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| RESEARCH ARTICLE

Generative AI and Second Language Vocabulary Processing: A Cognitive Study of Chinese EFL Learners

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| ABSTRACT
This study investigates the impact of AI-generated texts—specifically narrative, dialogic, and explanatory types—on lexical processing among Chinese English as a Foreign Language (EFL) learners. A mixed-methods approach was employed, combining quantitative measures of lexical decision speed and accuracy, semantic mapping, and retention rates with qualitative insights into strategy use and cognitive experience. Results indicate that dialogic texts significantly enhanced lexical access speed and accuracy, while narrative texts promoted deeper semantic integration and better long-term retention. Explanatory texts, though less effective overall, supported vocabulary learning through structured input, particularly for learners with lower working memory capacity. Regression analyses revealed that both working memory and language proficiency were significant predictors of lexical outcomes, with moderation effects showing that high-working-memory learners benefited more from narrative texts, whereas low-working-memory learners showed greater gains from dialogic texts. These findings highlight the importance of text type selection in vocabulary instruction and underscore the need for adaptive AI-driven systems that tailor content to individual learner profiles. The study contributes to both second language acquisition theory and the pedagogical application of generative artificial intelligence in language learning environments.

| KEYWORDS
AI-generated texts, lexical processing, working memory, language proficiency, adaptive learning.

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1. Introduction
In recent years, the integration of generative artificial intelligence (GenAI) into second language acquisition (SLA) research has opened new avenues for understanding how learners process and internalize vocabulary in digital environments (Liu & Reinders, 2025). As one of the most rapidly evolving technological tools, GenAI—encompassing large language models (LLMs) such as GPT, BERT, and their successors—offers unprecedented opportunities for personalized, context-rich language learning experiences (Law, 2024). This study explores how these technologies interact with the cognitive mechanisms underlying vocabulary processing among Chinese English as a foreign language (EFL) learners.

Vocabulary acquisition is widely recognized as a cornerstone of successful L2 development, particularly in reading comprehension and communicative competence (Nation, 2013). Lexical processing involves multiple cognitive stages, including word recognition, semantic activation, and integration into broader syntactic and discourse structures (Perfetti & Stafura, 2014). For Chinese EFL learners, these processes are further complicated by orthographic and phonological differences between their native language and English (Koda, 2007). The logographic nature of Chinese script contrasts sharply with the alphabetic system of English, which can affect phonological awareness, decoding strategies, and lexical access speed (Lallier & Carreiras, 2018).

Research has shown that effective vocabulary instruction must align with learners' cognitive profiles, especially when dealing with complex or unfamiliar words (McNamara & Magliano, 2009). Traditional approaches often rely on rote memorization or decontextualized drills, which may not adequately support deep lexical processing or long-term retention (Webb, 2019). In contrast, GenAI-powered platforms can dynamically generate meaningful contexts, provide immediate feedback, and simulate naturalistic input (Creely, 2024).

Moreover, studies have begun to explore how AI-generated texts influence lexical inferencing and contextual guessing—a key component of strategic reading behavior (Laufer & Hulstijn, 2001). For instance, GenAI can tailor sentence complexity and lexical density based on learner proficiency levels, thereby optimizing the balance between comprehensible input and cognitive challenge (VanPatten & Williams, 2015). This adaptability may be particularly beneficial for learners with limited working memory capacity, who often struggle with multitasking during reading tasks (Wen, 2016). Despite these promising developments, empirical research examining the cognitive impact of GenAI on lexical processing among Chinese EFL learners remains scarce. Most existing studies focus on pedagogical affordances or user perceptions rather than underlying cognitive mechanisms (Law, 2024). Therefore, this study aims to fill this gap by investigating how exposure to AI-generated texts influences lexical access speed, semantic mapping, and strategy use in a controlled experimental setting.

2. Literature Review

2.1 Lexical Processing in Second Language Reading

Lexical processing, which encompasses word recognition, phonological decoding, semantic activation, and syntactic integration, plays a critical role in second language (L2) reading comprehension (Perfetti & Stafura, 2014; Perfetti, 2007). For L2 learners, particularly those from logographic backgrounds like Chinese, these processes can be more challenging due to differences in orthographic and phonological systems between their native language and English (Lallier & Carreiras, 2018). Research indicates that proficient readers typically engage in automatic lexical processing, allowing them to allocate cognitive resources efficiently for higher-order comprehension tasks (Rayner et al., 2016). However, many Chinese EFL learners remain at a controlled stage of lexical processing, leading to increased cognitive load and slower reading speeds (Jiang, 2012).

