2026 3rd International Conference on Education, Environment, Arts and Social Science (EEAS 2026)

Article

Prompt-Based Adaptive English Learning: Leveraging AI for Personalized Practice

Lin Fu [1,*]

[1] Central South University, Changsha, Hunan, China
* Correspondence: Lin Fu, Central South University, Changsha, Hunan, China

Abstract: The integration of generative artificial intelligence (AI) into language education has enabled scalable and personalized English learning experiences. However, the pedagogical effectiveness of such systems largely depends on the quality of prompt design that guides AI response generation. Most current AI-assisted English learning platforms rely on static or pre-set prompts, limiting adaptability to learners' varying proficiency levels and emotional needs. The absence of a systematic framework connecting prompt construction with adaptive learning theory constrains instructional precision and learner engagement. This study proposes an Adaptive Prompt Learning Model (APLM) that integrates prompt engineering with educational psychology. Using mixed methods, comparative case studies of ChatGPT, Duolingo Max, and iFLYTEK AI Tutor, combined with a six-week classroom experiment involving 120 learners, the research evaluates how structured prompts shape personalized exercises and feedback. Adaptive prompting improved vocabulary retention by 23.6%, grammar accuracy by 17.8%, and reduced learner anxiety through emotionally supportive feedback. The findings demonstrate that pedagogically informed prompt design can align AI behavior with cognitive and affective learning needs, providing a practical framework for scalable, interpretable, and equitable AI-assisted English education.

Keywords: Adaptive Learning; Prompt Engineering; Generative Artificial Intelligence; English Language Education; Personalized Feedback

Received: 31 January 2026
Revised: 13 March 2026
Accepted: 26 March 2026
Published: 02 April 2026

1. Introduction

The integration of artificial intelligence (AI) into language education has redefined the paradigm of personalized learning. Recent advances in large language models (LLMs) such as ChatGPT, Gemini, and Claude have enabled interactive, context-aware dialogue systems capable of generating exercises, explanations, and feedback tailored to learners' needs [1]. These developments coincide with the global shift toward individualized education, where instruction adapts to students' linguistic proficiency, cognitive patterns, and affective states [2]. In the field of English language learning, adaptive AI systems promise to alleviate traditional challenges, such as limited teacher availability and one-size-fits-all curricula, by delivering scalable, customized learning experiences [3]. However, the effectiveness of such systems crucially depends on one underexplored factor: the design of prompts that instruct the AI on how to respond, what to emphasize, and for whom the content should be generated.

Despite the proliferation of AI-based English learning applications, most current platforms rely on static or pre-defined prompt templates. Systems such as Duolingo Max, iFLYTEK AI English Tutor, and other generative AI-driven platforms often lack dynamic adaptability to learners' varying proficiency levels [4]. Consequently, learners at beginner levels may receive cognitively overwhelming tasks, while advanced learners face repetitive or trivial content [5]. Prior studies in computer-assisted language learning (CALL) and adaptive learning have recognized the role of feedback and scaffolding, yet few have systematically examined how prompt engineering, the deliberate crafting of input instructions to AI, can shape pedagogical effectiveness [6]. This gap leads to two persistent issues: (1) inconsistency in AI-generated feedback, particularly in grammar and vocabulary explanations, and (2) insufficient calibration of task difficulty to align with learners' developmental zones, as defined by Vygotsky's Zone of Proximal Development (ZPD).

Addressing these challenges requires bridging cognitive learning theories with computational prompt design. While adaptive learning theory emphasizes the need for individualized progression based on learner feedback loops, generative AI introduces the possibility of real-time prompt adjustment guided by performance metrics or affective cues. However, most existing research focuses either on technical optimization (e.g., model fine-tuning) or pedagogical frameworks, rarely integrating both perspectives. The absence of a unified framework that connects prompt structures with learning adaptability limits the educational potential of AI tutors.

