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Adaptive Learning Based on Artificial Intelligence for English Learning Personalization: A Literature Review and Conceptual Synthesis

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Abstract

The diversity of proficiency levels, learning styles, and language acquisition pace among English as a Foreign Language (EFL) learners is often poorly accommodated by conventional one-size-fits-all teaching models. This article is a narrative literature review and conceptual synthesis that examines how Artificial Intelligence (AI)-based adaptive learning may support the personalization of English language learning, covering the systems' reported working mechanisms, the cognitive foundations of content design, reported perception, engagement, and language-related outcomes, and implementation challenges. Sources were purposively selected and grouped into direct evidence on AI in English learning, indirect evidence from two ADDIE-based instructional media development studies, and theoretical sources on multimedia learning and cognitive load. The reviewed literature describes AI-based systems that use Natural Language Processing, Automatic Speech Recognition, and knowledge tracing as being able to adjust grammar, vocabulary, pronunciation, and writing materials to learners' proficiency profiles. The direct evidence is largely perceptual and engagement-related: in a survey of 120 English teachers in Palembang, 78% perceived AI as supportive of personalized learning and 82% perceived increased student engagement, whereas evidence on measured language achievement is mixed. The two ADDIE-based studies concern neither AI nor English learning and are used only as indirect evidence of the instructional-design relevance of needs analysis. The synthesis suggests that AI-driven personalization may be pedagogically strengthened when aligned with cognitive load management principles (extraneous, essential, and generative processing). The article proposes a conceptual framework linking adaptive AI mechanisms, needs-based instructional design, multimedia cognitive design, and teacher mediation; this framework is a theoretical proposition that requires empirical testing and does not demonstrate the effectiveness of AI-based adaptive learning.

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1. Introduction

Learning English as a foreign language (EFL) faces the classic challenge of diversity in proficiency levels, learning styles, and speed of language mastery among students in a class. Conventional teaching models that apply a uniform approach (one-size-fits-all) are often unable to accommodate these differences, thus creating achievement gaps between learners, especially in the aspects of grammar, vocabulary, pronunciation, and writing skills (Br. Siregar et al., 2026). This condition emphasizes the need for a more responsive and personalized learning approach to the needs of each language learner.

The development of Artificial Intelligence (AI) technology opens up new opportunities to realize the personalization of English learning through the concept of adaptive learning, which is a system that dynamically adjusts the material, level of difficulty, and learning path based on each learner's performance data (Zawacki-Richter et al., 2019). Through technologies such as Natural Language Processing (NLP), Automatic Speech Recognition (ASR), machine learning, and knowledge tracing, AI systems are described as being able to analyze grammatical errors, pronunciation patterns, and progress in students' writing and speaking skills in real-time, then provide feedback and materials tailored to the specific needs of each individual (Zulfa et al., 2026). Chen et al. (2020) through bibliometric analysis emphasized that research on personalized learning in the intelligent learning environment has increased significantly since the last two decades, indicating the urgency of this topic in contemporary language education discourse. Alsayed and Bin Rasyid's (2025) systematic review of 20 studies of intelligent tutoring systems (ITS) in language learning also reports that systems that integrate NLP, speech recognition, and automated feedback appear most effective when aligned with communicative or task-based instructional approaches.

The cognitive foundation for personalizing learning content can also be traced from the Cognitive Theory of Multimedia Learning developed by Mayer (2009, 2014). This theory emphasizes that meaningful understanding occurs when learners succeed in combining verbal representations (words) and visual representations (images or animations) into working memory through three cognitive processes, namely selecting, organizing, and integrating information with prior knowledge (Mayer, 2014). Based on the Integrated Model of Text and Picture Comprehension (ITPC), multimedia is not just a tool for information transfer, but a cognitive tool that facilitates the formation of an integrated mental model of learners. This principle is relevant for AI-based adaptive learning systems, as effective personalization not only adjusts the difficulty of the material, but also requires paying attention to how the combination of text, audio, and visuals is presented so as not to overload the learner's naturally limited working memory capacity (Plass, Moreno, & Brünken, 2010).

