. However, for the majority of learners, who have weak foundational English skills and lack motivation, simply increasing the volume of listening practice results in more passive listening. They pick up only vague information and a few new words, leaving them unable to provide feedback [3-4]. In terms of speaking practice, students merely mechanically repeat general conversational phrases provided in textbooks, yet real-life communication differs significantly from textbook examples. Consequently, learners remain unable to express themselves fluently in actual situations [5-7]. Over time, despite considerable effort, learners see little corresponding progress; their interest in English wanes, and the outcomes of instruction may well run counter to the intended goals. At its root, this stems from insufficient mastery of vocabulary knowledge.

Declarative lexical knowledge representation is a crucial aspect of an individual's knowledge structure. Not only does it hold immense value in itself, but it also serves as the foundation and initial stage for adult English learners' acquisition of procedural knowledge, playing a significant role in the coordinated development of learners' cognitive abilities [8-10]. Cognitive psychologists argue that declarative knowledge is a crucial component of learning ability [11]. Therefore, in the era of data intelligence, research exploring the synergistic development of declarative lexical knowledge representations and cognitive abilities in adult English learners, empowered by word embedding models, holds significant practical importance.

This paper trains a model on a corpus of English text to be learned, generates word embedding vectors, calculates the similarity between English words, and performs word association analysis based on these similarity scores. A backend system was built using Spring Boot, and frontend pages were developed using Vue.js to design and implement a word association memory system. Within the constructed word embedding-based English learning environment, a 12-week experiment was conducted with 60 adult EFL learners. The study involved working memory capacity tests, declarative lexical knowledge representation tests, semantic network and social network analysis of vocabulary, and event-related potential analysis. The aim was to investigate the mechanisms underlying the synergistic development of declarative lexical knowledge representation and cognitive abilities in adult English learners within the word embedding model environment.

2. Basic concepts

2.1. Word Embedding Vector

The purpose of the word association memory system is to improve students' vocabulary retention efficiency for specific learning objectives. Therefore, before generating word embedding vectors, it is necessary to first collect corpus data corresponding to the learning scenarios based on the learning objectives. After collecting the corpus data, it must be preprocessed to meet the input requirements of the neural network. The steps for corpus preprocessing are shown in Figure 1.

During data preprocessing, the collected corpus data is first merged into a single file, and unnecessary characters—such as commas, periods, and numbers—are removed. Next, stop words in the English text are removed, such as "a," "the," and "of." A vocabulary is constructed based on the remaining corpus data. Following the N-gram approach, triplets are formed (treating three consecutive words as a triplet, where the first two words are used to predict the third). Finally, input features and output labels are constructed according to the input format requirements of the neural network. After data preprocessing, a corpus suitable for training is established. This corpus is then fed into a neural network-based word embedding model to train word embedding vectors tailored to a specific learning scenario.

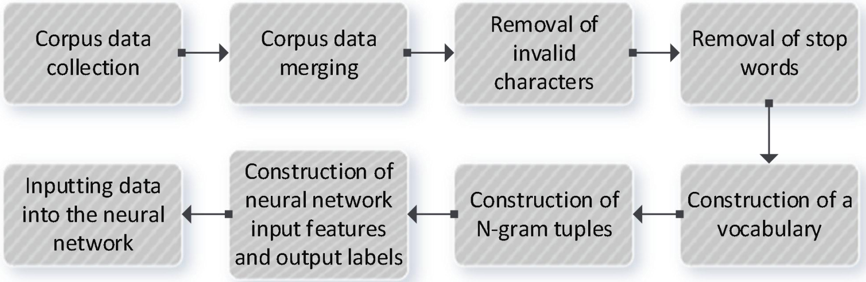


Figure 1. Corpus data processing process

High-dimensional dense word embedding vectors are typically generated through neural network training. To obtain word embedding vectors tailored to specific learning scenarios, this paper uses the PyTorch framework to construct a word embedding model based on neural network technology. The system employs the N-gram approach, treating three consecutive words as a single sample and using the first two words to predict the third. Therefore, two words are required as input. The embedding layer converts these two words into corresponding word embedding vectors, which are then passed through the output layer to generate an output vector (the dimension of the output vector is equal to the length of the vocabulary). Finally, the softmax function is applied to output the probability of each word in the vocabulary being the predicted word. During training, the neural network uses the cross-entropy loss function and the stochastic gradient descent method as the optimization algorithm, with a learning rate of 0.01.

