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The Processing Mechanism of Academic Morphological Awareness among English Majors from the Perspective of Cognitive Load Theory—Construction of a Dynamic Regulation Model Based on AI Hierarchical Prompting

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Abstract: *To optimize the training mode of academic morphological awareness for English majors, this paper adopts Cognitive Load Theory as the analytical framework, systematically clarifies the three-dimensional structure of academic morphological awareness, and explicates the dynamic interaction mechanism of intrinsic, extraneous, and germane cognitive loads during morphological processing. It confirms that the balanced regulation of cognitive load is the key to achieving efficient cognitive processing of academic morphemes. On this basis, this paper proposes targeted implementation strategies, including constructing a hierarchical academic morpheme resource library, building an Artificial Intelligence (AI) prompting dynamic regulation model integrated with multimodal evaluation, and improving the teaching collaboration mechanism. These strategies aim to break through the limitation of traditional morphological teaching that prioritizes knowledge indoctrination over cognitive principles, achieve targeted regulation of cognitive load, and ultimately construct a new academic morpheme training model integrating technological empowerment and cognitive mechanisms. By constructing a theoretical bridge for the synergistic integration of AI technology and second language teaching, this study proposes practical approaches for academic vocabulary teaching among English majors and pioneers a novel paradigm for the intelligent transformation of second language instruction.*

Keywords: *Cognitive Load Theory, English majors, academic morphological awareness, Artificial Intelligence (AI) dynamic regulation*

1. Introduction

Academic morphological awareness is a vital pillar for English majors to improve their academic vocabulary competence and text comprehension efficiency. Current teaching faces problems such as insufficient resource adaptation, lack of cognitive load regulation, and inadequate integration of technology and teaching, leading to students' cognitive overload and difficulty in forming structured morphological knowledge schemas. Based on the cognitive mechanism of second language vocabulary, this paper integrates Cognitive Load Theory and Artificial Intelligence (AI) technology into teaching, explores a scientific and efficient training path for academic morphological awareness, and constructs a hierarchical resource library and dynamic regulation model, providing a new perspective for improving the quality of academic teaching for English majors.

Morphological Awareness is one of the metalinguistic abilities that enable learners to reflect on, analyze, and manipulate the morphemic structure of words[1][2]. As a core metalinguistic ability in the field of second language vocabulary cognitive processing, the academic morphological awareness of English majors specifically refers to students' ability to perceive, represent, and apply the smallest semantic units in academic vocabulary. As a core component of academic language competence, it covers morpheme structure identification, semantic connotation analysis, and grammatical function judgment. The key feature that distinguishes it from general morphological awareness is that most word-forming morphemes are derived from Greek and Latin roots and affixes, and their second language cognitive processing relies on the bidirectional activation and connection mechanism between learners' native language morphological knowledge schemas and second language vocabulary networks.

From the perspective of word-formation processes, morphologically complex words in English are mainly formed through three methods: inflection, derivation, and compounding[3], corresponding to three types of morphological awareness, each with distinct functions in the mental representation and retrieval processing of academic vocabulary. Inflectional morphological awareness helps students quickly parse grammatical information such as noun number and verb tense in academic text reading, reducing the cognitive load of vocabulary recognition. Derivational morphological awareness assists students in expanding their academic vocabulary through the semantic orientation of affixes. Compounding morphological awareness supports students in decomposing complex academic compounds, activating the semantic representation of existing roots in the mental lexicon, and thereby improving the processing efficiency of professional vocabulary.

2. The Processing Mechanism of Academic Morphological Awareness among English Majors from the Perspective of Cognitive Load Theory

Cognitive Load Theory points out that human working memory capacity is limited, and when learning tasks exceed its processing threshold, cognitive load is generated, which affects learning outcomes[4][5]. The processing of academic morphological awareness among English majors is a multi-stage cognitive process with working memory as the central carrier, involving the dynamic interaction of intrinsic, extraneous, and germane cognitive loads. Its core links can be decomposed into four stages: morpheme identification, rule matching, meaning integration, and schema construction. The three types of loads have significant differences in their impact on cognitive processing at different stages.

Intrinsic cognitive load arises from the complexity of academic morphemes themselves and the matching degree between these morphemes and the existing morphological knowledge schemas in learner’s mental lexicon. It is a cognitive load determined by the inherent attributes of learning materials and mainly acts on the morpheme rule matching stage. Most academic morphemes are Greek and Latin roots and affixes, which have low homology with native language morphemes, making it difficult to activate native language transfer effects. Moreover, complex academic terms often contain multiple morpheme units, requiring working memory to simultaneously store and match morpheme combination rules, resulting in the consumption of a large amount of cognitive resources.