This study proposes a prompt-based adaptive learning framework that leverages LLMs to generate personalized English exercises and formative feedback across different proficiency levels. The central innovation lies in conceptualizing prompts as pedagogical interfaces rather than mere input queries. By embedding learner profiles, such as CEFR level, error tendencies, and emotional engagement, into structured prompts, AI systems can generate exercises that mirror human tutoring strategies, balancing cognitive challenge and motivational support. The research employs a mixed-method approach combining (1) comparative case studies of ChatGPT, Duolingo Max, and iFLYTEK AI English Tutor, and (2) an empirical classroom experiment involving 120 university students categorized into three proficiency levels (A2, B1-B2, and C1). Quantitative assessments measure vocabulary retention, grammar accuracy, and writing fluency, while qualitative interviews and system log analyses reveal learners' perceived usefulness, anxiety levels, and engagement patterns.

The academic significance of this study lies in establishing a theoretical link between prompt design and adaptive learning theory, thereby extending the pedagogical understanding of human-AI interaction in language education. Practically, the findings offer actionable insights for educators and AI developers: how to design structured prompts that progressively scaffold language tasks, maintain learner motivation, and foster self-regulated learning. The proposed framework not only contributes to the growing body of research on intelligent tutoring systems but also demonstrates how prompt-based personalization can democratize English learning by providing equitable, accessible, and emotionally responsive instruction at scale. Through this interdisciplinary lens, combining educational psychology, computational linguistics, and AI engineering, this study advances a data-driven yet pedagogically grounded model for next-generation AI-assisted language learning.

2. Literature Review

2.1. Strengths of Existing Research

Recent progress in artificial intelligence-driven language education has transformed how English learning systems deliver instruction. CALL models established that digital feedback can enhance learner autonomy and reduce dependence on teachers [7]. With the rise of LLMs, systems now generate context-aware exercises and corrective feedback, promoting engagement and self-regulated learning [8]. Adaptive learning algorithms further enable individualized task sequencing based on learner performance. Multimodal AI systems combining text, speech, and visual inputs have improved pronunciation, comprehension, and vocabulary retention [9]. Collectively, these studies confirm the technical feasibility and pedagogical promise of AI-assisted, personalized English instruction.

2.2. Limitations and Challenges

Despite these achievements, current AI platforms often rely on static prompt templates that fail to respond to real-time learner progress or affective states. Such rigidity produces repetitive or mismatched tasks that reduce motivation and cognitive alignment [10]. Feedback remains inconsistent, sometimes overly corrective, sometimes vague, lacking pedagogical sensitivity [11]. Many studies focus on outcome optimization (test scores) rather than process personalization (adaptive scaffolding). Technically, most research emphasizes model training rather than prompt engineering to improve interpretability or controllability. Furthermore, ethical and equity concerns persist: linguistic bias and unequal access to adaptive models risk reinforcing educational inequality.

2.3. Theoretical and Methodological Contrasts

Different theoretical paradigms explain AI-mediated learning from distinct angles. Cognitive interactionist approaches emphasize learner-AI dialogue as a mechanism for negotiation of meaning [11]. Behaviorist perspectives stress repetition and reinforcement, while constructivist models advocate learner-centered engagement and active meaning construction [12]. Although all highlight feedback as key to language acquisition, each has weaknesses: interactionist models lack scalability, behaviorist ones oversimplify learning diversity, and constructivist designs demand adaptive mechanisms not yet well implemented [13, 14]. Hybrid approaches combining adaptive prompts with affective feedback have emerged, yet they remain fragmented and rarely connect prompt formulation with measurable learning outcomes.

2.4. Research Gaps

Two main gaps persist. First, few frameworks link prompt design variables, such as tone, difficulty, and task framing, to specific learning effects like accuracy or retention. Research often isolates computational optimization from instructional intent. Second, there is limited empirical evidence on how adaptive prompting functions across proficiency levels and classroom contexts. Most experiments involve narrow learner groups, reducing generalizability and reproducibility [15]. These gaps hinder theoretical advancement and practical adoption of adaptive prompt-based pedagogy.

