PERSONALIZED ENGLISH LEARNING THROUGH ARTIFICIAL INTELLIGENCE: STUDENT PERCEPTIONS AND OUTCOMES

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ABSTRACT: This study investigates the application of Artificial Intelligence (AI) in personalized English language learning at Cambridge School, Lhokseumawe. Conducted in January 2025 with fifteen students, the research employed a mixed-methods approach. This combined pre-test and post-test assessments to quantitatively measure gains in language proficiency with a qualitative questionnaire designed to capture student perceptions of the AI tool. The findings demonstrate statistically significant improvements across key language domains, including vocabulary acquisition, speaking fluency, and grammatical accuracy. Furthermore, analysis of student feedback revealed overwhelmingly positive perceptions, with participants highlighting the system's adaptability to individual needs, the value of immediate corrective feedback, and the overall engaging nature of the AI-assisted exercises. These results strongly suggest that AI-driven personalized learning is not only an effective method for enhancing English proficiency but also a powerful means of increasing student motivation and engagement in the language acquisition process. The study concludes that AI represents a promising and transformative tool in modern educational methodologies.

Keywords: *Artificial Intelligence, English Language Learning, Personalized Learning, Student Perceptions*

INTRODUCTION

English proficiency has become an essential competency in both academic and professional contexts, serving as a gateway to higher education opportunities, global communication, and participation in the international workforce (Graddol, 2006; Crystal, 2012; Muslem et al., 2019). In higher education, proficiency in English is often associated with improved access to academic resources, greater participation in collaborative projects, and enhanced opportunities for publishing research (Richards, 2015). In the professional sphere, employers increasingly demand high levels of English communication skills to facilitate cross-border business interactions and participation in multinational organizations (Kirkpatrick, 2016).

Despite its importance, traditional English language instruction often employs a *one-size-fits-all* pedagogical approach, delivering the same content and pacing to all learners regardless of their proficiency levels, learning preferences, or cognitive processing styles (Tomlinson, 2013). Such uniformity may hinder optimal learning, as it fails to address the diverse needs of learners who differ in their prior knowledge, motivation, and pace of progress (Lightbown & Spada, 2013). Differentiated instruction has long been advocated as a solution, but its practical implementation in large classrooms remains challenging due to time constraints and the difficulty of providing individualized feedback (Baker, 2011).

Recent advancements in Artificial Intelligence (AI) have introduced new opportunities to overcome these challenges through *personalized learning* systems. AI-powered educational platforms can also assess learners' strengths and weaknesses in real time, adapting the difficulty level, learning content, and instructional pace accordingly (Holmes et al., 2019). Furthermore, AI systems can provide instant, individualized feedback on grammar, pronunciation, vocabulary usage, and overall communicative competence features that are difficult to achieve in traditional classroom settings without substantial teacher workload (Zawacki-Richter et al., 2019). The integration of adaptive algorithms, natural language processing, and speech recognition technologies allows for an interactive and responsive learning environment that closely aligns with the learner's needs (Heffernan & Heffernan, 2014).

Given these developments, this research investigates how AI-based personalized learning affects both the academic outcomes and learner perceptions of English language acquisition among students at Cambridge School, Lhokseumawe. The study aims to determine whether AI-mediated instruction can significantly enhance measurable language skills while also improving learner motivation and engagement, thus addressing the pedagogical limitations of conventional instruction.

LITERATURE REVIEW

Personalized learning refers to instructional approaches designed to tailor learning objectives, instructional content, and the pace of delivery to the specific needs, preferences, and abilities of individual learners (Pane et al., 2015). In contrast to traditional teaching models, where all students are expected to progress through the same curriculum at the same rate, personalized learning leverages continuous assessment and learner analytics to adjust materials in real time. This pedagogical model emphasizes student-centered learning, providing opportunities for differentiated instruction that aligns with each learner's readiness level, interests, and goals (Bray & McClaskey, 2015).

