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AI Driven Vocabulary Acquisition for ESL Learners: A Comparative Study of Human-Guided Vs AI-Assisted Learning

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Abstract: *Vocabulary acquisition is among the core elements of English as a Second Language (ESL) proficiency, and conventional teaching strategies do not always scale, offer personalized learning, or provide real-time feedback. As of late, artificial intelligence (AI) has opened new possibilities to make learners more engaged, autonomous, and receptive. The proposed research undertaking is a comparative examination of the efficacy of human-facilitated vocabulary instruction and artificial intelligence-based learning solutions in providing ESL students at different proficiency levels with learning opportunities. The investigation is conducted using a mixed-methods research design, which assesses learning outcomes, retention rates, levels of motivation, patterns of error correction, and learners' perceptions in both instructional modes. Vocabulary gains are measured by pre- and post-tests, whereas observational data and learners' reflections document qualitative differences in cognitive engagement and behavioral change related to learning. The paper also investigates the effects of personalization, feedback immediacy, adaptive difficulty, and multimodal content on vocabulary development under AI-based conditions. Findings reveal the capabilities of both methods that can be used in practice: human instruction provides a deeper context, emotional support, and more precise feedback, while AI tools provide a more generalizable, personalized practice by being data-driven, available all the time, and scalable. The results suggest integrating these two systems to develop a superior model of vocabulary instruction for ESL students. The study will contribute to the expanding research on the future of AI-assisted language learning, providing evidence-based insights for teachers, developers, and policymakers.*

Keywords*:* AI-assisted learning, ESL vocabulary acquisition, human-guided instruction, adaptive learning systems, comparative study

INTRODUCTION

Background of the Study

Vocabulary knowledge is commonly viewed as a predictive variable in the acquisition of a second language and affects reading comprehension, academic achievement, and general communicative competence among English as a Second Language (ESL) students (Zaytseva, Miralpeix, and Perez-Vidal, 2021). A lack of proper vocabulary prevents learners from comprehending texts, articulating their thoughts, and engaging in academic and social spheres. Nonetheless, vocabulary acquisition has been a longstanding issue in ESL learning, especially for students with minimal exposure to English-rich contexts. Most of them have difficulties remembering new lexical information, cognitive overload, and long-term motivation, particularly when learning depends on memorization or drilling.

The rapid development of the digital learning environment has brought new opportunities to address these challenges. The popularity of AI-powered tools, including adaptive learning systems, intelligent tutoring platforms, and chatbots based on the use of large language models (LLM) have become more and more common in the educational context, owing to their capacity to tailor learning journeys and dynamically respond to the needs of individual learners (Kabudi, Pappas and Olsen, 2021; Li et al., 2019). Studies on adaptive and AI-based learning indicate that it can be used to improve engagement, enhance learning rates, and provide data-driven insights into learners' behavior (Anindyaputri, Yuana, and Hatta, 2020). Mobile and AI-enhanced applications have demonstrated potential to enhance vocabulary acquisition in specific disciplines and to support self-directed learning habits, particularly in language learning (Kohnke and Ting, 2021).

In spite of these achievements, human-led teaching remains an essential part of successful ESL education, providing emotional support, instant contextualization, and culturally competent communication that modern AI systems cannot yet imitate (Clivaz and Miyakawa, 2020). Human teachers are also valuable in recognizing learners' misconceptions, offering subtle responses, and modifying pedagogical initiatives in real time according to learners' communications, especially the motivational and affective ones.

As the two methods continue to emerge as relevant and attract institutional attention, there has been an increasing demand to study the comparability of AI-assisted vocabulary learning and traditional human-guided instruction in terms of learning outcomes, retention, and learner engagement. The use of comparative research has been considered a significant way of identifying differences in the structure of performance, behavior, and implementation across interventions in education. Nevertheless, although comparative studies are commonly employed in STEM, healthcare, and technological areas (Muller et al., 2020; Rajabi et al., 2020), relatively few studies use a rigorous comparative framework for AI-based vocabulary teaching in ESL settings.