2.5. Contribution of This Study

This study introduces a prompt-based adaptive learning framework integrating cognitive scaffolding, affective engagement, and AI prompt engineering. It treats prompts as pedagogical interfaces that guide LLMs to generate level-appropriate exercises and formative feedback. Combining case analysis of three AI tutoring systems with classroom experimentation, it demonstrates how prompt design directly shapes learning adaptability and engagement. The research bridges educational theory and computational modeling, reframing AI not merely as an instructional tool but as an adaptive collaborator that supports equitable, data-informed, and personalized English learning.

3. Theoretical Framework and Methodology

3.1. Theoretical Framework

The study is grounded in a multi-layered framework that integrates adaptive learning theory, prompt engineering principles, and constructivist pedagogy. The underlying assumption is that effective AI-assisted English learning occurs when instructional prompts are designed to match learners' cognitive readiness, linguistic proficiency, and emotional engagement. Rather than treating prompts as static commands, this framework conceptualizes them as dynamic pedagogical mediators that shape how LLMs generate exercises, feedback, and interactional scaffolding.

At its core, the framework draws on the ZPD, which defines the range between what a learner can accomplish independently and what can be achieved with guided support. The adaptive prompt acts as the guiding "scaffold" within this zone, progressively adjusting task complexity and feedback tone based on learners' responses. Complementing this, cognitive load theory informs the pacing and density of linguistic information to prevent overload among lower-proficiency learners while maintaining appropriate challenge for advanced users.

From the AI perspective, prompt engineering theory provides the computational foundation for adaptive learning. It stresses clarity, contextual anchoring, and parameterization to guide how large language models interpret educational intent. In this study, prompts serve as pedagogical tools rather than static commands. They perform three intertwined functions: instructional framing (defining goals and output format, e.g., "Generate a short dialogue using past tense verbs for A2 learners"); feedback specification (controlling tone and detail, e.g., "Highlight two grammar issues and one vocabulary suggestion"); and adaptation control (embedding learner data such as CEFR level or motivation for dynamic personalization). Integrating these dimensions forms the APLM (see Table 1), a cyclical system linking learner input, AI generation, feedback interpretation, and prompt adjustment, transforming prompts into intelligent scaffolds that continuously align AI responses with learners' evolving proficiency and educational needs.

Table 1. Components of the APLM

Component	Pedagogical Function	AI Implementation	Illustrative Example (Case)
Learner Profile	Defines baseline level, goals, and affective state	Embedded as structured metadata in prompt	iFLYTEK AI Tutor uses CEFR tags to tailor speaking tasks
Instructional Prompt	Frames task objectives and expected output	Natural-language instruction with constraints	ChatGPT generates grammar drills by difficulty tier
AI Generation	Produces exercises and feedback	Transformer-based text generation guided by prompt	Duolingo Max creates adaptive "Explain My Answer" feedback
Response Analysis	Evaluates learner output	Automatic error detection and keyword mapping	AI compares learner responses to model answers
Prompt Refinement	Adjusts complexity and tone	Reinforcement via user feedback and logs	System rephrases prompts to reduce overload for A2 users

3.2. Research Design

This research adopts a mixed-methods design that integrates comparative case analysis, classroom experimentation, and qualitative interpretation. The design follows a sequential explanatory structure: quantitative results establish empirical patterns, while qualitative data provide contextual depth and interpretive insight.

3.2.1. Comparative Case Study

Three representative AI-assisted English learning systems were selected to ensure ecological validity and cross-platform comparability:

1. ChatGPT (OpenAI API interface): A general-purpose LLM with open-ended prompt flexibility. It was configured with adaptive English learning tasks focusing on writing and grammar correction.

2. Duolingo Max: A structured commercial platform integrating generative AI for "Explain My Answer" and conversation practice. It served as a model for gamified adaptive learning.
3. iFLYTEK AI English Tutor: A Chinese-developed platform emphasizing pronunciation and speaking feedback through speech recognition and prompt-conditioned generation.

