Investigating the Effects of Adaptive AI-Generated EFL Learning Materials on Cognitive Load, Engagement, and Retention

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Abstract

This study investigates the effects of adaptive AI-generated learning materials on cognitive load, engagement, and retention among university students learning English as a Foreign Language (EFL). Using a quasi-experimental design, 120 intermediate-level undergraduates were randomly assigned to either an experimental group, which used an AI-adaptive learning platform, or a control group, which relied on traditional textbook materials, over a four-week intervention. Cognitive load was assessed via the NASA-TLX, engagement through the Student Engagement Scale, and retention using immediate and delayed post-tests. The findings showed that students in the experimental group experienced significantly less from extraneous cognitive load, which refers to the unessential mental effort that does not support learning. In contrast, these students also demonstrated significantly greater behavioral, emotional and cognitive engagement with the learning process, as well as much better retention success compared to those in a control group. Quantitative feedback revealed informative evidence that such attributes as user-tailoring, real-time feedback, and interactive design were overwhelmingly identified as significant merits of the AI system in use. These findings offer strong empirical evidence of the pedagogical value of AI-driven adaptive EFL materials, highlighting their potential benefit for cognitive load management and learners' intrinsic motivation which enhances learning. The study highlights the great importance and contribution of AI-based personalization in higher education EFL classes, as a potential tool to serve better the individual needs and cognitive difficulties students face while learning at university.

Keywords: Adaptive learning, AI-generated materials, EFL, cognitive load, learner engagement, retention

1. Introduction

English as a Foreign Language (EFL) posits many cognitive and motivational problems to the undergraduate students. The EFL learners frequently have to make intricate grammatical decisions and to enlarge their vocabulary range, work on listening, speaking, reading, and writing, which may lead to high cognitive load (Mudhsh et al., 2025; Sweller, 2011; Sweller et al., 2019). The increased cognitive load may result in low learning efficiency, frustration, and disengagement especially when learning resources are not matched with the level of proficiency or the background knowledge (Rahman et al., 2025; Paas et al., 2003). Furthermore, it is important to achieve the progress in EFL language learning and the process of an active task performance that will result in a better understanding, retention, and practice of language skills (Fredricks et al., 2004; Reeve et al., 2004).

Recent developments of adaptive learning technologies, which use Artificial Intelligence (AI) power, have demonstrated significant promise in overcoming these issues (Nemorin, 2024). Systems based on AI are able to monitor the performance of learners in real time and adapt dynamically to their instructional materials, such as difficulty level, sequence of tasks, and the modality of content delivery to meet the needs of each learner (Mohammed et al., 2025; Zawacki-Richter et al., 2019; Cheng et al., 2022). It is hypothesized that such personalization will maximize cognitive load, minimize extraneous mental effort and maximize germane load, which is the number of mental resources used in schema construction and meaningful learning (Mayer, 2014; Sweller et al., 2019). In addition, AI has the potential to increase the engagement of multimodal, adaptive feedback and gamified learning experiences, which have demonstrated effectiveness in enhancing motivation and learning in language learning (Manzano-León et al., 2022; Dede, 2014). Although these are the possible theoretical benefits, there is a lack of empirical studies on the effect of AI-generated adaptive materials in EFL classrooms. Majority of current research is centered on general adaptive learning systems or AI in higher education, in general without the measurement of cognitive load, engagement, and knowledge retention as a systematic measurement (Zawacki-Richter et al., 2019; Cheng et al., 2022).

To a greater extent, there is a lack of research on the role of adaptive AI materials in long-term language skill retention, which is a vital measure of learning efficiency (Mayer, 2014). Hence, this study seeks to address this lapse by considering the impact of adaptative AI-generated EFL learning resources on cognitive load, engagement and retention among university students. The study aims to deliver evidence-based insights into the pedagogical possibilities of AI in higher learning of language by combining the concepts of cognitive load theory, engagement research, and AI-supported personalization. In particular, it examines the hypotheses that extraneous cognitive load can be minimized through AI-adaptive materials, that learners engage better and that AI-adaptive instructional materials can increase short- and long-term retention rates in comparison to traditional and non-adaptive instructional materials.

Research Questions:

1. Do AI-generated adaptive EFL materials reduce cognitive load compared to traditional materials?
2. Do these materials increase learner engagement?
3. Do students using AI-generated materials retain information more effectively than those using traditional resources?

2. Literature Review

2.1 Adaptive Learning in Language Education

Adaptive learning has become one of the most revolutionary methods in the learning environment providing individualized learning that addresses the needs of individual learners. Keller (2009) defines adaptive learning as the education systems which change the teaching content, speed, and teaching strategies, according to the performance of the learners, the previous known information, learning styles and the mental activities. This strategy is in contrast to the conventional one-size-fits-all teaching methodology which does not always respond to the varied abilities and may result in mental overload or poor learning outcomes in learners. The concept of adaptive learning systems is becoming more frequently used in language instruction, specifically in the English as a Foreign Language (EFL) setting, where the learners need to learn vocabulary, grammar, pronunciation, and communicative competence simultaneously (Manzano-León et al., 2022).

Adaptive EFL learning research indicates that the systems can performance based on great efficiency and acquisition of knowledge (Nemorin, 2024). Manzano-León et al. (2022) noted that adaptive learning platforms that used personalized scaffolding improved acquisition of vocabulary, as well as grammar comprehension, among students in the university. Adaptive systems make sure that learners are kept within a zone of proximal development, neither too easy as to lead to boredom, nor too challenging as to become frustrated (Vygotsky, 1978; Zawacki-Richter et al., 2019). The extent of personalization can contribute to the overall growth of intrinsic motivation in learners since the work becomes meaningful and directly corresponds to the level of their competence (Dede, 2014).