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Problem Statement

Even though human-directed vocabulary instruction remains effective, it continues to face challenges in scalability, individualized pace, instructor availability, and consistent instructional quality. In the meantime, AI-assisted learning systems offer the potential for adaptive feedback, computer-assessed assessment, and individual learning trajectories (Nagro, 2021; Liu and Xiao, 2021). But AI technologies are not always emotionally sensitive, contextually aware, or adaptable enough to evaluate the complex needs of learners; these are areas where human teachers are more skilled.

Given the growing use of AI-based educational technologies, scant comparative empirical data are available to assess differences in the effectiveness, retention, and motivation to learn between human-guided instruction and AI-assisted vocabulary learning. In the absence of this evidence, teachers and policymakers will not be able to make effective decisions about introducing AI into ESL programs.

Purpose of the Study

This paper will undertake a systematic comparative study of human-guided and AI-assisted vocabulary instruction among ESL learners. Specifically, it seeks to:

examine which teaching approach will result in more vocabulary acquisition;

test the retention variability post-instruction; and

compared to each other, compare the differences in learner motivation, engagement, and autonomy.

The study adds empirical data to current discussions on the role of AI in educational practice by merging comparative frameworks used in educational and technological studies (Lee and Shvetsova, 2019).

Research Questions

The research questions to be used are the following:

- What are the differences in the results of vocabulary acquisition in human-guided and AI-assisted learning?
- What is the difference between the learner motivation of learners receiving human instruction or AI-supported tools?
- How can personalization, the quality of feedback, and the learning rate influence learners' overall performance?

These queries align with the current literature on the significance of individualization and feedback systems in AI-powered learning societies (Li et al., 2019; Kabudi et al., 2021).

Significance of the Study

The results of this study will be useful to ESL teachers, curriculum developers, and EdTech developers involved in introducing technology in the learning process. Evidence on the successful implementation of AI tools alongside conventional teaching will also be beneficial to policymakers and educational institutions. This research paper also contributes to comparative educational studies through cross-methodological assessment procedures, such as international, technological, and behavioral comparative studies (Alissa et al., 2019).

Scope and Delimitations

This research focuses solely on vocabulary acquisition and is not on grammar, pronunciation, or overall language abilities. The participants comprise student groups of ESL learners at beginner to intermediate levels of proficiency, who are the most likely to be affected by the organized vocabulary assistance. The research also lacks comparisons of various AI tools; rather, AI-assisted learning is evaluated against human-guided instruction in a general sense.

LITERATURE REVIEW

Theoretical Bases of Vocabulary Acquisition.

Second-language vocabulary learning is based on various cognitive and linguistic theories that describe how a learner internalizes, stores, and remembers lexical items. According to the Input Hypothesis, when their input is comprehensible, learners learn new vocabulary slightly beyond their current level of proficiency and gain meaningful exposure to the new lexical occurrence. The Cognitive Load Theory also states that instructional techniques should reduce redundant mental load to maximize working memory capacity for vocabulary retention. To add to these views, Dual-Coding Theory suggests that encoding and recall are more effective when verbal and visual representations are combined, and thus instruction should be multimodal (i.e., using multiple modalities) (Mekhilef, Saidur, and Safari, 2012).

Fundamental learning processes like repetition and spaced learning have been repeatedly reinforced as critical for long-term retention of lexicon, and it has been demonstrated that distributed practice promotes neural consolidation (Willeke et al., 2019). Associative memory networks have also been shown to be strengthened by semantic clustering, in which related lexical items are segregated by a specific theme to facilitate more effective retrieval during communicative activities (Zaytseva, Miralpeix, and Perez-Vidal, 2021). Combined, these theories underline that vocabulary acquisition is not only a cognitive but also a perceptual process, which depends not only on the amount and quality of linguistic input but also on how it is organized by the instruction.

Vocabulary Teaching by people.