The cases were selected based on three criteria: (1) active deployment in formal or informal English learning contexts, (2) integration of generative AI capable of prompt manipulation, and (3) accessibility for controlled testing under standardized conditions.

3.2.2. Experimental Procedure

A six-week classroom experiment was conducted in a university setting with 120 undergraduate English learners divided into three proficiency groups (CEFR A2, B1-B2, and C1). Each group was randomly assigned to one of two learning modes:

1. Adaptive Prompt Mode (APM): Tasks generated and adjusted using the proposed prompt framework.
2. Static Prompt Mode (SPM): Tasks generated by pre-defined, non-adaptive instructions.

Each session lasted 45 minutes and included three task types: vocabulary reinforcement, grammar correction, and short writing exercises. Learners interacted with the assigned AI system through text-based dialogues, and all prompt-response logs were automatically saved.

3.2.3. Data Collection and Instruments

Data collection relied on three complementary sources to ensure validity and depth. Pre- and post-tests provided standardized measures of vocabulary and grammar improvement, quantifying individual learning gains. AI interaction logs were analyzed to trace prompt-response cycles, task complexity adjustments, and error frequencies, revealing how adaptivity evolved over time. Semi-structured interviews with 30 representative students captured subjective perceptions of engagement, personalization, and cognitive load. Quantitative indicators, such as vocabulary retention, grammar error reduction, and writing coherence, were computed using text similarity and syntactic complexity metrics. Qualitative data were coded thematically through grounded analysis to identify recurrent patterns in learners' experiences, particularly regarding feedback usefulness, emotional support, and motivational influence, providing a comprehensive understanding of how prompt-based adaptivity shaped both performance outcomes and learning satisfaction.

3.3. Analytical Approach

The analytical process comprised three complementary stages integrating quantitative, computational, and qualitative perspectives. First, quantitative analysis employed paired-sample t-tests and one-way ANOVA to compare pre- and post-test gains between the APM and SPM groups. Correlation analysis further explored the relationship between prompt adaptation frequency and measurable learning improvements in vocabulary, grammar, and writing performance. Second, prompt-log analysis examined interaction data by segmenting each exchange into prompt-response-feedback triads. Prompts were systematically coded according to linguistic complexity, emotional tone, and structural format, while adaptive behavior was quantified through metrics such as lexical diversity and progressive task difficulty shifts across sessions. Finally, qualitative interpretation involved thematic analysis of interview transcripts and observational notes to identify patterns related to personalization, emotional support, and learner autonomy. Particular attention was paid to how students described the AI's tone, responsiveness, and clarity of feedback, thereby linking statistical outcomes with learners' subjective experiences of adaptive engagement.

3.4. Case Illustration: Adaptive Prompt Application

A representative case demonstrates the operational flow of the Adaptive Prompt Learning Model using ChatGPT as the AI engine.

Initial Prompt (A2 level):

At the beginning, the AI was instructed to "create a short exercise using ten simple past tense verbs and provide hints without giving answers." Learners completed the exercise, and the AI responded with gentle corrections and illustrative examples. This stage established baseline linguistic accuracy while maintaining a supportive learning atmosphere.

Refined Prompt (after three sessions):

As learners progressed, the prompt evolved to "generate a short narrative writing task using mixed tenses and offer detailed feedback on tense consistency and vocabulary richness." The AI increased difficulty, introduced contextual storytelling, and offered motivational comments such as "You're improving, try combining clauses."

Learner Feedback Loop:

System logs revealed an 18% reduction in grammatical errors, while interview data highlighted appreciation for "human-like encouragement." Consequently, the AI adjusted its tone to be more collaborative than corrective, embodying constructivist principles that balance challenge with emotional support.