Referring to the Triarchic Theory of Cognitive Load (Plass et al., 2010), designing good learning content, including content personalized by AI, needs to manage three cognitive goals: reducing extraneous processing due to irrelevant design elements, managing essential processing so that material complexity does not burden working memory, and encouraging generative processing so that learners are motivated to organize and integrate new material in depth.

This principle is in line with Jack Koumi's Video Screenwriting Framework which emphasizes that audiovisual learning media needs to be designed through hook, signpost, facilitate attentive viewing, elucidate, texture, and consolidate stages, so that viewing activities are not reduced to passive activities (warm bath syndrome), but still trigger minds-on activities (Koumi, 2006). Thus, AI-based adaptive learning systems that only focus on the automation of material adjustments without paying attention to the principles

of cognitive load management risk producing personalization that is technically efficient but less pedagogically effective.

Previous research has reported positive perceptions of, and engagement with, AI integration among English learners and teachers. Budiyanto et al. (2025), in a survey of 120 English teachers in Palembang, found that 78% of respondents perceived that AI supports personalized learning, 82% perceived that AI increases student engagement, and 75% reported increased learning motivation, although 45% of teachers reported internet access constraints and 52% expressed concerns over the lack of training in the use of technology.

Hockly (2023) emphasized that although AI offers efficient content personalization, it cannot replace the essential human mediation in fostering intercultural competence and affective engagement of language learners. Waziana et al. (2024) reported that EFL students in Indonesia perceived AI chatbots such as ChatGPT and Gemini as improving their vocabulary, syntactic variation, and grammatical accuracy. Alsofyani and Barzanji (2025), in a study of EFL students in Saudi Arabia, found that ChatGPT-based feedback produced writing outcomes comparable to teacher feedback, while Wang and Han (2025) reported that ChatGPT feedback was associated with significant gains in affective and behavioral engagement. However, these studies generally focused on perceptions, engagement, and writing outcomes of generative AI use, without explicitly examining whether the resulting content design had taken into account the principles of managing learners' cognitive load.

Most of the studies that have been mentioned focus on evaluating the impact of generative AI technology without explicitly elaborating on how systematic instructional design principles, such as ADDIE (Analysis, Design, Development, Implementation, Evaluation) models, as well as multimedia cognitive design principles such as Cognitive Theory of Multimedia Learning and Cognitive Load Theory, may strengthen the validity and effectiveness of personalization generated by AI systems. This gap is important to answer, given that the success of language learning personalization appears to depend not only on the sophistication of algorithms, but also on the accuracy of learning needs analysis and cognitive load management at the system design stage (Gong et al., 2023).

Studies on the development of digital learning media based on the ADDIE model, such as the development of Google Sites-based e-learning with the TIME learning model (Rahadian et al., 2024) and interactive animated video learning media for computer system materials (Rahadian et al., 2026), illustrate how a systematic analysis of learning needs in the early stages of development is associated with learning products that obtain high validity and favorable user responses.

These two studies involve neither AI nor English language learning, and their validity scores do not measure personalization or language outcomes; they are therefore treated in this review only as indirect evidence of the instructional-design relevance of needs analysis. Their methodological principles, which also refer to the TIME Model and Learning Flow (Objectives, Indicators, Learning Materials, Evaluation) framework (Rahadian, 2021), may serve as a reference for the design of AI-based adaptive learning systems in the EFL context, so that personalization is grounded in learners' actual needs and cognitive capacity rather than in technical automation alone.

To clarify how the components discussed above relate to personalized EFL learning, this article proposes a conceptual framework (Table 1). The framework is a theoretical proposition derived from the reviewed literature; it has not been empirically tested, and the strength of the evidence behind each component differs, as indicated in the last column.