Recent studies have emphasized the importance of working memory capacity in facilitating efficient lexical processing (Wen, 2016). Learners with lower working memory may struggle with multitasking during reading, such as simultaneously decoding words and integrating them into broader discourse structures (Baddeley, 2012). Understanding how these cognitive limitations interact with AI-based scaffolding could offer insights into optimizing learning environments for diverse learner profiles.

2.2 Cognitive Mechanisms in Vocabulary Acquisition

Vocabulary acquisition involves both incidental and intentional learning processes, where incidental learning occurs through meaningful context and intentional learning involves deliberate memorization and practice (Nation, 2013). Effective vocabulary instruction should integrate both approaches to promote deep lexical knowledge, including form-meaning connections, collocational awareness, and syntactic flexibility (Webb, 2008).

From a cognitive perspective, lexical knowledge is stored in a multidimensional mental lexicon, where words are represented semantically, phonologically, orthographically, and morphologically (Perfetti & Hart, 2001). Recent research has highlighted the importance of morphological awareness in enhancing vocabulary learning, particularly for learners whose native languages do not rely heavily on derivational morphology (Goodwin, 2018). Morphological instruction has been shown to improve word recognition and comprehension among Chinese EFL learners by leveraging structural patterns within words (Li, Zhao, & Zhang, 2022).

2.3 Cross-Linguistic Transfer in Lexicon Development

Cross-linguistic transfer plays a significant role in L2 vocabulary development, especially when learners have limited exposure to the target language (Koda, 2007). Conceptual knowledge and semantic structures can facilitate L2 word recognition and meaning construction (Kroll & Sunderman, 2005). For example, cognates or conceptually overlapping terms may allow learners to activate prior knowledge from their first language (L1), thereby enhancing lexical inferencing and retention (Dijkstra & van Heuven, 2002). However, negative transfer can also occur when learners misapply L1 strategies to L2 contexts. For instance, reliance on character-based decomposition—a common strategy in Chinese reading—may hinder English word segmentation and phrasal processing (Chung, Chen & Geva, 2019). Recent studies have explored how digital tools, including AI-generated texts, can mitigate these challenges by providing structured input that aligns with learners' cognitive needs (Gao, Wang & Lee, 2023).

2.4 Emerging Role of Generative AI in Vocabulary Learning

The integration of generative artificial intelligence (GenAI) into language learning has introduced novel tools for vocabulary instruction (Liu & Reinders 2025). GenAI models, such as GPT-3 and BERT, can generate contextually rich, linguistically varied texts tailored to individual learner needs (Law, 2024). These systems offer dynamic scaffolding by generating glosses, paraphrased sentences, and usage examples in real time, supporting both incidental and intentional vocabulary learning. Empirical studies suggest that AI-generated texts can enhance lexical inferencing by embedding unknown words within semantically supportive contexts (Gao, Wang & Lee, 2023). For example, Zhao (2023) found that learners exposed to AI-generated narratives showed improved word retention compared to those using static textbook materials.

Additionally, GenAI tools can provide immediate feedback on vocabulary use, enabling learners to refine their lexical knowledge iteratively (Li, 2023). Moreover, adaptive features of AI platforms allow for personalized learning experiences based on user performance, such as adjusting sentence complexity or offering targeted vocabulary exercises (VanPatten & Williams, 2015). This level of customization aligns well with cognitive theories of optimal input difficulty, suggesting that AI-enhanced environments may better support cognitive engagement and lexical depth than traditional methods.

Recent advancements have also explored the potential of AI-driven conversational agents, such as chatbots, to simulate naturalistic interactions and promote vocabulary learning through dialogue (Kim & Lee, 2021). These agents can adapt their responses based on learners' proficiency levels, providing just-in-time support and encouraging active participation in communicative tasks.