2.2. Word Association Memory System

Once the word embedding vectors are obtained, it is possible to calculate the associations between words and, consequently, use these associations to facilitate word learning. To enhance user convenience, this paper designs and implements a word association memory system based on Spring Boot and Vue. The system comprises a word management module, an association calculation module, and a user management module. The system architecture is shown in Figure 2.

The word management module is responsible for managing learning scenarios and the word information associated with those scenarios. Word information includes the word's definition and its embedding vector. Note that the word vectors for the same word may differ across different learning scenarios.

The Correlation Calculation Module calculates the relevance between words and identifies the top N words most closely related to the currently selected word. To prevent the system from repeatedly recommending words the user has already learned, the system applies a weighting adjustment to the relevance of previously learned words, thereby prioritizing the recommendation of unstudied related words.

The User Management Module handles user login, registration, and management operations, and records the words users have learned in various contexts, along with the time spent learning them.

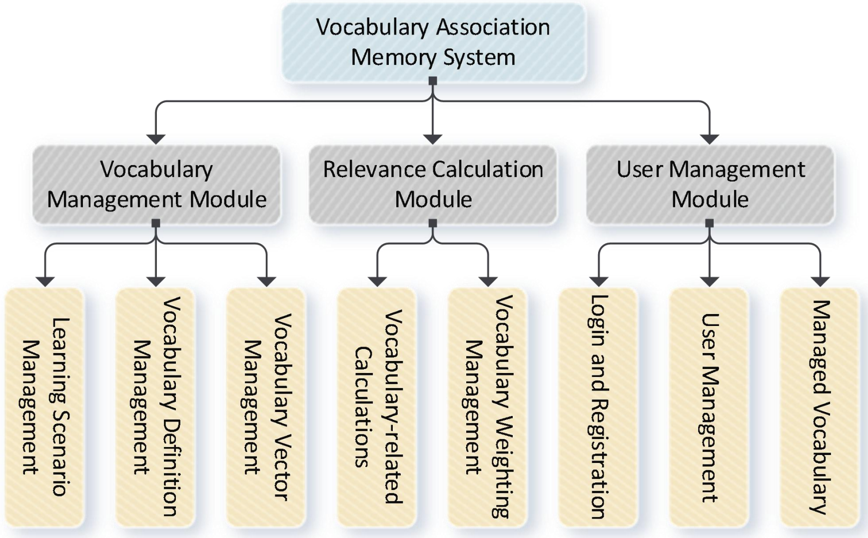


Figure 2. The word association memory system structure

3. Research Design

3.1. Study Population

This study focuses on adult EFL learners (aged 25–45) and aims to examine the synergistic development of their declarative lexical knowledge representations and cognitive abilities within a vocabulary memory system based on the word embedding model. Participants were recruited from an open university and an online language learning community, with the following inclusion criteria:

Language proficiency: Intermediate to advanced English proficiency, with Vocabulary Level Test (VLT) scores ranging from 3,000 to 5,000 word items; participants have not yet reached the level of automaticity typical of native speakers and have room for improvement. Age and Educational Background: Aged 25–45, holding an associate's degree or higher; no systematic English study within the past year; and no prior exposure to word embedding-based intelligent learning tools. Cognitive and Health Status: No history of attention deficit, dyslexia, or neurological disorders; normal visual acuity or corrected vision; right-handed (for ERP experiments). Informed Consent: Voluntary participation and signing of an informed consent form, with a commitment to complete the entire experimental process.

A total of 60 eligible participants were recruited and randomly assigned to an experimental group (n = 30, using a word memory system based on word embedding models) and a control group (n = 30, using a traditional digital word list). There were no significant differences between the two groups in terms of age, gender, educational background, pre-test vocabulary size, or working memory capacity ($P > 0.05$). For the ERP sub-experiment, 20 participants from the experimental group (10 males and 10 females) were selected for EEG recording.