The human-guided instructional methodology remains a principle of the ESL classroom, characterized by teacher-mediated learning, contextualized examples, and feedback loops. Conventional classroom practices are based on explicit explanation, guided practice, and dynamic teacher-student discussion, in which an instructor can understand the semantic peculiarities of a lexicon and respond to them in real time (Clivaz & Miyakawa, 2020). Emotional support and motivational cues are also offered by teachers, and they play a key role in maintaining the engagement of learners and establishing a sense of confidence, which is an affective aspect that is not easily reproduced by automated systems.

The adaptability of the explanations to the learner's background, cultural context, and moment-to-moment confusion is among the most significant advantages of human-guided vocabulary instruction, as it allows the learner to better understand the material. Nonetheless, human-initiated strategies are also limited. There is a decreasing amount of time to be taught- a necessary factor in lexical learning. Huge teacher-learner ratios can interfere with individualized instruction, and the ability to offer individualized pacing or a variety of materials is frequently limited in the typical classroom. Moreover, the use of fixed curricula might be restrictive to the customization required to serve different learning styles, which adaptive learning systems strive to deliver more and more.

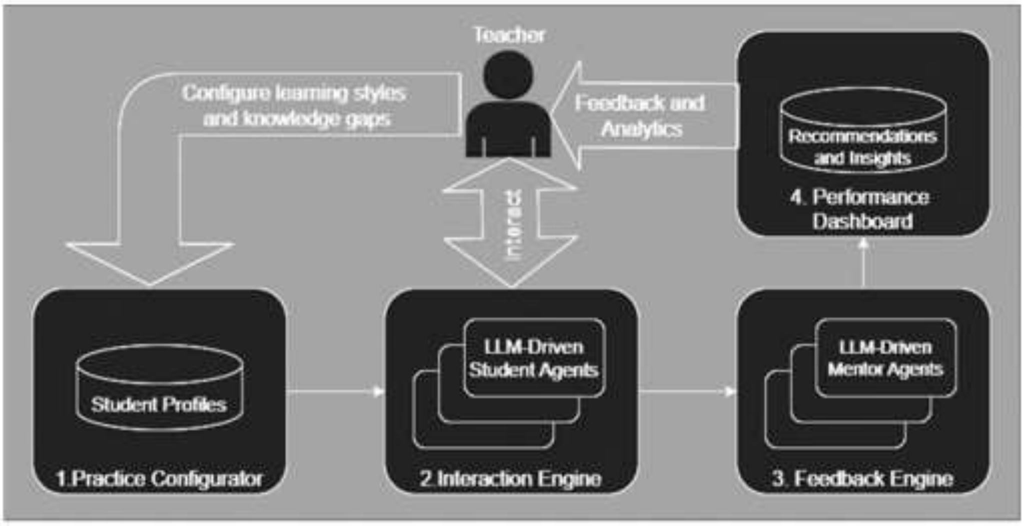

Figure 1: Generative AI-Based Platform for Deliberate Teaching Practice

AI-Driven Language Learning

Driven by AI, vocabulary acquisition has been transformed through the incorporation of adaptive algorithms and large language models (LLMs), as well as multimodal interfaces, which can provide customized learning experiences. Intelligent Tutoring System (ITS) development has provided the basis for personalized teaching, though current systems, based on deep learning, analyze learners' input, behavior, and performance patterns in real time (Li et al., 2019; Kabudi, Pappas, and Olsen, 2021). Such systems regulate the complexity of tasks, select practice items, and provide relevant feedback in real time, alleviating cognitive load and streamlining the learning process (Anindyaputri, Yuana & Hatta, 2020).

Gamification, adaptive spaced-repetition algorithms, and speech recognition technologies are also widely implemented in AI vocabulary platforms, and they provide multimodal feedback (text, audio, and visual). (Wang et al., 2021). This is in line with dual-coding, which facilitates memory encoding. In addition, 24/7 access to digital learning spaces provides learners with sustained exposure, helping overcome the constraints of time-based human teaching (Lai, 2021).