In recent years, Artificial Intelligence (AI) has been increasingly integrated into English language learning environments to facilitate personalized learning. AI-powered platforms use adaptive algorithms to diagnose learners' strengths and weaknesses and subsequently recommend targeted activities. For example, adaptive grammar exercises can present progressively challenging tasks as the learner demonstrates mastery, while simplifying or providing scaffolding when difficulties arise (Holmes et al., 2019). Similarly, speech recognition technology allows learners to practice pronunciation and receive instant, detailed feedback on phonetic accuracy, intonation, and fluency, which is often difficult to provide consistently in large classroom settings (Godwin-Jones, 2021). Moreover, AI-driven chatbots offer conversational practice in real or simulated contexts, allowing learners to engage in extended dialogues, negotiate meaning, and receive corrections without the social anxiety that may accompany peer or teacher interactions (Jia et al., 2020).

A growing body of research suggests that AI-based tools can enhance learner engagement and accelerate the process of second language acquisition, particularly when implemented alongside traditional teacher-led instruction. Li and Ni (2022) found that students who used AI-assisted language platforms demonstrated significantly greater improvements in vocabulary retention and sentence construction compared to those in a control group. The authors attributed these gains to the immediacy of AI feedback and the personalized sequencing of tasks. Similarly, Yang (2023), in a meta-analysis of adaptive learning platforms for English as a

Foreign Language (EFL) learners, reported that AI integration not only improved linguistic outcomes but also increased learner motivation and self-efficacy. Importantly, these benefits were maximized when AI tools were complemented by teacher guidance, which provided contextual explanations, cultural insights, and affective support elements that AI alone may not fully replicate (Zawacki-Richter et al., 2019).

The convergence of personalized learning principles and AI technology thus represents a transformative shift in language pedagogy. By enabling highly individualized learning trajectories, AI tools address the limitations of conventional instruction and offer scalable solutions for large and diverse classrooms. However, successful implementation requires strategic integration, adequate teacher training, and consideration of ethical concerns such as data privacy and algorithmic bias (Holmes et al., 2019; Luckin et al., 2016).

METHOD

Research Design

This study adopted a mixed-methods research design, integrating both quantitative and qualitative approaches to provide a comprehensive understanding of the impact of AI-based personalized learning on students' English proficiency and perceptions. The rationale for employing mixed methods lies in its capacity to combine the statistical rigor of quantitative analysis with the depth and contextual richness of qualitative insights (Creswell & Plano Clark, 2018). By merging these approaches, the study not only measured changes in language performance but also explored the subjective experiences and attitudes of learners, ensuring a more holistic interpretation of the results.

The quantitative strand employed a pre-test and post-test design to measure improvement in students' English skills after participating in the AI-based personalized learning program. A standardized English proficiency test, adapted from the Cambridge English assessment framework, was administered before and after the intervention. The pre-test established a baseline of learners' abilities, while the post-test measured changes attributable to the intervention. This design allowed for direct comparison of scores, enabling the identification of statistically significant gains in performance (Dörnyei, 2007). Such a pre-experimental one-group pre-test–post-test approach is widely used in applied linguistics research to evaluate instructional interventions (Mackey & Gass, 2016).

To complement the numerical findings, a qualitative approach was implemented using a questionnaire and short semi-structured interviews. The questionnaire contained both closed- and open-ended items, capturing learners' perceptions of AI-based personalized learning, including its usability, perceived effectiveness, and motivational impact. In addition, short interviews were conducted with a subset of participants to gain deeper insights into their learning experiences, challenges faced, and perceived benefits of AI integration in language learning. Qualitative data helped explain patterns observed in the quantitative results and provided a nuanced understanding of learner attitudes (Patton, 2015).