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Table 1. Proposed Conceptual Framework: Components and Their Expected Contribution to Personalized EFL Learning

Component	Expected contribution to personalized EFL learning	Basis and type of evidence
AI adaptive mechanisms (NLP, ASR, knowledge tracing)	Diagnose learners' grammar, vocabulary, pronunciation, and writing performance, and adjust material, difficulty, and feedback to individual proficiency profiles	Zulfa et al. (2026), system description; Alsayed & Bin Rasyid (2025), systematic review
Needs-based instructional design (ADDIE, TIME model)	Anchors adaptation in analyzed learner needs and in aligned objectives, indicators, materials, and evaluation	Rahadian (2021); Rahadian et al. (2024, 2026); indirect (not AI, not English learning)
Multimedia cognitive design (CTML, CLT, Koumi's framework)	Regulates how adapted text, audio, and visuals are presented: reduces extraneous processing, manages essential processing, and encourages generative processing	Mayer (2014); Plass et al. (2010); Koumi (2006); theoretical
Teacher mediation	Provides authentic communicative interaction, affective and intercultural support, and guidance against over-reliance on automated feedback	Hockly (2023), conceptual; Wang & Han (2025), empirical

Based on this description, this article aims to (1) review how the working mechanisms of AI-based adaptive learning systems in English language learning are described in the literature, (2) synthesize the reported perceptions, engagement, language outcomes, and personalization outcomes, distinguishing direct evidence on AI from indirect evidence on instructional design, and (3) propose a conceptual framework relating systematic instructional design and multimedia cognitive design to AI-based learning personalization, together with implementation challenges and recommendations for English teaching in Indonesia.

2. Method

This study is a narrative (integrative) literature review with a descriptive qualitative approach. This design was chosen because the purpose is to synthesize and interpret findings from published scientific sources and to develop a conceptual framework, rather than to collect primary data or to estimate the effectiveness of an intervention. The review was not conducted as a systematic review or meta-analysis and did not follow a registered protocol (for example, PRISMA); its conclusions are therefore interpretive and should not be read as pooled evidence of effectiveness.

The sources were purposively selected and grouped into four categories according to study type and evidential role. The first category is direct evidence on AI in English language learning (EFL/ESL/ELT). It comprises empirical studies, namely teacher and student surveys, interviews, and experimental or mixed-methods studies of ChatGPT feedback (Budiyanto et al., 2025; Waziana et al., 2024; Alsofyani & Barzanji, 2025; Wang & Han, 2025); secondary syntheses (Alsayed & Bin Rasyid, 2025; Br. Siregar et al., 2026; Zawacki-Richter et al., 2019; Chen et al., 2020); and a conference paper describing an AI-based adaptive learning platform (Zulfa et al., 2026). The second category is indirect evidence from two research and development (R&D) studies of learning media based on the ADDIE model: Google Sites-based e-learning with the TIME model (Rahadian et al., 2024) and

interactive animated video learning media for computer system materials (Rahadian et al., 2026).

These two studies were included because they document how systematic needs analysis is operationalized in digital media development; they involve neither AI nor English language learning, so their validity and student-response scores are not treated as evidence of AI-based English personalization. The third category is theoretical literature on multimedia learning and cognitive load, namely the Cognitive Theory of Multimedia Learning (Mayer, 2009, 2014), Cognitive Load Theory (Plass, Moreno, & Brünken, 2010), and Jack Koumi's Video Screenwriting Framework (Koumi, 2006), which are used as analytical lenses to assess the pedagogical suitability of AI-personalized content. The fourth category is conceptual and pedagogical argument literature (Hockly, 2023; Gong et al., 2023), used to frame the role of human mediation and of pedagogical frameworks in AI adoption.

Sources were identified through purposive searches of online journal databases using the keywords "adaptive learning", "artificial intelligence", "personalized learning", "English language teaching/EFL", and "cognitive load in multimedia learning". Sources were retained when they met the criteria of topic relevance, methodological clarity, and, for empirical studies, availability of research data. Because this is a narrative review, the specific databases, search dates, publication-year limits, and screening counts were not recorded under a formal protocol and are therefore not reported; this is acknowledged as a limitation (Section 4). In addition, both ADDIE-based R&D studies were co-authored by members of the present author team, which is disclosed here as a potential source of selection bias.

