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Unpeeling AI-Personalized Learning in Augmented Reality Environments via PLS-SEM: Cognitive Load, Adaptivity, and Learning Gains are on the Table

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Abstract

The implementation of Artificial Intelligence (AI) and Augmented Reality (AR) in educational settings has become an innovative approach for individualized learning, providing immersive and adaptable experiences for students. Understanding the effects of cognitive load and adaptivity on learning outcomes in AI-enhanced AR environments is essential for refining instructional strategies. This study investigated the relationships between cognitive load, adaptivity, and learning gains among 258 English as a Foreign Language (EFL) learners using SmartPLS. The results indicated that intrinsic cognitive load ($\beta = 0.726$, $p < 0.001$) and extraneous load ($\beta = -0.432$, $p < 0.001$) had significant effects on learning gains, whereas germane load showed a positive influence ($\beta = 0.314$, $p < 0.01$). Adaptivity also contributed significantly, with learners' perceptions of adaptivity ($\beta = 0.578$, $p < 0.001$) and system personalization ($\beta = 0.611$, $p < 0.001$) emerging as the most influential subcomponents, though its overall impact was smaller than that of cognitive load. These findings emphasize the importance of managing cognitive load and integrating tailored adaptive features to maximize learning outcomes in AI-enhanced AR settings. Strategies that reduce extraneous load and enhance germane load can substantially improve learning experiences for lower-intermediate EFL learners.

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Introduction

The rapid growth of educational technology has created new potential to improve teaching and learning, with AI and AR leading these innovations (Bamanger, 2025; Tan et al., 2025). As education evolves, there is growing acknowledgment of the transformative potential of modern technologies in conventional learning contexts, with research highlighting how digital and intelligent technologies are reshaping educational practices, promoting new pedagogical designs, and enhancing engagement and learning outcomes across diverse settings (Çelik & Baturay, 2024). Personalized learning, which tailors educational experiences to the specific requirements and preferences of individual learners, has emerged as a primary emphasis in the quest for enhanced learning outcomes, with meta analytic evidence showing that technology enhanced personalized learning significantly improves cognitive and noncognitive skills and overall academic performance in higher education contexts (Tudor et al., 2025). AI-driven personalized learning has the potential to customize instructional material in accordance with the learner's existing knowledge, preferred learning method, and cognitive abilities (Halkiopoulos & Gkintoni, 2024). AI-driven personalized learning systems can create educational tools that are exceptionally effective, engage learners, and optimize their cognitive load, adaptability, and learning outcomes when integrated with AR, which enriches the learning experience through immersive, interactive, and spatially enhanced environments (Cinar et al., 2024).

Cognitive Load Theory asserts that excessive cognitive demands can impede learning by exceeding the limited capacity of working memory, making it difficult for learners to process, integrate, and transfer new information effectively (Sweller et al., 2019). Cognitive load theory asserts that high cognitive demands might impede learning by overloading learners' mental capacity (de Jong, 2010). Consequently, managing cognitive load is essential for promoting successful learning, based on Cognitive Load Theory, which posits that learning is hindered when instructional demands exceed the limited capacity of working memory. Cognitive overload occurs when learners are required to process more information than their cognitive resources allow, leading to reduced retention and impaired performance (Sweller et al., 2011; Evans et al., 2024). In contrast to such fixed instructional demands that may induce overload, adaptivity in learning environments refers to the ability of educational systems to dynamically adjust instructional content, pacing, and support in response to learners' ongoing performance, difficulties, and needs, thereby helping to optimize cognitive processing and learning outcomes (Demartini et al., 2024). Adaptive learning systems can maintain learners' engagement at an ideal difficulty level, reducing irritation while fostering profound involvement (Ezzaim et al., 2023). Ultimately, learning gains signify the enhancements in knowledge, abilities, and competences derived from educational experiences (Evans et al., 2018). These improvements are often evaluated via assessments or performance assignments that gauge the learner's comprehension and application of the material (Ilie et al., 2024). The relationship among cognitive load, adaptability, and learning outcomes is essential, as research indicates that

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adaptive learning approaches that dynamically adjust to individual learner needs can reduce unnecessary cognitive burden and contribute to more effective processing and improved educational results in technology-enhanced environments (Chernikova et al., 2025; Zhu et al., 2025).

The incorporation of AI and AR into personalized learning environments could potentially support improvements in educational outcomes. The immersive features of augmented reality may improve learning by offering interactive, contextually rich experiences that facilitate a deeper comprehension of abstract ideas and intricate information (Fidan & Tunce, 2019). Simultaneously, AI systems can evaluate data from learners' interactions and adaptively modify instructional material to enhance learning experiences. Research on AI-driven adaptive learning technologies shows that machine learning algorithms analyze learner activity patterns and performance data to tailor content delivery, pacing, and feedback to individual needs (Gligorea et al., 2023). Nevertheless, empirical evidence on the synergistic effects of AI-driven personalized learning in augmented reality settings remains relatively limited, indicating a need for further investigation. Existing studies increasingly explore the integration of AI and augmented reality in educational contexts; yet, relatively few have examined how their combined use influences cognitive load, adaptivity, and learning outcomes within personalized learning environments (Liu et al., 2025; Gkintoni et al., 2025).

Many studies have examined the influence of augmented reality on learning outcomes, demonstrating generally positive effects on comprehension and academic performance (e.g., Gandolfi & Ferdig, 2025; Li et al., 2021; Tobar-Muñoz et al., 2017). However, relatively few of these investigations have directly addressed the significance of cognitive load or the potential of adaptive features to alleviate overload in these contexts. Additional studies have examined AI's capacity to personalize learning and its impact on cognitive load and academic achievement (Kaplan et al., 2021; Li et al., 2021); nevertheless, there is a deficiency of research that integrates AR's immersive learning environment into this paradigm. Despite the increasing body of research examining AI and AR individually or in combination, relatively few studies have explicitly explored how their integration affects cognitive load, adaptivity, and learning outcomes within personalized learning environments (Farhood et al., 2025; Wang et al., 2025).

Consequently, further research is warranted to investigate the potential benefits of combining AI and AR in learning settings, particularly regarding their potential to support cognitive processing, adaptive learning, and enhanced educational outcomes. This study seeks to explore the associations between AI-driven personalized learning in augmented reality environments and learners' cognitive load, adaptability, and learning outcomes through SEM analysis. To this end, the following research questions are formulated:

- What is the relationship between cognitive load and learning gains among EFL learners?
- What is the relationship between adaptivity and learning gains among EFL learners?

Literature review

AI-Personalized Learning in Education

Educational technology research has increasingly prioritized the potential of AI to transform personalized learning environments by enabling adaptive, data driven instruction tailored to individual learners' needs (Gligorea et al., 2023). The objective of personalized learning is to transcend conventional one-size-fits-all approaches by accommodating the distinctive strengths, interests, and requirements of individual learners (Shemshack & Spector, 2020). However, existing research often assumes that personalization automatically leads to improved learning outcomes without sufficiently interrogating the pedagogical conditions under which such benefits emerge. AI facilitates this customization by evaluating learner data (e.g., test scores, interaction patterns) and offering feedback or modifying the learning trajectory (Das et al., 2023); however, the effectiveness of these mechanisms depends heavily on the validity of the data sources and the interpretability of algorithmic decisions.

Recent studies suggest that AI has the potential to enhance student engagement and learning outcomes, although findings vary across contexts (Heydarnejad, 2025a; Heydarnejad, 2025b; Jaboob et al., 2024). This variability indicates that AI-driven personalization is not universally effective and may amplify existing instructional inequalities if contextual factors are overlooked. In contrast to non-adaptive learning environments, Tan et al. (2025) illustrated that AI-powered systems that dynamically adapt content delivery based on individual requirements and analyze learners' progress achieved superior performance on assessments. Nevertheless, such performance gains are often measured through short-term outcomes, leaving questions about long-term learning transfer and sustainability insufficiently addressed.

Additionally, the capacity of AI to offer immediate feedback is frequently cited as essential for promoting learner autonomy and supporting formative assessment practices (Ba et al., 2025). Yet, over-reliance on automated feedback may risk reducing opportunities for reflective learning and meaningful human–teacher interaction. The integration of AI into learning systems is further beset by obstacles, including implementation complexity, ethical concerns, and algorithmic bias. Accordingly, Gerlich (2025) emphasizes that effective AI application requires a nuanced understanding of deployment contexts, as the educational impact of AI-driven systems is highly context dependent. This underscores the need for future research to move beyond technological affordances and critically examine how instructional design, data governance, and contextual alignment shape AI's educational value. To maximize effectiveness, the quality and quantity of data, as well as the design of underlying algorithms, must be carefully aligned with clearly defined learning objectives.

Augmented Reality (AR) in Education

Unique opportunities for personalized learning are provided by AR, which overlays digital content on the real world, resulting in interactive, immersive, and context-rich learning environments (Bacca-Acosta et al., 2022). While AR is frequently portrayed as inherently engaging, this assumption often overlooks how instructional design mediates the relationship between immersion and meaningful learning. AR promotes direct engagement with content, which can enhance learners' comprehension of intricate concepts and spatial awareness (Al-Ansi et al., 2023); however, empirical evidence suggests that these benefits are uneven and highly sensitive to task complexity and learner characteristics.