3.2. Testing and Data Collection

(1) Working Memory Capacity Test

To measure cognitive ability, this experiment drew on research methods used by relevant scholars and employed a reading span test to assess the participants' working memory capacity. The Reading Span Test assesses a participant's ability to simultaneously store and process information and is one of the key methods for evaluating working memory capacity. The test consists of 60 complex English sentences that scroll across the computer screen. The test sentences are divided into four major groups, each comprising five subgroups, with the number of sentences per subgroup increasing from one to five. Following each source sentence, a judgment sentence is presented. The source and judgment sentences may agree or disagree in meaning, with this occurrence randomized. Regardless of whether the judgment is correct, a new word appears on the screen one second later, followed by the prompt "Please recall the word from just now." This process repeats until the testing for each subgroup is complete. The scoring criteria for this working memory capacity test are based on the judgment of sentence meaning and the recall of the final word. There are 60 test sentences. Correct judgment of sentence meaning earns 1 point, and correct recall of the word at the end of the sentence earns 1 point, for a total of 120 points.

(2) Declarative Vocabulary Knowledge Representation Test

The Declarative Vocabulary Knowledge Representation Test was designed based on the principles and methods of the A Vocabulary Size Test. The number of test words was determined using a 50:1 ratio, and words were selected in order of frequency, resulting in a total of 50 words. To prevent test-takers from guessing the correct answer by selecting one of four options, we designed five answer choices: one correct answer among the first four, three distractors, and a fifth option labeled "E: Do not know". Participants receive one point for each correct answer. The test's reliability coefficient is 0.772.

The Declarative Vocabulary Depth Knowledge Representation Test was designed based on the framework of the Vocabulary Knowledge Scales, using vocabulary included in the new English curriculum standards. This test is primarily used to measure the process and extent of vocabulary knowledge acquisition for second-language learners. The questionnaire requires participants to complete a five-step self-assessment: never seen the word; seen it but do not know the meaning; seen it and can provide a possible translation or synonym; recognize the word and can provide a translation or synonym; and can construct a sentence using the word. A total of 80 words were selected, including 25 adjectives, 24 nouns, 25 verbs, 3 adverbs, and 3 conjunctions. Participants marked their responses according to the instructions, thereby measuring the process and extent of their in-depth knowledge acquisition of a word. A five-point rating scale was designed, with a maximum score of 5 and a minimum score of 1. Scores for each question were determined based on the participant's responses, and the sum of the 40 questions constituted the participant's vocabulary depth test score. The reliability coefficient of the questionnaire was 0.793.

(3) Concor Analysis of Lexical Semantic Networks

In a free association task (where participants are given a set of keywords such as occupation, emotion, and education, and asked to associate with each word for 2 minutes while recording all output words), the Concor function in the network analysis software Ucinet partitions all nodes based on the similarity of connections between them, grouping nodes with similar connection patterns into the same cluster. Concor works by calculating correlation coefficients to assess the similarity of connections established between two nodes within the network. Specifically, the correlation coefficients between each pair of nodes are first calculated to construct a correlation matrix. The maximum value in a cell of this matrix is 1, indicating that the connection patterns of the two nodes (how many nodes they are connected to and which specific nodes) are exactly the same; the minimum value is -1, indicating that the connection patterns are completely different. The values in the correlation matrix typically range between 1 and -1; the closer a value is to 1, the higher the similarity between the two nodes' connectivity patterns, while the closer it is to -1, the greater the difference. Although generally only a few cells will have values of 1 or -1, if the correlation matrix is iterated repeatedly, eventually all cell values will converge to 1 or -1. Nodes corresponding to the value 1 are highly similar and are assigned to the same cluster, while those corresponding to -1 are less similar and are assigned to another cluster, thereby dividing all nodes into two major groups. Using the same method, each group is further subdivided: the two groups are divided into four, the four into eight, and so on, until the smallest group contains only three members. The result of the Concor analysis is that nodes are divided into multiple clusters, with nodes within the same cluster exhibiting similar connectivity patterns and comparable positions within the network.