Data were analyzed through descriptive content analysis in three stages: (1) data reduction through the identification of AI-based adaptive learning concepts and working mechanisms in the collected literature; (2) data presentation by grouping findings according to study type (direct empirical evidence, secondary synthesis, indirect instructional-design evidence, and theoretical sources) and according to outcome type (perceptions, engagement, language outcomes, and personalization outcomes), as well as their suitability with cognitive load management principles; and (3) interpretive comparison of findings across the four categories of sources to develop a conceptual framework relating systematic instructional design, multimedia cognitive design, and AI-based English learning personalization. Findings from different study types were compared qualitatively and were not pooled or weighted.

3. Results

The findings are presented by evidence type: system descriptions and reviews (Section 3.1), theoretical sources (Section 3.2), indirect instructional-design evidence (Section 3.3), and direct empirical evidence on perceptions, engagement, language outcomes, and personalization outcomes (Section 3.4). Table 2 consolidates them.

3.1 Working Mechanism of AI-Based Adaptive Learning Systems (System Descriptions and Reviews)

The reviewed literature describes AI-based adaptive learning systems in English learning as combining several technologies, namely Natural Language Processing (NLP) to analyze and correct grammatical structures and word choices, Automatic Speech Recognition (ASR) to assess pronunciation accuracy, emotion detection to monitor learners' level of engagement and confidence, and knowledge tracing to track language competency mastery over time (Zulfa et al., 2026). Zulfa et al. (2026) describe one platform that integrates seven AI technologies, namely ASR, NLP, emotion detection, large language

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model, machine translation, deep knowledge tracing, and gamification, and that is designed to adjust lesson difficulty based on response time, answer accuracy, and the learner's emotional state. This source is used here to illustrate the intended mechanism rather than as evidence of learning outcomes.

Alsayed and Bin Rasyid (2025), in a systematic review of 20 studies of intelligent tutoring systems in language learning, reported that systems that integrate NLP and speech recognition appeared most effective when aligned with constructivist, communicative, or task-based approaches, with positive outcomes reported for vocabulary acquisition, pronunciation, and learner motivation, although the accuracy of voice recognition and system responsiveness remained identified limitations.

Waziana et al. (2024), in a study of EFL students' perceptions, reported that of 100 EFL students surveyed, ChatGPT was the most widely used AI chatbot (78 respondents), followed by Gemini (31 respondents) and Perplexity (17 respondents), with the main reasons for use being ease of access and perceived effectiveness in providing instant grammatical and vocabulary feedback. These are usage and perception data. General-purpose chatbots are not adaptive learning systems in the strict sense, so this source illustrates AI-supported feedback rather than adaptive personalization.

3.2 Cognitive Foundations of Adaptive Learning Content Design (Theoretical Sources)

Mayer's (2014) Cognitive Theory of Multimedia Learning proposes that meaningful understanding is formed through three cognitive processes, namely selecting relevant verbal and visual information, organizing the information into verbal and pictorial models in working memory, and integrating the two models with the learner's prior knowledge. This suggests that materials personalized by AI systems, such as a combination of grammar correction text and audio-visual pronunciation displays, should be designed so as not to cause excessive duplication of verbal and visual information that could burden the learner's working memory. This is a theoretical implication that was not examined in the reviewed AI studies.

Cognitive Load Theory (Plass et al., 2010) identifies three goals for managing mental capacity that are relevant to adaptive content design, namely reducing extraneous processing (for example, by eliminating irrelevant elements of AI feedback), managing essential processing (for example, through gradual structuring of the difficulty of language material), and encouraging generative processing (for example, through tasks that motivate learners to integrate AI corrections into existing language knowledge). These examples are applications proposed in this review, not findings of the cited source.

Jack Koumi's Video Screenwriting Framework (Koumi, 2006) specifies ten elements of audiovisual learning design, namely hook, signpost, facilitate attentive viewing, enable individual construction, sensitize, elucidate, texture, reinforce, consolidate, and link. These elements can serve as an evaluative framework for video or animation materials produced or recommended by AI-based adaptive learning systems, particularly to prevent audiovisual material from being reduced to passive spectacle (warm bath syndrome) and to ensure that it still triggers minds-on activities.