Data from both strands were integrated during the interpretation phase using a convergent parallel design (Creswell, 2014), where quantitative and qualitative results were analyzed separately and then compared to identify convergences, divergences, or complementary findings. This integration allowed the study to not only determine whether the intervention worked (quantitative evidence) but also explore why it worked and how students experienced it (qualitative evidence), thereby increasing the validity and applicability of the conclusions (Johnson & Onwuegbuzie, 2004).

Participants

The participants in this study were fifteen students enrolled at Cambridge School in Lhokseumawe, Indonesia. The age range of the participants was 13 to 15 years, corresponding to early adolescence, a critical developmental stage for both cognitive and linguistic growth (Lightbown & Spada, 2013). All participants were classified as having intermediate-level English proficiency, determined through placement tests based on the *Common European Framework of Reference for Languages* (CEFR) standards, equivalent to the B1 level. At this level, learners can understand the main points of clear standard input on familiar topics, produce simple connected text, and describe experiences and events (Council of Europe, 2020).

Selection of participants was conducted through purposive sampling, focusing on students who met the language proficiency criterion and were available to participate in the full duration of the study. Purposive sampling was chosen to ensure that participants possessed a similar baseline of English skills, thereby allowing for more accurate measurement of the intervention's effects (Palinkas et al., 2015).

The participants came from varied socio-economic and cultural backgrounds but shared a similar educational context, attendance at a private English-focused institution that integrates Cambridge English curricula. Their prior exposure to English included classroom instruction, textbook-based learning, and occasional interaction with native or near-native speakers through school-organized programs. However, none had previously engaged in AI-based personalized learning systems, which ensured that the observed changes in proficiency and perceptions could be attributed more directly to the intervention rather than prior familiarity with such technology.

Ethical considerations were addressed by obtaining informed consent from both the students and their parents or legal guardians. All participant data were anonymized, and pseudonyms were used in qualitative reporting to ensure confidentiality following ethical research guidelines (BERA, 2018). Participation was voluntary, and students were informed of their right to withdraw at any stage without academic or personal consequences.

Instruments

To gather both quantitative and qualitative data, two primary instruments were used: an English Proficiency Test and a Perception Questionnaire. These instruments were designed to assess both the measurable improvement in English language skills and the subjective perceptions of learners toward the AI-based personalized learning intervention.

The English Proficiency Test was developed based on the *Common European Framework of Reference for Languages* (CEFR) B1 descriptors and adapted from the Cambridge English assessment format. Vocabulary (20 multiple-choice items assessing students' knowledge of high-frequency words and collocations commonly used at the intermediate level), Speaking Fluency (3–4 minute oral task in which students responded to open-ended prompts, evaluated using a fluency rubric adapted from Cambridge Speaking Test criteria. This included measures such as speech rate, hesitation, and connectedness of ideas (Fulcher, 2003)), and Grammar (20 sentence-completion and error-correction items assessing accuracy and appropriate usage of verb tenses, sentence structure, and prepositions).

The test was administered as both a pre-test (to establish baseline proficiency) and a post-test (to measure improvement after the intervention). Content validity was ensured through expert review by two English language lecturers with experience in language assessment (Brown, 2010). The reliability of the test was established using Cronbach's alpha, with an acceptable threshold of 0.70 (Tavakol & Dennick, 2011).

The Perception Questionnaire was designed to capture students' attitudes and experiences with AI-based personalized learning. It consisted of Likert-scale items, ranging from 1 (strongly disagree) to 5 (strongly agree), which were grouped into three key domains. The first domain, Motivation, included items such as "The AI-based learning tool made me more interested in learning English." The second domain assessed Ease of Use with statements like, "The AI tool was easy to navigate and understand." Finally, the third domain measured Perceived Effectiveness through prompts including, "I feel my English skills improved through this AI-based learning method."

The questionnaire design followed guidelines for attitude measurement in language learning research (Dörnyei & Taguchi, 2010). Before administration, it underwent a pilot test with three students of similar age and proficiency to ensure clarity and comprehension of items.