Despite these promising findings, there remains a need for further research specifically examining the cognitive impact of GenAI on lexical processing among Chinese EFL learners. Most existing studies focus on pedagogical affordances or user perceptions rather than underlying psychological mechanisms (Li, 2023). Therefore, this study aims to address this gap by investigating how exposure to AI-generated texts influences lexical access speed, semantic mapping, and strategic processing in a controlled experimental setting.

3. Method

3.1 Research Design

The study adopted a mixed-methods approach combining quantitative and qualitative elements to gain comprehensive insights into the effects of various AI-generated text formats on vocabulary learning outcomes. Specifically, a between-subjects experimental design was implemented to compare three types of texts: narrative, dialogic, and explanatory. These formats were chosen based on their potential to facilitate different aspects of vocabulary acquisition.

3.2 Participants

Participants were recruited from an undergraduate population at a university in China. A total of 120 students participated in the study, with each participant randomly assigned to one of three conditions (n = 40 per group). All participants were native Mandarin speakers with no reported history of reading or language disorders. Their English proficiency level ranged from intermediate to advanced, as determined by their scores on the College English Test Band 4 (CET-4) administered at the beginning of the academic year. Participation was voluntary, and informed consent was obtained from all participants prior to the start of the experiment.

3.3 Materials

3.3.1 AI-Generated Texts

Three sets of AI-generated texts were prepared for this study using a state-of-the-art natural language generation system. Each set contained five passages, approximately 500 words each, covering a variety of topics relevant to the participants' interests and academic needs. The texts were designed to be comparable in terms of readability and complexity but differed in structure and style. Narrative texts focused on storytelling, featuring characters, events, and settings that created a coherent storyline. Dialogic texts emphasized conversational exchanges, presenting information through dialogue and interaction between multiple speakers. Explanatory texts adopted a more formal tone, providing factual information and explanations about specific subjects without narrative or conversational elements. To ensure consistency across conditions, all texts were reviewed by two independent raters who evaluated their suitability according to predefined criteria, including coherence, relevance, and linguistic accuracy.

3.3.2 Vocabulary Tests

Two types of vocabulary tests were developed to assess immediate and delayed recall of target words introduced in the AI-generated texts. The immediate recall test consisted of 20 items selected from the passages, requiring participants to provide definitions or synonyms for each word. The delayed recall test, administered one week later, included the same items plus an additional 20 distractor words to measure long-term retention.

3.3.3 Cognitive Load Questionnaire

A self-report questionnaire was used to gauge participants' perceived cognitive load during the reading tasks. The questionnaire comprised 10 items rated on a 7-point Likert scale, addressing aspects such as mental effort, ease of understanding, and engagement with the material.

3.4 Procedures

The experiment took place over two sessions held one week apart. In the first session, participants completed a pre-test consisting of demographic questions and the CET-4 to establish baseline proficiency levels. They then read one of the three types of AI-generated texts and immediately afterward performed the lexical decision task (LDT), which involved deciding whether presented letter strings were actual English words or non-words. Reaction times and accuracy rates were recorded as measures of lexical access efficiency. Following the LDT, participants completed the immediate vocabulary recall test and the cognitive load questionnaire. One week later, they returned for the second session, during which they performed the delayed vocabulary recall test. Throughout both sessions, participants were encouraged to ask questions and clarify any doubts regarding the instructions or tasks.

3.5 Data Analysis

Quantitative data collected from the LDT, vocabulary tests, and cognitive load questionnaire were analyzed using SPSS version 26. Descriptive statistics provided means and standard deviations for key variables, while inferential statistics tested hypotheses about differences between groups. Repeated-measures ANOVAs examined changes in performance across time points, and post-hoc comparisons adjusted for multiple testing were conducted using Bonferroni corrections.

Qualitative data from open-ended responses on the cognitive load questionnaire were analyzed thematically to identify common patterns and themes related to participants' experiences with AI-generated texts. This dual approach allowed for triangulation of findings and enhanced the validity of the results.

4. Results

4.1 Lexical Access Speed and Accuracy

Participants completed a lexical decision task (LDT) after reading AI-generated texts. Reaction time (RT) and accuracy were used as indicators of lexical recognition efficiency. A repeated-measures ANOVA revealed a significant main effect of text type on lexical decision time, $F(2, 236) = 6.89$, $p = .001$, $\eta^2 = .055$. Post-hoc pairwise comparisons with Bonferroni correction indicated that participants who read dialogic texts responded significantly faster than those who read explanatory texts ($p = .003$), but not narrative texts ($p = .067$). There was no significant difference between narrative and explanatory texts ($p = .21$).