Moreover, adaptive learning facilitates the self-controlled learning process through offering instant feedback, tracking of progress, and personalized suggestions. This helps the learners to establish objectives, track their advancement, and adjust plans, which is a vital skill in self-directed learning in the EFL (Zimmerman, 2002; Manzano-León et al., 2022). Also, adaptive systems are able to combine several modalities (visual, auditory, interactive) to support the various modalities of learning and cognitive preferences, further enhancing the learning experience (Mayer, 2014). In spite of these benefits, studies show that adaptive learning technologies are not fully used in EFL higher education, which means that empirical research is necessary to test their effectiveness in a real classroom setting (Cheng et al., 2022).

2.2 AI-Generated Learning Materials

The recent advances in the field of Artificial Intelligence (AI) have increased the range of adaptive learning, allowing AI-generated learning content (Rahman et al., 2025; Ng et al., 2022). The AI generated content uses machine learning and natural language processing (NLP) to create individualized exercises, reading passages, grammar drills, listening activities, and interactive tasks based on the profile of an individual learner (Cheng et al., 2022, Mudhsh et al., 2025). While being as dynamic as compared to the performance of a real expert in digital media (with its inherent unpredictability), AI-generated content can dynamically respond to the performance of a learner, thus offering immediate scaffolding and adjusting task difficulty to the optimal level of cognitive engagement (Paas et al., 2003).

AI finds its way to language teaching because of its ability to implement adaptive teaching in scale (Ng et al., 2022). The AI systems are able to analyze the responses of learners in real-time, identify the patterns of errors and create specific content to fill particular gaps in the knowledge. As an example, when a student continues to use a specific grammatical structure in a wrong way, the system can create exercises based on that specific structure and add complexity over time (Zawacki-Richter et al., 2019). Likewise, reading passages generated by AI may also use vocabulary in line with the current proficiency of learners, thus minimizing the cognitive load in addition to promoting a gradual language development (Cheng et al., 2022).

In addition to cognitive adaptation, AI-generated resources also increase engagement in learners with the help of interactivity and multimodality. As an illustration, it is possible to design interactive quizzes with immediate feedback, gamified activities, and dynamically moving dialogues that emulate real-life communication contexts with the AI (Manzano-León et al., 2022). These characteristics not only make the learning process more interesting but also create a greater number of possibilities in terms of active participation, which is an essential precondition of retention and the rise of skills (Fredricks et al., 2004; Mayer, 2014). Personalization at scale can also be provided by AI-generated learning materials, which is a long-standing problem in language teaching: the fact that the

level of student proficiency is heterogeneous (Nowell et al., 2017). The conventional classroom training is usually not able to simultaneously support both the novices, middle-range and higher-level training. In comparison, adaptive platforms operated by AI are capable of providing differentiated content to every learner, making sure that the instruction is neither too difficult nor too difficult to respond to the cognitive and linguistic limitations of a specific individual (Zawacki-Richter et al., 2019).

2.3 Cognitive Load in Language Learning

The study of how adaptive AI-generated materials influence the results of the learning process can be theoretically explained with the application of cognitive load theory (Sweller, 2011; Sweller et al., 2019). The theory postulates that the working memory has a small capacity, and the instructional resources are to be optimally structured to reduce the amount of unnecessary or extraneous load and focus on the amount of germane cognitive load, i.e., resources spent on meaningful learning and schema building (Paas et al., 2003). Cognitive load may be added in EFL situations because the processing requirements of unfamiliar vocabulary, grammar, pronunciation and comprehension of written and spoken language are performed simultaneously (Sweller et al., 2019).

Adaptive AI-generated materials can strategically manage cognitive load by:

1. Reducing extraneous load: Presenting information in a clear, concise, and coherent format, avoiding unnecessary complexity or redundancy (Mayer, 2014).
2. Managing intrinsic load: Gradually introducing complex language structures in accordance with learners' proficiency levels (Sweller et al., 2019).
3. Enhancing germane load: Providing tasks that encourage active cognitive processing, such as problem-solving, critical thinking, and application of language rules in meaningful contexts (Paas et al., 2003).

The adaptive learning has been empirically studied and shown to be effective in the management of cognitive load. Zawacki-Richter et al. (2019) found they had lower self-reported extraneous cognitive load and at the same time higher task performance among learners who used AI-adaptive materials than their counterparts who used traditional materials. On the same note, Cheng et al. (2022) established that AI-based exercises were more efficient in terms of processing since it matched the difficulty of the task and the personal proficiency enabling learners to immerse in the content without experiencing cognitive overload. Cognitive load, especially in retention, is particularly important and the cognitive load that is too high interferes with the process of sealing information to the long-term memory (Sweller, 2011). In reducing the needless cognitive load and encouraging meaningful interaction, AI-generated adaptive materials result in a favorable environment to the long-term acquisition of vocabulary, grammar, and communicative capabilities.

2.4 Engagement and Retention

The involvement of the students has been widely known to be an essential indicator of academic success and language learning success (Fredricks et al., 2004; Reeve et al., 2004). Engagement is behavioral, emotional, and cognitive (i.e., active participation, sustained attention, interest, and self-regulated learning strategies are used) (Fredricks et al., 2004; Rahman et al., 2025). Repeated practice, the willingness to take risks when using the language, and a more thorough understanding of linguistic structures all require engagement in EFL learning (Manzano-León et al., 2022).