The efficacy of AR in educational contexts has been supported by recent studies. Hwang and Chien (2022) demonstrated that AR use in science education enhances learning experiences by enabling visualization of abstract concepts. Despite these promising findings, much of the existing research relies on controlled experimental settings, raising questions about scalability and transferability to authentic classroom environments. Beyond cognitive benefits, AR has been shown to increase student motivation and foster a sense of agency through interactive simulations (Gandolfi & Ferdig, 2025). Yet, motivation gains do not consistently translate into sustained learning improvements unless they are accompanied by structured pedagogical guidance. Similarly, AR's capacity to create context-rich environments supports experiential learning and real-world problem-solving (Alkhabra et al., 2023); nevertheless, poorly aligned contextual elements may distract learners and dilute instructional focus.

Despite its considerable potential, several challenges constrain the effective implementation of AR. One major obstacle is the requirement for technological infrastructure capable of supporting AI-driven personalized AR applications, including appropriate devices and software (Arena et al., 2022). When such infrastructure is inadequate, AR environments may increase extraneous cognitive load and limit system adaptivity, thereby constraining learning gains in AR-based EFL contexts. Furthermore, the success of AR experiences is contingent upon pedagogically sound designs that are meaningfully integrated into the curriculum (Chang, 2021). This highlights a persistent gap in the literature between technological innovation and instructional coherence, suggesting that future research should critically examine not only what AR can do, but under what conditions it meaningfully supports learning.

Cognitive Load and Personalized Learning

Cognitive Load Theory, proposed by Sweller (1988), posits that the human brain has a limited capacity for information processing, implying that instructional design must regulate cognitive demands to improve learning efficacy. While this principle is well established, its application in personalized learning environments remains theoretically underexplored and empirically inconsistent. In tailored learning settings, managing cognitive load is particularly critical, as learners may experience overload when confronted with material that exceeds their cognitive capacity, resulting in diminished engagement and retention (Zhu et al., 2024). Personalization alone does not guarantee optimal cognitive load management and may, in some cases, exacerbate cognitive demands if adaptations are poorly calibrated.

Recent research has examined how AI-driven tailored learning systems may alleviate cognitive stress. For instance, Gkintoni et al. (2025) investigated the role of AI in regulating cognitive load by adaptively modifying material complexity and learning tempo according to learners' performance. Their findings suggest that adaptive systems can reduce cognitive overload and enhance learners' ability to focus on germane learning activities. However, studies in this area often prioritize performance-based outcomes over direct measures of cognitive processing, thereby limiting insight into how learners internally allocate cognitive resources. Consequently, the mechanisms through which AI adaptations support deeper learning remain insufficiently specified.

Similarly, AR-based interventions provide illustrative examples of how technological affordances may both support and challenge cognitive load regulation. For example, AR has been shown to reduce extraneous cognitive load by incorporating visual and interactive elements that clarify complex material, thereby facilitating information processing (Gonnermann-Müller & Krüger, 2024). Yet, the multimodal richness of AR environments can simultaneously introduce additional sources of cognitive demand, particularly when learners must coordinate multiple streams of information. Accordingly, while adaptive systems and AR may assist in regulating cognitive load, they must be carefully designed to avoid increasing intrinsic cognitive load, which is inherent to the complexity of the learning content. For instance, Kim et al. (2024) demonstrated that although AR systems provide visual cues and interactive simulations, they may overwhelm learners when task complexity exceeds their cognitive capabilities. These findings underscore the need for a more nuanced balance between personalization, content complexity, and learner readiness when integrating AI and AR into instructional design.

Adaptivity and Learning in AI-AR Environments

Adaptivity is a key component of personalized learning environments, as systems are designed to continuously adjust to learners' evolving needs. Recent advancements in AI and AR technologies have enabled increasingly adaptive learning experiences (Ouyang et al., 2022; Ouyang & Jiao, 2021). However, the presence of adaptivity alone does not guarantee instructional effectiveness, as its impact depends on how learner data are interpreted and translated into pedagogically meaningful adjustments. AI-driven personalized systems utilize data from student interactions to assess progress and modify learning content and difficulty in real time (Kabudi et al., 2021), yet such data-driven adaptations may oversimplify learning processes if they rely primarily on observable behaviors rather than deeper cognitive indicators.

Previous studies examining adaptivity in AI–AR environments suggest potential benefits for learner engagement and achievement. For example, Ironsi (2023) investigated an AI-powered AR system in an academic context and reported that adaptive learning environments supported learners' engagement with complex concepts by dynamically adjusting instructional content based on individual progress. The study further indicated that adaptivity can promote deep learning by maintaining an appropriate level of challenge without overwhelming learners. Nevertheless, these conclusions are largely drawn from short-term engagement and

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performance measures, leaving open questions about the durability and transferability of such learning gains.

Similarly, research on AI-powered adaptive systems provides illustrative evidence of motivational benefits. Eltahir and Babiker (2024) found that adaptive systems adjusting content based on learner data were associated with higher motivation and performance than static learning environments. While these findings are promising, they also raise concerns about the extent to which adaptive mechanisms can accommodate diverse learning strategies and avoid reinforcing narrow learning pathways. Taken together, the literature suggests that adaptivity is most effective when embedded within well-aligned instructional designs that balance responsiveness, cognitive challenge, and learner autonomy, rather than functioning as a purely technical feature of AI–AR systems.

Learning Gains in AI-AR Environments

Learning gains denote the quantifiable improvements in knowledge and skills following an educational intervention (Jaboob et al., 2024). AI- and AR-based personalized learning systems have been widely reported to influence learning outcomes by enhancing instructional experiences and affording learners greater autonomy over their learning trajectories (Poupard et al., 2024). However, reported learning gains vary considerably depending on instructional context, assessment design, and the extent to which personalization is pedagogically aligned with learning objectives. For example, İslim et al. (2024) demonstrated that augmented reality environments can improve learning outcomes in disciplines such as physics and mathematics by enabling learners to interact with visual models that support conceptual understanding. These findings underscore the potential benefits of visual interactivity, yet they also indicate the need for caution regarding the generalizability of such gains beyond domain-specific tasks or short-term assessments. Similarly, Holmes et al. (2019), in their review of AI in education research, reported that AI-driven personalized learning systems were associated with improvements in test scores and retention rates, particularly when systems dynamically adapted to learners' progress. Nevertheless, the review also suggests that many studies rely on standardized outcome measures, which may not fully capture higher-order learning or long-term knowledge transfer.

Moreover, the integration of AR with AI-driven personalization is often assumed to amplify learning gains through increased immersion and engagement, yet empirical evidence remains context dependent. For instance, Lin and Chen (2024) found that AI-driven AR systems improved students' performance in problem-solving tasks by providing adaptive learning environments tailored to individual needs. Despite these promising findings, it remains unclear how such systems scale across diverse learner populations and whether increased immersion consistently translates into durable learning improvements. Taken together, the literature indicates that learning gains associated with AI- and AR-based personalization are contingent upon careful instructional design, meaningful assessment strategies, and alignment between technological affordances and cognitive learning processes.

Method

Participants

The participants consisted of 258 EFL learners enrolled in lower-intermediate English courses at multiple private language institutes in Iran. The learners were aged between 15 and 18 years, including 116 females and 142 males. Initially, 287 learners were invited to participate in the study; however, 29 incomplete or invalid responses were excluded during data cleaning, resulting in a final sample of 258 valid cases. Participants were recruited from language institutes located in Khorasan Razavi, Isfahan, Tehran, and Shiraz provinces, where they were actively studying English as a foreign language. Prior to inclusion in the final sample, all participants completed a brief screening questionnaire designed to assess their prior experience with AI-supported learning tools and their access to AR-compatible devices (e.g., smartphones or tablets). Only learners who reported prior exposure to AI- and AR-based educational applications and confirmed regular access to AR-enabled devices were included in the study. This screening ensured that all participants possessed the minimum technological familiarity required to meaningfully engage with the AI-enhanced AR learning environment examined in this research.

Instrumentation

The study employed an online questionnaire as the primary instrument for data collection. Prior to administering the main scales, a screening section was included to ensure that remote participants possessed adequate prior knowledge and experience with AI- and AR-based learning environments. This screening assessed participants' prior exposure to AI and AR technologies, frequency of use, and self-reported competence in educational contexts. Participants who did not meet the minimum experience criteria were excluded from the study. Following the screening section, the questionnaire comprised three validated instruments adapted for the context of AI-enhanced AR learning environments. Sample questions for each instrument were included in the questionnaire to illustrate the constructs being measured.

Cognitive Load

Cognitive load was measured using a modified version of the Cognitive Load Scale developed by Leppink et al. (2013). The scale assesses four dimensions: Intrinsic Load (5 items), Extraneous Load (5 items), Germane Load (5 items), and Overall Perceived Cognitive Load (10 items). All items were rated on a seven-point Likert scale. Minor wording modifications were made to align the items with AI-AR learning tasks while preserving the original construct definitions. The internal consistency of the scale in the present study was acceptable ($\alpha = 0.877$). Sample questions included: "The learning tasks in the AI-enhanced AR environment were very complex." (Intrinsic Load), "The way information was presented in the AI-AR system was unclear or confusing." (Extraneous Load), "The AI-AR activities helped me to better

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understand the learning material." (Germane Load), and "Overall, using the AI-AR system required a high level of mental effort." (Overall Cognitive Load).