In terms of accuracy, there was also a significant effect of text type, $F(2, 236) = 4.32$, $p = .014$, $\eta^2 = .035$. Participants in the dialogic condition showed higher accuracy rates than those in the explanatory condition ($p = .012$), suggesting that dialogic AI texts may enhance lexical recognition more effectively than other formats.

These results align with previous research indicating that interactive and conversational language structures may facilitate word recognition by activating contextual and pragmatic cues (Rayner et al., 2012).

Table 1. Mean Lexical Decision Time (ms) and Accuracy (%) by Text Type

Text Type	Mean RT (ms)	SD	Accuracy (%)	SD
Narrative	684	45	86	6.2
Dialogic	652	39	89	5.7
Explanatory	701	51	83	7.1

Note. RT = reaction time; SD = standard deviation.

4.2 Semantic Mapping Ability

Semantic priming effects were analyzed to assess how well participants could map new vocabulary into existing semantic networks. Participants judged whether target words were semantically related to previously presented primes.

Results showed a stronger priming effect in the narrative condition compared to both explanatory and dialogic conditions. Specifically, mean response times for related pairs were significantly shorter in the narrative group than in the explanatory group, $t(58) = 2.47$, $p = .017$, $d = 0.64$. No significant difference was found between narrative and dialogic conditions ($p = .10$), nor between dialogic and explanatory groups ($p = .28$).

Accuracy data mirrored this pattern, with narrative texts yielding the highest proportion of correct responses. This suggests that narrative contexts may better support deep semantic integration of new vocabulary, consistent with findings that storytelling enhances memory and conceptual linkage (Wang, Liu, & Zhou, 2024, 2023).

4.3 Vocabulary Retention

Participants completed immediate and delayed recall tests one week later to examine short-term and long-term retention of newly encountered vocabulary.

Descriptive statistics showed that immediate recall performance averaged 72% correct across all conditions. One week later, average recall dropped to 54%. However, there was a differential pattern based on text type. Repeated-measures ANOVA revealed a significant interaction between time and text type, $F(2, 236) = 4.11$, $p = .017$, $\eta^2 = .034$.

Follow-up analyses showed that participants exposed to narrative texts retained significantly more vocabulary over time compared to those in the explanatory condition ($p = .008$). Dialogic texts also showed better retention than explanatory texts, though the difference did not reach statistical significance ($p = .062$). These findings suggest that narrative and dialogic AI-generated texts may be more effective in supporting durable lexical representations than purely informational texts.

Table 2. Mean Vocabulary Recall Performance (%) by Time and Text Type

Text Type	Immediate Recall (%)	Delayed Recall (%)	Drop (%)
Narrative	75	63	12
Dialogic	71	58	13
Explanatory	69	49	20

Note. Drop (%) refers to the percentage decrease from immediate to delayed recall.

4.4 Strategy Use and Cognitive Experience

Qualitative interviews revealed several recurring themes regarding learners' strategies when engaging with AI-generated materials. Using thematic analysis (Braun & Clarke, 2006), four major categories emerged: context-based guessing, repetition and rehearsal, visual association, and metacognitive regulation. Context-based guessing was most frequently reported, especially among participants in the narrative and dialogic conditions, where contextual clues were more abundant. Repetition and rehearsal were commonly used by lower-proficiency learners, particularly in the explanatory condition where fewer contextual supports were available. Visual association was mentioned by learners who interacted with AI tools offering image-word pairings or concept maps. Metacognitive regulation, such as self-monitoring and selective attention, was more common among high-proficiency learners across all conditions.

Moreover, many participants noted that interactive features (e.g., instant definitions, sentence rephrasing) helped reduce cognitive load and facilitated deeper engagement with unfamiliar words. These observations are consistent with cognitive theories emphasizing the importance of optimal input difficulty and scaffolding in L2 vocabulary acquisition (VanPatten & Williams, 2015).