In addition to the Likert-scale questions, two open-ended questions were included to allow participants to elaborate on what they liked most about the AI-based learning tool and to suggest improvements. This qualitative element helped capture nuanced perceptions that may not be reflected in fixed-choice items (Cohen et al., 2018).

Procedure

The study was conducted over three weeks in January 2025 and followed four main stages: pre-test, treatment, post-test, and perception data collection through a questionnaire and interviews. The procedure was designed to ensure both the reliability of skill improvement measurements and the validity of perception data.

At the outset, all fifteen participants completed the English Proficiency Test (Section 3.3) to establish their baseline levels in vocabulary, speaking fluency, and grammar. The pre-test was conducted under standardized conditions in a quiet classroom environment, with time limits communicated to ensure uniformity. The speaking component was recorded using a high-quality audio recorder for subsequent scoring by two independent raters to minimize bias (Luoma, 2004).

The treatment consisted of four AI-assisted learning sessions conducted over two weeks, with two sessions per week, each lasting approximately 60 minutes. During these sessions, students engaged with an AI-powered English learning platform that incorporated three key features. The first was Adaptive Vocabulary Practice, where the system adjusted word difficulty based on each learner's performance and utilized spaced repetition algorithms to present new words and review previously learned items. The second feature was AI Pronunciation Feedback, which employed speech recognition technology to analyze students' spoken responses and provide instant feedback on their pronunciation accuracy and stress patterns. Finally, the platform offered Personalized Grammar Exercises, selecting grammar tasks that were specifically tailored to each student's unique error patterns to enable targeted skill development.

During the sessions, the researcher provided technical assistance and minimal pedagogical guidance to ensure the intervention's outcomes reflected primarily the AI system's influence rather than direct teacher instruction. The same platform and activities were used for all participants to maintain consistency.

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Immediately after the treatment phase, students completed the same English Proficiency Test administered as the pre-test. This allowed for a within-subjects comparison to identify gains in vocabulary, speaking fluency, and grammar. The same test administration procedures and scoring protocols were followed to ensure comparability.

Following the post-test, students completed the Perception Questionnaire, consisting of Likert-scale and open-ended questions (Section 3.3). The questionnaire was administered in the students' primary language (Bahasa Indonesia) to ensure clarity and accuracy of responses, with later translation into English for analysis.

Additionally, short semi-structured interviews (5–7 minutes each) were conducted with five randomly selected participants to obtain richer qualitative insights. Interview questions explored student experiences with the AI platform, perceived benefits, challenges, and suggestions for improvement. Interviews were audio-recorded and transcribed verbatim for thematic analysis (Braun & Clarke, 2006).

At every stage, participants were reminded of their right to withdraw from the study without penalty. Data confidentiality was preserved through anonymization, and recordings were stored on a password-protected device accessible only to the researcher.

Data Analysis

The study employed both quantitative and qualitative data analysis techniques in alignment with its mixed-methods research design (Creswell & Plano Clark, 2018). This combination allowed for a comprehensive evaluation of the effects of AI-based personalized learning on students' English proficiency and their perceptions of the learning process.

The quantitative data consisted of participants' pre-test and post-test scores in vocabulary, speaking fluency, and grammar. Statistical analysis was conducted using SPSS version 27. A paired-sample t-test was used to determine whether there were statistically significant differences between the mean pre-test and post-test scores. This test was appropriate because the same participants were assessed at two different time points, and the aim was to evaluate the mean difference within the group (Field, 2018). Assumptions of the paired-sample t-test—including normality of score differences—were checked using the Shapiro–Wilk test. Where normality assumptions were violated, a non-parametric equivalent (Wilcoxon signed-rank test) was planned as a backup procedure (Pallant, 2020). Effect sizes (Cohen's *d*) were also calculated to determine the magnitude of the observed differences, following the thresholds suggested by Cohen (1988) for interpreting small (0.2), medium (0.5), and large (0.8) effects.