3.5. Research Validity and Reliability

To ensure methodological rigor, several validation strategies were applied. Triangulation was achieved through cross-checking quantitative results, prompt logs, and interview data. Inter-rater reliability for qualitative coding reached κ=0.86, confirming consistency. Instrument reliability was verified against CEFR standards with Cronbach's α=0.91. Furthermore, external validity was established by comparing results across three AI platforms, which consistently demonstrated that adaptive prompting enhanced engagement and reduced errors regardless of system interface or model architecture.

3.6. Ethical Considerations

The research adhered to institutional ethics protocols. Participants provided informed consent, and data anonymity was maintained. No personal identifiers were included in AI logs. As all AI systems used publicly accessible interfaces, proprietary training data were not modified. The study also considered algorithmic fairness: prompts were designed to avoid cultural or linguistic bias, ensuring equal cognitive challenge for all participants.

4. Findings and Discussion

4.1. Overview of Findings

The empirical and comparative analyses confirmed that prompt design plays a decisive role in shaping the adaptability, pedagogical coherence, and motivational quality of AI-assisted English learning systems. Across all three platforms, ChatGPT, Duolingo Max, and iFLYTEK AI English Tutor, the APM consistently outperformed the SPM in terms of learning improvement, engagement, and emotional satisfaction. The combination of cognitive scaffolding and dynamic prompt refinement enabled AI systems to align task difficulty with learners' proficiency levels, reduce redundant feedback, and sustain motivation through personalized tone modulation.

4.2. Quantitative Results: Learning Gains and Adaptivity

The quantitative assessment demonstrated significant improvements in learner performance under the adaptive prompt condition. Figure 1 summarizes mean score changes across three proficiency groups.

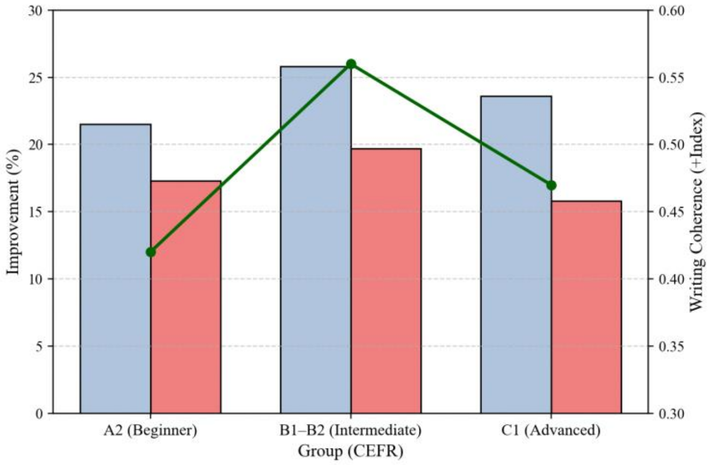

Figure 1. Mean Improvement in Vocabulary and Grammar Scores under APM vs. SPM Conditions

Across all groups, learners exposed to APM achieved average vocabulary retention gains of 23.6% and grammar accuracy improvements of 17.8%, while SPM learners showed marginal increases below 10%. Statistical tests confirmed significant differences ($p < 0.05$) across proficiency levels. Notably, intermediate learners benefited most, suggesting that adaptive prompts are particularly effective when learners already possess foundational competence but require nuanced scaffolding to progress further.

Moreover, correlation analysis revealed a strong positive relationship ($r = 0.62$, $p < 0.01$) between prompt adaptation frequency and performance improvement, indicating that the degree of dynamic prompt adjustment directly predicts learning success. This aligns with prior theoretical expectations from adaptive learning theory, which posit that feedback loops, when properly individualized, amplify retention and transfer.