The adaptive materials created by AI generate more interactive content in a number of ways. To begin with, personalization makes tasks to be on a suitable level of challenge, thus making them not very frustrating and boring (O'Dea & O'Dea, 2023). Second, instant performance feedback promotes a feeling of improvement and success in the workplace, which then builds motivation (Dede, 2014). Third, multimodal presentation (text, audio, visuals, active elements) addresses the variety of learning preferences and makes the learners cognitively and emotionally engaged (Mayer, 2014). All these features facilitate the maintained behavioral and cognitive involvement, which subsequently facilitate efficient learning and memory.

The capacity to memorize and retrieve what has been learned, known as retention is directly associated with cognitive load and engagement. Research shows that the learners are better able to remember the information when the learner is actively engaged in the process, and the instructional materials are cognitively optimized (Mayer, 2014; Sweller, 2011). AI-adaptive systems also help in retention by separating repetition of a vocabulary, creating individualized learning activities, and displaying information step-by-step in accordance with the performance of the learners (Zawacki-Richter et al., 2019). Moreover, adaptive feedback assists learners in correcting misconception on the spot, ensuring that the errors are not entrenched in long-term memory, which can destroy the effectiveness of the retention process in the conventional learning setting (Cheng et al., 2022).

2.5 Research Gap

Despite the existing theoretical and empirical data on the individual advantages of adaptive learning, AI-generated learning, optimizing cognitive load, and engagement, there is little research that has systematically investigated the overall effect of these technologies on EFL students in higher education. The majority of the studies have considered these variables independently where either adaptive learning effectiveness or cognitive load are considered in studying language learning, but there has been no integration of engagement and retention as an overall measurement (Manzano-León et al., 2021; Zawacki-Richter et al., 2019). Besides, current research frequently applies to short-term evaluations, which do not offer much clarity of the long-term impacts of AI-created adaptive materials and retention. Although it is possible that the initial performance improvements will be noted, it is not clear that they can be sustained as learning outcomes, especially in such a complicated area as the acquisition of grammar and academic writing in EFL settings (Mayer, 2014; Cheng

et al., 2022).

This gap underscores the need for empirical investigations that simultaneously measure cognitive load, engagement, and retention, offering a holistic understanding of how AI-generated adaptive materials impact EFL learning outcomes. Such research can inform instructional design, demonstrating how AI personalization can be strategically leveraged to maximize learning efficiency, motivation, and long-term skill acquisition.

The literature highlights that adaptive learning and AI-generated materials hold significant potential for transforming EFL education by:

1. Personalizing instruction based on learner performance and cognitive capacity.
2. Managing cognitive load effectively to optimize learning and schema construction.
3. Enhancing engagement through immediate feedback, multimodal content, and gamified features.
4. Supporting long-term retention of language skills through personalized practice and adaptive reinforcement.

Although these findings are promising, the effect of the combination of AI-generated adaptive materials on cognitive load, engagement, and retention is under-researched in EFL higher education. This gap requires filling to comprehend the pedagogical importance of the adaptive learning powered by AI and to create evidence-based measures that would improve language learning.

3. Method

3.1 Research Design and Participants

This study employed a quasi-experimental design to examine the effects of adaptive AI-generated learning materials on cognitive load, engagement, and retention among university-level EFL learners. A total of 120 undergraduate students enrolled in English language courses at NUML Rawalpindi participated in the study. All participants were classified as intermediate-level learners based on their placement test scores and prior coursework. The participants were randomly assigned to either an experimental group (n = 60) or a control group (n = 60). Both groups received instruction over a four-week period, with the type of instructional material serving as the independent variable. Cognitive load, engagement, and retention were measured as dependent variables.

3.2 Instruments and Measures

Three instruments were used to collect quantitative data. Cognitive load was measured using the NASA Task Load Index (NASA-TLX) developed by Hart and Staveland (1988). Learner engagement was assessed using the Student Engagement Scale developed by Fredricks, Blumenfeld, and Paris (2004), which measures behavioral, emotional, and cognitive engagement. Retention was evaluated using researcher-developed pre-tests, immediate post-tests, and delayed post-tests aligned with vocabulary, grammar, reading, and listening objectives covered during the intervention.

3.3 Reliability and Validity

To ensure reliability, Cronbach's alpha coefficients were calculated for the engagement scale and retention tests. The Student Engagement Scale demonstrated acceptable internal consistency ($\alpha > .80$). The retention tests were reviewed by two EFL experts to ensure content validity and alignment with course objectives. Pilot testing was conducted with a small group of students (n = 20) prior to the main study to refine test items and confirm clarity. The NASA-TLX instrument has been widely validated in educational research and demonstrates strong reliability in measuring perceived cognitive workload.

3.4 Procedure

The study was conducted over a four-week period. Both groups participated in four sessions per week, each lasting 90 minutes. The experimental group used adaptive AI-generated learning materials, while the control group used traditional non-adaptive instructional materials. Cognitive load questionnaires were administered after each session. Engagement surveys were distributed weekly. Retention was measured using immediate post-tests at the end of the intervention and delayed post-tests two weeks later. Qualitative feedback was collected through open-ended questionnaires at the conclusion of the study to supplement quantitative findings.

3.5 Experimental Group

The experimental group was provided with adaptive AI-based learning resources aimed at developing vocabulary, grammar, reading, listening, and interactive language training. These materials were developed through an AI learning platform that can monitor and personalize the performance in real time. The difficulty of the tasks, content choice, and modality (text, audio, and interactive activities) were automatically moderated depending on the individual performance and progression of learners. Features included:

- Vocabulary exercises with immediate feedback and contextual examples.
- Grammar quizzes with adaptive difficulty levels.
- Reading passages tailored to students' proficiency and thematic interests.
- Listening activities incorporating interactive comprehension tasks.

