

# RECONCEPTUALIZING AI-MEDIATED VOCABULARY ACQUISITION: AFFORDANCES, COGNITIVE PARADOXES, AND THE ZONE OF OPTIMAL FRICTION

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## 1 ABSTRACT

*This conceptual paper investigates the theoretical paradox of integrating Generative AI (GenAI) into L2 vocabulary acquisition. Mapping Large Language Model affordances onto the three lexical processing stages noticing, retrieval, and generation reveals a structural shift toward automated scaffolding and co-creation. Synthesizing Cognitive Load Theory and the Involvement Load Hypothesis, we argue that while GenAI minimizes extraneous load via adaptive prompting, its frictionless delivery eviscerates task-induced involvement by neutralizing critical Search and Evaluation parameters. This cognitive offloading removes desirable difficulties, trapping EFL learners within a superficial illusion of competence. To resolve this dilemma, this study introduces the AI-Mediated Cognitive Engagement Model (ACEM), a two-dimensional matrix engineered to regulate Optimal Cognitive Friction within generative digital tasks. The paper concludes with actionable prompt architectures to transition AI from a cognitive crutch to a pedagogical challenger, outlining future neurocognitive research pathways (fMRI, eye-tracking, EEG) to validate AI-mediated lexical retention depth.*

**Keyword:** *Generative AI, Vocabulary Acquisition, Cognitive Load Theory, Involvement Load Hypothesis, Desirable Difficulties, Optimal Cognitive Friction.*

## 1. INTRODUCTION

The landscape of Second Language Acquisition (SLA) and L2 vocabulary development is undergoing a paradigm shift driven by Generative Artificial Intelligence (GenAI). For decades, Computer-Assisted Language Learning (CALL) systems operated as passive repositories. Early computational vocabulary assessment relied on traditional Natural Language Processing (NLP) for automatic question generation (Aldabe et al., 2006), rule-based distractor generation (Aldabe & Maritxalar, 2010; Jiang & Lee, 2017), or fill-in-the-blank quizzes (Sakaguchi et al., 2013). While controlling item difficulty computationally (Susanti et al., 2017), these legacy systems remained constrained by rigid domain ontologies or static corpora (Papasalouros et al., 2008).

Conversely, contemporary GenAI powered by Large Language Models (LLMs) like ChatGPT and Claude functions as autonomous, interactive agents offering real-time negotiation of meaning, adaptive scaffolding, and dynamic context generation. This evolution is vital in post-pandemic online communities where digital communication accelerates linguistic adaptation,

forcing learners to negotiate complex socio-pragmatic meanings, affective communication, and digital slang (Phi et al., 2025). Concurrently, the digital ecology has been reshaped by theory-driven gamified instruction. Integrating game elements significantly stimulates behavioral, cognitive, and affective engagement by satisfying basic psychological needs (Luu et al., 2025; Luu et al., 2025). Aligned with Self-Determination Theory, Flow Theory, and the ARCS model, these structures foster sustained intrinsic motivation and reduce language anxiety in specific sociocultural contexts (Luu et al., 2025; Luu, Nguyen, et al., 2025).

However, GenAI integration introduces a critical theoretical paradox. From Technology Affordance Theory (Hutchby, 2001) and Cognitive Load Theory (Sweller, 1988) perspectives, GenAI optimizes efficiency. It eliminates extraneous load by removing the split-attention effect inherent in traditional dictionaries or manual note-taking (Makany et al., 2009), streamlining word explanation and morphological breakdown. Yet, this frictionless delivery threatens to eradicate desirable difficulties (Bjork & Bjork, 2011), the

deliberate cognitive obstacles necessary for deep processing.

According to the Involvement Load Hypothesis (ILH) (Laufer & Hulstijn, 2001), effective lexical retention depends on the task-induced involvement load (Need, Search, Evaluation). Traditionally, unknown words forced deep lexical inferencing (Haastrup, 2008) or contextual and morphological integration (Mori, 2002). When AI preemptively services queries, Search and Evaluation are neutralized, creating an illusion of competence. This paradox highlights a prominent research gap. Non-English majors in Vietnamese public universities chronically face vocabulary bottlenecks and a lack of learning interest (Luu & Le, in press). While employing compensatory digital tactics, their strategic involvement relies heavily on external aids rather than proactive cognitive strategies (Luu & Le, in press). To alleviate this, existing frameworks advocate explicit instruction, usage-based approaches, and structured scaffolding (Luu, 2025).