3.3 Instructional Design Evidence (Indirect Evidence)

Two ADDIE-based R&D studies are reviewed as indirect evidence. Neither involves AI or English language learning, and their validation and response scores describe the quality and acceptance of the media that were developed, not personalization or language outcomes. In the Google Sites-based e-learning study, the analysis of students' learning needs was the basis for designing the material; material experts rated feasibility at 95.00% and media experts at 94.55% (category "Very Valid"), and a trial with 52 students in three

stages obtained scores of 94.00%, 92.00%, and 88.00% (category "Excellent") (Rahadian et al., 2024).

Similarly, the development of ADDIE-based interactive animated video learning media for computer system materials reported a high level of feasibility and acceptance among students for technical and abstract materials designed on the basis of a learning needs analysis (Rahadian et al., 2026). Taken together, these studies indicate the instructional-design relevance of needs analysis in digital media development, but they cannot be used to infer that needs analysis improves AI-based personalization.

3.4 Direct Evidence on Perceptions, Engagement, Language Outcomes, and Personalization

Perceptions. In a survey of 120 English teachers in Palembang, Budiyanto et al. (2025) reported that 78% of respondents perceived that AI supports personalized learning, 82% perceived that AI increases student engagement, and 75% reported increased learning motivation; 45% reported internet access constraints and 52% expressed concern over the lack of training in the use of AI technology. Through thematic analysis of EFL student interviews, Waziana et al. (2024) identified three subthemes of perceived impact on vocabulary (vocabulary improvement, contextual vocabulary learning, and consistency of language style) and three on grammar (increased grammatical accuracy, reduction of repetition, and increased clarity and coherence). These are self-reported perceptions, not measured learner outcomes.

Engagement. Wang and Han (2025) reported that ChatGPT feedback significantly increased affective engagement (estimated 0.45) and behavioral engagement (estimated 0.29) of EFL students.

Language outcomes. Alsofyani and Barzanji (2025), in a study of EFL students in Saudi Arabia, did not find a significant difference in posttest scores between the group that received ChatGPT feedback and the group that received teacher feedback, although a perception survey showed a very positive attitude towards the use of ChatGPT for academic writing. Wang and Han (2025) additionally reported a significant interaction between group and time on writing performance (estimated 4.19). Measured language outcomes in the direct evidence are therefore limited to writing and are mixed.

Personalization outcomes. In the studies synthesized here, personalization is addressed only through teacher perceptions (Budiyanto et al., 2025) and system descriptions (Zulfa et al., 2026); none reports a measure of personalization itself, such as the degree to which materials or feedback were matched to individual learner profiles. Evidence that AI-based adaptive learning improves personalization is therefore indirect and preliminary.

Risks. Wang and Han (2025) also reported concerns about over-reliance on AI that could reduce students' ability to proofread their writing independently.

A summary of the findings, separated by evidence type and outcome, is presented in Table 2 below.

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Table 2. Summary of the Reviewed Evidence by Study Type and Outcome