Adaptivity

Adaptivity was assessed using an adapted instrument grounded in the adaptive learning systems framework proposed by Dominic et al. (2015). This framework conceptualizes adaptivity as a system's ability to dynamically personalize content, feedback, and learning pathways based on learner performance and preferences. The instrument was tailored to reflect AI-driven real-time personalization in AR learning environments. The scale consisted of four subscales: Learner Perception of Adaptivity (5 items), System Personalization (5 items), Feedback Effectiveness (5 items), and Engagement with Adaptive Learning (5 items), measured on a five-point Likert scale. The internal consistency of the scale was acceptable ($\alpha = 0.842$). Sample questions included: "The AI-AR system adapted the learning content to match my learning needs." (Learner Perception of Adaptivity), "The system personalized activities based on my previous performance." (System Personalization), "The feedback provided by the AI system helped me improve my learning." (Feedback Effectiveness), and "I felt more engaged because the learning system adjusted to my progress." (Engagement with Adaptive Learning).

Learning Gains

Learning gains were assessed using a self-report Learning Gains Questionnaire (LGQ) designed to measure learners' perceived improvements across multiple learning domains. The instrument was adapted from established self-reported learning gains frameworks commonly used in educational research and aligned with the instructional objectives of the AI-AR learning environment. The LGQ comprised 30 items organized into six subscales: Cognitive Learning Gains (5 items), Affective Learning Gains (5 items), Skill-Based Learning Gains (5 items), Higher-Order Learning Gains (5 items), Comparative Gains (5 items), and Self-Reflection on Learning Progress (5 items). All items were rated on a five-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree), with higher scores indicating greater perceived learning gains. Sample items included "I gained a better understanding of the course content through the AI-AR activities" (Cognitive Learning Gains), "The AI-AR learning experience increased my interest in learning English" (Affective Learning Gains), and "I improved my ability to apply what I learned in practical tasks" (Skill-Based Learning Gains). Additional items addressed higher-order thinking, comparative learning experiences, and reflection on progress. The internal consistency of the LGQ in the current study was acceptable, with a Cronbach's alpha coefficient of 0.867, indicating satisfactory reliability.

Evidence for validity was established through multiple procedures. First, content validity was supported through expert review, whereby specialists in educational technology and language learning evaluated the items for clarity, relevance, and alignment with the study objectives. Minor revisions were made based on their feedback to improve item wording and domain coverage. Second, construct validity was examined using factor-analytic procedures, which confirmed that the items loaded appropriately onto their intended subscales and reflected the proposed multidimensional structure of learning gains. Finally, face validity was established through pilot testing with a small group of learners, who reported that the questionnaire items were understandable and representative of their learning experiences in the AI-AR environment. Together, these results indicate that the LGQ demonstrates adequate validity and reliability for assessing learners' perceived learning gains in the context of AI-AR–supported instruction.

Data Collection

An online survey was administered to all participants who passed the screening questionnaire during the Fall semester of 2024. This method allowed the study to reach a diverse group of learners, enabling them to complete the survey remotely at their convenience. All participants provided informed permission and were told that their participation was entirely voluntary, with the ability to withdraw at any moment without consequence. The participants were further informed of the anonymity of their replies, and all data was anonymized prior to processing. The questionnaire assessed cognitive load, adaptivity, and learning gains in AI-driven AR learning environments using validated and context-adapted scales. Sample items were included to illustrate how each construct was operationalized. Participants were apprised of the study's objective, the voluntary nature of their participation, and the confidentiality of their responses prior to completion of the online survey. In order to guarantee data integrity, only questionnaires that were fully completed were retained for subsequent statistical analysis. Incomplete responses were excluded from the analysis.

Data Analysis

The data gathered from participants was examined via Partial Least Squares Structural Equation Modeling (PLS-SEM), with the SMART PLS program applied for statistical analysis. PLS-SEM was used due to its appropriateness for examining intricate interactions across variables with very limited sample sizes or on the case of deviation from normality (Hair et al., 2017). The analysis adhered to a bifurcated methodology:

1. Measurement Model: The validity and reliability of the measurement model were evaluated by the assessment of item outer loadings, composite reliability, and average variance extracted (AVE) values. Furthermore, discriminant validity was assessed with the Fornell-Larcker criteria and the HTMT ratio.

2. Structural Model: The structural model was assessed by analyzing the path coefficients and R^2 values. Bootstrapping was used to assess the statistical significance of the path coefficients. Effect sizes (f^2) were computed to evaluate the strength of the connections between the variables.

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Findings

This section presents the study's findings on the effects of cognitive load and adaptivity on learning outcomes in AR environments for EFL learners. Data were analyzed using PLS-SEM via SmartPLS, which allowed for the assessment of relationships among latent constructs and their respective sub-dimensions. The Kolmogorov–Smirnov (K-S) test results for normality are summarized in Table 1. In the following, key structural relationships are illustrated in Model 1 and Model 2, which provide visual summaries of the significant paths between constructs and their contributions to overall and sub-dimension learning gains.

Table 1

Results of the Kolmogorov-Smirnov (K-S) Test for Normality

	Kolmogorov-Smirnov Z	Asymp. Sig. (2-tailed)
Intrinsic Load	0.182	0.000
Extraneous Load	0.138	0.000
Germane Load	0.169	0.000
Overall Perceived Cognitive Load	0.127	0.000
Cognitive Load	0.107	0.000
Learner Perception of Adaptivity	0.104	0.000
System Personalization	0.079	0.000
Feedback Effectiveness	0.120	0.000
Engagement with Adaptive Learning	0.111	0.000
Adaptivity	0.146	0.000
Cognitive Learning Gains	0.109	0.000
Affective Learning Gains	0.068	0.005
Skill-Based Learning Gains	0.144	0.000
Higher-Order Learning Gains	0.136	0.000
Comparative Gains	0.133	0.000
Self-Reflection on Learning Progress	0.119	0.000
Learning Gains	0.066	0.009

The K-S test indicated that most measures in this study deviate from a normal distribution, with the majority of Asymp. Sig. values being 0.000. While this suggests that the data are not suitable for parametric tests that assume normality, the use of PLS-SEM via SmartPLS is appropriate, as it is robust to violations of normality and can handle non-normally distributed data for analyzing relationships among latent constructs.

The following table presents the original sample loadings and T-statistics for various constructs, including cognitive load, learner perceptions, system personalization, feedback effectiveness, engagement with adaptive learning, and learning gains. These measures provide valuable insights into the significance and contribution of each question item to its corresponding construct.

Table 2

Analysis of Question Loadings and T-Statistics

		Questions	Original Sample	T -Statistics
Cognitive Load	Intrinsic Load	C1	0.708	17.328
		C2	0.710	15.258
		C3	0.736	19.522
		C4	0.764	25.766
		C5	0.857	26.164
	Extraneous Load	C6	0.767	28.466
		C7	0.730	19.291
		C8	0.703	18.166
		C9	0.716	16.141
		C10	0.624	12.433
	Germane Load	C11	0.779	30.038
		C12	0.743	17.747
		C13	0.848	29.559
		C14	0.680	16.210
		C15	0.673	18.196
	Overall Perceived Cognitive Load	C16	0.722	18.587
		C17	0.888	35.388
		C18	0.896	37.307
		C19	0.749	19.878
		C20	0.768	21.389
		C21	0.816	27.280
		C22	0.847	46.124
		C23	0.769	20.203
		C24	0.825	31.436
		C25	0.673	14.630
Adaptivity	Learner Perception of Adaptivity	A1	0.780	20.269
		A2	0.841	41.024
		A3	0.787	26.409
		A4	0.853	40.372
		A5	0.866	57.657
	System Personalization	A6	0.823	31.219
		A7	0.833	33.217
		A8	0.850	31.240
		A9	0.862	35.217
		A10	0.786	24.231
	Feedback Effectiveness	A11	0.836	40.231
		A12	0.727	22.777
		A13	0.838	42.311

		A14	0.846	38.317
		A15	0.858	36.367
	Engagement with Adaptive Learning	A16	0.737	25.204
		A17	0.800	32.078
		A18	0.559	15.976
		A19	0.641	18.819
		A20	0.865	44.316
Learning Gains	Cognitive Learning Gains	L1	0.689	13.086
		L2	0.724	16.524
		L3	0.823	37.250
		L4	0.754	28.622
		L5	0.614	19.544
	Affective Learning Gains	L6	0.824	31.002
		L7	0.810	33.875
		L8	0.874	39.852
		L9	0.767	21.640
		L10	0.770	29.697
	Skill-Based Learning Gains	L11	0.742	26.644
		L12	0.642	15.898
		L13	0.684	17.491
		L14	0.697	18.610
		L15	0.812	39.425
	Higher-Order Learning Gains	L16	0.585	9.854
		L17	0.646	10.420
		L18	0.752	19.555
		L19	0.797	26.626
		L20	0.796	40.697
	Comparative Gains	L21	0.751	28.981
		L22	0.651	14.333
		L23	0.808	32.030
		L24	0.779	29.075
		L25	0.683	14.138
	Self-Reflection on Learning Progress	L26	0.641	13.839
		L27	0.716	18.077
		L28	0.892	36.723
		L29	0.672	15.025
		L30	0.621	14.835

All measurement items demonstrated statistically significant loadings and provided strong support for their respective constructs (Table 2). The Cognitive Load dimensions—including intrinsic, extraneous, germane, and overall perceived cognitive load—exhibited generally high factor loadings and substantial T-statistics, indicating that the items reliably captured different aspects of learners' cognitive processing. Similarly, the Adaptivity construct, encompassing learner perception of adaptivity, system personalization, feedback effectiveness, and engagement with adaptive learning, showed robust indicator loadings, confirming the reliability of these measures in representing adaptive learning features. The Learning Gains construct and its sub-dimensions (cognitive, affective, skill-based, higher-order, comparative gains, and self-reflection on learning progress) also demonstrated acceptable to strong loadings across indicators, with particularly strong contributions observed for affective learning gains and higher-order learning outcomes. Overall, these results confirm that the measurement model is well supported, providing a reliable foundation for subsequent structural model analysis.