Nevertheless, classical vocabulary acquisition frameworks, including the ILH (Laufer & Hulstijn, 2001), Nation's tripartite model (Noticing, Retrieval, Generation) (Nation, 2013), and contemporary explicit instruction frameworks (Luu, 2025), were conceived for environments dominated by static materials or traditional evaluation metrics (Read, 2000; Schmitt et al., 2020). Consequently, they lack parameters to account for adaptive GenAI affordances. Furthermore, while modern motivational models leverage gamification to sustain intrinsic drive in collectivist EFL settings (Luu et al., 2025; Luu, Nguyen, et al., 2025), there remains a severe dearth of conceptual frameworks synthesizing cognitive psychology, motivational design, and generative technology under the threat of cognitive offloading. To address this theoretical vacuum, this study addresses two research questions:

- RQ1: How do the interactive affordances of generative AI redefine the traditional stages of vocabulary acquisition (noticing, retrieval, and generation)?
- RQ2: In what ways does AI-mediated vocabulary learning manipulate learners' cognitive load, and what are the theoretical implications for long-term lexical retention?

## 2. CRITICAL REVIEW

To map the transformative influence of Generative Artificial Intelligence (GenAI), we must look at how its interactive affordances (Hutchby, 2001) structurally alter the three classical stages of vocabulary acquisition outlined by Nation (2013): noticing, retrieval, and generation.

### Stage 1: Noticing

Traditionally, noticing occurs when a learner encounters an unfamiliar lexical item within a static text and intentionally isolates it, often through highlighting or margin notes. This conventional practice requires the learner to actively employ lexical inferencing procedures to extract semantic value from context (Haastrup, 2008) or integrate structural clues from internal word parts (Mori, 2002).

In a GenAI-mediated ecology, however, this phase is fundamentally automated. Rather than requiring the learner to look up an unknown word or wrestle with contextual ambiguity, the GenAI system pre-emptively segments text, predicts vocabulary deficiencies based on the learner's user profile, bolds relevant items, and appends instantaneous, context-specific definitions. Consequently, the learner undergoes a structural shift: from *Active Search and Inferencing* to *Guided/Automated Noticing*. While this hyper-scaffolded intervention keeps the flow of reading intact, it effectively bypasses the initial cognitive struggle necessary for learners to register structural salience and build independent strategic competence (cf. Luu & Le, in press; Phi, in press; Phi et al., 2025).

### Stage 2: Retrieval

Retrieval relies heavily on the mental reconstruction of a word's formal and semantic attributes after a period of delay. In traditional Computer-Assisted Language Learning (CALL) and self-directed environments, this stage is mediated through fixed flashcards, digital gamified applications, or static vocabulary exercises where item difficulty remains linear (Luu, Nguyen, Nguyen, Le, Le, & Do, 2025; Luu, Nguyen, Do, & Nguyen, 2025).

GenAI redefines retrieval by making it dynamic through *Adaptive Prompting*. Instead of repeating a uniform, predictable set of testing cards, a Large Language Model (LLM) evaluates the learner's

previous lexical errors and constructs real-time, situational role-plays, simulation tasks, and targeted quizzes that shift in linguistic difficulty depending on user performance. The retrieval path is no longer a static, repetitive loop; it evolves into a fluid landscape where the AI acts as an agile interrogator, constantly adjusting the contextual framing to tease out the target word.

### Stage 3: Generation

The generation phase represents the productive application of a newly acquired word within spontaneous composition or conversational structures, testing the depth of the learner's collocation and syntactical schema (Schmitt et al., 2020). Traditionally, this is achieved through independent sentence or essay production, a solitary task often characterized by delayed corrective feedback and vulnerability to structural errors (Luu & Bui, in press; Luu & Nguyen, in press). GenAI collapses this isolation through Co-creation.

When a learner attempts to utilize a new word within an AI interface, they do not produce output in a vacuum. Instead, they draft rough sentences, which the GenAI model immediately refines, adjusts for stylistic elegance, and extends into broader pragmatic variations, such as contemporary digital slang or formal academic registers (cf. Luu, 2025; Phi, Anh, Truc, Dung, Vi, & Thu, 2025). The generation phase changes from an *Independent Production* task into an *AI-Collaborative Generation* process. The learner's output becomes an evolving, dialogic product co-authored by the machine.

### 3. THE COGNITIVE PARADOX OF GENAI IN VOCABULARY LEARNING

From an instructional standpoint, GenAI elegantly resolves cognitive overload by minimizing extraneous load (Sweller, 1988). It eliminates the split-attention effect typical of traditional dictionary-switching and serves as an ultimate external cognitive aid (cf. Makany et al., 2009) by handling morphology, etymology, and phonetics instantly (Luu & Nguyen, in press; Nguyen & Luu, in press). This allows the learner's working memory to focus its finite resources entirely on macro-textual propositions.

However, this frictionless delivery triggers a critical pedagogical trade-off: it severely degrades germane load and eviscerates the task-induced

involvement load essential for long-term lexical retention, as conceptualized by the Involvement Load Hypothesis (ILH; Laufer & Hulstijn, 2001). Because GenAI operates as an omniscient, preemptive interlocutor, the Search element drops to zero, and the automated provision of optimal collocations neutralizes the Evaluation index (cf. Read, 2000). Consequently, by removing vital desirable difficulties (Bjork & Bjork, 2011), GenAI induces cognitive passivity. This creates a superficial illusion of competence where the AI's fluent performance and instant scaffolding are mistaken by the user for actual, consolidated long-term vocabulary schema and learner self-efficacy.