Aspect	Findings	Source and study type
A. Direct evidence on AI in English learning		
Personalization mechanism	NLP, ASR, emotion detection, and knowledge tracing are described as enabling real-time material adjustment (no outcome data used)	Zulfa et al. (2026); conference paper, system description
Intelligent tutoring systems in language learning	Positive outcomes reported for vocabulary, pronunciation, and motivation across 20 studies; speech recognition accuracy and responsiveness remain limitations	Alsayed & Bin Rasyid (2025); systematic review
Teacher perceptions	78% perceived support for personalization; 82% perceived increased engagement; 75% perceived increased motivation; 45% reported internet access constraints; 52% reported concern over lack of training	Budiyanto et al. (2025); survey of 120 teachers
Student use and perceptions	ChatGPT used by 78 of 100 respondents; perceived improvement in vocabulary and grammar	Waziana et al. (2024); survey and interviews
Engagement	Significant increase in affective (0.45) and behavioral (0.29) engagement	Wang & Han (2025); empirical study
Language outcomes	No significant difference in posttest writing scores between ChatGPT and teacher feedback, with positive perceptions; a significant group and time interaction on writing performance (4.19)	Alsofyani & Barzanji (2025); Wang & Han (2025)
Personalization outcomes	Not measured directly in the studies synthesized; inferred from teacher perceptions and system descriptions	Budiyanto et al. (2025); Zulfa et al. (2026)
Risk of reliance on AI	Concern that reliance on automated feedback may reduce independent proofreading ability	Wang & Han (2025); empirical study
B. Indirect evidence: instructional design (not AI, not English learning)		
Validity of ADDIE-based e-learning	Material experts 95.00%; media experts 94.55% (category "Very Valid")	Rahadian et al. (2024); R&D study
Student response to e-learning media	88.00%-94.00% (category "Excellent") across three trial stages (52 students)	Rahadian et al. (2024); R&D study
Acceptance of animated video media	High feasibility and student acceptance reported	Rahadian et al. (2026); R&D study
C. Theoretical sources (not empirical findings)		
Multimedia cognitive foundation	Understanding is formed through selecting, organizing, and integrating verbal and visual information	Mayer (2014)
Cognitive load management	Three goals: extraneous, essential, and generative processing	Plass et al. (2010)
Audiovisual design	Ten elements: hook, signpost, elucidate, texture, consolidate, etc.	Koumi (2006)

4. Discussion

The reviewed literature suggests that AI-based English learning personalization may depend not only on algorithmic sophistication but also on the accuracy of needs analysis at the design stage and on the management of learners' cognitive load. This is offered as a theoretical interpretation of the reviewed sources, not as an empirically demonstrated explanation, because none of the reviewed studies tested these relationships together. The working mechanisms described in Section 3.1, such as difficulty adjustment based on learner performance, and the reported alignment of intelligent tutoring systems with the communicative approach (Alsayed & Bin Rasyid, 2025) can be read alongside the Cognitive

Theory of Multimedia Learning and Cognitive Load Theory (Section 3.2). Read together, they suggest that AI-driven personalization should ideally adjust not only the level of difficulty but also the way verbal and visual information is presented, so as to avoid extraneous processing that burdens working memory (Mayer, 2014; Plass et al., 2010). A system that only speeds up or slows down material, without regard to the selection, organization, and integration of information, could be algorithmically efficient but cognitively less optimal; this remains a proposition to be tested.

The needs analysis principle of the ADDIE model is relevant here only as indirect, instructional-design evidence. The Google Sites-based e-learning study (Rahadian et al., 2024) and the interactive animated video study (Rahadian et al., 2026) report high validity and favorable user responses for media developed through systematic design, which is consistent with the view that systematic design contributes to the quality of digital learning products. However, these studies did not involve AI or English language learning, and their scores do not show that needs analysis improves AI-based personalization.

Their relevance is therefore limited to instructional-design relevance, and the integration of ADDIE with AI is a proposed framework (Table 1) rather than an established finding. The proposal is consistent with Koumi's (2006) argument that audiovisual material needs to be designed through stages such as hooking, signposting, elucidating, and consolidating in order to trigger minds-on activities, and with the argument of Gong et al. (2023) that the effectiveness of AI adoption in language education requires a pedagogical framework that places AI as an integral part of the teaching process.

The direct evidence reviewed is mostly perceptual and engagement-related. The high level of teacher support for AI-based personalization (78%) and the perceived increase in student engagement (82%) reported by Budiyanto et al. (2025) are perceptions; they are associated with, but do not demonstrate, the improvements in vocabulary and grammar perceived by students in Waziana et al. (2024). Wang and Han (2025) reported significant increases in affective and behavioral engagement. By contrast, Alsofyani and Barzanji (2025) found no significant difference in posttest scores between the ChatGPT group and the teacher group.