(4) ERP Experiment

A task measuring declarative lexical knowledge representations in adult learners using a word-embedding model, where the target word is the lexical representation and the prime is either the English equivalent or a non-equivalent translation of the target word. First, a fixation mark “+” was presented in the center of the computer screen for 250 ms to alert the participant. Subsequently, the prime was presented for 500 ms, followed by the target word for 500 ms. After the participant responded, a random blank screen appeared for 600–800 ms, followed by the next trial. If the participant did not respond within 500 ms, a blank screen appeared for 1000 ms.

The experiment was conducted in the Language and Brain Science Laboratory at a university, with each participant completing the task individually. Prior to the experiment, participants were informed that two words would appear sequentially in the center of the computer screen, and their task was to quickly and accurately determine whether the second word was the corresponding translation of the first. If so, they were to press the “F” key on the keyboard with their left index finger; otherwise, they were to press the “J” key with their right index finger. Hand assignments were cross-balanced across participants. After every 64 trials, the system automatically prompted the participant to take a break; the participant could resume the experiment by pressing the spacebar. To help participants familiarize themselves with the experimental procedure, practice trials were designed prior to the formal experiment, using materials similar to those in the main experiment. Each session lasted approximately half an hour.

The experimental equipment consists of a Neuroscan Curry 8 workstation. Reference electrodes are placed on both mastoid processes to record horizontal and vertical eye movements. The bandpass filter is set to 0.01–100 Hz, the sampling mode is DC, the sampling rate is 1000 Hz per channel, and scalp impedance is less than 5 kΩ. A standardized electrode cap is used to record 32-channel electroencephalogram (EEG).

3.3. Data Analysis

After collecting and organizing all the data, SPSS 17.0 statistical software was used to perform descriptive statistical analysis, independent samples t-tests, and one-way analysis of variance (ANOVA). To accurately interpret the relationship between participants’ declarative lexical knowledge representations and cognitive abilities, the author also conducted supplementary qualitative research on the test batteries. A 5 (brain region) × 2 (hemisphere) × 2 (priming type) repeated-measures ANOVA was performed on the mean amplitude of the N400 component in the collected ERP data. Changes in the lexical representation structure of adult English learners before and after word embedding model training were calculated, including network density and node centrality.

4. Experimental Results and Analysis

4.1. Representation of Declarative Vocabulary Knowledge

To assess the breadth of vocabulary knowledge among English learners, the author analyzed the test scores of 60 participants to determine the overall status of their declarative vocabulary knowledge. The specific results of the declarative vocabulary knowledge are shown in Table 1. The mean total score for the vocabulary breadth test was 92.11 points, with a minimum score of 85 and a maximum score of 138. According to the evaluation criteria—which stipulate that a correct response rate of 80% or higher in each dimension of lexical breadth indicates a solid grasp of vocabulary at that level—the overall lexical breadth of the participants did not reach a satisfactory level [mean = 92.11 < 120 (150 × 80%)]. Furthermore, regarding the five dimensions of lexical knowledge breadth, the average total scores for each dimension, ranked from highest to lowest, are as follows: 5,000-word vocabulary (27.72 points), 2,000-word vocabulary (26.68 points), 3,000-word vocabulary (26.35 points), academic vocabulary (20.11 points), and 10,000-word vocabulary (18.52 points). According to the evaluation criteria, the average total scores for the test subjects’ vocabulary breadth across the 2,000-word, 3,000-word, and 5,000-word dimensions all exceeded 24 points (24 = 30 × 80%). This indicates that the students have achieved a solid grasp of vocabulary knowledge across these three dimensions. However, the average total scores for both the 10,000-word vocabulary level and academic vocabulary dimensions were below 24 points (24 = 30 × 80%), indicating that students’ mastery of the 10,000-word vocabulary and academic vocabulary is not yet solid, and that the 10,000-word vocabulary, in particular, is somewhat challenging for them. Furthermore, the study found that compared to the 2,000-word, 3,000-word, and 5,000-word vocabulary levels, students’ mastery of the 10,000-word vocabulary was relatively weak.