These materials were designed to optimize cognitive load, increase engagement through personalized challenges, and enhance retention via repeated, targeted practice.

3.6 Control Group

Control group was provided with conventional teaching materials such as standardized tasks on vocabulary, grammar, reading

comprehension and listening. The selection of materials was based on the popular textbooks on EFL, found in the university level. All activities were not adaptive and were presented to all participants in an identical manner, which is typical of the classroom without AI-assisted customization.

3.7 Instruments

3.7.1 Cognitive Load

The NASA Task Load Index (NASA-TLX) which was developed by Hart and Staveland (1988) was used in measuring the cognitive load. This multidimensional measure measures the perceived mental workload in 6 subscales which include mental demand, physical demand, temporal demand, performance, effort, and frustration. The participants were asked to rate each subscale on a scale of 21 points and the overall cognitive load score was found at the end of the session.

3.7.2 Engagement

The Student Engagement Scale created by Fredricks, Blumenfeld and Paris (2004) was used to measure engagement. The scale indicates three domains of engagement, namely behavioral, emotional, and cognitive on a 5-point Likert-like scale. Questions on participation in tasks, interest in learning activity and effort in performing assignments are included.

3.7.3 Retention

The EFL knowledge and skills were assessed through the combination of pre-tests, post-tests, as well as delayed post-tests. Pre-tests provided the baseline proficiency in vocabulary, grammar, reading comprehension as well as listening skills. Immediate learning outcomes were measured by the use of post-tests that were conducted at the end of the 4-week program. Two weeks later, delayed post-tests were applied in order to assess the retention of the learned material in the long-term. The test items were matched with the content of experimental and control group to make comparisons.

3.7.4 Procedure

It was carried out in 4 weeks in the campus of NUML Rawalpindi. The participants were in groups of four sessions of 90 minutes per week during which the experimental group used AI-generated adaptive materials and the control group used traditional materials.

- Cognitive load assessments were administered at the end of each session using the NASA-TLX questionnaire.
- Engagement questionnaires were distributed weekly to capture ongoing levels of behavioral, emotional, and cognitive engagement.
- Retention tests were administered at the end of the program (post-test) and two weeks after the program concluded (delayed post-test) to measure both immediate and sustained learning outcomes.

The program was followed by the administration of retention and delayed post-test (two weeks after the program ended) to assess both the short-term and different (delayed) and long-term learning outcomes. The members of the experimental group were given the access to the AI platform during classes and during optional practice time outside the classes, during which the system can constantly modify the content based on their progress. The members of the control group performed all exercises in paper or standard digital version without adaptive features. Moreover, the qualitative feedback was gathered by using both the open-ended questionnaires at the conclusion of the study. The respondents were questioned regarding their perception of the learning materials, engagement, and problems, and general experience. This qualitative data gave information about subjective experience of learners and supplemented quantitative measures.

3.8 Data Analysis

The SPSS (version 28) was used to analyze quantitative data. Independent-samples t-tests were used to compare cognitive load, engagement as well as retention between the experimental and the control groups. ANOVA was used in repeated measures to compare the changes over time especially when considering the retention scores in immediate post-tests and delayed post-tests. The thematic analysis was used to analyze qualitative data, and six steps of the process described by Braun and Clarke (2006) were followed. The responses were coded to find out common themes concerning engagement, cognitive effort, perceived usefulness and general satisfaction with the learning materials. Quantitative and qualitative analysis mixed made it possible to gain a complex insight into the effect of AI-generated adaptive materials on EFL learning outcomes.

4. Results

4.1 Cognitive Load

The NASA-TLX questionnaire was used to measure cognitive load and it consists of six items which measure the perceived mental workload according to six domains: mental demand, physical demand, temporal demand, performance, effort, and frustration (Hart and Staveland, 1988). A major difference was found in the extraneous cognitive load of the experimental group (AI-generated adaptive materials) relative to the control group (traditional materials) with significant difference to the experimental group being ($M = 32.5$, $SD = 5.4$) whereas the control group is ($M = 45.8$, $SD = 6.1$); $t(118) = 12.23$, $p = .001$. This means that adaptive materials were useful in minimizing unnecessary mental processes that had to be used by the learners instead of concentrating on meaningful language activities.

Table 1. Cognitive Load Scores (NASA-TLX)

Group	N	Mean	P-Value
Experimental (AI)	60	32.5	<.001
Control (Traditional)	60	45.8	

Table 1 has the comparison of the cognitive load scores as measured through NASA-TLX between the experimental group, which used AI-generated adaptive material and the control group, which used traditional instructional material. The findings show that the experimental group had significantly lower cognitive load (M = 32.5, SD = 5.4) as compared to control group (M = 45.8, SD = 6.1). This was significantly different, t(118) = 12.23, p =<.001 and proved that AI-generated adaptive materials were indeed useful in alleviating the perceived mental workload of learners completing the tasks at hand.

