Empirical Analysis of Knowledge Graph-Based Adaptive Teaching in English Vocabulary Education

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Abstract: Traditional college English vocabulary teaching is characterized by fragmented knowledge presentation, unified rigid instruction, and disjointed theoretical and practical training. These drawbacks lead to learners' mechanical rote memorization, redundant cognitive consumption and poor long-term vocabulary retention. In the context of intelligent education, knowledge graph (KG) technology can visualize lexical semantic associations and support personalized learning, effectively remedying the deficiencies of conventional vocabulary instruction. This study constructs a KG-based adaptive English vocabulary teaching framework and develops a three-stage teaching workflow covering pre-class exploration, in-class targeted interpretation and post-class consolidation. A 16-week quasi-experiment was conducted with 60 English major undergraduates, who were equally randomized into an experimental group receiving KG adaptive teaching and a control group adopting traditional linear teaching. Multiple quantitative and qualitative instruments, including vocabulary tests, cognitive load scales, learning logs and interviews, were applied for data collection. The results demonstrate that KG-enabled adaptive teaching significantly improves students' vocabulary proficiency, semantic understanding depth and long-term retention. It also reduces extraneous cognitive load, optimizes cognitive resource allocation and facilitates active lexical knowledge construction. This study validates the effectiveness of KG-based adaptive teaching in English vocabulary education, providing reliable empirical evidence and practical references for intelligent foreign language teaching reform.

Keywords: Knowledge Graph; Adaptive Teaching; English Vocabulary Education; Smart Teaching; Cognitive Load; Teaching Empirical Analysis

1. Introduction

With the advancement of educational digitalization, college English teaching is shifting toward intelligent and personalized learning. Vocabulary serves as the core foundation of English language competence, yet traditional vocabulary teaching still faces notable drawbacks. Dominated by textbook-based linear instruction and mechanical rote memorization, it isolates the morphological, semantic, collocation and pragmatic relations of vocabulary knowledge. Such rigid one-size-fits-all teaching leads to fragmented lexical cognition, low learning efficiency and poor long-term vocabulary retention, failing to meet the demand for student-centered adaptive learning.

Knowledge graph (KG) technology can visualize implicit semantic associations of vocabulary, construct systematic lexical knowledge networks, and support personalized learning diagnosis and path recommendation. Although existing studies have confirmed the potential of KG in vocabulary teaching, most focus on theoretical design and technical exploration, while empirical studies on its adaptive teaching effects and cognitive optimization mechanisms remain insufficient.

To fill this research gap, this study constructs a KG-based adaptive English vocabulary teaching framework. Through a 16-week quasi-experiment, it systematically explores the teaching effectiveness and cognitive optimization mechanism of the proposed method, and three core research questions are put forward as follows.

RQ1: How to construct a knowledge graph-based adaptive teaching framework suitable for college English vocabulary education?

RQ2: Compared with traditional teaching, can KG-enabled adaptive teaching significantly improve students' comprehensive vocabulary competence, including vocabulary breadth, semantic depth and long-term retention?
RQ3: How does adaptive KG teaching optimize students' multi-dimensional cognitive load and reshape learners' lexical cognitive processing mechanism?

2. Theoretical Framework and Rationale

2.1 Cognitive Load Theory (CLT)

Cognitive Load Theory (CLT) categorizes learning cognition into three dimensions: intrinsic cognitive load determined by knowledge complexity, extraneous cognitive load induced by unreasonable instructional design, and germane cognitive load generated during knowledge schema construction. Effective teaching design aims to reduce extraneous load, stabilize intrinsic load, and maximize germane load for deep learning. Traditional vocabulary teaching scatters systematic lexical knowledge, forcing students to consume substantial cognitive resources in sorting out implicit semantic relations and resulting in severe cognitive redundancy. As a visualized semantic tool, knowledge graphs externalize implicit lexical logic, reduce ineffective cognitive consumption, and allow learners to allocate more cognitive resources to deep semantic understanding and knowledge internalization [1,2].