Table 1. The overall situation of the knowledge of the stated vocabulary

	N	Mean	Minimum	Maximum	SD

2000 words	60	26.68	20	30	3.052
3000 words	60	26.35	18	30	4.233
5000 words	60	27.72	20	30	3.185
10,000 words	60	18.52	10	26	3.789
Academic vocabulary	60	20.11	15	25	5.235
Vocabulary knowledge span	60	92.11	85	138	11.456

To assess the depth of vocabulary knowledge among English learners, the author analyzed the scores on the vocabulary depth test administered to 60 participants, thereby obtaining an overall picture of their vocabulary depth. The specific results are shown in Table 2. The average total score on the vocabulary depth test was 105.19 points, with a minimum score of 88 and a maximum score of 142. According to the five-level standards for measuring students' vocabulary depth, the total score for the vocabulary depth test is 160 points. Scores below 60% of the total score—that is, below 96 points—are classified as low level; scores between 96 and 112 are classified as lower-middle level, scores between 112 and 128 as middle level, scores between 128 and 144 as upper-middle level, and scores above 144 as high level. It can be seen that the overall level of the participants' vocabulary knowledge depth is only at the lower-middle level (96 < average score = 105.19 < 112).

In addition, this in-depth vocabulary assessment consists primarily of two sections: the in-depth semantic knowledge test and the in-depth collocation knowledge test. For the semantic section, the average total score was 48.12 points, with a minimum score of 35 points and a maximum score of 70 points. For the collocation section, the average total score was 56.76 points, with a minimum score of 50 points and a maximum score of 71 points. In the vocabulary knowledge depth test, both the semantics and collocation sections are worth 80 points each. Students must score at least 60% in each of these two areas—that is, 48 points or higher—to pass; otherwise, they fail. Therefore, in this test, the examinees demonstrated a good grasp of vocabulary depth in the semantics section (average score = 48.12 > 48), while their mastery of vocabulary depth in the collocation section was relatively better (average score = 56.76 > 48).

Table 2. The overall situation of the knowledge depth of the declarative vocabulary

	N	**Mean**	**Minimum**	**Maximum**	**SD**
Semantics	60	48.12	35	70	7.825
Collocation	60	56.76	50	71	8.259
Vocabulary knowledge depth	60	105.19	88	142	16.151

4.2. Cognitive Development

To examine whether the environment in which the word embedding model is applied affects the working memory capacity (one of the core indicators of cognitive ability) of adult EFL learners, this study administered pre- and post-tests using the Working Memory Span Test to all participants. The Working Memory Span Test consists of 42 items, including arithmetic equation judgment and word recall. One point is awarded for each correctly judged equation and one point for each correctly recalled word, for a total of 84 points. Participants' working memory capacity scores reflect their information processing ability (as measured by arithmetic judgment scores) and information storage ability (as measured by word recall scores). The working memory capacity score is calculated by dividing the sum of information processing and storage scores by the total number of items. Descriptive statistics for working memory capacity in both groups are shown in Table 3. The significance level of the independent samples t-test comparing the mean scores between the experimental and control groups was 0.000, indicating a significant difference in working memory scores between the two groups. Therefore, the experimental group demonstrated superior cognitive development compared to the control group, suggesting that the word embedding model can enhance cognitive development.