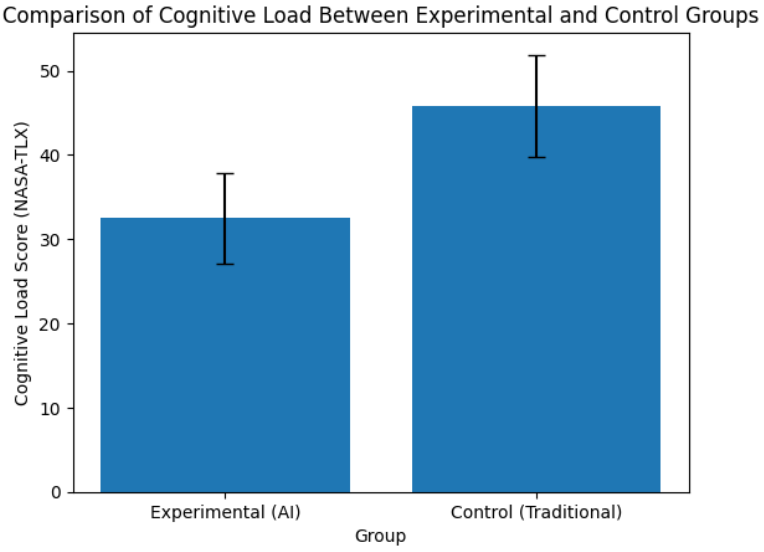

Figure 1. Bar chart comparing cognitive load scores for both groups

Figure 1 presents the overall cognitive load scores, assessed by the NASA-TLX, in the experimental group based on the use of AI-generated adaptive EFL material and the control group based on the use of traditional instructional material. As compared to the control group (M = 45.8, SD = 6.1), the experimental group showed a significantly reduced perceived cognitive load (M = 32.5, SD = 5.4). Group difference was statistically significant t (118) = 12.23, p <.001 implying that the effect of adaptive AI-generated materials in reducing the mental workload of learners is strong.

The reduced cognitive load in the experimental group indicates that personalization by AI was effective to reduce extraneous cognitive load and instead aid more efficient processing of tasks. Further analysis of NASA-TLX sub components showed that the mental and time demands of learners in the experimental condition were lower and those they had a higher perceived task performance than learners in the control group. These results suggest that adaptive AI materials were able to minimize cognitive effort enabling learners to devote more cognitive resources to meaningful language processing instead of task complexity management.

4.2 Engagement

Student Engagement Scale was used to measure engagement, behavioral, emotional, and cognitive engagement. The experimental group said that it was more engaged (M = 4.2, SD = 0.6) than the control group (M = 3.5, SD = 0.7), t(118) = 6.14, p <. 001. The participants emphasized the interaction, motivation, and individualization of AI materials by their competency, whereas the participants in the control group referred to repetitive and less engaging tasks.

Fig. 2 Weekly engagement scores for both groups over 4 weeks

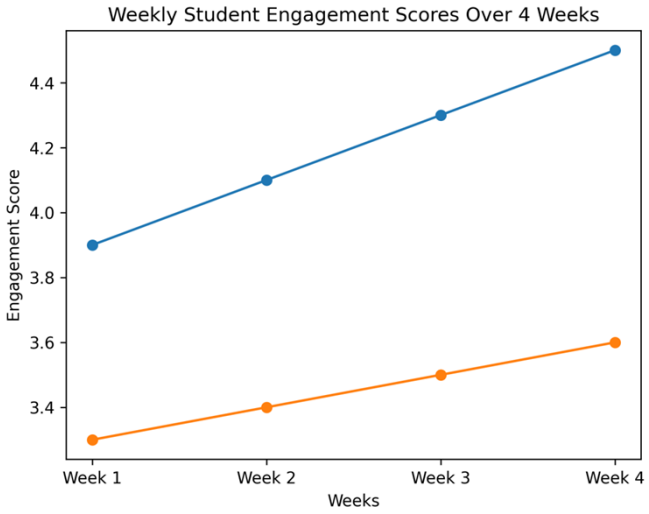

Figure 2 shows the variations in the levels of student engagement in the four-week intervention of the two groups. The experimental group was found to have consistently better engagement levels and the levels were increasing steadily since the Week 1-Week 4. Conversely, the control group recorded a significant increase in engagement only to a modest level. The increased distance between the two groups shows that the adaptive materials generated by AI did not only result in a greater overall engagement but maintained and improved the engagement of learners in behavioral, emotional, and cognitive levels throughout the duration of the intervention. These results are in line with statistically significant group differences in Table 2 and highlight the importance of adaptive personalization and interactivity in ensuring the learners remain engaged when using EFL.

4.3 Retention

The retention was assessed by carrying out immediate post-tests and delayed post-tests after two weeks of program completion.

Table 2. Immediate and Delayed Retention Scores

Group	Immediate Post-Test (%)	SD	Delayed Post-Test (%)
Experimental (AI)	86	7	82
Control (Traditional)	74	9	70

Table 03 indicates that the experimental group scored higher on immediate (M = 86% and delayed retention, M = 82% and 70% respectively), F (1,118) = 28.45, p <.001 as compared to the control group. This shows that AI-adaptive materials are helpful in short-term learning and long-term consolidation of language knowledge.

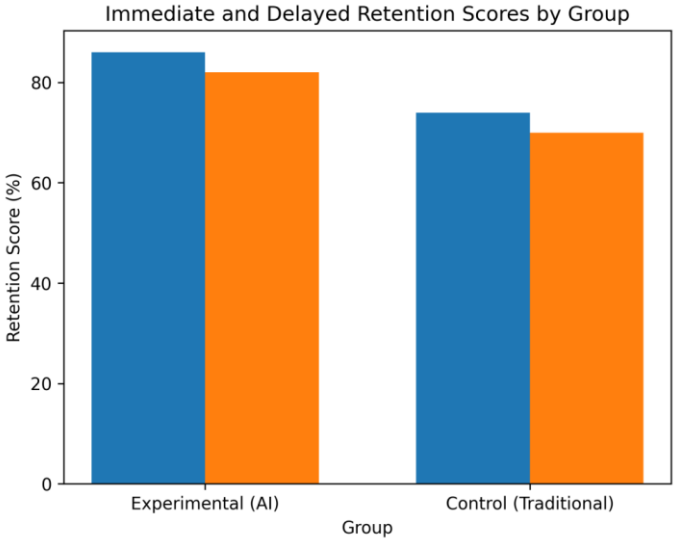

Figure 3. Immediate vs. delayed retention for both groups

Figure 3 presents the comparison of the immediate and delayed retention scores in the experimental group and control group. The

experimental group scored higher on the immediate post-test (M = 86%) and the delayed post-test conducted two weeks after (M = 82%) than the control group, which scored lowly in the immediate (M = 74%), and the delayed test (M = 70%). The comparison between conditions proved to be statistically significant, $F(1,118) = 28.45$, $p < .001$, which is a strong influence of the AI-generated adaptive materials on retention of learning.