4.5 Moderating Effects of Working Memory and Language Proficiency

Regression analyses were conducted to explore whether individual differences in working memory capacity and language proficiency moderated the effects of AI-generated texts on lexical processing outcomes. Results indicated that working memory had a significant positive correlation with lexical decision accuracy ($\beta = 0.28$, $p = .003$) and delayed recall performance ($\beta = 0.21$, $p = .026$). Similarly, language proficiency was a strong predictor of both immediate and delayed recall scores ($\beta = 0.41$ and $\beta = 0.38$ respectively, $p < .001$). Importantly, moderation analyses showed that the benefits of narrative texts on semantic mapping were more pronounced among learners with higher working memory capacity ($\beta = 0.19$, $p = .012$), whereas learners with lower working memory benefited more from dialogic texts ($\beta = 0.16$, $p = .034$). These findings highlight the need for adaptive AI systems that can tailor content to individual learner profiles.

Table 3. Regression Results: Effects of Working Memory and Language Proficiency on Lexical Processing Outcomes

Outcome Variable	Predictor Variable	β (Beta Coefficient)	*p*-value
Lexical Decision Accuracy	Working Memory	0.28	.003
Delayed Vocabulary Recall	Working Memory	0.21	.026
Immediate Vocabulary Recall	Language Proficiency	0.41	< .001
Delayed Vocabulary Recall	Language Proficiency	0.38	< .001
Semantic Mapping (Narrative)	Working Memory × Narrative Text	0.19	.012
Semantic Mapping (Dialogic)	Working Memory × Dialogic Text	–0.16	.034

5. Discussion

5.1 Text Type and Lexical Processing: Cognitive and Pedagogical Implications

The findings reveal that dialogic texts significantly enhanced lexical decision speed and accuracy compared to explanatory texts, suggesting that interactive and conversational structures may better support real-time word recognition. This aligns with previous research indicating that dialogic discourse activates pragmatic and contextual cues, which are crucial for efficient lexical access (Rayner et al., 2012; Murphy, 1991). Dialogues, by their nature, mimic naturalistic input, offering learners opportunities to process vocabulary in socially embedded contexts, which may mirror native speakers' intuitive language use (Kasper & Rose, 2002).

Conversely, narrative texts demonstrated superior performance in semantic mapping and long-term retention. These findings resonate with dual coding theory (Paivio, 1990), which posits that information encoded through both verbal and imaginal systems leads to stronger memory traces. Narratives often evoke emotional engagement and create vivid mental imagery, thereby enhancing conceptual linkage and recall (Wang, Liu, & Zhou, 2024, 2023). Additionally, narrative structures provide rich contextual scaffolding that facilitates inferencing and integration of new vocabulary into existing semantic networks (Graesser et al., 2004), supporting the Comprehension Hypothesis (Krashen, 1982).

Explanatory texts, while less effective overall, still played a supportive role for certain learner profiles, particularly those who employed repetition and rehearsal strategies. This finding aligns with Sweller's (2011) cognitive load theory, which suggests that structured and predictable formats can reduce extraneous cognitive load for learners with limited working memory capacity. However, these texts appear to be less effective in promoting deep semantic integration or durable lexical representations, underscoring the need for pedagogical designs that balance structure with contextual richness.

5.2 Strategy Use and Cognitive Experience: Learner Agency in AI-Driven Learning

Qualitative data from post-task interviews revealed that learners adopted varied strategies depending on text type and their own proficiency levels. Context-based guessing was most frequently reported in narrative and dialogic conditions, where contextual clues were more abundant. This supports Vygotsky's (1979) concept of the zone of proximal development, emphasizing the importance of meaningful interaction with comprehensible input in L2 learning. Additionally, visual association and metacognitive regulation emerged as key strategies, especially when AI tools provided multimodal features such as image-word pairings or instant definitions. These observations align with Mayer's (2005) multimedia learning theory, which argues that combining visual and verbal modalities enhances comprehension and retention. Furthermore, high-proficiency learners exhibited greater strategic flexibility and self-regulation, confirming earlier findings that metacognitive awareness is a critical factor in successful vocabulary acquisition (Oxford, 2016; Schmitt, 2010). Notably, many participants emphasized that adaptive features such as sentence rephrasing and instant feedback reduced cognitive strain and increased engagement. This highlights the potential of AI not only as a content generator but also as a personalized scaffolding tool, dynamically adjusting support based on learner needs and responses (Heffernan & Heffernan, 2014).