This pattern suggests that the association between AI feedback and measured language achievement is more varied than its association with affective and motivational dimensions. One possible interpretation, drawn from Cognitive Load Theory, is that abundant AI feedback may raise engagement but may not automatically improve cognitive scores unless essential processing is also managed (Plass et al., 2010); this interpretation is speculative and was not tested in the reviewed studies. The consistency of positive perceptions across teacher, student, and experimental contexts is in line with the growing research attention to personalized learning in intelligent learning environments documented by Chen et al. (2020), but it does not itself establish effectiveness.

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The findings regarding internet access constraints (45%) and teacher training shortages (52%) reported by Budiyanto et al. (2025) suggest that the benefits of these technologies may not be realized evenly, in line with the challenges of implementing educational technologies commonly found in developing countries. The concern about over-reliance on AI reported by Wang and Han (2025) is also relevant to Hockly's (2023) warning that AI cannot replace human mediation in fostering intercultural competence and affective engagement, given that language learning inherently involves authentic social interaction that is difficult to replicate by automated systems. The limitations of speech recognition accuracy and system responsiveness identified by Alsayed and Bin Rasyid (2025) further indicate that AI-based personalization, while promising, still requires technical and pedagogical refinement, including alignment with cognitive load principles, before it can be relied upon in complex language learning contexts.

The theoretical implication of this review is the need for a conceptual framework that integrates systematic instructional design (such as ADDIE), multimedia cognitive design (the Cognitive Theory of Multimedia Learning and Cognitive Load Theory), and the technical architecture of adaptive AI systems, together with teacher mediation (Table 1). This framework is proposed as a theoretical interpretation and not as an empirically validated model. In practical terms, the reviewed literature suggests that curriculum developers and English teachers may treat AI as a complementary tool whose design pays attention to cognitive load management, rather than as a substitute for the role of teachers in facilitating authentic communicative interactions, and that adequate digital literacy training is advisable before the technology is widely adopted.

This study has several limitations. First, it is a narrative literature review that synthesizes secondary findings without primary data collection; the databases, search dates, and screening counts were not recorded under a formal protocol, so the selection of sources may be incomplete or biased. Second, the direct evidence is dominated by perceptions, engagement, and writing outcomes involving general-purpose generative AI tools, and none of the reviewed studies measured the personalization outcomes of a purpose-built adaptive system for English learning. Third, the ADDIE-based studies are indirect evidence, and both were co-authored by members of the present author team (Rahadian et al., 2024, 2026). Future research is suggested to develop and field-test a prototype of an AI-based English adaptive learning system that explicitly integrates ADDIE needs analysis and cognitive load management, in order to empirically test the conceptual linkages proposed in this article, and to apply systematic review procedures (for example, PRISMA) to strengthen the evidence base.

5. Conclusion

This article is a narrative literature review and conceptual synthesis, and its conclusions are conceptual propositions that require future empirical testing rather than demonstrated effects. Drawing on the reviewed literature, it is proposed that (1) AI-based adaptive learning shows potential to support the personalization of English learning through real-time adjustment of grammar, vocabulary, pronunciation, and writing tasks to learners' proficiency profiles, although the direct evidence reviewed concerns mainly perceptions and engagement and the evidence on language achievement is mixed; (2) the instructional-design relevance of systematic needs analysis, as illustrated by the ADDIE-based studies, suggests that personalization may be better anchored when adaptation follows analyzed learner needs, with the integration of ADDIE and AI offered as a proposed framework; and (3) multimedia cognitive design principles, particularly Cognitive Load Theory, suggest that personalized content should manage extraneous, essential, and

generative processing in order to support the building of an integrated mental model. Teacher and student perceptions point to the relevance of AI, although implementation is limited by digital infrastructure gaps, teacher technology literacy, and the risk of reduced authentic communicative interaction.

AI-based adaptive learning should therefore be positioned as a pedagogical partner that complements, rather than replaces, English teachers. Future research should develop and field-test AI-based adaptive systems for English learning that explicitly integrate ADDIE needs analysis and cognitive load principles into the system architecture, measure personalization and language outcomes directly, and thereby test the propositions put forward here.

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