Extraneous cognitive load is an ineffective cognitive load caused by the presentation method of teaching materials and task design. Instead of contributing to knowledge construction or schema formation, it mainly impedes attention focusing and cognitive resource allocation in the morpheme identification stage. Based on the Attention Resource Theory, learners’ attention resources are limited, and redundant information in teaching materials occupies working memory resources, hindering the identification and processing of core morphemes.

Germane cognitive load constitutes the effective component of cognitive load, which motivates learners to actively invest cognitive resources in constructing morphological knowledge schemas and ultimately achieving skill automation. It is an essential element promoting the development of academic morphological awareness and mainly acts on the meaning integration and schema construction stages. According to the Vocabulary Schema Theory, learners’ active sorting out of morpheme combination rules, drawing of semantic network diagrams, and induction of semantic characteristics of the same morpheme in different academic contexts can integrate isolated morphological knowledge into structured schemas, which are then stored in long-term memory[6].

From the perspective of the dynamic interaction of the three types of loads, intrinsic cognitive load is determined by the inherent attributes of materials and cannot be completely eliminated, but its intensity can be reduced by activating learners’ existing knowledge schemas; extraneous cognitive load can be completely avoided by optimizing the presentation of teaching materials and task design; guiding learners to invest cognitive resources can increase germane cognitive load, effectively promote the construction of morphological knowledge schemas, and thereby reduce the intrinsic cognitive load of subsequent processing. The balanced regulation of the three is the path to realize the efficient processing of academic morphological awareness among English majors.

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3. Strategies for Improving Students' Academic Morphological Awareness under Cognitive Load Theory

3.1 Constructing a Hierarchical Academic Morpheme Resource Library to Lay a Cognitive Adaptation Foundation for AI Prompting

3.1.1 Hierarchical Division

In the construction of the AI hierarchical prompting dynamic regulation model, cultivating students' academic morphological awareness requires the introduction of a hierarchical academic morpheme resource library to lay a cognitive adaptation foundation for AI prompting. In this stage, teachers need to divide the resource library into multiple levels, including the basic level, reinforcement level, and expansion level, according to the phased characteristics of student's cognitive processing abilities, with each level corresponding to a different cognitive load threshold.

The basic level focuses on the explicit presentation of single high-frequency academic morphemes, with the core goal of reducing extraneous cognitive load. Resource presentation should follow the principle of attention resource allocation, reducing the ineffective consumption of working memory by simplifying visual symbols, eliminating redundant information, and fixing morpheme presentation positions, helping learners quickly establish the connection between morpheme forms and core semantics. The reinforcement level introduces implicit association rules of morpheme combination, oriented towards activating germane cognitive load. With the help of dynamic semantic network diagrams, it guides learners to independently discover the combination rules of roots and affixes, and semantic variations of the same morpheme in different professional contexts, promoting the transformation of isolated morphological knowledge into structured schemas. The expansion level embeds cross-linguistic transfer tasks, aiming to promote high-level cognitive reconstruction. By comparing the semantic correspondence between native language and target language morphemes, and the general rules of interdisciplinary morphemes, it improves the transfer and application ability of morphological knowledge.

A dynamic transition mechanism based on task performance should be set between different levels, with core judgment indicators including morpheme identification accuracy $\geq$ 80%, rule matching reaction time $\leq$ 1.5 seconds, and subjective cognitive load score $\leq$ 30 points. When the AI system detects that a learner has achieved this standard in 3 consecutive task groups, it automatically triggers a level-up prompt and synchronously adjusts the task complexity and cognitive load parameters of the next level.

For example, the basic level selects the high-frequency academic morpheme "chrono-" (meaning "time"). Teachers design visual morpheme cards: the front side marks the core semantics of "chrono- = time", and the back side is matched with derivative words such as "chronology" and "chronic", highlighting "chrono-" in bold, and supplementing the combination form of "morpheme + suffix" with minimalist line diagrams, reducing extraneous cognitive load by simplifying visual information. The reinforcement level uses AI to generate dynamic semantic network diagrams, with "chrono-" as the core node, extending branches associated with affixes such as "-meter" and "-logy", marking compound words such as "chronometer" and "chronobiology", guiding students to summarize the extension rules of affixes on morpheme semantics and activating germane cognitive load. The expansion level sets cross-linguistic transfer tasks, selecting Chinese academic expressions related to "time" to compare with "chrono-" derivatives, guiding students to analyze the semantic correspondence between different language, triggering high-level cognitive reconstruction through morpheme transfer between native language and target language, and promoting cross-linguistic integration of morphological knowledge.