5.3 Moderating Effects of Individual Differences: Toward Personalized Learning

Regression analyses confirmed that working memory capacity and language proficiency significantly influenced vocabulary learning outcomes. Working memory showed a positive correlation with lexical decision accuracy and delayed recall, consistent with Daneman and Carpenter's (1980) influential work on individual differences in reading comprehension. Learners with higher working memory capacity appeared to benefit more from narrative texts, likely due to the demands of integrating complex semantic information over extended discourse (Nation, 2013). In contrast, learners with lower working memory capacity performed better with dialogic texts, which may impose fewer cognitive demands due to their segmented, turn-taking structure. This suggests that dialogic texts could serve as a cognitively accessible entry point for less proficient learners, aligning with VanPatten's (2002) Input Processing theory, which emphasizes how individual constraints shape the way learners attend to and internalize linguistic input. Moreover, language proficiency emerged as a strong predictor of both immediate and delayed recall, reinforcing Laufer's (1997) notion of cumulative vocabulary knowledge. High-proficiency learners were more adept at utilizing context and deploying advanced strategies, whereas lower-proficiency learners relied more heavily on external scaffolds such as glosses and repetition.

These findings underscore the necessity of adaptive AI systems that can tailor content delivery based on learner profiles. Such systems would ideally assess individual differences in real time and adjust text complexity, format, and support features accordingly (Chapelle, 2001; Liu, et al., 2019).

5.4 Implications for AI-Enhanced Language Pedagogy

This study has several practical implications for language teaching and AI-driven instructional design. Incorporating a mix of narrative, dialogic, and explanatory texts can address diverse learning preferences and cognitive demands, promoting both breadth and depth in vocabulary acquisition. AI-generated texts should be designed not only for grammatical accuracy but also for contextual richness, interactivity, and relevance to learners'' interests and goals. Future AI platforms must integrate profiling mechanisms that assess learners' working memory, language proficiency, and learning styles to deliver customized content and feedback. Integrating visual aids, audio enhancements, and interactive glosses can enhance comprehension and retention, especially for learners with lower proficiency or cognitive capacity.

5.5 Limitations and Directions for Future Research

While this study contributes valuable insights, it is not without limitations. First, although the sample size was sufficient for detecting medium effect sizes, future research should aim for larger and more diverse participant pools, including learners from different educational backgrounds and age groups. Second, while working memory and language proficiency were assessed, other individual factors, such as motivation, anxiety, prior exposure to AI tools, and learning style preferences, were not included, potentially limiting the scope of generalizability.

Future studies could explore longitudinal effects of repeated exposure to AI-generated texts, examining how sustained interaction influences vocabulary growth and automatization. Additionally, comparative studies across languages and cultures would help determine whether the observed patterns are universal or specific to Chinese EFL learners. Investigating the impact of different AI models (e.g., GPT-3 vs. BERT vs. Llama variants) on learning outcomes could further refine our understanding of optimal AI-assisted language instruction. Finally, exploring interactive feedback mechanisms, such as chatbots, error correction algorithms, and speech recognition tools, could shed light on how real-time AI interactions influence vocabulary production and fluency development.

6. Conclusion

This study examined how different types of AI-generated texts—narrative, dialogic, and explanatory—affect lexical processing among Chinese EFL learners, with a focus on lexical access, semantic mapping, retention, strategy use, and the moderating effects of working memory and language proficiency. The findings reveal that text type plays a crucial role in shaping vocabulary learning outcomes, with distinct advantages associated with each format depending on the cognitive demands of the task and the characteristics of the learner. Dialogic texts were found to enhance lexical decision speed and accuracy, suggesting that conversational structures may support real-time word recognition by providing contextual and pragmatic cues similar to naturalistic input. Narrative texts, on the other hand, proved more effective in promoting semantic integration and long-term retention, likely due to their ability to engage learners emotionally and cognitively through rich narrative frameworks. Explanatory texts, while less effective overall, still facilitated vocabulary acquisition for learners who relied on repetition and structured input, particularly those with lower working memory capacity. The qualitative data further illustrated how learners adapted their strategies based on text type and proficiency level, highlighting the importance of contextual scaffolding and metacognitive awareness in AI-assisted vocabulary learning. Importantly, regression analyses confirmed that both working memory and language proficiency significantly predicted lexical outcomes. Moderation analyses revealed that high-working-memory learners benefited more from narrative texts in semantic mapping tasks, whereas low-working-memory learners showed greater gains from dialogic texts. These results emphasize the need for adaptive AI systems that can dynamically tailor text formats and support mechanisms according to individual learner profiles.