### 4. PROPOSED CONCEPTUAL MODEL

To resolve this paradox and establish stable pedagogical guidelines for digital task design, this study introduces the AI-Mediated Cognitive Engagement Model (ACEM). This model synthesizes Cognitive Load Theory (Sweller, 1988), the Involvement Load Hypothesis (Laufer & Hulstijn, 2001), and Affordance Theory (Hutchby, 2001) into a two-dimensional matrix designed to evaluate and regulate cognitive processing in GenAI-driven environments. The Horizontal Axis (X-Axis) - AI Affordance Support Level measures the operational passivity or generativity of the technology, ranging from low/passive tools (static lookups) to high/generative agents (automated scaffolding and instant co-creation).

The Vertical Axis (Y-Axis) - Learner Cognitive Engagement / Involvement Load tracks the depth of the user's mental processing, ranging from superficial interaction (skimming, outsourcing cognitive labor) to deep processing (evaluation, effortful schema construction).

The defining principle of the ACEM is the construct of Optimal Cognitive Friction. Technology should not serve as an agent of total cognitive offloading. Instead, it must be engineered to supply an optimal degree of difficulty that preserves the Search and Evaluation components of the task. While early automated item and quiz generation software sought to regulate item difficulty merely by adjusting surface-level distractor options in a rigid testing format (Aldabe & Maritxalar, 2010; Aldabe et al., 2006; Jiang & Lee, 2017; Papasalouros et al., 2008; Sakaguchi et al., 2013; Susanti et al., 2017), the

ACEM focuses on regulating difficulty dynamically within the interactive, generative workflow itself.

In the Passive/Outsourcing Quadrant (High Affordance / Low Engagement), the AI model functions merely as a cognitive crutch. The tool satisfies all user demands instantly, delivering complete definitions, translation equivalents, and flawless sample compositions. The learner's extraneous load is minimized, but the essential parameters of Search and Evaluation are completely bypassed. Germane load falls to zero, trapping the learner within a state of technological dependency where real-time digital comprehension is mistaken for permanent memory encoding.

Conversely, in the Zone of Optimal Friction (High Affordance / High Engagement), the AI is strategically restricted through intentional prompt architectures or task boundaries to act as a *Challenger* or an *Active Scaffold*. Instead of supplying an immediate definition or translation, the AI is prompted to respond with contextual riddles, highlight structural anomalies, or offer target constraints that force the learner to run deep semantic evaluations. By utilizing the generative affordances of the model to produce dynamic, customized challenges rather than quick answers, the task layout protects the task-induced Involvement Load. This ensures that the reduction of structural distractions serves exclusively to unlock capacity for Germane Load, directly supporting the transition of lexical knowledge into the long-term mental lexicon.

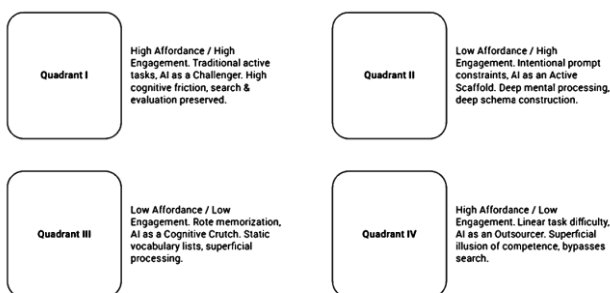


Figure 1. Conceptual framework

## 5. CONCLUSION

This conceptual analysis critically examines the paradox at the intersection of GenAI affordances, Cognitive Load Theory, and the Involvement Load Hypothesis. While GenAI minimizes extraneous load, its frictionless delivery erases the desirable

difficulties required for deep semantic processing by neutralizing Search and Evaluation parameters, risking a superficial illusion of competence.

Without direct empirical data, the primary limitation of this study is that the precise thresholds where AI transitions from a productive scaffold to a counterproductive crutch remain theoretically deduced, omitting individual learner differences such as native language background, anxiety, or baseline motivation (Luu, Nguyen, Do, & Nguyen, 2025; Phi, in press; Phi, Đông, & Huang, 2025). To validate the proposed AI-Mediated Cognitive Engagement Model (ACEM), future research must transcend self-reported metrics. There is an urgent need for empirical investigations employing advanced neurocognitive and physiological methodologies such as eye-tracking, fMRI, and EEG to monitor visual fixation during AI reading tasks and map neural activation patterns during co-creation. Such biological data will help establish data-driven guidelines for engineering the optimal cognitive friction necessary for long-term lexical retention in the age of artificial intelligence.

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