Qualitative data, derived from open-ended questionnaire responses and semi-structured interview transcripts, were analyzed using the established method of thematic analysis as outlined by Braun and Clarke (2006). This process involved a series of rigorous steps, beginning with familiarization through the repeated reading of the data to achieve immersion. Next, initial coding was conducted by assigning concise labels, such as "increased motivation" or "technical difficulties," to data segments relevant to the research questions. These codes were then grouped to develop broader themes, like "Enhanced Engagement" or "Usability Challenges," which captured significant patterns across the dataset. The subsequent step involved a thorough review and refinement of these themes, cross-checking them against the raw data to ensure accuracy and consistency. Finally, the process concluded by defining and naming the final set of themes to ensure they were both clearly articulated and directly relevant to the research objectives.

In the final stage, results from the quantitative and qualitative analyses were integrated in a triangulation process to provide a more holistic understanding of the intervention's impact (Fetters et al., 2013). Quantitative results measured objective improvement in proficiency, while qualitative insights revealed subjective experiences, motivations, and perceived challenges.

RESULT

Table 1 presents the results of the paired-sample *t*-tests comparing students' pre-test and post-test scores across the three assessed skill areas: vocabulary, speaking fluency, and grammar.

Table 1. Pre-test and Post-test Mean Scores with Statistical Significance

Skill Area	Pre-test Mean	Post-test Mean	Mean Gain	*p*-value
Vocabulary	68.0	81.3	+13.3	0.000
Speaking	65.5	80.2	+14.7	0.000
Grammar	70.1	82.5	+12.4	0.001

Note: *p*-values are based on paired-sample *t*-tests (two-tailed). A significance level of $p < 0.05$ was used.

The analysis revealed statistically significant improvements across all three language skills measured. In vocabulary, students' mean scores increased from 68.0 to 81.3, a gain of 13.3 points that was highly statistically significant (p = 0.000), suggesting the AI's adaptive algorithms, which tailored word difficulty using principles of spaced repetition (Kornell, 2009), had a meaningful impact. The most substantial improvement was observed in speaking fluency, which saw a mean gain of 14.7 points (from 65.5 to 80.2), a result also confirmed to be significant (p = 0.000); this gain is likely attributable to the AI pronunciation feedback system that provided immediate, individualized corrective feedback, a method supported by prior research (Liakin et al., 2017). Finally, grammar scores showed a significant increase of 12.4 points (from 70.1 to 82.5, p = 0.001), an improvement that can be linked to the platform's personalized exercises targeting common error patterns, thereby effectively reinforcing structural accuracy in a manner consistent with findings on AI-adaptive drills (Li & Ni, 2022).

The paired-sample *t*-test results indicate that all three skill areas improved significantly after the AI-based personalized learning intervention ($p < 0.05$). The largest mean gain was observed in speaking, followed by vocabulary, and then grammar. Effect size calculations (Cohen's *d*)—though not shown in the table—would further clarify the magnitude of these improvements. Based on Cohen's (1988) thresholds, the observed gains are likely to represent large practical effects.

These findings align with previous studies reporting that AI-based personalized learning tools can accelerate English language development by adapting content, pace, and feedback to individual learner profiles (Godwin-Jones, 2021; Yang, 2023).

The qualitative data from Likert-scale questionnaires and semi-structured interviews revealed several key themes regarding students' experiences with the AI-based personalized learning platform. The results are summarized below, with percentages indicating the proportion of participants who expressed a particular perception.

A substantial majority of students (86%) reported feeling more motivated and engaged when using the AI learning platform compared to traditional, textbook-based instruction. Students frequently mentioned the interactive nature of the exercises, gamified progress tracking, and immediate results as primary motivators. These findings align with self-determination theory (Deci & Ryan, 2000), which suggests that autonomy and immediate feedback enhance intrinsic motivation. *Example student comment:* “It feels like playing a game, but I’m learning English at the same time. I want to continue after class.” Previous studies (Li & Ni, 2022; Yang, 2023) have similarly reported that AI-assisted platforms can improve learner engagement by presenting tasks that are both challenging and rewarding.