2.2 Constructivist Learning Theory

Constructivist learning theory holds that learning is an active knowledge construction process rather than passive knowledge acceptance. English vocabulary knowledge features systematicity and associativity, and effective lexical learning relies on continuous iteration and optimization of personal knowledge schemas. Traditional teaching lacks effective learning scaffolding, hindering learners' association between new and existing lexical knowledge. Knowledge graphs provide visualized interactive scaffolding for adaptive vocabulary learning, enabling students to actively explore lexical correlation rules and realize meaningful personalized learning progression [3,4].

2.3 Adaptive Learning Theory

Adaptive learning theory advocates differentiated teaching design based on individual learning differences. Traditional unified vocabulary teaching ignores students' differentiated lexical mastery and personalized learning weaknesses. By analyzing learning behavior and error data, knowledge graphs can accurately identify learners' weak vocabulary knowledge points, push personalized learning paths and targeted consolidation tasks, and realize student-centered adaptive differentiated teaching [5]. The cognitive mechanism and learning advantages of knowledge graph (KG)-driven adaptive vocabulary learning compared with traditional vocabulary learning are intuitively illustrated in Figure 1.

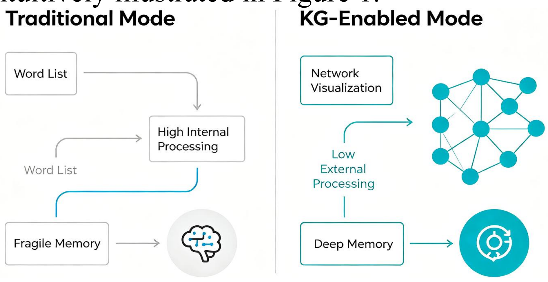

Figure 1. Cognitive Differences between Traditional and KG-Driven Adaptive Vocabulary Learning

This schematic diagram presents the cognitive mechanism of two learning paradigms. The traditional mode relies on learners' internal mental processing to integrate discrete vocabulary knowledge, resulting in high extraneous cognitive load and fragile fragmented memory. In contrast, the KG-enabled adaptive mode externalizes implicit semantic and morphological relationships through visualized network visualization, reduces unnecessary cognitive consumption, and facilitates systematic lexical schema construction and personalized progressive learning.

3. Methodology

3.1 Participants

This study adopts a 16-week quasi-experimental design. Participants are 60 second-year English major undergraduates from a private university in Guangzhou, with consistent basic English proficiency and no prior experience of KG-based vocabulary learning. They are randomly divided into an experimental group (KG adaptive vocabulary teaching, N=30) and a control group (traditional linear vocabulary teaching, N=30). Pre-experiment homogeneity tests on CET-4 scores and vocabulary pre-test results confirm no significant between-group differences ($p>.05$), ensuring experimental validity. The detailed pre-experiment homogeneity test data of the two groups is shown in Table 1.

Table 1. Pre-experiment Homogeneity Test of Two Groups of Participants

Index	Group	N	Mean	SD	t	p
CET-4 Score	Experimental Group	30	526.35	8.62	0.682	.498
	Control Group	30	524.18	9.15		
Pre-test Vocabulary Proficiency	Experimental Group	30	70.26	6.32	0.513	.610
	Control Group	30	69.58	6.75		

3.2 Construction of English Vocabulary Knowledge Graph for Adaptive Teaching

Different from pure technical KG construction research, this study focuses on teaching adaptability and personalized learning services [6]. Guided by college English vocabulary teaching syllabi and student learning characteristics, this study constructs a domain-specific lexical knowledge graph via ontology definition, hybrid knowledge extraction and expert verification, to support adaptive learning path recommendation and learning defect diagnosis [7]. The full-cycle construction and application workflow of the adaptive teaching-oriented English vocabulary knowledge graph is demonstrated in Figure 2.