Table 3. The two groups operate the span description statistics

Working memory capacity	**N**	**Mean**	**SD**
Experimental group	30	0.6712	0.8899
Control group	30	0.4535	0.0692

4.3. Changes in the Structural Characteristics of Lexical Semantic Representation Networks

(1) Changes in the Macro-Structure of Lexical Semantic Networks

Table 4 presents the macro-level parameters of the lexical semantic networks for "occupation" vocabulary across the two groups. A comparison of the structural characteristics of the second-language lexical semantic representation networks between the two groups reveals the following features:

a) Both networks are small-world networks (with small-world indices greater than 1), but the experimental group's network exhibits a stronger small-world characteristic (5.678 > 3.011). The average path length in the lexical semantic networks of both groups is short, not exceeding 3, indicating that, on average, only one or two intermediate words are needed to establish a connection between any two words.

b) The experimental group's network shows significant expansion, as it contains more word nodes, has a longer network diameter, and exhibits a longer average path length.

c) The semantic connectivity density was lower in the experimental group's network, as its average weighted degree (24.115) was lower than that of the control group (47.118), and its network density (0.049) was also lower than that of the control group (0.149).

d) The word embedding model reduced the centrality of English learners' networks. To compare network centrality, this study followed standard practices in network structure research by constructing 100 random networks with the same size and density as the control and experimental group networks. The centrality of each random network was calculated, yielding 100 random values for centrality. The difference between the centrality of the control and experimental group networks and their corresponding 100 random values was then calculated to obtain the expected centrality for each group. A paired-sample t-test was conducted on the expected values of the two groups after controlling for random factors. The results showed that the centrality of the experimental group's lexical semantic network was significantly lower than that of the control group (t = -2.539, p = 0.015).

Table 4. The overall structure of the two groups of lexical semantic networks

Parameter	**Control group**	**Experimental group**
Scale	53	166
Density	0.149	0.049
Diameter	5	7
Average weighting	47.118	24.115
Mean path length	2.585	2.823
Central potential (%)	8.35	2.05*
Little world index	3.011	5.678
Modular degree	0.188	0.312
Random network module degree	0.271	0.311

(2) Stability of Central Nodes in Lexical Semantic Networks

To identify the central lexical items representing "occupations" for English learners, we conducted a centrality analysis on the lexical semantic networks of the two groups and identified the top 12 words by centrality (i.e., those with a centrality score greater than 40). The central lexical items in the two groups' lexical semantic networks are shown in Table 5. The results show that the overlap rate of central words between the two networks reached 66.67%, indicating that the central words exhibit good stability across the two levels of semantic fluency tests. Additionally, an independent samples t-test revealed a significant decrease in standardized centrality (t = 10.551, p = 0.000). This finding is consistent with the earlier observation of decreased network density, suggesting that although the total number of nodes increased, the density of semantic connections did not increase proportionally.

Although the central nodes were shared by the lexical semantic networks of both groups, indicating good stability, the centrality of other nodes showed significant fluctuations. For example, words such as "pilot," "pianist," "violinist," and "computer programmer" appeared frequently in the control group and occupied central positions in the lexical semantic network; however, their centrality in the experimental group dropped to 25th, 40th, 45th, and 47th place, respectively, making them peripheral words. The new words entering the top 12 in the experimental group were "student," "nurse," "singer," and "artist." These words are simple to spell and have strong connections to high-frequency words (such as "teacher," "doctor," and "actor"); they have already been integrated into the critical framework of the network, but their centrality has not yet fully manifested in the control group's network.

Table 5. The central words in the two groups of lexical semantic networks

Control group			**Experimental group**		
Vocabulary	Center degree	Standardized center	Vocabulary	Center degree	Standardized center
Doctor	130	9.82	**Doctor**	135	2.15
Cook	103	8.05	**Teacher**	132	2.19

Pilot	103	7.83	Student	101	1.64
Pianist	94	7.21	**Actor**	74	1.23
Teacher	105	7.21	**Engineer**	73	1.22
Driver	94	7.01	**Scientist**	64	1.09
Violinist	86	6.59	**Driver**	60	0.97
Engineer	92	6.39	**Worker**	53	0.89
Computer programmer	62	4.58	Singer	58	0.86
Scientist	57	3.96	Nurse	46	0.75
Actor	44	3.14	Artist	44	0.77
Worker	44	3.11	**Cook**	42	0.78