3.1.2 AI Prompt Dynamic Regulation

The dynamic regulation of AI prompting should take the hierarchical resource library as the carrier and rely on the multimodal cognitive load evaluation module to achieve precise matching between prompt content and learner's real-time processing status. This module needs to integrate eye-tracking data (fixation duration, number of regression), operational behavior data (response latency, error type), and subjective self-assessment data (simplified cognitive load scale) to construct a quantitative indicator system, accurately distinguishing the intensity levels of intrinsic, extraneous, and germane cognitive loads.

When the evaluation result indicates that the intrinsic cognitive load is excessively high—

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specifically, students struggle with matching the rules of complex morpheme combinations—the AI prompt will automatically switch to a step-by-step decomposition mode. It decomposes the complex morpheme structure into several subtasks and guides students to accomplish these subtasks step by step via progressive prompting. If the extraneous cognitive load exceeds the threshold—in particular, when the resource presentation method interferes with attention focusing—the prompt system needs to optimize the information presentation channel, adopt an audio-visual dual-channel integration strategy, and convert lengthy textual explanations into interactive animations or voice prompts, thereby reducing the cognitive resource occupation of a single channel. When the germane cognitive load is insufficient—namely, learners only engage in shallow memory rather than in-depth knowledge construction—AI should deliver challenging tasks that require learners to independently design academic vocabulary containing target morphemes, mark word-formation rules, and embed such vocabulary in professional contexts for sentence construction. Subsequently, by comparing similar expressions in academic corpora, the construction of morphological knowledge schemas is reinforced.

When the intrinsic load is too high, such as when students analyze the structure of “asynchronous” (a- + syn- + chrono- + ous), eye-tracking data shows that the time spent fixating on the prefix “syn-” accounts for more than 50% and the response latency reaches 25 seconds. The AI prompt automatically switches to a step-by-step decomposition mode: it first guides students to identify the meanings of the prefixes a- (meaning “not”) and syn- (meaning “together”), then reaffirms the core semantics of the root “chrono-”, and finally analyzes the function of the adjective suffix “-ous”, thereby gradually guiding students to deduce the overall meaning of the word.

If the extraneous load exceeds the standard, such as when basic-level students have a task completion rate of less than 60% in understanding “chronicle” through text reading, AI converts the text explanation into an animation form. The animation simulates the process of ancient historians recording events in chronological order, accompanied by a simultaneous voice prompt: “chrono-” means time, and “-icle” refers to a small document; together, it means a document recording the progress of time, reducing information interference through audio-visual dual-channel integration.

When the germane load is insufficient, such as when expansion-level students quickly complete cross-linguistic comparison tasks with an accuracy rate of 90%, AI pushes challenging tasks, requiring students to independently design three academic vocabulary containing “chrono-”, mark word-formation rules, and embed them in academic contexts to make sentences. For example, “chronosensitive” (chrono- + sensitive → time-sensitive) can be used in “Some biological rhythms are chronosensitive to environmental changes”. Subsequently, AI extracts similar expressions from academic corpora to compare with the vocabulary designed by students, strengthening the schema construction of morpheme combination. All prompts are strictly limited within the cognitive goals of the corresponding level to avoid prompt information overload or deviation from current task requirements.

3.2 Improving AI Technical Support and Teaching Collaboration Mechanism to Consolidate the Foundation of Cognitive Load Regulation

3.2.1 AI System Support

Under the guidance of Cognitive Load Theory, improving AI technical support is of great significance, which requires building an underlying technical architecture supporting dynamic regulation. Among them, the AI system needs to embed a multimodal cognitive load evaluation module to quantify the intensity of student’s intrinsic, extraneous, and germane cognitive loads.

In terms of technical implementation, to mitigate the lag in cognitive load assessment caused by data latency, an edge computing framework can be adopted to offload data processing tasks to terminal devices [7]. To expand the data sample size while protecting students' privacy and improve the generalization ability of the load assessment model, federated learning technology can be leveraged to achieve cross-class and cross-campus sharing of cognitive data [8]. To predict students' cognitive load thresholds under different task scenarios and adjust teaching activities accordingly, AI algorithms can be introduced to embed the cognitive load prediction function and construct individual cognitive feature profiles for students based on historical data.