Table 3

Reliability and Validity Reports

Constructs		Average Variance Extracted (AVE)	Cronbach's Alpha	Composite Reliability
Cognitive Load	Intrinsic Load	0.573	0.786	0.857
	Extraneous Load	0.503	0.883	0.915
	Germane Load	0.559	0.890	0.918
	Overall Perceived Cognitive Load	0.653	0.812	0.855
	total	0.572	0.806	0.778
Adaptivity	Learner Perception of Adaptivity	0.622	0.705	0.811
	System Personalization	0.683	0.728	0.820
	Feedback Effectiveness	0.691	0.720	0.817
	Engagement with Adaptive Learning	0.604	0.711	0.801
	total	0.641	0.848	0.874
Learning Gains	Cognitive Learning Gains	0.524	0.718	0.814
	Affective Learning Gains	0.656	0.871	0.905
	Skill-Based Learning Gains	0.515	0.705	0.810
	Higher-Order Learning Gains	0.519	0.763	0.842
	Comparative Gains	0.543	0.737	0.826
	Self-Reflection on Learning Progress	0.512	0.715	0.802
	total	0.545	0.824	0.849

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As shown in Table 2, the measurement indicators demonstrate adequate reliability and validity, supporting the use of the constructs in the structural model.

Table 4

The Report of Correlation Analysis

	Cognitive Load	Adaptivity	Learning Gains
Cognitive Load	0.756		
Adaptivity	0.611**	0.801	
Learning Gains	0.726**	0.578**	0.738

Correlation is significant at the 0.01 level (2 tailed).**

Table 4 presents the correlation coefficients between the constructs of Cognitive Load, Adaptivity, and Learning Gains. The results show significant positive correlations between all constructs. Cognitive Load and Adaptivity have a moderate correlation of 0.611, which is statistically significant at the 0.01 level. Similarly, Cognitive Load and Learning Gains show a strong positive correlation ($r = 0.726$), reflecting a substantial linear association between the two measures. The correlation between Adaptivity and Learning Gains is moderate at 0.578, suggesting that perceived adaptivity is also positively related to learning gains. The interpretations of correlation strengths follow the guidelines suggested by Cohen (1988) and Schober et al. (2018).

Although detailed statistical results are presented in Tables 1–7, the primary findings of the study are summarized visually in the simplified SEM diagrams (Models 1 & 2). These figures highlight the significant structural relationships among the main constructs and provide an intuitive overview of the model results, while the tables are retained to ensure transparency and statistical completeness.

Figure 1

The Schematic Depiction of Path Coefficient Values (Model 1)

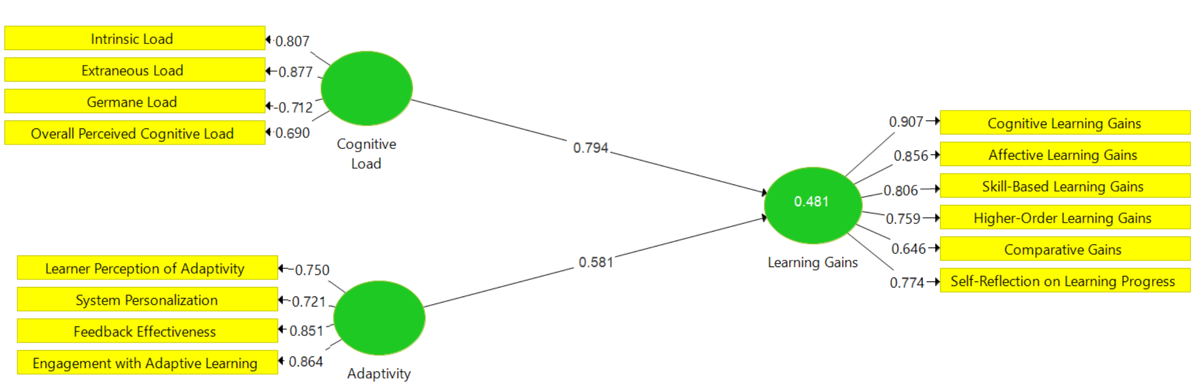

Figure 2

T-values for Path Coefficient Significance (Model 1)

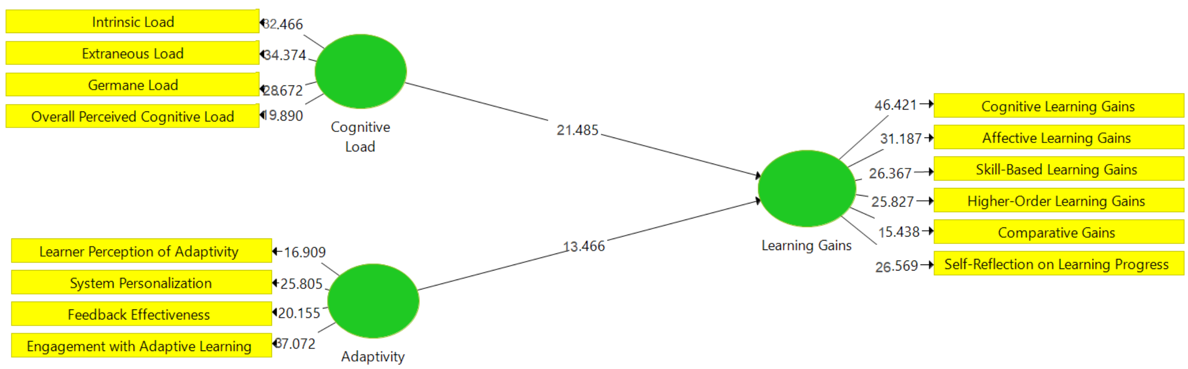

Table 6

The Fit Indices of the First Model

	R^2	Q^2
Learning Gains	0.481	0.192

$GOF=\sqrt{0.624 * 0.481}=0.548$

Model Fit Indicators: R^2, Q^2, and GOF for Learning Gains Table 6 provides key model fit indicators for Learning Gains, including R^2, Q^2, and the Goodness of Fit (GOF). The R^2 value for Learning Gains is 0.481, indicating that approximately 48.1% of the variance in learning gains is explained by the model. The Q^2 value of 0.192 suggests a moderate predictive relevance for the model. The GOF is calculated as 0.548, using the formula $\sqrt{0.624 * 0.481}$, reflecting an acceptable overall model fit. This combination of R^2, Q^2, and GOF values supports the robustness of the model in explaining and predicting learning gains.

Table 5

Path Analysis Results

Paths			Path Coefficient	T Statistics	Test Results
Cognitive Load	→	Learning Gains	0.794	21.485	Supported
Adaptivity	→	Learning Gains	0.581	13.466	Supported

Table 5 presents the results of the path analysis for Cognitive Load and Adaptivity predicting Learning Gains. The path coefficient from Cognitive Load to Learning Gains is 0.794 with a T-statistic of 21.485, indicating a strong and statistically significant positive relationship, which is supported. Similarly, the path coefficient from Adaptivity to Learning Gains is 0.581 with a T-statistic of 13.466, also showing a positive and significant relationship, which is likewise supported. These results suggest that both cognitive load and adaptivity positively influence learning gains, confirming the model's relevance.

Figure 3

The Schematic Depiction of Path Coefficient Values (Model 2)