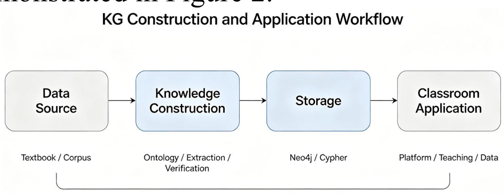

Figure 2. Workflow of English Vocabulary Knowledge Graph for Adaptive Teaching

The full-cycle workflow includes multi-source vocabulary data collection, hybrid knowledge extraction and verification, graph database storage, and adaptive teaching application, covering personalized path push, error diagnosis and targeted consolidation training.

3.2.1 Ontology construction and schema definition

Based on college English vocabulary teaching objectives, this study defines core entity classes and semantic relations covering vocabulary morphology, semantics, collocation and pragmatics, laying a foundation for differentiated learning and targeted teaching intervention. The entity-relationship ontology schema of the constructed English vocabulary knowledge graph is displayed in Figure 3.

Core Entity Classes: Word, Morpheme, Synonym & Antonym, Collocation, Pragmatic Register

Core Semantic Relations: has_root, has_affix, derives_from, synonym_of, antonym_of, collocates_with, has_register

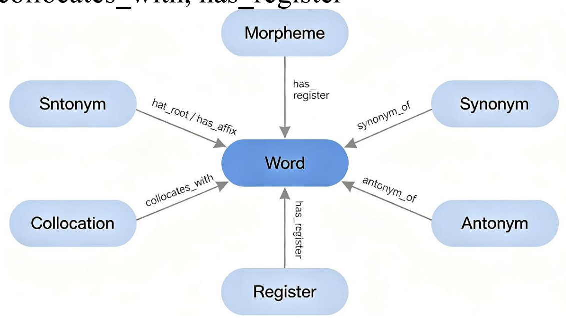

Figure 3. Entity-Relationship Ontology Schema of English Vocabulary Knowledge Graph

The ontology framework takes vocabulary as the core, builds multi-dimensional semantic association networks, and provides structural support for subsequent adaptive learning path generation and learning defect diagnosis.

3.2.2 Hybrid knowledge extraction and manual verification

Table 2. Standard Sample of Vocabulary Knowledge Triplets

Subject	Predicate (Relation)	Object	Attribute Supplement
Creativity	Has_Root	Create	Abstract Noun
Creativity	Collocates_With	Foster	Academic Collocation
Reject	Has_Root	Ject	Verb Root (meaning: throw)
Reject	Has_Prefix	Re-	Prefix (meaning: back)

A hybrid knowledge extraction method combining rule-based algorithms and corpus statistical analysis is adopted to acquire standardized lexical knowledge triplets, with expert manual verification to guarantee teaching practicability. High-frequency lexical morphological structures, semantic distinctions and authoritative collocations are screened to form teachable knowledge units for college students' adaptive learning. The standard samples of vocabulary knowledge triplets extracted in this study are presented in Table 2.

3.2.3 Platform construction for adaptive teaching

This study adopts the Neo4j graph database to store lexical knowledge triplets and build a web-based visualized interactive learning platform. The platform automatically records learning tracks and exercise error data, intelligently identifies individual lexical learning weaknesses, generates personalized learning paths and pushes targeted consolidation resources, realizing data-driven adaptive vocabulary teaching.

3.3 Experimental Teaching Procedure

The experiment lasts 16 weeks. The two groups adopt unified teaching syllabi, content and assessment criteria, with teaching mode as the sole experimental variable.

3.3.1 Control group: Traditional unified vocabulary teaching

The control group adopts conventional textbook and PPT-based linear teaching. Teachers explain vocabulary definitions, word formation and collocations in a unified order. Students memorize scattered lexical knowledge mechanically and finish unified after-class exercises without differentiated guidance and personalized knowledge sorting.

3.3.2 Experimental group: KG-based adaptive vocabulary teaching

The experimental group adopts a KG-enabled closed-loop adaptive teaching model, including pre-class personalized preview, in-class targeted teaching and after-class precise consolidation. The three-stage closed-loop adaptive vocabulary teaching model adopted by the experimental group is summarized in Figure 4.

1. **Pre-class adaptive exploration**: The platform pushes personalized lexical network resources based on students' historical learning data, guiding active sorting of morphological and semantic associations and independent discovery of learning difficulties.