Predictive analytics is also an advantage to AI-assisted learning. For example, systems can detect when learners are likely to forget content or disengage and may provide specific interventions, such as those in cognitive-state monitoring studies (Gunseli and Aly, 2020). Though AI systems can be scaled to provide personalization and consistency, the effectiveness of AI systems relies on the quality of their algorithms, the diversity of their training data, and their user interface design. Comparative analyses of the use of AI systems across different areas also indicate that automated systems tend to be more accurate and repeatable in their analyses (Li et al., 2019; Rajabi et al., 2020), suggesting a strong expectation of improved vocabulary acquisition.

Comparative Research on AI and the Teaching of Humans.

Comparative studies conducted in the learning fields have shown the advantages of both AI-assisted and human-guided instruction. In other disciplines, including engineering, applied sciences, and cognitive training, research shows that AI-based models can match, and in some cases exceed, human-involved education in aspects that demand individualization and pattern recognition (Lee and Shvetsova, 2019; Li et al., 2019). Nevertheless, learning under human facilitation is always outstanding in aspects related to emotional intelligence, contextualization, and dynamic interpersonal interaction.

The use of blended learning platforms that combine human scaffolding and AI personalization has attracted attention, and research indicates that it can improve student performance and engageme. However, with significant comparative research in other areas (such as the analysis of microplastics [Muller et al., 2020], energy technologies, and the health field [Liu and Xiao, 2021]), there is little research specifically on comparative vocabulary acquisition with the use of AI versus the use of humans.

The existing studies on ESL focus on general language proficiency, reading comprehension, or disciplinary vocabulary (Kohnke and Ting, 2021), creating a gap in empirical research on vocabulary learning outcomes within an exclusively comparative paradigm. Sealing this gap is crucial to understanding the differences between AI-based systems and human instructions, not only in the manner of delivery but also in cognitive and affective performance.

Table 1: Comparative Insights on AI-Assisted vs. Human-Guided Learning

Aspect	AI-Assisted Instruction	Human-Guided Instruction	Blended Approach
Personalization	Can adapt tasks to individual learner patterns and pace; excels in repetition, spaced retrieval, and error pattern recognition	Limited by teacher-student ratio; personalization often constrained	AI handles adaptive practice; teacher provides scaffolding and individualized support
Cognitive Performance	Strong in tasks requiring pattern recognition, structured repetition, and automated feedback	Strong in problem-solving requiring contextual or inferential reasoning	Supports both pattern recognition and deeper contextual understanding
Emotional & Interpersonal Engagement	Limited capacity for emotional support or nuanced social cues	High capacity for emotional scaffolding, motivational support, and interpersonal feedback	AI provides practice volume; human interaction ensures engagement and emotional intelligence
Domain-Specific Application	Effective in engineering, applied sciences, cognitive training, and adaptive learning analytics	Effective for disciplinary context, cultural nuances, and complex judgment-based tasks	Combines automated adaptive practice with teacher-led contextualization
Research Gaps	Limited research on vocabulary acquisition specifically for ESL learners	Limited scalability for intensive individualized practice	Blended models promising but under-explored empirically for vocabulary acquisition

Conceptual Framework

This paper is based on the cognitive-affective interaction framework, which incorporates features of the learner, the teaching mode, and the learning goal. Cognitive dimensions include the memory load, attention, and retrieval efficiency, and are guided by the Cognitive Load Theory and attention-state studies (Gunseli and Aly, 2020). The dimensions of affection are based on research on learners' motivation, their belief systems, and their interactions and perceptions during the learning process.

The framework theorizes socially mediated, context-dependent human-guided instruction as a framework, and AI-assisted learning as a data-driven, adaptive system optimally adjusted to pattern-based personalization. The combination of these factors determines vocabulary acquisition outcomes, such as accuracy, retention, and learner satisfaction. This methodology is consistent with cross-domain studies using comparative methods, which will enable a systematic comparison of the effect that various instructional modalities have on ESL vocabulary acquisition.