For example, when the system detects that a student is about to enter a high-load state, it will automatically reduce the information density of the interface or switch to a more concise interaction mode. The optimization of the technical architecture should undergo a pressure test every semester to ensure that it can stably support concurrent cognitive load evaluation for more than five hundred people.

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For example, the multimodal cognitive load evaluation module embedded in the AI system relies on the edge computing framework to sink data processing to students' terminal devices. When students complete "chrono-" morpheme tasks, the terminal processes eye-tracking data (fixation point distribution, blinking frequency) and operational data (click speed, task duration) in real time, generating cognitive load evaluation results without uploading to the cloud, avoiding intervention lag caused by data delay. Using federated learning technology, multiple universities share anonymous cognitive data of students in "chrono-" morpheme learning, integrating high-load scenario data of students from University A in learning "synchronize" and relevant data of students from University B. The AI model optimizes the prompting strategy for the combination structure of "syn- + chrono-" by analyzing these cross-university data, while ensuring the security of students' personal information. The system is equipped with an AI prediction algorithm, which predicts the risk of cognitive overload when a student learns "parachronism" (para- + chrono- + ism → anachronism) based on their historical learning data (such as high intrinsic load in learning "diachronic"). It automatically hides irrelevant information on the task interface (such as additional extended examples), retaining only word structure decomposition and core definitions to reduce extraneous load.

3.2.2 Teaching Collaboration Mechanism

The core of the teaching collaboration mechanism is to establish a closed-loop linkage between AI technical intervention and teacher decision-making guidance, realizing a hierarchical response of "data monitoring - initial AI intervention - teacher calibration - model optimization", ensuring that cognitive load regulation conforms to both technical logic and teaching reality. This process is divided into three stages.

3.2.2.1 Real-time Monitoring and Initial Intervention

The first stage is real-time monitoring and initial intervention. The AI system automatically triggers hierarchical prompts based on cognitive load evaluation results: when the load is within a safe range, the prompt is presented in an implicit form, such as dynamically highlighting core morphemes, without interfering with students' independent processing; when the load is close to the threshold, the system pushes semi-structured prompts, such as popping up simplified diagrams of morpheme combination rules; when the load exceeds the standard, it forcibly interrupts the current task and pushes structured step-by-step prompts to help students decompose difficulties.

For example, the AI system real-time monitors the cognitive load status of the whole class in each level of "chrono-" morpheme tasks. When most students have a safe load in learning "chronic" (long-term) at the basic level, the task interface automatically highlights the "chrono-" part of the word, prompting the core morpheme in an implicit form; some students have a load close to the threshold in learning "chronometer", and the system pops up a semi-structured prompt, showing the word-formation logic of "chrono- + meter" and comparing it with the word-formation method of "thermometer". A few students have excessive load in learning "asynchronous", and the system forcibly interrupts the task, guiding them to analyze the meanings of prefixes "a-" and "syn-", core morpheme "chrono-", and suffix "-ous" step by step.

3.2.2.2 Teacher Intervention and Strategy Calibration

The second stage is teacher intervention and strategy calibration. Teachers view the cognitive load heat map through the teaching console, identify high-load concentration areas, and combine the detailed data report generated by AI to judge the core cause of excessive load—whether it is the excessive difficulty of morpheme combination rules (high intrinsic load) or improper material presentation (high extraneous load), and then manually adjust teaching strategies.

For example, teachers monitor that the reinforcement level "synchronize" learning area shows high-load concentration. Data analysis shows that learners have obstacles in understanding the semantics of the prefix "syn-", so they decompose the task into three sub-tasks: identifying the meaning of "syn-", analyzing the core semantics of "chrono-", and integrating the function of suffix "-ize"; at the same time, they supplement simple words such as "synonym" (syn- + onym → synonym) and "synthesis" (syn- + thesis → synthesis) to help learners establish prefix cognitive schemas and reduce the overall cognitive load of morpheme processing.

3.2.2.3 Feedback Integration and Model Optimization

The third stage is feedback integration and model optimization. The AI system conducts correlation analysis between the teaching strategies adjusted by teachers and the original load data, generates a hierarchical strategy effect evaluation model and report, and optimizes the hierarchical prompting

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algorithm accordingly: if a strategy significantly reduces the load without affecting task completion quality, it will be included in the system's default prompt library; if the strategy effect is not significant, it will be marked as a scenario requiring manual intervention for teachers' subsequent reference. The response cycle of the above collaboration mechanism should be controlled within 5 minutes to ensure that the teaching rhythm is not interrupted by technical intervention.