2. **In-class targeted interpretation**: Combining KG visualized networks and pre-class learning data, teachers focus on explaining universal difficult vocabulary and individual learning weaknesses to implement adaptive teaching intervention.

3. **After-class precise consolidation**: The system intelligently diagnoses lexical learning defects, generates exclusive learning paths for individual students, and pushes matched exercises to achieve targeted knowledge consolidation.

The teaching system realizes data-driven adaptive teaching, realizing personalized preview, targeted classroom teaching and precise after-class consolidation, which breaks through the limitations of traditional unified vocabulary instruction.

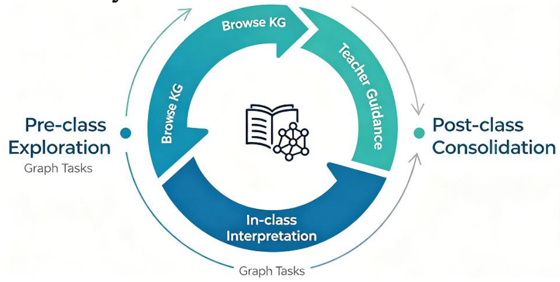

Figure 4. Three-stage Closed-loop Adaptive Vocabulary Teaching Model

3.4 Research Instruments and Data Collection

3.4.1 Vocabulary proficiency comprehensive test

A self-compiled vocabulary proficiency test covering vocabulary breadth recognition and semantic depth application is adopted. Pre-test and post-test are conducted to evaluate students' overall vocabulary learning effect, with good reliability and validity (Cronbach's α=.84) [8].

3.4.2 Multi-dimensional Cognitive Load Scale

A 7-point Likert scale is used to measure intrinsic, extraneous and germane cognitive load. The scale has high reliability (Cronbach's α=.81) and effectively reflects cognitive differences between the two teaching modes [9].

3.4.3 Learning behavior log and semi-structured interview

The platform automatically records students' learning tracks and error data. Post-experiment semi-structured interviews are conducted to collect subjective learning feedback, supplementing qualitative empirical data.

4. Research Results and Data Analysis

4.1 Comparative Analysis of Vocabulary Learning Effect

Independent samples t-test results show that the experimental group achieves a significantly higher post-test vocabulary score (M=82.40, SD=5.20) than the control group (M=76.10, SD=6.80, t=3.85, p<.01). The KG adaptive teaching mode effectively improves students' comprehensive vocabulary competence, especially in semantic depth understanding and practical collocation application. The detailed independent samples t-test results of post-test vocabulary proficiency are shown in Table 3.

Table 3. Independent Samples T-test of Post-test Vocabulary Proficiency

Group	N	Mean	SD	t	p	Effect Size (d)
Experimental Group	30	82.40	5.20	3.85	<.01	0.98
Control Group	30	76.10	6.80	-	-	-

4.2 Multi-dimensional Cognitive Load Optimization Effect

Significant between-group differences are observed in cognitive load dimensions. The experimental group presents lower extraneous cognitive load and higher germane cognitive load, while no significant difference is found in intrinsic cognitive load. The results indicate that KG adaptive teaching does not reduce the inherent difficulty of vocabulary knowledge, but optimizes learners' cognitive resource allocation and promotes deep lexical learning. The specific comparative data of the three-dimensional cognitive load of the two groups are listed in Table 4, and the intuitive comparison results are visualized in Figure 5.

Table 4. Comparative Data of Three-dimensional Cognitive Load

Cognitive Load Dimension	Experimental Group (M±SD)	Control Group (M±SD)	t	p
Extraneous Cognitive Load	2.45±0.52	3.80±0.65	8.72	<.001
Intrinsic Cognitive Load	4.21±0.46	4.18±0.51	0.23	.819
Germane Cognitive Load	5.12±0.48	3.65±0.58	9.25	<.001