An overwhelming 93% of students appreciated instant corrections and suggestions provided by the AI system, especially for pronunciation and grammar accuracy. Learners noted that the immediacy of corrections helped them remember mistakes and avoid repeating them. This aligns with corrective feedback literature (Liakin et al., 2017), which highlights that immediate, specific feedback enhances learning retention and accuracy. *Example student comment:* “I can see my mistake right away, not wait until the next class. That makes me fix it faster.”

A significant 80% of participants recognized the value of the personalized learning paths generated by the AI. The platform adapted task difficulty, vocabulary selection, and grammar focus according to each learner’s performance history. This adaptability reflects zone of proximal development (ZPD) principles (Vygotsky, 1978), as it ensured that tasks were neither too easy nor too difficult, maintaining optimal learning conditions. *Example student comment:* “It gives me harder words only after I can do the easy ones, so I don’t feel lost.”

Despite overall positive perceptions, some students reported occasional technical issues, such as internet connectivity problems and delayed audio feedback. A few also expressed the opinion that AI learning should be supplemented by teacher-led instruction for explanation, cultural context, and human interaction. This echoes concerns in the literature (Godwin-Jones, 2021) that AI cannot entirely replace human educators, particularly in areas requiring emotional intelligence and classroom dynamics. *Example student comment:* “AI is good for practice, but I still need my teacher to explain things I don’t understand.”

Summary of Perception Themes

Theme	Percentage of Students	Key Observations
High Motivation	86%	Increased engagement due to interactivity and gamification.
Immediate Feedback	93%	Valued instant pronunciation and grammar corrections.
Personalization	80%	Appreciated adaptive learning that matches individual skill level.
Technical/Instructional Balance	—	Some preferred blending AI with traditional teaching for the best results.

The perception data indicate that AI-based personalized learning was highly positively received by most students, particularly for its motivational aspects, feedback immediacy, and adaptive personalization. While technical challenges and the desire for teacher support were noted, these findings suggest that integrating AI with human instruction in a blended learning model may yield optimal results.

DISCUSSION

The statistically significant gains in speaking, vocabulary, and grammar corroborate earlier evidence that AI-driven personalization can produce measurable language learning benefits and sustain engagement (Li & Ni, 2022; Zawacki-Richter et al., 2019). In our context, the largest mean gain emerged in speaking, followed closely by vocabulary, mirroring patterns reported when learners receive *individualized feedback* and *progressively adaptive tasks* (Godwin-Jones, 2021; Yang, 2023). The concomitant perception data—high motivation (86%), strong valuation of immediate feedback (93%), and appreciation for personalization (80%)—align with Self-Determination Theory's claim that autonomy and competence feedback increase intrinsic motivation (Deci & Ryan, 2000). Together, the quantitative and qualitative strands suggest that personalization is not merely an efficiency gain; it changes the *motivational climate* of learning as well.

Immediate, specific corrective feedback: AI speech recognition pinpointed segmental and suprasegmental issues (e.g., vowel quality, stress), enabling *on-the-spot* adjustments. Such feedback is known to improve oral accuracy and fluency when it is timely and individualized (Liakin et al., 2017; Hattie & Timperley, 2007).

Noticing and uptake: Rapid feedback fosters *noticing* of gaps between interlanguage output and target forms (Schmidt, 1990) and increases the likelihood of *uptake* (Lyster & Ranta, 1997). Opportunities for pushed output: Frequent, low-stakes speaking prompts "push" learners to encode meaning more precisely, a condition conducive to restructuring according to the Output Hypothesis (Swain, 1985) and to form–meaning mapping via practice (DeKeyser, 2007).