4.4. ERP Analysis of Declarative Vocabulary Representation

(1) Reaction Time and Accuracy

Table 6 presents the reaction times and accuracy scores for the high-level and low-level groups. In this experiment, trials falling outside three standard deviations were excluded, resulting in a total of 93 trials, accounting for 2.62% of the total trials. Analysis of variance (ANOVA) revealed a significant main effect of priming type, F = 29.885, $p < 0.01$. Reaction times in the irrelevant group were significantly longer than those in the relevant group. Neither the main effect of declarative vocabulary knowledge level nor the interaction between priming type and declarative vocabulary knowledge level was significant. Analysis of variance (ANOVA) revealed a significant main effect of priming type, F = 82.055, $p < 0.01$. The accuracy rate in the irrelevant group was significantly lower than that in the relevant group. The main effects of the level of declarative lexical knowledge representation, priming type, and trilingual proficiency, as well as their interactions, were all insignificant. Based on the reaction times and accuracy rates in this experiment, the irrelevant group exhibited significantly longer reaction times and significantly lower accuracy rates than the relevant group. This indicates that when the English prime and the Chinese target word are in a translation relationship, the activation of the prime's lexical representation not only accelerates the retrieval of the target word's lexical representation but also improves accuracy. Therefore, based on the behavioral data, a significant cross-linguistic lexical priming effect was observed in the experiment—that is, a priming effect arising from the connection between the prime and the target word at the lexical level in a lexical judgment task.

Table 6. The high level group and the low level group reacted (ms) and accuracy (%)

Trial classification		**High level**	**Low level**
Independent group reaction	MEAN	895(135)	1025(552)
Dependent group reaction	MEAN	755(123)	841(342)
Independent - Dependent group reaction	MEAN	145(20)	175(200)
	p	0.000	0.000
Irrelevant group accuracy	MEAN	87.1(5.5)	84.8(9.2)
Relevant group accuracy	MEAN	95.5(4.5)	92.7(8.9)
Irrelevant - Relevant group accuracy	MEAN	-8.3(1.7)	-7.9(0.2)
	p	0.000	0.000

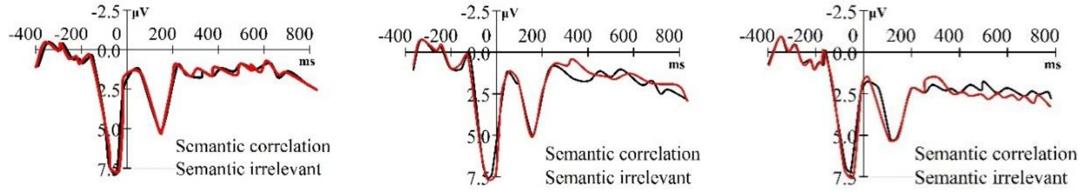
(2) ERP Data

Figure 3 shows the ERP waveforms for the target word produced by English learners under irrelevant and relevant conditions. Based on the waveforms, a 350–650 ms time window was selected to analyze the N400.

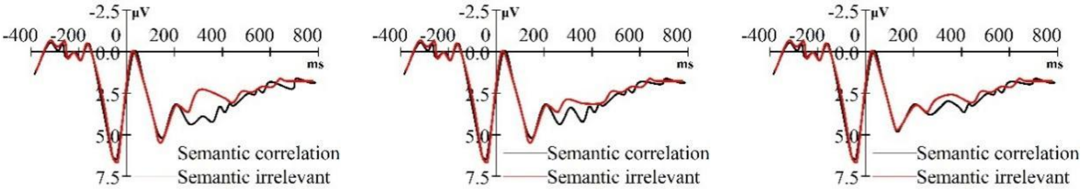
A 5×2×2×2 repeated-measures analysis of variance (ANOVA) conducted on ten electrodes across five brain regions and both hemispheres revealed a significant main effect of prime type (F=17.89, $p<0.05$; 2.22±0.33 μV vs. 3.08±0.39 μV), with the irrelevant condition eliciting a significantly larger N400 amplitude than the relevant condition. The interaction between prime type and brain region was significant (F=8.82, $p<0.05$). Further simple effects analysis revealed that the prime type effect was not significant in the frontal region ($p>0.1$); however, it was significant in the anterior-central, central, posterior-central, and posterior regions ($p<0.01$), with larger amplitudes observed in the irrelevant condition.