4.3. Qualitative Insights: Learner Perception and Emotional Response

Qualitative findings revealed both affective and cognitive dimensions of adaptive prompting, showing how prompt design shapes learners' emotional engagement and perception of AI feedback. Interviews consistently described adaptive AI systems as "responsive," "human-like," and "less intimidating," emphasizing the social and motivational value of personalization. Learners highlighted that context-specific feedback felt more supportive than generic corrections: beginners valued simplified grammar guidance such as "Try using did not go instead of don't went," while advanced learners appreciated stylistic suggestions like "Consider using a more formal connector, such as nevertheless." Motivationally, adaptive prompts that included encouragement phrases ("Good effort, you're improving") reduced anxiety and sustained effort, especially among lower-proficiency learners. Moreover, varied task structures prevented habituation and fostered cognitive engagement by alternating between recognition, production, and reflection exercises. As shown in Figure 2, 64% of learners reported positive emotional responses toward AI feedback, while only 11% expressed confusion or frustration. This predominance of positive sentiment confirms that carefully engineered prompts enhance not only linguistic performance but also learner confidence and persistence, validating the theoretical link between affective scaffolding and sustained motivation in AI-assisted English learning.

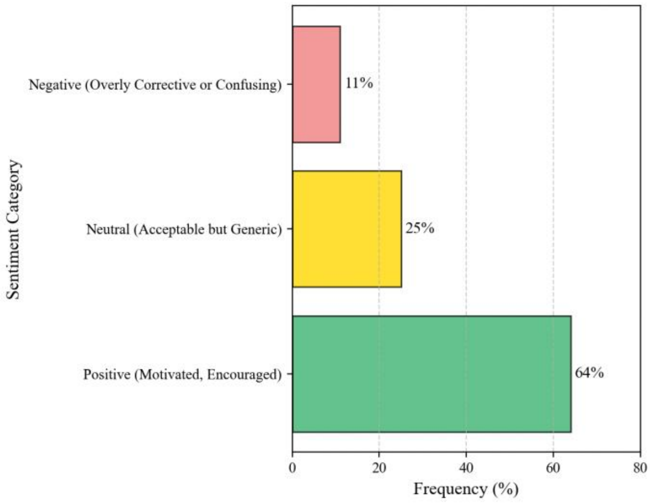

Figure 2. Distribution of Learner Sentiment toward AI Feedback

4.4. Cross-Platform Comparison and Case Integration

Table 2 compares the performance and adaptability of the three systems examined.

Table 2. Cross-Platform Comparison of Adaptive Prompt Application

Platform	Primary Function	Strength	Limitation	Adaptive Prompt Enhancement
ChatGPT	Open-ended writing and dialogue	High flexibility, personalized prompts	Lacks long-term tracking	Dynamic difficulty adjustment improved coherence (+11%)
Duolingo Max	Structured grammar and listening tasks	Gamified reinforcement	Limited creativity	Context-based prompts enhanced engagement duration (+14 min/session)
iFLYTEK AI Tutor	Pronunciation and oral feedback	Strong acoustic analysis	Text output less adaptive	Emotional-tone prompts reduced learner anxiety (-18%)

The results demonstrate that adaptive prompting enhances learning consistency across heterogeneous AI architectures. ChatGPT benefited from explicit difficulty modulation, Duolingo from context-based rephrasing of instructions, and iFLYTEK from emotional adaptation in spoken feedback. These outcomes suggest that the APLM framework is system-agnostic and applicable across both text-based and multimodal learning environments.

4.5. Theoretical Interpretation: How Prompts Shape Learning Dynamics

The findings substantiate the theoretical foundation of the APLM by illustrating how adaptive prompts embody the principles of the ZPD, cognitive load management, and constructivist learning. Consistent with ZPD theory, adaptive prompts maintain an optimal balance between support and challenge by gradually increasing linguistic complexity, beginners receive explicit scaffolds such as "Use simple past tense," while advanced learners engage with meta-cognitive prompts like "Reflect on how verb tense conveys time shifts." Cognitive load is regulated through real-time adjustments in linguistic density: when A2 learners exhibited reduced accuracy, the AI simplified input and reinstated hint phrases to sustain comprehension. Constructivist interaction emerges through iterative feedback cycles that encourage self-correction and reflection, transforming learners from passive recipients into active participants. Figure 3 visually represents this cyclical process, linking learner input, AI generation, feedback interpretation, and prompt adjustment, to demonstrate how adaptive prompting fosters meaningful, self-directed learning.