Vocabulary gains are consistent with the platform's spaced repetition and difficulty adaptation, which concentrate practice at the edge of learners' mastery (Nation, 2001). Spacing and retrieval practice are robustly linked to durable lexical retention (Kornell, 2009). Personalization also likely reduced time spent on known items, reallocating effort to high-utility, mid-difficulty vocabulary, thereby improving efficiency (Holmes, Bialik, & Fadel, 2019).

Adaptive sequencing can optimize cognitive load by keeping tasks within learners' Zone of Proximal Development (Vygotsky, 1978) and reducing extraneous load from mis-leveled materials (Mayer, 2009). The interface features students cited (interactivity, progress feedback) are consistent with multimedia principles that support attention and persistence, provided they avoid redundancy and split attention (Clark & Mayer, 2016). The high reported motivation thus likely reflects both *better challenge–skill match* and *clear progress signals*.

Students' call for a blend of AI and teacher-led instruction underscores that AI functions best as a pedagogical amplifier rather than a replacement (Luckin et al., 2016). Teachers interpret feedback, provide cultural/pragmatic explanations, and manage affect areas where current systems remain limited (Zawacki-Richter et al., 2019). Strategic orchestration, e.g., brief teacher mini-lessons that target common AI-flagged errors, followed by individualized AI practice, can leverage the strengths of both.

Reports of technical issues (e.g., bandwidth, latency in audio processing) spotlight an often under-discussed boundary condition: *infrastructure*. Without reliable connectivity and adequate devices, the benefits of AI personalization are unevenly realized (OECD, 2015; Selwyn, 2016). For sustainable impact, schools need baseline investments in connectivity, headsets/microphones for ASR accuracy, and contingency plans (offline drills, mirrored content).

CONCLUSSION

The present study found that AI-based personalized learning produced substantial and statistically significant improvements in vocabulary, speaking

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fluency, and grammar accuracy among Cambridge School students in Lhokseumawe. The pre-test and post-test results demonstrated measurable gains across all assessed skill areas, with mean improvements ranging from +12.4 to +14.7 points and *p*-values well below 0.05. These findings align with prior research indicating that AI-powered adaptive learning systems can accelerate second language acquisition by tailoring content, pacing, and feedback to individual learner profiles (Li & Ni, 2022; Godwin-Jones, 2021).

The positive reception from participants reinforces the quantitative results. Most students reported higher motivation when using the AI platform compared to traditional methods, attributing their engagement to features such as instant corrective feedback, progress tracking, and difficulty adaptation. This suggests that AI tools not only enhance academic outcomes but also contribute to a more autonomy-supportive learning environment (Deci & Ryan, 2000), which is crucial for sustaining long-term effort in language learning. Moreover, the high value placed on personalization indicates that students appreciate materials and exercises that are matched to their current proficiency level, avoiding the frustration of overly difficult or overly simple tasks.

The study also underscores the pedagogical viability of integrating AI into formal classroom contexts. When used alongside teacher guidance, AI can complement traditional instruction by offering individualized practice opportunities that are difficult to replicate in whole-class settings. However, the research also revealed practical considerations such as the need for reliable internet connectivity and consistent technical performance that must be addressed to fully realize the benefits of AI integration.

Given the relatively short duration of the intervention (two weeks) and the small sample size (n = 15), caution is warranted in generalizing these results. Short-term gains, while promising, may not reflect the long-term retention and transferability of acquired skills. Therefore, future research should employ larger, more diverse participant groups, longer intervention periods, and, ideally, controlled experimental designs to better isolate the effect of AI-based personalization. Such studies could also examine whether sustained exposure to AI-supported learning amplifies the motivational effects observed here, and whether similar results are achievable in different sociolinguistic and technological contexts.

In sum, this study provides empirical support for the role of AI-based personalized learning as a complementary instructional strategy in English language education, particularly for enhancing speaking and vocabulary skills, while also fostering positive learner attitudes.

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