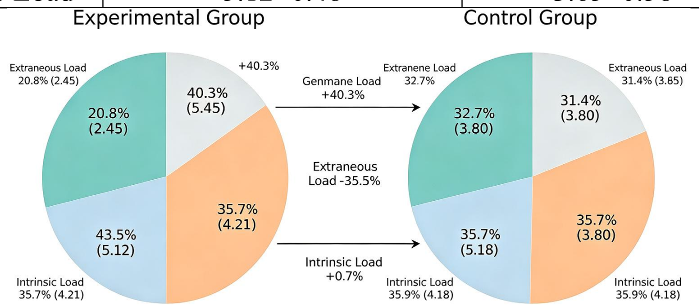

Figure 5. Comparative Bar Chart of Three-Dimensional Cognitive Load between Two Groups

Error bars represent standard deviation (SD). The adaptive KG teaching mode effectively reduces invalid cognitive consumption and improves effective learning cognitive load.

4.3 Long-term Vocabulary Retention Effect

A delayed retention test shows that the experimental group's vocabulary retention rate reaches 89.2%, while the control group only achieves 72.5%. The results verify that the KG-based systematic semantic network and adaptive repeated consolidation mechanism effectively alleviate vocabulary forgetting caused by mechanical memorization and improve the sustainability of learning effects.

5. In-depth Teaching Case Analysis

5.1 Morphological Visualization and Adaptive Word Family Learning

Taking the -ject root word family as the teaching case, traditional teaching simply lists derivative words and causes confused morphological cognition. In contrast, the KG adaptive teaching mode constructs a radial morphological network to visualize prefix and root derivation logic. The platform pushes targeted exercises based on individual learning weaknesses, helping students build systematic morphological awareness and master word formation rules adaptively. The visualized semantic network of the "-ject" morphological word family is demonstrated in Figure 6.

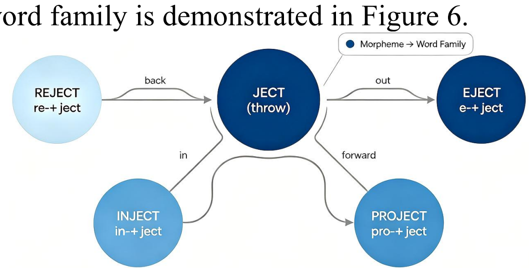

Figure 6. Visualized Semantic Network of the "-ject" Morphological Word Family

Note. The visualized network externalizes abstract word formation logic, supporting students' personalized sorting and targeted consolidation of vocabulary word families.

5.2 Fine-Grained Synonym Discrimination and Adaptive Pragmatic Training

To address the difficulty of English synonym discrimination, the KG platform visualizes fine-grained semantic and pragmatic register differences between similar words. It pushes differentiated scenario-based exercises according to students' error characteristics, compensating for the defects of unified teaching and improving students' precise lexical application ability.

6. Discussion

This empirical study systematically validates the effectiveness of KG-based adaptive teaching in college English vocabulary education. Different from prior technical-oriented KG research, this study focuses on adaptive teaching effects and cognitive optimization, with three core findings concluded as follows:

First, KG adaptive teaching eliminates the fragmentation of traditional vocabulary learning, constructs systematic lexical semantic networks, and promotes the transformation from passive mechanical memorization to active associative learning.

Second, visualized KG teaching optimizes learners' cognitive resource allocation, reduces extraneous cognitive load caused by disordered knowledge sorting, and facilitates deep lexical knowledge internalization.

Third, the data-driven adaptive teaching mode breaks the limitations of one-size-fits-all teaching, realizes personalized path recommendation and targeted error correction, and significantly improves students' vocabulary competence and long-term retention performance.

7. Conclusion

This study constructs a KG-enabled adaptive teaching framework for college English vocabulary instruction and verifies its positive teaching effects via quasi-experiments. The results confirm that the proposed teaching mode significantly improves students' vocabulary breadth, semantic depth understanding and long-term retention, optimizes multi-dimensional cognitive load, and realizes intelligent and personalized vocabulary teaching. This study provides reliable empirical evidence and practical references for the intelligent reform of college English vocabulary education and the integrated application of knowledge graph technology in foreign language adaptive teaching.

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