4.3 Qualitative Feedback

In order to have a deep insight into the experiences of learners with the instructional materials, the qualitative data were collected using open-ended questionnaires that were given to all participants at the conclusion of the four weeks intervention. This qualitative aspect was meant to supplement the quantitative results by getting subjective perceptions of the students regarding the learning process, the structure of instruction, and the engagement as a whole. Thematic analysis was used to analyze the responses in accordance with the six-phase model of Braun and Clarke (2006) that allowed identifying, coding, and interpreting recurrent patterns throughout the data set. In the process, a number of salient themes were identified, especially in people who participated in the experimental group and interacted with AI-generated adaptive learning materials.

On the whole, the qualitative data supports the quantitative results, as it showed that AI-generated adaptive materials have a positive impact on the perception of the learning process among learners. The opportunity to work at their paces, get instant feedback, and enjoy the interactivity of learning materials, among others, allowed participants to be more motivated and actively engaged and improved learning performance. On the other hand, the experiences of the control group highlight the drawbacks of the traditional, non-adaptive materials, especially in the context of the interaction with the learners and providing personalized assistance.

4.3.1 Personalization and Individualized Learning

Personalization was among the most noticeable themes that were found in the experimental group. The respondents mentioned multiple times that AI-generated materials were highly relevant to their personal level of proficiency and learning requirements. Students claimed that the modular property of the tasks permitted the students to work on a particular area of linguistic deficiency in the form of grammar structures, vocabulary gaps, or reading comprehension issues, and not use their time on what they had already mastered. This feeling of a personalized teaching was viewed as effective and conducive to teaching. As one participant stated, “Tasks matched my level perfectly and helped me focus on the areas I struggled with the most.”

This sense of individualization seemed to cause a decrease in frustration and confidence in learners. Instead of being overwhelmed or disengaged, students also felt that the learning process was manageable and not too challenging. The results are consistent with the findings of research that indicates that personalized instructional design is associated with more efficient cognitive processing by eliminating extraneous cognitive load and enabling learners to focus their cognitive resources on meaningful learning processes. The qualitative data therefore supports the quantitative findings of a much lower cognitive load in the students of the experimental group.

4.3.2 Immediate Feedback and Error Awareness

The second important theme was the importance of immediate feedback in facilitating learning. The members of the experimental group always emphasized the importance of correcting and explaining given in real time after the completion of the task. Students indicated that the immediate feedback has made it possible to see their mistakes and know the cause of their mistakes and correct their learning strategies. One learner remarked, “I learned from mistakes immediately, which helped me remember rules better and avoid repeating errors.”

This instant feedback was found to be especially helpful in grammar acquisition and vocabulary use, in which common mistakes can be formed very quickly unless corrected in the near future. The participants also mentioned that explanations in a timely manner assisted in making clear the misunderstanding and supporting proper language use, which led to the enhancement of retention. The qualitative information can therefore explain the qualitative data of a higher retention score in the experimental group during the immediate and delayed post-tests.

Engagement, Motivation, and Learning Enjoyment

Interaction and enthusiasm became a third theme of students who were using AI-generated adaptive materials. The learning activities were reported by many participants to be interactive, enjoyable, and motivating and focused on the gamified aspects, distinctive type of tasks, and visual stimulation. These features were found to be reported by learners to have made the learning process less tedious but more fulfilling and thus they were willing to remain active during the four-week program. As one participant noted, “Learning was fun and challenging; I felt motivated to complete all tasks and try new exercises.” Students also highlighted that the adaptive difficulty of tasks contributed to a sense of accomplishment, as challenges increased gradually in response to their progress. This balance between challenge and support appeared to foster positive emotional engagement and intrinsic motivation. These qualitative insights closely mirror the quantitative findings, which showed significantly higher behavioral, emotional, and cognitive engagement scores for the experimental group. Moreover, they align with existing literature emphasizing the role of interactivity and personalization in enhancing learner engagement in EFL contexts.

4.3.3 Limitations of Traditional Instructional Materials

Conversely, the respondents in the control group who utilized traditional textbook-based resources indicated that there were a number of limitations that were recurrent. According to many of the students, the instructional tasks were repetitive, uniform, and poorly addressed to

the individual learning needs. Students observed that doing the same exercises as other pupils no matter the level of proficiency made the exercises boring or Di inspiring One participant commented, “All tasks were the same for everyone, and I often felt bored completing exercises I already knew”.

Moreover, respondents in control groups said they were frustrated when there was a long or slow response to a question or the instructor did not explain anything, stating that it was difficult to understand what was going wrong and what they were doing right. As one student stated, “I had to wait to see the correct answers, which made it harder to understand my mistakes and improve”. These responses underscore the limitations of conventional, non-adaptive instructional approaches in addressing learner diversity and maintaining motivation, particularly in heterogeneous EFL classrooms.