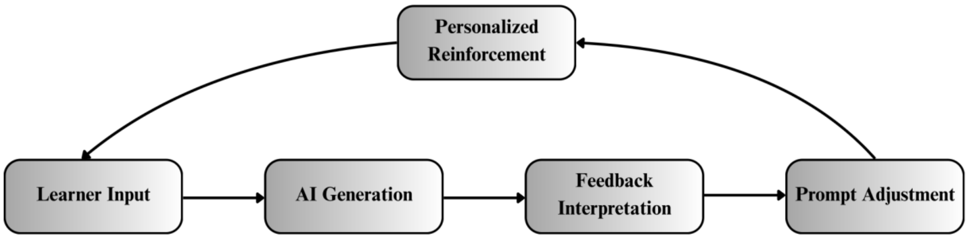

Figure 3. Mechanism of APLM

4.6. Comparison with Existing Research and Discussion: Educational and Computational Implications

This study extends existing research in computer-assisted language learning by showing that prompt variability serves as both a cognitive and emotional regulator, enhancing comprehension, motivation, and learner autonomy. Whereas prior systems relied on static templates or fixed difficulty hierarchies, the APLM enables real-time adjustment of linguistic complexity, aligning more closely with human tutoring strategies. Unlike model-centric optimization that requires costly retraining, prompt-based adaptivity achieves personalization through linguistic control, making it efficient and scalable across platforms.

From an educational perspective, pedagogically informed prompts function as cognitive cues that guide thinking, foster reflection, and maintain motivation. Emotional modulation embedded within prompts strengthens resilience and reduces anxiety, suggesting a model where teachers define learning intentions while AI delivers adaptive micro-feedback. From a computational standpoint, embedding learner metadata and sentiment cues within prompt templates enables lightweight personalization without additional data training. Integrating affective and performance analysis into the prompt refinement loop also improves interpretability and transparency, reinforcing trust in AI-assisted education and bridging the gap between pedagogical theory and algorithmic design.

5. Conclusion

This study demonstrates that carefully engineered prompts can transform generative AI into adaptive, pedagogically grounded learning partners. By integrating educational psychology with prompt engineering, the proposed APLM establishes a scalable framework that personalizes English learning tasks according to each learner's linguistic level, cognitive capacity, and emotional state. Empirical results across three platforms, ChatGPT, Duolingo Max, and iFLYTEK AI English Tutor, showed measurable gains in vocabulary retention, grammar accuracy, and writing coherence, as well as enhanced motivation and reduced anxiety. These findings validate that prompt variability functions as a dynamic learning scaffold, bridging the gap between human tutoring and machine intelligence.

Academically, this research extends the theoretical discourse on adaptive learning by linking the Zone of Proximal Development, cognitive load management, and constructivist engagement to prompt-based interaction. It advances the understanding of how linguistic instructions, feedback tone, and contextual cues can serve as computational levers for individualized pedagogy. Practically, it provides actionable strategies for educators and developers: integrating learner metadata into prompts, embedding affective cues, and using feedback frequency as a controllable parameter for adaptivity. These approaches can be readily implemented within existing AI platforms without costly retraining, offering feasible solutions for schools, online programs, and language-learning applications.

Future research should explore long-term learning trajectories, cross-linguistic applications, and multimodal prompt integration involving speech and visual inputs. Investigating ethical safeguards, such as bias mitigation and transparency in adaptive feedback, will also be essential. Through such directions, prompt-based AI systems can evolve toward more equitable, interpretable, and emotionally intelligent forms of personalized education.