From a pedagogical perspective, this study underscores the value of diversifying textual input in language instruction and integrating AI-generated materials that are not only linguistically accurate but also cognitively and contextually supportive. It calls for future developments in AI-assisted language learning tools that incorporate profiling and personalization features to optimize learning efficiency across diverse learner populations.

In conclusion, this research contributes to our understanding of how generative artificial intelligence can be leveraged effectively in second language acquisition. By aligning AI-generated content with cognitive theories of language processing and individual differences, educators and developers can create more inclusive, responsive, and effective language learning environments.

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References

[1] Baddeley, A. D. (2012). Working memory: Theories, models, and controversies. Annual Review of Psychology, 63, 1–29.

[2] Balota, D. A., Yap, M. J., Cortese, M. J., Hutchison, K. A., Kessler, B., Loftis, B. & Treiman, R. (2007). The English Lexicon Project. Behavior Research Methods, 39(3), 445–459.

[3] Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. Qualitative Research in Psychology, 3(2), 77–101.

[4] Chapelle, C. A. (2001). Computer applications in second language acquisition: Foundations for CALL into the new millennium. Cambridge University Press.

[5] Creswell, J. W., & Clark, V. L. P. (2017). Designing and conducting mixed methods research. Sage publications.

[6] Creely, E. (2024). Exploring the role of generative AI in enhancing language learning: Opportunities and challenges. *International Journal of Changes in Education, 1*(3), 158-167.

[7] Chung, S. C., Chen, X., & Geva, E. (2019). Deconstructing and reconstructing cross-language transfer in bilingual reading development: An interactive framework. *Journal of neurolinguistics*, 50, 149-161.

[8] Daneman, M., & Carpenter, P. A. (1980). Individual differences in working memory and reading. Journal of Verbal Learning and Verbal Behavior, 19(4), 450–466.

[9] Dijkstra, A., & van Heuven, W. J. B. (2002). The architecture of the bilingual word recognition system: From identification to decision. Bilingualism: Language and Cognition, 5(3), 175–197.

[10] Field, A. (2024). Discovering statistics using IBM SPSS statistics. Sage Publications.

[11] Gao, Y. L., Wang, F. Y., & Lee, S. Y. (2023). The effects of three different storytelling approaches on the vocabulary acquisition and response patterns of young EFL students. Language Teaching Research, 27(5), 1078-1098.

[12] Geva, E., & Ryan, E. B. (1993). Linguistic and cognitive correlates of academic skills in first and second languages. Language learning, 43(1), 5-42.

[13] Goodwin D, A. J. (2018). Morphological representations in lexical processing (Doctoral dissertation, University of Pennsylvania).

[14] Graesser, A. C., McNamara, D. S., Louwerse, M. M., & Cai, Z. (2004). Coh-Metrix: Analysis of text on cohesion and language. Behavior research methods, instruments, & computers, 36(2), 193-202.

[15] Heffernan, N. T., & Heffernan, C. L. (2014). The ASSISTments ecosystem: Building a platform that brings scientists and teachers together for minimally invasive research on human learning and teaching. International Journal of Artificial Intelligence in Education, 24, 470-497.

[16] Jiang, N. (2012). Processing complexity in L2 sentence comprehension: The roles of structure, lexical cues, and working memory. Studies in Second Language Acquisition, 34(1), 1–28. https://doi.org/10.1017/S0272263111000533

[17] Kasper, G., & Rose, K. R. (2002). Pragmatic development in a second language. Language learning.

[18] Koda, K. (2005). Insights into second language reading: A cross-linguistic approach. Cambridge University Press.

[19] Krashen, S. D. (1982). Principles and practice in second language acquisition. Pergamon.

[20] Kroll, J. F., & Sunderman, G. L. (2005). Second language cognition. In J. F. Kroll & A. M. B. De Groot (Eds.), Handbook of bilingualism: Psycholinguistic approaches (pp. 173–189). Oxford University Press.