4.3.4 Summary of Qualitative Findings

On the whole, the qualitative results substantially corroborate the quantitative ones by showing that AI-generated adaptive materials significantly affected the perceptions of personalization, quality of feedback, engagement, and motivation of learners. The students who were in the experimental group appreciated the fact that they were able to learn at their own pace, get instant guidance, and be exposed to interactive content, which made the learning process more effective and satisfying. On the other hand, the responses of the control group emphasize the ongoing issues with the conventional teaching resources, especially regarding the interaction and personalized assistance of the learners. Collectively, these results present strong support to the pedagogical benefits of AI-adaptive learning resources in EFL teaching in higher education.

5. Discussion

This study aimed at investigating the implications of adaptive AI-generated English as a Foreign Language (EFL) learning tools on the cognitive load, engagement, and retention of university students. The findings have shown that learners with adaptive AI materials had much lower perceived cognitive load levels, more engagement, and higher retention, both immediately after learning and in a delayed test as compared to their learner counterparts who were exposed to traditional textbook-based materials. These findings were supported by qualitative learner feedback reporting higher perceptions of personalization, instant corrective feedback and greater levels of motivation. Combined, these results contribute to a growing body of empirical evidence proposing that adaptive AI technologies can boost important dimensions of language learning outcomes (Wah, 2025; Zawacki-Richter et al., 2019).

5.1 Cognitive Load and Cognitive Processing

One of the key findings of this study was the high level of decrease in extraneous cognitive load with participants who used adaptive AI learning materials. The Cognitive Load Theory (CLT) claims that the human working memory is limited and that teaching methods that minimize wasted cognitive load allow more effective processing and schema building (Sweller, 2011). Adaptive AI systems that vary task difficulty and sequence content on-the-fly allow reducing the number of irrelevant cognitive requirements, enabling learners to allocate their cognitive resources to constructive language processing. This is consistent with the recent studies that revealed that AI-based adaptive learning systems have the potential to better cognitive load management and increase focus and retention in higher education settings (Crompton & Burke, 2023). Precisely, adaptive AI tools which adjust the complexity of instructional material according to performance data allow learners to access content at their learning best and eliminate unnecessary work to systematically easy or difficult tasks (Wah, 2025; Sweller, 2011).

This is the real time customization of personalization that reflects the wider idea of the zone of proximal development (ZPD) of educational psychology, where there is optimal learning at a point of challenge that matches the learner readiness (Vygotsky, 1978). Through scaffolding of instructions and progressive increment in task difficulty when learners are already ready, adaptive AI tools place learners in their ZPD better than unresponsive materials.

However, it should be noted, that the decrease in extraneous cognitive load might indirectly lead to the focus on the procedural and declarative knowledge and consequently on more profound conceptual thinking (Sweller et al., 2019). Although reducing unnecessary mental load favors language acquisition and retention of underlying language features, germane cognitive load, which involves the effort that is applied toward schema building and transfer, demands task demands that facilitate meaningful problem solving and critical reflection. Future studies are needed to understand how the load minimization and the possibility of higher-order thinking can be balanced in AI-mediated language settings through instructional designs.

5.2 Engagement and Motivation

In line with quantitative findings, learners in the experimental group portrayed much greater engagement. Engagement in educational research is behavioural, emotional as well as cognitive, such as persistence, attention, interest and strategic effort (Fredricks et al., 2004). Adaptive AI materials are enriched by these aspects and offer customized challenges, interactive tasks and instant feedback which are known to be highly effective to promote greater engagement and motivation among learners. Empirical research including systematic reviews whose synthesis articles were published recently substantiate the existence of the positive relationship between using AI and the engagement of a learner during a language learning situation.

The applications of AI to offer personalized feedback and adaptive assistance are also linked to enhancing behavioral engagement (active participation and long-lasting cognitive attention) (Mohammed et al., 2025; Wah, 2025; Wei, 2023). The qualitative feedback in the present research indicated that learners have reported adaptive AI activities as fun, challenging in a good way and engaging, which is reflective of

research that reveals gamified and interactive AI settings have the potential to induce intrinsic motivation and lessen anxiety during language learning (Bachiri et al., 2023). Increased enjoyment and positive attitudes to learning, in turn, correlate with an increased persistence and academic resilience, especially in EFL circumstances (Almaiah et al., 2022).

Moreover, learner attitudes and technology acceptance tend to mediate engagement effects in learning environments promoted by AI. Research based on constructs like the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM) indicate that students with the perception that AI tools are helpful, simple to use, and supportive find it easier to continue their tasks, think cognitively, and implement self-regulated learning processes (Wei, 2023). These are critical elements of the Self-Determination Theory (SDT) which holds that intrinsic motivation is based on feelings of competence, autonomy, and relatedness (Ryan and Deci, 2020). Learners are more motivated and are more active when they feel that an AI system is attentive to their inherent needs or needs and helps them advance.

5.3 Retention and Long-Term Learning

Additionally, one of the strongest results of this research was the enhanced retention of the experimental group, directly after the intervention and at the delayed test two weeks later. One of the fundamental indicators of successful learning is retention particularly in the complex areas like vocabulary, grammar, and mastery of the whole language (Mudhsh et al., 2025). The ability of adaptive AI to customize repetitive practice, track progress, and differentiate task difficulty probably allowed spaced rehearsal and meaningful retrieval practice procedures that are known to enhance memory and entrench long-term learning (Roediger and Butler, 2010). This retention improvement is consistent with such studies on adaptive learning systems that show and support the idea that individualized instruction pathways and specialized practice can boost memory retention and recall in learning institutions (Wah, 2025).