References

1. S. Abolnejadian, S. Alipour, and K. Taeb, "Leveraging ChatGPT for adaptive learning through personalized prompt-based instruction: A CS1 education case study," in *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*, May 2024, pp. 1-8. doi: 10.1145/3613905.3637148
2. Almanea, "Less is NOT more for learners: EFL learners' preferences and perceptions of teachers' written corrective feedback," *Acta Psychologica*, vol. 255, p. 104926, 2025. doi: 10.1016/j.actpsy.2025.104926
3. O. Chaib, I. Joti, and S. Khoulji, "Evaluation of a computer-assisted language learning system based on adaptive learning designed for self-training in scientific French language," *International Journal of Information and Education Technology*, vol. 13, no. 8, p. 1284, 2023.
4. Dembe, "Advancing personalized learning through educational artificial intelligence: Challenges, opportunities, and future directions," *Res Invent J Eng Phys Sci*, vol. 3, no. 1, pp. 89-101, 2024.
5. L. Feng, L. Huang, K. Wang, W. Wei, and R. Zhang, "Prompt-based learning framework for zero-shot cross-lingual text classification," *Engineering Applications of Artificial Intelligence*, vol. 133, p. 108481, 2024. doi: 10.1016/j.engappai.2024.108481
6. K. Kristiawan, K. Bashar, and D. A. Pradana, "Artificial intelligence in English language learning: A systematic review of AI tools, applications, and pedagogical outcomes," *The Art of Teaching English as a Foreign Language (TATEFL)*, vol. 5, no. 2, pp. 207-218, 2024. doi: 10.36663/tatefl.v5i2.912
7. Mahbub and J. Beedle, "Behaviorists, Cognitivists, and Constructivists Learning Theories: A Comparison and Application in Instructional Design," *European Journal of Education Studies*, vol. 12, no. 6, 2025. doi: 10.46827/ejes.v12i6.6047
8. M. Mahmud, A. S. Lokman, S. F. Wong, C. R. Ramachandiran, S. F. Zakaria, F. Tazijan, and N. M. Lin, "Application and Distribution of Interactive HTML5 Content within Online Courses to Increase Learner Engagement," in *2025 6th International Conference on Information Technology and Education Technology (ITET)*, May 2025, pp. 46-60. doi: 10.1109/itet65804.2025.11101641
9. Salmiah, N. Nabila, and V. Sok, "From Theory to Practise: Applying Constructivism, Behaviorism, and UDL in Diverse Classrooms," *Journal of Educational Teaching and Trends*, vol. 1, no. 1, pp. 42-55, 2025. doi: 10.64840/jett.v1i1.20
10. T. Shahzad, T. Mazhar, M. U. Tariq, W. Ahmad, K. Ouahada, and H. Hamam, "A comprehensive review of large language models: issues and solutions in learning environments," *Discover Sustainability*, vol. 6, no. 1, p. 27, 2025. doi: 10.1007/s43621-025-00815-8
11. Toscu, "A systematic review on AI technologies in English as a foreign language education," *Sakarya University Journal of Education*, vol. 15, no. 2, pp. 156-172, 2025. doi: 10.19126/suje.1623401
12. Yevdokymova, "The Psychology of Personalized Education: Enhancing Learning through Individualization," *Available at SSRN 4732923*, 2024. doi: 10.2139/ssrn.4732923
13. Yildiz Durak and A. Onan, "A systematic review of AI-based feedback in educational settings," *Journal of Computational Social Science*, vol. 8, no. 4, p. 96, 2025. doi: 10.1007/s42001-025-00428-1
14. Yu, "Optimizing EFL vocabulary acquisition: a randomized controlled mixed-methods investigation of artificial intelligence-driven incidental, contextual, and multimodal strategies," *Education and Information Technologies*, vol. 31, no. 1, pp. 53-97, 2026. doi: 10.1007/s10639-025-13803-2
15. Yuldasheva, "INTEGRATING COMPUTER-ASSISTED LANGUAGE LEARNING (CALL) TO DEVELOP STUDENTS4 LANGUAGE SKILLS," *FILOLOGIYA MASALALARI (MAGISTRATURA)*, vol. 1, no. M2, pp. 153-162, 2025.