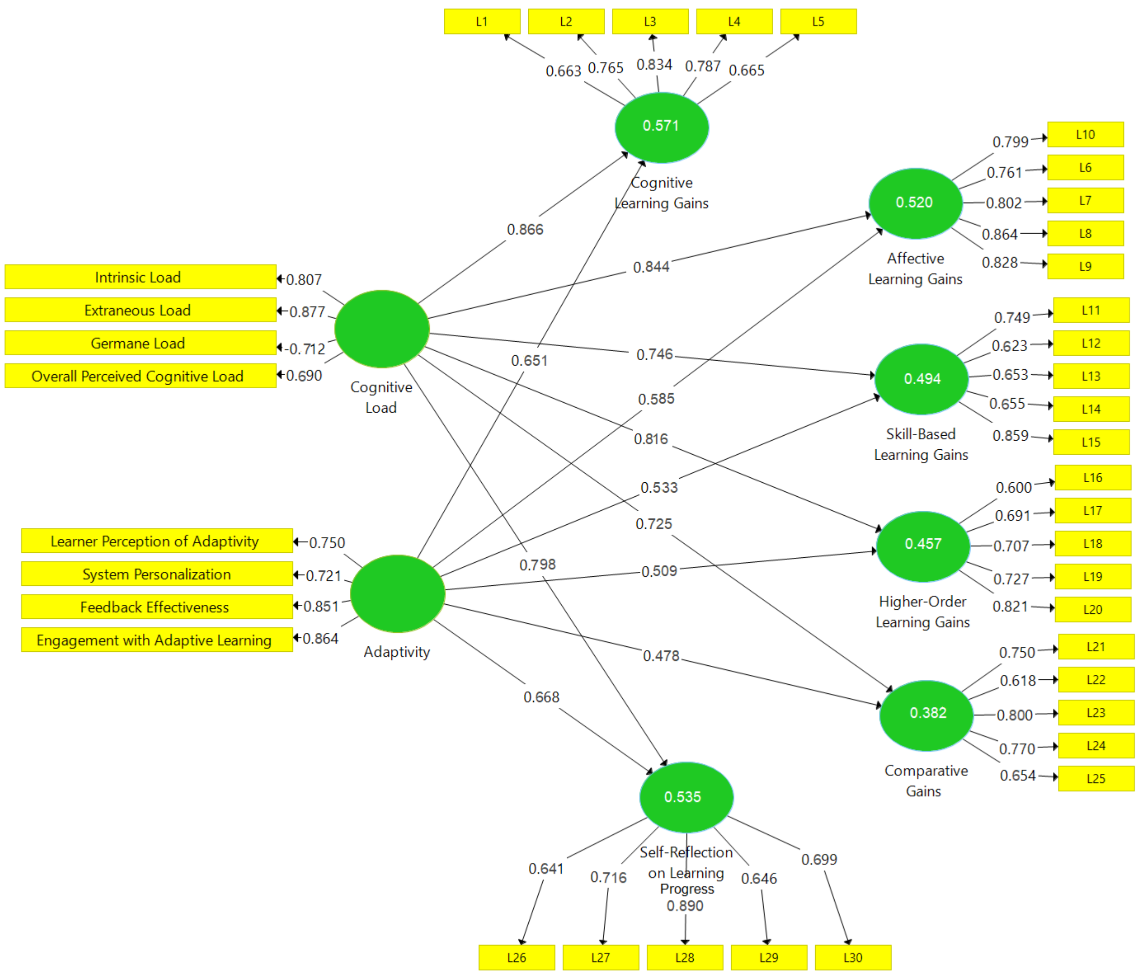

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Figure 4

T-values for Path Coefficient Significance (Model 2)

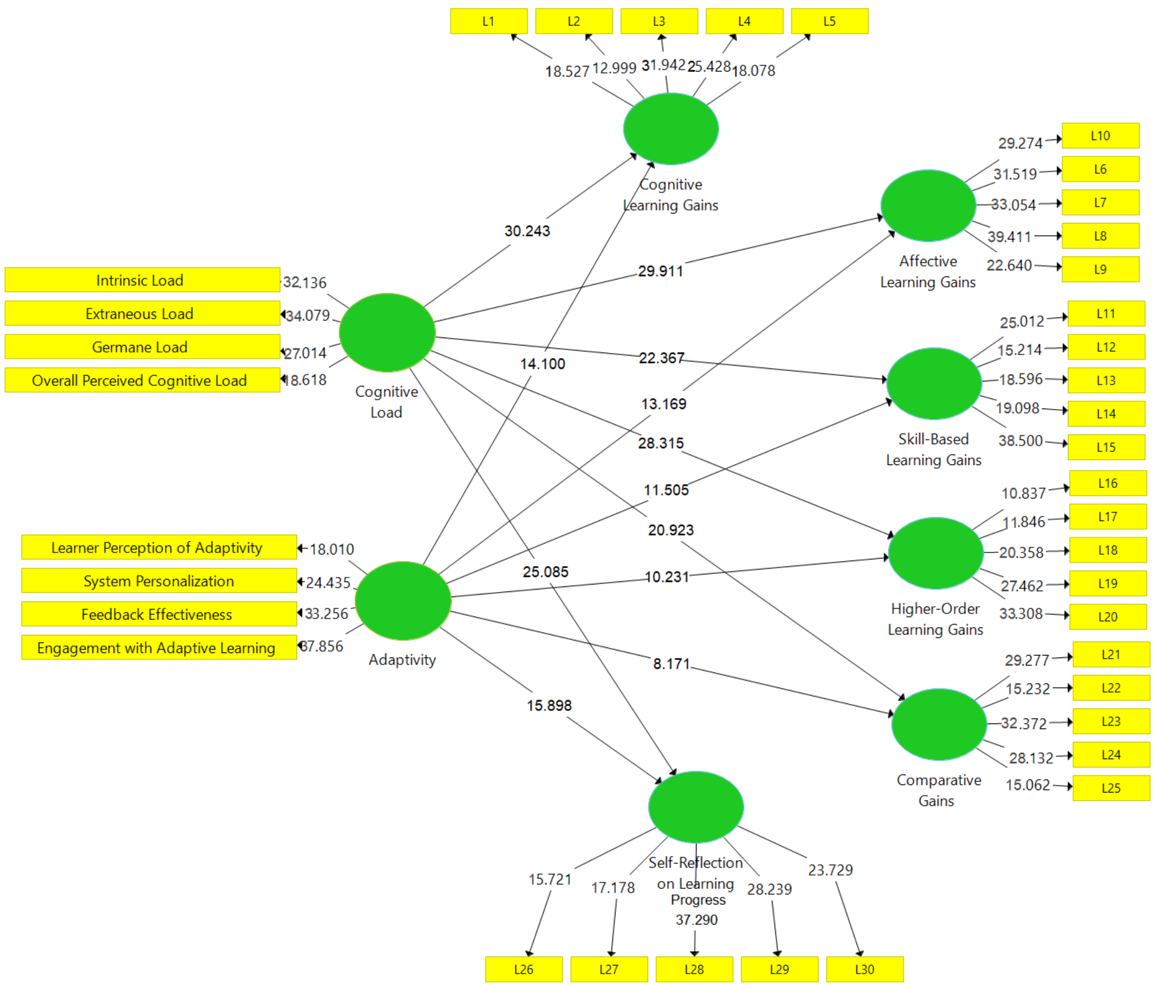

Table 6

The Fit Indices of the Second Model

	R^2	Q^2
Cognitive Learning Gains	0.571	0.289
Affective Learning Gains	0.520	0.221
Skill-Based Learning Gains	0.494	0.208
Higher-Order Learning Gains	0.457	0.185
Comparative Gains	0.382	0.176
Self-Reflection on Learning Progress	0.535	0.243

$GOF=\sqrt{0.564 * 0.493}=0.527$

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Table 6 provides the R^2, Q^2, and Goodness of Fit (GOF) values for the sub-dimensions of Learning Gains, including Cognitive Learning Gains, Affective Learning Gains, Skill-Based Learning Gains, Higher-Order Learning Gains, Comparative Gains, and Self-Reflection on Learning Progress. The R^2 values for these sub-dimensions range from 0.382 to 0.571, indicating varying levels of variance explained by the model. Specifically, Cognitive Learning Gains has the highest R^2 value of 0.571, suggesting that the model explains 57.1% of the variance in cognitive learning gains, while Comparative Gains has the lowest R^2 at 0.382. The Q^2 values, which measure predictive relevance, range from 0.176 to 0.289, with Cognitive Learning Gains showing the highest value of 0.289, indicating the model has moderate predictive relevance across these sub-dimensions. The overall GOF for the model, calculated as $\sqrt{0.564 * 0.493}$, equals 0.527, suggesting an acceptable overall model fit. This combination of R^2, Q^2, and GOF values supports the validity and predictive relevance of the model in explaining the different dimensions of learning gains.

Table 7

Path Analysis Results

Paths			Path Coefficient	T Statistics	Test results
Cognitive Load	→	Cognitive Learning Gains	0.866	30.243	Supported
Cognitive Load	→	Affective Learning Gains	0.844	29.911	Supported
Cognitive Load	→	Skill-Based Learning Gains	0.746	22.367	Supported
Cognitive Load	→	Higher-Order Learning Gains	0.816	28.315	Supported
Cognitive Load	→	Comparative Gains	0.725	20.923	Supported
Cognitive Load	→	Self-Reflection on Learning Progress	0.798	25.085	Supported
Adaptivity	→	Cognitive Learning Gains	0.651	14.100	Supported
Adaptivity	→	Affective Learning Gains	0.585	13.169	Supported
Adaptivity	→	Skill-Based Learning Gains	0.533	11.505	Supported
Adaptivity	→	Higher-Order Learning Gains	0.509	10.231	Supported
Adaptivity	→	Comparative Gains	0.478	8.171	Supported
Adaptivity	→	Self-Reflection on Learning Progress	0.668	15.898	Supported

For Cognitive Load, all paths to the sub-dimensions of learning gains are significant and supported. The path coefficient from Cognitive Load to Cognitive Learning Gains is 0.866 (T-statistic = 30.243), indicating a very strong positive relationship. Similarly, the paths from Cognitive Load to Affective Learning Gains (0.844, T = 29.911), Skill-Based Learning Gains (0.746, T = 22.367), Higher-Order Learning Gains (0.816, T = 28.315), Comparative Gains (0.725, T = 20.923), and Self-Reflection on Learning Progress (0.798, T = 25.085) are all statistically significant, demonstrating that Cognitive Load positively influences all sub-dimensions of learning gains. For Adaptivity, all paths to the learning gains sub-dimensions are also significant and supported. The path from Adaptivity to Cognitive Learning Gains is 0.651 (T = 14.100), while the path to Affective Learning Gains is 0.585 (T = 13.169), indicating moderate positive relationships. The path coefficients for Adaptivity to Skill-Based Learning Gains (0.533, T = 11.505), Higher-Order Learning Gains (0.509, T = 10.231), and Comparative Gains (0.478, T = 8.171) are smaller but still significant, suggesting moderate positive influences. The strongest path for Adaptivity is to Self-Reflection on Learning Progress (0.668, T = 15.898), indicating a strong relationship.