A 5×2×2 repeated-measures analysis of variance (ANOVA) conducted on the five electrodes of the midline revealed a significant main effect of stimulus type (F=23.03, $p<0.01$; 2.75±0.48 μV vs. 3.99±0.51 μV), with the irrelevant condition eliciting a significantly larger N400 amplitude than the relevant condition. The interaction between priming type and electrode was significant (F = 3.99, $p < 0.05$).

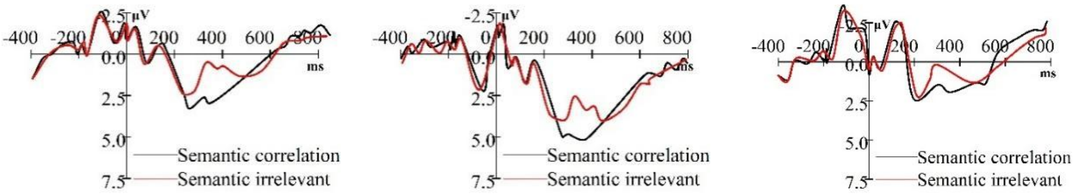
Further simple effects analysis revealed that the priming type effect was significant across all five electrodes ($p < 0.05$), with larger amplitudes observed in the irrelevant condition.



(a) F3 (b) Fz (c) F4



(d) C3 (e) Cz (f) C4



(g) C3 (h) Cz (i) C4

Figure 3. ERP waveform generated by English learners' target words

Based on the EEG data, within the 350–650 ms time window, the irrelevant condition elicited a significantly larger N400 amplitude than the relevant condition across all electrodes in the four brain regions (antero-central, central, centro-posterior, and posterior) and the midline. The N400 effect observed in this experiment may reflect a reduction in the difficulty of lexical representation retrieval. The significantly larger N400 amplitude elicited by the irrelevant condition compared to the relevant condition suggests that the activation of the lexical representation of the priming word in the relevant condition facilitated the cognitive processing of the target word's lexical representation by the participants. Reaction times, accuracy, and N400 metrics consistently indicate that a cross-linguistic lexical priming effect was generated in the experiment. There is strong connectivity in the lexical representation of declarative vocabulary among English learners. Furthermore, participants' English proficiency did not affect reaction times, accuracy, or N400 amplitude. Therefore, the connectivity strength of the lexical layer for declarative vocabulary is not influenced by English proficiency.

English vocabulary acquisition among adult learners relies primarily on the learners themselves. Teachers should provide strategic guidance tailored to the current online environment to effectively enhance learners' vocabulary acquisition outcomes. With the rapid development of internet and information technology, we must continue to explore and experiment to identify effective pathways for vocabulary learning in this new context.

5. Conclusion and Discussion

The empirical results of this experiment indicate that word embedding models have a positive impact on vocabulary learning among adult English learners. Using word embedding models to support vocabulary learning can enhance students' representational levels of declarative vocabulary knowledge and promote the development of their English cognitive abilities. At the same time, students expressed high satisfaction with the intelligent assistance provided by the word embedding model, noting that it enhances the enjoyment and personalization of the learning experience. Compared to traditional methods, the word embedding approach exhibits reduced centrality in the semantic network of declarative lexical knowledge. Supported by central nodes, new nodes selectively connect to existing ones, leading to increased network partitioning. The selective nature of connections between nodes results in the nonlinear characteristics of network development, which is the underlying reason for the complex dynamic patterns observed in the development of the mental lexicon. Declarative vocabulary representations are directly interconnected, and cognitive levels do not influence these connections.

Overall, the Word embedding model facilitates the synergistic development of declarative vocabulary knowledge representations and cognitive abilities among adult English learners. In summary, word embedding models can serve as AI-assisted tools to help adult English learners resolve doubts and provide contextual examples during the vocabulary learning process; however, they cannot completely replace traditional learning methods and interpersonal communication. The best approach is to combine word embedding models with other learning resources and real-world communication to enhance learners' English vocabulary proficiency from multiple perspectives.

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