Within the EFL field, adaptive AI text could assist the learners to construct more robust linguistic schemas by addressing the language elements in a more specific manner with regards to the needs of the learners. When the development needs to be too fast or too slow, it leads to scaffolding that is tailored, which reinforces language patterns and builds neural representations of language constructs. The interaction between cognitive load decrement and increased engagement might be part of the retention gains being observed. Students who feel that their cognitive load is manageable but they feel engaged and motivated tend to encode and consolidate learning more easily. Modern theories of adaptive learning focus on this cognitive-motivational interaction as one of the keys to effective learning results.

5.4 Pedagogical Implications

This study has a number of significant implications on the EFL teaching in higher education. First, they substantiate the fact that adaptive AI systems can supplement the conventional teaching and learning process through the provision of personal tailored and data-driven pedagogical assistance, which is hard to accomplish in large or diverse classes. Being intelligent tutors, adaptive AI systems have the potential to track the responses of learners in real-time, dynamically change the instruction content, and issue corrective feedback including a real-time one, all of which encourage instructors to concentrate on communicative practices, socio-cultural background, and higher-order learning.

Practically, the instructional practice can be integrated with the adaptive AI tools in the framework of blended learning when AI takes care of the individual practice and remediation, and human educators facilitate discussions, exemplify communicative proficiency, and develop critical thinking. This assimilation matches pedagogical frameworks that present the role of technology as an ally, rather than a substitute, of human teachers (Wah, 2025; Ryan and Deci, 2020). The learners of this research appreciated individualization and instant feedback, which underlines the need to create AI–based models that reinforce learner agency and responsiveness. Students would feel more competent and autonomous, which are fundamental predictors of intrinsic motivation when they believe that a system is aware of its needs and adapts to them (Ryan and Deci, 2020). Additionally, teachers and curriculum developers are advised to appreciate the fact that digital literacy can mediate the effectiveness of learners in using adaptive AI technologies. It has been shown that more digitally proficient learners are better equipped to take advantage of individualized AI feedback and customized learning experiences, which highlights that scaffolded assistance is needed to foster language and digital abilities.

6. Conclusion

The purpose of the study was to examine the efficiency of adaptive AI-generated EFL learning resources in connection with cognitive load, student engagement, and knowledge retention among university students. The results are very convincing that AI-based adaptive teaching can significantly improve the quality and the effectiveness of EFL learning in the context of higher education. Adaptive AI materials were demonstrated to lower unnecessary mental workloads, generate lasting engagement and promote immediate learning and long-term language knowledge retention by dynamically aligning the instruction content with the level of proficiency and the progress of learners. One of the main contributions of this research is its combined analysis of cognitive efficiency, involvement, and retention in one teaching framework. The findings indicate that individualized scaffolding and prompt feedback play a significant role to help a learner to distribute cognitive resources more efficiently so that they can be able to concentrate on processing significant language parts instead of the complexity of the tasks they are engaged in. Besides, the interactive and adaptive qualities of AI-generated content were discovered to facilitate the increased behavioral, emotional, and cognitive engagement levels, which further led to the more sustainable learning results.

Collectively, these results enlarge the current theoretical outlook by demonstrating how the principles of cognitive loads optimization and learner engagement can be implemented by AI-assisted learning in real EFL classrooms. In addition to its empirical input, the research has

valuable pedagogical implications to higher education. With university populations becoming more and more diverse with regards to various learners and the challenge of digital transformation, adaptive AI systems offer a promising solution to the provision of personalized and scalable language education. Such systems can facilitate traditional teaching when wisely incorporated into the curriculum design and offer individualized practice, timely feedback, and overall support out of the classroom. Future studies are needed to determine the long-term effects of prolonged AI-adaptive learning, discover its applicability in various levels of proficiency and linguistic ability, and determine how AI-generated materials can best be incorporated into blended and instructor-led learning systems. All in all, the paper highlights how adaptive AI tools can indeed be used to augment EFL didactics without substituting the primary role of human instructors in second language acquisition.

6.1 Limitations and Future Research

Although results have been found, this study is associated with a number of limitations, which are worth considering. To start with, the study has been carried out in one setting of an institution, which can have a negative impact on the broader extrapolation of findings to other cultural, language, or education settings. The application of this design in future research should be replicated in various universities and various groups of learners to make sure that it is applicable in general.

Second, the two-week delayed test gave an idea of the short-term retention, but longer longitudinal follow-ups (three months and six months) would have offered more knowledge about the adaptive AI influence on the long-term language proficiency and fluency acquisition. Third, although qualitative data showed a high level of learner perceptions of personalization and engagement, research can be done in the future to examine the extent to which certain AI design features, including feedback modality, gamification elements, or learner control options, affect learning outcomes differently. It could be useful to use physiological data (e.g., EEG) or real-time engagement indicators to obtain finer-granular evidence in terms of cognitive and affective learning processes. Lastly, although adaptive AI seems to be of potential use when it comes to cognitive load reduction and retention, instructional designers ought to think about striking the balance between adaptive support and the possibility to engage in independent language use and higher-order problem-solving. Maintaining consistency in order not to make learners overly dependent on AI scaffolding at the cost of critical reflection and independent language deployment is an important factor in creating effective AI-human hybrid learning systems.

AI Usage Disclosure: The authors used AI-assisted tools for language editing and improving clarity. No AI tools were used for generating references, interpreting data, or producing original research content. All intellectual contributions and final decisions were made by the authors.

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Author contributions

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Informed consent

Obtained.

Ethics approval

The study was conducted in accordance with institutional research ethics guidelines, and participation was voluntary. The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE). **Provenance and peer review**

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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