Discussion

This research examined the relationships between cognitive load, adaptivity, and learning outcomes in AI-personalized learning environments incorporating AR for lower-intermediate EFL learners. The results indicated that cognitive load had a greater impact than adaptivity on learning outcomes. Adaptivity, although impactful, had a somewhat less influence on the same outcomes. More precisely, the study's results indicate a substantial association between cognitive load and learning gains, consistent with the predictions of Cognitive Load Theory (Sweller, 2011). This idea posits that when learners' cognitive resources are overwhelmed, their ability to absorb information efficiently diminishes, leading to reduced learning results. The findings also support previous studies on the role of cognitive load in interactive and multimedia learning settings. For example, Liu et al. (2021) revealed that increased cognitive load from intricate multimedia presentations in AR environments resulted in diminished recall and lower learning performance. Similarly, Candido and Cattaneo (2025) found that extraneous cognitive load in multimedia learning can hinder knowledge acquisition. Moreover, Sweller et al. (2011) also emphasized that excessive cognitive burden from poorly designed instructional materials negatively affects learning outcomes. These findings underscore that unnecessary cognitive load, whether from inadequately designed educational materials or suboptimal teaching methods, might hinder the learning process.

The results emphasize that the inherent complexity of the learning material significantly influences learning outcomes, a finding consistent with Cognitive Load Theory, which posits that high element interactivity and intrinsic cognitive load can constrain learning when instructional materials exceed learners' processing capacity (Sweller, 1988; Sweller et al., 2011). This finding corresponds with recent research by Jamil et al. (2023), which showed that instructional materials aligned with learners' existing cognitive abilities enhance engagement and lead to greater cognitive learning gains. The research indicates that when activities are suitably hard and align with the learner's zone of proximal development (Vygotsky, 1978), they

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may optimize relevant load, hence fostering profound cognitive processing. This sort of load facilitates the development of new schemas and eventually boosts learning. The study's results indicate a substantial adverse effect of total perceived cognitive load on learning outcomes. When learners see their tasks as cognitively burdensome, it may result in irritation, anxiety, or disengagement, which, as shown by Alvandi et al. (2025), may impede self-regulated learning and emotional learning outcomes. The negative correlation between perceived cognitive load and learning gains observed in the present study (see Table 4) is consistent with Skulmowski and Xu (2022), who argued that elevated extraneous cognitive load in digital and online learning environments can reduce learners' motivation to engage in learning activities, thereby negatively affecting academic outcomes. In AI-driven AR learning settings, relevant load was seen to favorably affect skill acquisition outcomes. Germane load refers to the cognitive resources that learners allocate to comprehend and organize incoming knowledge. The positive relationship between adaptivity and learning gains identified in the present study (see Figures 3 & 4) corroborates the findings of Huang and Mok (2025)., who reported that learning systems that effectively promote active engagement and problem-solving support learners in achieving higher levels of skill-based learning and advanced cognitive abilities.

When comparing the structural path coefficients in the present study, cognitive load exhibited a stronger association with learning outcomes than adaptivity. Nevertheless, adaptivity still demonstrated a meaningful relationship with learning outcomes, with engagement in adaptive learning and feedback effectiveness emerging as the most influential subfactors of adaptivity (see Table 4 / Figures 3 & 4). The present findings are conceptually consistent with prior experimental research by Mejeh et al. (2024) as well as Teng and Huang (2025), which demonstrated that individualized learning environments providing timely and accurate feedback are associated with improved cognitive and emotional learning gains. Although these studies employed experimental designs and focused on learning gains rather than adaptivity, their results support the broader notion that personalized and responsive learning features—closely related to perceived adaptivity—are beneficial for learner outcomes. Furthermore, learners' perceptions of adaptivity play a critical role in shaping higher-order learning outcomes, as Faber et al. (2024) demonstrated that learning environments perceived as adaptable—particularly those tailored to learners' specific needs—significantly enhance engagement and self-reflection on learning progress. Learners who recognize that the system customizes the learning experience to their individual needs are more likely to be intrinsically motivated to tackle challenging tasks and reflect on their learning, thereby enhancing their critical thinking and problem-solving abilities.

Nonetheless, involvement with adaptive learning, while positively associated with learning gains, had a lesser impact relative to the other subfactors. This indicates that although learner involvement is significant, it is not the only factor influencing learning gains. The quality and efficacy of the adaptive characteristics are more crucial in determining results. Theodorio (2024) contend that involvement is crucial, although it should be integrated with meticulously crafted instructional methodologies and tailored interventions to achieve optimum learning results. Similarly, Jaboob et al. (2024) noted that adaptive systems fostering active engagement via tailored learning pathways significantly enhance learning results compared to systems that only modify information without addressing the learner's individual requirements and progress.

The examination of the impact of cognitive load and adaptivity on learning outcomes is notably important inside AI-enhanced augmented reality settings. The discovery that cognitive load significantly impacts learning outcomes more than adaptivity highlights the essential need to create learning environments that reduce cognitive overload while effectively calibrating difficulty to align with the learner's skill level. This outcome aligns with recent research by Gandolfi and Ferdig (2025), which indicated that an adaptive learning environment, while advantageous, cannot mitigate the effects of suboptimal task design that overwhelms the learner's cognitive capability. In summary, the research offers significant insights into the impact of cognitive load and adaptability on learning outcomes in AR settings for EFL learners. While adaptivity does play a role in shaping learning outcomes, the findings indicate that cognitive load is a more critical determinant of learner performance. Specifically, managing cognitive load effectively can enhance learners' engagement, facilitate skill acquisition, and promote higher-order learning outcomes, such as problem-solving and application of language skills in realistic contexts. These results underscore the importance of not only designing adaptive learning environments but also carefully structuring instructional materials and activities to align with learners' cognitive capacities.

For English language pedagogy, these findings have several practical implications. First, instructors and curriculum designers should consider integrating AI-powered AR tools that dynamically adjust content difficulty, pacing, and modality based on individual learners' cognitive load. Such tools can help ensure that learners are challenged sufficiently without becoming overwhelmed, which is crucial for maintaining motivation and sustaining learning over time. By monitoring and modulating cognitive load, teachers can create more effective and personalized learning experiences that support vocabulary retention, grammar comprehension, reading and listening fluency, and communicative competence in authentic contexts. Moreover, adaptive AR systems can facilitate differentiated instruction by providing tailored scaffolding for learners with varying proficiency levels. For example, novice learners may receive additional guidance, simplified tasks, or multimodal cues, while more advanced learners can engage in complex problem-solving activities or collaborative language practice. This individualized approach not only enhances immediate learning outcomes but also fosters long-term language development by promoting learner autonomy, self-regulation, and sustained engagement. Ultimately, leveraging AI-powered AR technologies with careful attention to cognitive load management offers a promising avenue for transforming EFL instruction, enabling more efficient, effective, and learner-centered pedagogical practices.

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Conclusion

This research investigated the impact of cognitive load and adaptivity on learning outcomes in AI-personalized learning environments that incorporate augmented reality (AR) for lower-intermediate EFL learners. A key finding of this study is that cognitive load exerts a greater influence on learning gains than adaptivity, highlighting the central role of cognitive processing in AI-enhanced AR learning. Specifically, intrinsic load, germane load, and extraneous load significantly influenced learners' cognitive and emotional outcomes, whereas total perceived cognitive load negatively affected learning gains. Although adaptivity—including feedback efficacy, system customization, and learner perceptions of adaptivity—also contributed to learning outcomes, its effect was comparatively smaller than that of cognitive load.

The novelty of this study lies in its systematic examination of how different components of cognitive load interact with adaptive features in AI-powered AR environments to influence EFL learning outcomes. By disentangling the relative contributions of cognitive load and adaptivity, the study provides new insights into the design principles of personalized learning systems. Specifically, it demonstrates that reducing unnecessary cognitive load while ensuring tasks are appropriately challenging can maximize engagement, skill acquisition, and overall learning effectiveness. At the same time, adaptive features such as individualized feedback and system responsiveness are needed to be carefully aligned with cognitive load management to fully enhance their impact.

This study emphasizes that cognitive load should remain a central consideration in instructional design, even in the context of emerging AI and AR technologies. According to the results (Figures 3 and 4), learners achieve the greatest gains when they are neither overwhelmed by irrelevant information nor under-stimulated by tasks that exceed their current cognitive capacity. Thus, the most effective AI-powered AR learning systems are those that balance cognitive load, provide timely feedback, and deliver individualized experiences.

Finally, optimizing cognitive load in conjunction with adaptive learning strategies can substantially enhance the educational experience, offering educators and instructional designers practical guidance for developing AI- and AR-based learning tools. Future research should continue to explore the dynamic interactions between cognitive load and adaptivity, particularly their effects on long-term learning and the moderating role of individual learner differences. Overall, by providing actionable insights for the development of future educational technologies aimed at enhancing cognitive engagement, learning efficiency, and skill development, this study makes a novel contribution to the growing field of personalized learning in AR environments.