For example, data shows that students' cognitive load in completing decomposed tasks is reduced by 30%, and the accuracy rate of word understanding is increased by 25%. The system includes this decomposition strategy into the default prompt library, which is automatically called in similar high-load scenarios subsequently; for another expansion-level task strategy with insignificant effect after adjustment, the system marks it as a scenario requiring manual intervention, displays relevant data on the teacher console for teachers' reference in subsequent teaching plan optimization. The entire collaboration mechanism, from AI monitoring to teacher adjustment and model optimization, has a response cycle controlled within 4 minutes to ensure that normal teaching rhythm is not interrupted.

3.2.3 Ethical Boundaries and Security Protection

The collaboration between technology and teaching needs to establish clear ethical boundaries and security protection mechanisms to ensure the compliance and humanity of intervention behaviors. At the technical level, it is necessary to set a safe threshold for cognitive load regulation, clarify the trigger conditions and intensity upper limit of AI intervention, prohibit forced intervention in the teaching process when learners' load does not reach a dangerous level, and limit the prompt frequency to no more than 3 times per minute to avoid new cognitive overload caused by excessive prompting; embed an ethical review module to automatically conduct compliance checks on prompt content, requiring prompt language to adopt constructive feedback and eliminate negative evaluations. At the data security level, data desensitization technology is adopted to retain only the morphological processing behavior characteristics of learners, delete personal identification information such as names and student IDs, in line with educational data security specifications. At the teacher level, a teacher competence decision support system is built, providing teachers with ethical evaluation suggestions for strategy adjustment by analyzing historical ethical dispute cases, helping teachers predict the possible impact of teaching intervention on learners' cognitive styles and emotional attitudes, and realizing the balance between technical rationality and teaching humanity.

3.3 A Multidimensional Verification System for Strategy Effectiveness

For the three core implementation strategies proposed above—construction of a hierarchical academic morpheme resource library, establishment of an AI prompting dynamic regulation model integrated with multimodal evaluation, and improvement of the teaching collaboration mechanism—this study further constructs a three-dimensional verification model covering cognitive load monitoring, morphological awareness testing, and academic ability transfer, systematically evaluating the strategy implementation effect through quantitative analysis.

The cognitive load monitoring dimension adopts the simplified National Aeronautics and Space Administration Task Load Index (NASA-TLX) scale, comparing learners' subjective cognitive load scores before and after strategy implementation, and synchronously combining objective data such as eye movement trajectories and operational behaviors to comprehensively determine the regulation effect of the three types of cognitive loads. The morphological awareness testing dimension focuses on three core tasks: morpheme identification, rule matching, and vocabulary generation, to measure the improvement of learners' morphological structure awareness, semantic awareness, and grammatical awareness. The academic ability transfer dimension collects learners' academic papers and translated texts, verifying the positive promotion effect of improved morphological awareness on core academic abilities by analyzing the changes in the accuracy of professional term use and vocabulary complexity. The above verification data will serve as the core basis for the iteration of the hierarchical academic morpheme resource library and the optimization of the AI prompting algorithm, ultimately forming a closed-loop improvement mechanism of "strategy implementation - effect verification - model iteration".

4. Conclusion

Taking Cognitive Load Theory as the analytical framework, this paper conducts a systematic exploration of the connotative characteristics, cognitive processing mechanisms, and improvement

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strategies of academic morphological awareness among English majors. The study clarifies the three core dimensions of academic morphological awareness, reveals the dynamic interaction mechanism of the three types of cognitive loads in morpheme processing, and confirms that the balanced regulation of cognitive load is the key to achieving efficient processing of academic morphemes. The proposed strategies, including the construction of a hierarchical academic morpheme resource library, the development of an AI-enabled dynamic regulation model, and the improvement of teaching collaboration mechanism, break through the limitation of traditional morphological teaching that emphasizes knowledge indoctrination over cognitive principles, and further construct an innovative academic morpheme training model integrating technological empowerment and cognitive principles. Theoretically, this study expands the application boundary of Cognitive Load Theory in the field of second language vocabulary research, building a theoretical bridge for the in-depth integration of AI technology and second language teaching. Practically, it provides feasible implementation paths for academic vocabulary teaching of English majors, facilitating the transformation of the teaching model from standardized indoctrination to personalized guidance. This study still has certain limitations. In future research, variables such as learners' cognitive styles and emotional factors can be incorporated to optimize the cognitive regulation model, and longitudinal studies can be carried out to investigate the long-term impact of the strategies, thereby advancing the research on second language teaching towards a more precise and scientific direction.

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