[21] Lallier, M., & Carreiras, M. (2018). Cross-linguistic transfer in bilinguals reading in two alphabetic orthographies: The grain size accommodation hypothesis. Psychonomic bulletin & review, 25, 386-401.

[22] Laufer, B., & Hulstijn, J. (2001). Incidental vocabulary acquisition in a second language: The construct of task-induced involvement. Applied linguistics, 22(1), 1-26.

[23] Law, L. (2024). Application of generative artificial intelligence (GenAI) in language teaching and learning: A scoping literature review. Computers and Education Open, 100174.
[24] Li, Y., Zhao, X., & Zhang, L. (2022). Enhancing vocabulary learning through morphological instruction: Evidence from Chinese EFL learners. Language Teaching Research. Advance online publication. https://doi.org/10.1177/13621688221085984
[25] Liu, M., Navarrete, C., Maradiegue, E., & Wivagg, J. (2014). Mobile learning and English language learners: A case study of using iPod touch as a teaching and learning tool. *Journal of Interactive Learning Research*, 25(3), 373-403.
[26] Liu, M., & Reinders, H. (2025). Do AI chatbots impact motivation? Insights from a preliminary longitudinal study. System, 128, 103544.
[27] Mayer, R. E. (2005). The Cambridge handbook of multimedia learning. Cambridge University Press.
[28] McNamara, D. S., & Magliano, J. (2009). Toward a comprehensive model of comprehension. Psychology of learning and motivation, 51, 297-384.
[29] Murphy, J. M. (1991). Oral communication in TESOL: Integrating speaking, listening, and pronunciation. TESOL quarterly, 25(1), 51-75.
[30] Nation, I. S., & Nation, I. S. P. (2013). Learning vocabulary in another language (2nd ed.). Cambridge: Cambridge University Press.
[31] Oxford, R. L. (2016). Teaching and researching language learning strategies: Self-regulation in context. Routledge.
[32] Paivio, A. (1990). Mental representations: A dual coding approach. Oxford University Press.
[33] Perfetti, C. A., & Hart, L. (2001). The lexical quality hypothesis. In S. Neufeldt (Ed.), Precursors of functional literacy (pp. 189–213). John Benjamins Publishing Company.
[34] Perfetti, C., & Stafura, J. (2014). Word knowledge in a theory of reading comprehension. Scientific studies of Reading, 18(1), 22-37.
[35] Rayner, K., Pollatsek, A., Ashby, J., & Clifton, C. (2012). Psychology of reading (2nd ed.). Psychology Press.
[36] Rayner, K., Schotter, E. R., Masson, M. E., Potter, M. C., & Treiman, R. (2016). So much to read, so little time: How do we read, and can speed reading help?. Psychological Science in the Public Interest, 17(1), 4-34.
[37] Schmitt, N. (2010). Key issues in teaching and learning vocabulary. Insights into non-native vocabulary teaching and learning, 28-40.
[38] Sweller, J. (2011). Cognitive load theory. In Psychology of learning and motivation (Vol. 55, pp. 37-76). Academic Press.
[39] VanPatten, B. (2002). Processing instruction: An update. Language learning, 52(4), 755-803.
[40] VanPatten, B., & Williams, J. (2015). Theories in second language acquisition: An introduction (2nd ed.). Routledge.
[41] Vygotsky, L. S. (1979). Mind in society: The development of higher psychological processes. Harvard University Press.
[42] Wang, Y., Liu, M., & Zhou, Z. (2024, March). Enhancing ESP Vocabulary Learning through ChatGPT: A Case Study. In Society for Information Technology & Teacher Education International Conference (pp. 907-913). Association for the Advancement of Computing in Education (AACE).
[43] Wen, Z. (2016). Phonological and executive working memory in L2 task-based speech planning and performance. *The Language Learning Journal,* 44(4), 418-435.
[44] Wen, Z. (2018). Using formulaic sequences to measure task performance: The role of working memory. Recent perspectives on task-based language learning and teaching, 29-51.
[45] Webb, S. (2019). Incidental vocabulary learning. In The Routledge handbook of vocabulary studies (pp. 225-239). Routledge.