This research illustrates that cognitive load has a big effect on how much you learn in AI-AR settings. How well EFL students understand and remember things is directly affected by cognitive load, especially internal, external, and relevant load. The results show that improving learning outcomes can be achieved by lowering brain load that isn't needed while still pushing students in the right way. In line with Mayer's multimedia principles (2009), educational technologies should focus on reducing unnecessary load by making content and visual design simpler. This will help students focus on important tasks without being interrupted. Adapting the level of challenge to each learner's needs can also help keep the right amount of internal load, which keeps students from getting too overwhelmed and keeps them interested. The study also talked about how important it is for personalized learning methods to be able to change. Cognitive load had a bigger effect on learning gains than adaptivity. However, individual feedback, system personalization, and how learners saw adaptivity were all very important in making them more engaged. As Hattie and Timperley point out, to get the most out of these effects, AI systems should give individuals fast, personalized feedback that helps them figure out their strengths and weaknesses. AI can also change learning paths based on how each person is doing, making sure that students are always pushed without being too much. Giving students chances to think about their progress and ways of learning can also help them become more engaged and better able to control their own behavior. For AI-driven AR worlds to work, they need to have flexible features and ways to handle brain load. AR settings should be made with the user in mind, with material that is both engaging and not too hard to understand. Progressive building in AR tasks, where the level of difficulty rises as students get better, makes sure that they are properly pushed. Gamification features like keeping track of your progress and giving prizes can also make people more interested, which can lead to higher-order learning gains and drive. And finally, the results show that we need to do more study into how flexible AR learning settings affect people in the long run. In the future, researchers should look into how differences between people, like what they already know and how motivated they are, affect how cognitive load, adaptability, and learning results interact with each other. Cross-cultural studies could also help us understand how different types of students use flexible learning tools. This kind of study can help improve the design of AR learning tools so that they work well for a wide range of people and situations.

This work offers significant insights into the effects of cognitive load and adaptability on learning outcomes in AI-personalized augmented reality settings. Nevertheless, there are a number of constraints that should be taken into account, as they also indicate potential areas for future research. This research used self-report measures, which may not consistently represent learners' authentic cognitive experiences or their real learning results. To mitigate this restriction, further research should include more objective measures of cognitive load, including physiological markers (e.g., eye-tracking or heart rate variability) or performance-based evaluations of learning. Furthermore, this study took place in English language institutions, focusing on EFL learners. Future research could extend this study to include learners from different disciplines to see if the findings hold across various academic domains. Additionally, the study focused on a short-term timeframe, with data collected during a single semester. Long-term retention and the transfer of skills to real-world contexts are critical aspects of effective learning, and future studies could investigate these aspects by conducting longitudinal research. Tracking learners' progress over an extended period would offer insights into how AI and AR environments influence long-term learning outcomes, such as the retention of language skills or the ability to apply knowledge in real-life scenarios. Finally, the study did not account for individual learner characteristics, such as motivation, prior knowledge, or learning preferences, which may play a significant role in how learners interact with AI-powered AR systems. Future research may explore how individual differences, including learner motivation, self-regulated learning skills, and prior knowledge, affect the experience of cognitive load and the effectiveness of adaptive learning features.

Bio-data

The authour contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

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References

Al-Ansi, A. M., Jaboob, M., Garad, A., & Al-Ansi, A. (2023). Analyzing augmented reality (AR) and virtual reality (VR) recent development in education. *Social Sciences & Humanities Open*, *8*(1), 100532. https://doi.org/10.1016/j.ssaho.2023.100532

Alkhabra, Y. A., Ibrahem, U. M., & Alkhabra, S. A. (2023). Augmented reality technology in enhancing learning retention and critical thinking according to STEAM program. *Humanities and Social Sciences Communications*, *10*(1). https://doi.org/10.1057/s41599-023-01650-w

Alvandi, M., Faruji, L. F., & Salehi, M. (2025). Relationship among EFL Learners' Self-Regulated Learning Strategy Use, Speaking Anxiety and Speaking Strategy Use. *International Journal of Instruction*, *18*(1), 379–396. https://doi.org/10.29333/iji.2025.18121a

Arena, F., Collotta, M., Pau, G., & Termine, F. (2022). An overview of augmented reality. *Computers*, *11*(2), 28. https://doi.org/10.3390/computers11020028

Ba, S., Yang, L., Yan, Z., Looi, C. K., Gašević, D. (2025). Unraveling the mechanisms and effectiveness of AI-assisted feedback in education: A systematic literature review. *Computers and Education Open*, 9, 100284. https://doi.org/10.1016/j.caeo.2025.100284.

Bacca-Acosta, J., Tejada, J., Fabregat, R., Kinshuk, N., & Guevara, J. (2022). Scaffolding in immersive virtual reality environments for learning English: an eye tracking study. *Educational Technology Research and Development*, *70*(1), 339–362. https://doi.org/10.1007/s11423-021-10068-7

Bamanger, E. (2025). Augmented reality in EFL education: transforming high school student achievement through interactive learning tools. *Journal of Technology Studies, 50*(1). 30-41. https://doi.org/10.21061/jts.439

Candido, V., & Cattaneo, A. (2025). Applying cognitive theory of multimedia learning principles to augmented reality and its effects on cognitive load and learning outcomes, Computers in Human Behavior Reports, 18, 100678, https://doi.org/10.1016/j.chbr.2025.100678

Chang, Y. (2021). Applying the ARCS Motivation Theory for the assessment of AR Digital Media Design Learning Effectiveness. *Sustainability*, *13*(21), 12296. https://doi.org/10.3390/su132112296

Cinar, O. E., Rafferty, K., Cutting, D., & Wang, H. (2024). AI-Powered VR for enhanced learning compared to traditional methods. *Electronics*, *13*(23), 4787. https://doi.org/10.3390/electronics13234787

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates. https://doi.org/10.4324/9780203771587

Çelik, F., & Baturay, M.H. (2024). Technology and innovation in shaping the future of education. *Smart Learn. Environ.* 11, 54. https://doi.org/10.1186/s40561-024-00339-0

Chernikova, O., Sommerhoff, D., Stadler, M., Holzberger, D., Nickl, M., Seidel, T., …Heitzmann, N. (2025). Personalization through adaptivity or adaptability? A meta-analysis on simulation-based learning in higher education. *Educational Research Review*, 46, Article 100662. https://doi.org/10.1016/j.edurev.2024.100662

De Jong, T. (2009). Cognitive load theory, educational research, and instructional design: some food for thought. *Instructional Science*, *38*(2), 105–134. https://doi.org/10.1007/s11251-009-9110-0

Demartini, C. G., Sciascia, L., Bosso, A., & Manuri, F. (2024). Artificial Intelligence Bringing Improvements to Adaptive Learning in Education: a case study. *Sustainability*, *16*(3), 1347. https://doi.org/10.3390/su16031347

Dominic, M., Britto, A. X., & Francis, S. (2015). A Framework to Formulate Adaptivity for Adaptive e-Learning System Using User Response Theory. *International Journal of Modern Education and Computer Science,* *7*(1), 23–30. https://doi.org/http://dx.doi.org/10.5815/ijmecs.2015.01.04

Eltahir, M. E., & Babiker, F. M. E. (2024). The Influence of Artificial intelligence Tools on Student Performance in e-Learning Environments: case study. *The Electronic Journal of e-Learning*, *22*(9), 91–110. https://doi.org/10.34190/ejel.22.9.3639

Evans, C., Howson, C. K., & Forsythe, A. (2018). Making sense of learning gain in higher education. *Higher Education Pedagogies*, *3*(1), 1–45. https://doi.org/10.1080/23752696.2018.1508360

Evans, P., Vansteenkiste, M., Parker, P., Kingsford-Smith, A., & Zhou, S. (2024). Cognitive Load Theory and Its Relationships with Motivation: a Self-Determination Theory Perspective. *Educational Psychology Review*, *36*(1). https://doi.org/10.1007/s10648-023-09841-2

Ezzaim, A., Dahbi, A., Haidine, A., & Aqqal, A. (2023). AI-Based Adaptive Learning: A Systematic mapping of the literature. *JUCS - Journal of Universal Computer Science*, *29*(10), 1161–1198. https://doi.org/10.3897/jucs.90528

Faber, T. J. E., Dankbaar, M. E. W., Van Den Broek, W. W., Bruinink, L. J., Hogeveen, M., & Van Merriënboer, J. J. G. (2024). Effects of adaptive scaffolding on performance, cognitive load and engagement in game-based learning: a randomized controlled trial. *BMC Medical Education*, *24*(1). https://doi.org/10.1186/s12909-024-05698-3

Farhood, H. Nyden, M., Beheshti, A., & Muller, S. (2025). Artificial intelligence-based personalised learning in education: a systematic literature review. *Discov Artif Intell* 5, 331 https://doi.org/10.1007/s44163-025-00598-x

Fidan, M., & Tuncel, M. (2019). Integrating augmented reality into problem based learning: The effects on learning achievement and attitude in physics education. *Computers & Education*, *142*, 103635. https://doi.org/10.1016/j.compedu.2019.103635

Gandolfi, E., & Ferdig, R. E. (2025). Exploring the relationship between motivation and augmented reality presence using the augmented reality presence scale (ARPS). *Educational Technology Research and Development*. https://doi.org/10.1007/s11423-025-10446-5

Gerlich, M. (2025). AI Tools in Society: Impacts on cognitive offloading and the future of critical thinking. *Societies*, *15*(1), 6. https://doi.org/10.3390/soc15010006

Gkintoni, E., Antonopoulou, H., Sortwell, A., Halkiopoulos, C. (2025). Challenging Cognitive Load Theory: The Role of Educational Neuroscience and Artificial Intelligence in Redefining Learning Efficacy. *Brain Sci,* *15*(2), 203. https://doi.org/10.3390/brainsci15020203.

Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P. (2023). *Adaptive learning using artificial intelligence in e-learning: A literature review. Education Sciences,* *13*(12), 1216. https://doi.org/10.3390/educsci13121216

Gonnermann-Müller, J., & Krüger, J. M. (2024). Unlocking Augmented Reality Learning Design Based on Evidence from Empirical Cognitive Load Studies—A Systematic Literature Review. *Journal of Computer Assisted Learning*. https://doi.org/10.1111/jcal.13095

Hair, J.F., Hult, G.T.M., Ringle, C.M. & Sarstedt, M. (2017). *A Primer on Partial Least Squares Structural Equation Modeling (PLS-SEM)*. 2nd Edition, Sage Publications Inc., Thousand Oaks, CA.

Halkiopoulos, C., & Gkintoni, E. (2024). Leveraging AI in E-Learning: Personalized Learning and Adaptive Assessment through Cognitive Neuropsychology—A Systematic Analysis. *Electronics*, *13*(18), 3762. https://doi.org/10.3390/electronics13183762

Heydarnejad, T. (2025a). Unmasking the Impacts of Self-evaluation in AI-supported Writing Instruction on EFL Learners' Emotion Regulation, Self-competence, Motivation, and

Writing Achievement. *Computers and Education: Artificial Intelligence*, 9, 100494. https://doi.org/10.1016/j.caeai.2025.100494

Heydarnejad, T. (2025b). Disclosing motivation and educational self-efficacy in AI-enhanced EFL learning via a lenz into reflective thinking, academic mindfulness, and teacher support. *Discov Psychol* 5, 145. https://doi.org/10.1007/s44202-025-00502-9

Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in Education: Promises and implications for teaching and learning*. http://oro.open.ac.uk/60255/

Huang, J., & Mok, K.H. (2025). Contributions of tertiary students' background factors, learning strategies, behavioural engagement, and cognitive skills to problem solving in technology-rich environments: Evidence from 24 countries. *High Educ*. https://doi.org/10.1007/s10734-025-01474-4

Hwang, G., & Chien, S. (2022). Definition, roles, and potential research issues of the metaverse in education: An artificial intelligence perspective. *Computers and Education Artificial Intelligence*, *3*, 100082. https://doi.org/10.1016/j.caeai.2022.100082

Ilie, S., Forbes, K., Curran, S., & Vermunt, J. D. (2024). Higher education students' conceptions of learning gain. *Active Learning in Higher Education*. https://doi.org/10.1177/14697874241270461

Ironsi, C. S. (2023). Investigating the use of virtual reality to improve speaking skills: insights from students and teachers. *Smart Learning Environments*, *10*(1). https://doi.org/10.1186/s40561-023-00272-8

İslim, Ö. F., Namlı, Ş., Sevim, N., Özçakır, B., & Lavicza, Z. (2024). Augmented Reality in Mathematics Education: A Systematic review. *Participatory Educational Research*, *11*(4), 115–139. https://doi.org/10.17275/per.24.52.11.4

Jaboob, M., Hazaimeh, M., & Al-Ansi, A. M. (2024). Integration of generative AI techniques and applications in student behavior and cognitive achievement in Arab higher education. *International Journal of Human-Computer Interaction*, 1–14. https://doi.org/10.1080/10447318.2023.2300016

Jamil, N., Belkacem, A. N., & Lakas, A. (2023). On enhancing students' cognitive abilities in online learning using brain activity and eye movements. *Education and Information Technologies*, *28*(4), 4363–4397. https://doi.org/10.1007/s10639-022-11372-2

Kabudi, T., Pappas, I., & Olsen, D. H. (2021). AI-enabled adaptive learning systems: A systematic mapping of the literature. *Computers and Education Artificial Intelligence*, *2*, 100017. https://doi.org/10.1016/j.caeai.2021.100017

Kaplan, A. D., Cruit, J., Endsley, M., Beers, S. M., Sawyer, B. D., & Hancock, P. A. (2021). The effects of virtual reality, augmented reality, and mixed reality as training Enhancement Methods: A Meta-Analysis. *Human Factors the Journal of the Human Factors and Ergonomics Society*, *63*(4), 706–726. https://doi.org/10.1177/0018720820904229

Kim, J., Kim, M., Yoo, J., & Park, M. (2024). Augmented reality in delivering experiential values: moderating role of task complexity. *Virtual Reality*, *28*(1). https://doi.org/10.1007/s10055-023-00896-8

Leppink, J., Paas, F., Van der Vleuten, C.P.M. Gog, T. V., & Van Merriënboer, J. J. G. (2013). Development of an instrument for measuring different types of cognitive load. Behav Res 45, 1058–1072. https://doi.org/10.3758/s13428-013-0334-1

Li, F., Wang, X., He, X., Cheng, L., & Wang, Y. (2021). How augmented reality affected academic achievement in K-12 education – a meta-analysis and thematic-analysis. *Interactive Learning Environments*, *31*(9), 5582–5600. https://doi.org/10.1080/10494820.2021.2012810

Lin, H., & Chen, Q. (2024). Artificial intelligence (AI)-integrated educational applications and college students' creativity and academic emotions: students and teachers' perceptions and attitudes. BMC Psychol. 12(1), 487. https://doi.org/10.1186/s40359-024-01979-0

Liu, T., Lin, Y., & Kalyuga, S. (2021). Effects of complexity-determined system pausing on learning from multimedia presentations. *Australasian Journal of Educational Technology*, 102–114. https://doi.org/10.14742/ajet.7267

Mejeh, M., Sarbach, L., & Hascher, T. (2024). Effects of adaptive feedback through a digital tool – a mixed-methods study on the course of self-regulated learning. *Education and Information Technologies*, *29*(14), 1–43. https://doi.org/10.1007/s10639-024-12510-8

Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education Artificial Intelligence*, *2*, 100020. https://doi.org/10.1016/j.caeai.2021.100020

Ouyang, F., Zheng, L., & Jiao, P. (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies*, *27*(6), 7893–7925. https://doi.org/10.1007/s10639-022-10925-9

Poupard, M., Larrue, F., Sauzéon, H., & Tricot, A. (2024). A systematic review of immersive technologies for education: Learning performance, cognitive load and intrinsic motivation. *British Journal of Educational Technology*, *56*(1), 5–41. https://doi.org/10.1111/bjet.13503

Schober, P., Boer, C., & Schwarte, L. A. (2018). Correlation coefficients: Appropriate use and interpretation. *Anesthesia & Analgesia,* *126*(5), 1763–1768. https://doi.org/10.1213/ANE.0000000000002864

Shemshack, A., & Spector, J. M. (2020). A systematic literature review of personalized learning terms. *Smart Learning Environments*, *7*(1). https://doi.org/10.1186/s40561-020-00140-9

Skulmowski, A., & Xu, K. M. (2022). Understanding Cognitive Load in Digital and Online Learning: a New Perspective on Extraneous Cognitive Load. *Educational Psychology Review*, *34*(1), 171–196. https://doi.org/10.1007/s10648-021-09624-7

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science, 12*(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Sweller, J. (2011). Cognitive Load Theory. In *The Psychology of learning and motivation/The psychology of learning and motivation* (pp. 37–76). https://doi.org/10.1016/b978-0-12-387691-1.00002-8

Sweller, J., van Merriënboer, J. J. G., & Paas, F. (2019). Cognitive architecture and instructional design: 20 years later. *Educational Psychology Review, 31*(2), 261–292. https://doi.org/10.1007/s10648-019-09465-5

Tan, X., Cheng, G., & Ling, M. H. (2025). Artificial intelligence in teaching and teacher professional development: A systematic review. *Computers and Education: Artificial Intelligence*. 8, 100355. https://doi.org/10.1016/j.caeai.2024.100355

Teng, M. F., & Huang, J. (2025). Incorporating ChatGPT for EFL writing and its effects on writing engagement. *International Journal of Computer-Assisted Language Learning and Teaching*, *15*(1), 1–21. https://doi.org/10.4018/ijcallt.367874

Theodorio, A. O. (2024). Examining the support required by educators for successful technology integration in teacher professional development program. *Cogent Education*, *11*(1). https://doi.org/10.1080/2331186x.2023.2298607

Tobar-Muñoz, H., Baldiris, S., & Fabregat, R. (2017). Augmented Reality Game-Based Learning: Enriching students' experience during reading comprehension activities. *Journal of Educational Computing Research*, *55*(7), 901–936. https://doi.org/10.1177/0735633116689789

Tudor, I., Dlab, M. H., & Hoić-Božić, N. (2025). Personalized learning in secondary and higher education: a systematic literature review of technology-enhanced approaches. *International Journal of Educational Methodology, 11*(3), 359-375. https://doi.org/10.12973/ijem.11.3.359

Vogt, G., Atwong, C., & Fuller, J. (2005). Student assessment of learning gains (SALGains): An online instrument. *Business Communication Quarterly,68*(1), 36–43. https://doi.org/10.1177/1080569904273332

Vygotsky, L. (1978). *Mind in Society: the development of higher psychological processes*. https://ci.nii.ac.jp/ncid/BA03570814

Wang, S., Wang, F., Zhu, Z., Wang, J., Tran, T., & Du, Z. (2024). Artificial intelligence in education: A systematic literature review. *Expert Systems With Applications*, *252*, 124167. https://doi.org/10.1016/j.eswa.2024.124167

Zhu, B., Chau, K. T., & Mokmin, N. a. M. (2024). Optimizing cognitive load and learning adaptability with adaptive microlearning for in-service personnel. *Scientific Reports*, *14*(1). https://doi.org/10.1038/s41598-024-77122-1