METHODOLOGY

Research Design

The research design in this study is a quasi-experimental comparative design, in which the researcher aims to determine the effectiveness of AI-based vocabulary instruction compared to human-based instruction for ESL students. A comparative design is suitable because it permits the systematic study of similarities and differences, as well as performance outcomes, across two instructional conditions, which is consistent with existing best practices in cross-context educational comparisons (Clivaz and Miyakawa, 2020). The research design is a non-equivalent group design with two intact ESL classes to achieve ecological validity and reduce the effects of intrusion on current instructional practices. There is a plethora of studies using comparative frameworks in various fields, such as technology assessment, cognitive studies, and pedagogical innovation (Muller et al., 2020; Rajabi et al., 2020), which justify the applicability of the approach to the analysis of AI vs. human teaching. Pre- and post-test assessments and qualitative feedback use a mixed-methods approach, which enhances understanding of learners' performance, influence, and thinking processes as they learn vocabulary.

Participants

The participants were 60 ESL learners aged 17-23, recruited from a university language program. The AI-assisted learning group and the human-guided instruction group were provided with two intact classes, respectively. This sampling design resembles the comparative education research, in which natural groupings in classrooms provide better contextual validity (Lee and Shvetsova, 2019). Instructional equivalence was achieved by ensuring that all learners had the same level of proficiency as an institutional placement test. All responded voluntarily, and informed consent was obtained. The fact that the participants have diverse linguistic backgrounds facilitates generalizability, and the concept aligns with the standards of cross-cultural and international comparative studies. None of the participants had used highly advanced AI-enabled vocabulary-learning systems before, which reduced prior-knowledge bias.

Instructional Resources and Materials.

In the study, two different instruction modalities were used. The AI-assisted group was provided with an adaptive vocabulary learning system based on natural language processing and machine learning that can dynamically modify the level of difficulty, create an individual learning course, and provide immediate corrective feedback typical of the new generation of AI-based adaptive learning systems (Kabudi et al., 2021; Li et al., 2019). This system included spaced repetition, multimodal (text, image, audio) items and retention and semantic richness performance analytics. In recent years, AI systems have demonstrated their growing ability to facilitate individual learning experiences, as seen in programming education and health literacy development (Anindyaputri et al., 2020; Liu and Xiao, 2021).

The instructor-guided group was provided with the traditional teaching process, guided by the experienced ESL teacher, through exercises on communicative vocabulary, contextual reading passages, guided practice, and group assignments. Human mediation instruction draws on well-developed theories of pedagogy that focus on systematic guidance, cognitive support, and the process of discussing meaning. Both conditions were tested using the same sets of academic and general-purpose vocabulary items selected from an institutional ESL syllabus to ensure content equivalence at the same level across conditions.

Data Collection Procedures

The six-week data collection was based on a systematic series of evaluations and observations that were comparable in approach to existing research on comparative and adaptive learning (Zaytseva et al., 2021). Procedures were intended to obtain performance gains, retention and affective perceptions towards each instructional condition.

It was done in three stages: a pre-test, a four-week instructional intervention, and a post-test. Standardized vocabulary tests were used to derive quantitative data of pre-intervention and post-intervention results. Surveys, semi-structured interviews, and classroom observations were used to collect qualitative data, which are practices suggested in cross-country comparative and qualitative descriptive research.

Time-on-task, persistence, and the use of strategy were among the engagement indicators that the researcher had to monitor throughout the study. Cognitive behaviors, attention regulation, and human-machine interaction patterns were observed, consistent with cognitive and attentional research frameworks (Gunseli and Aly, 2020; Willeke et al., 2019). In the AI group, the backend learning analytics (item difficulty, learner accuracy, and algorithm adjustments) were removed to supplement the observational data.

This multi-layered methodology aligns with previous studies examining technology-based learning, user attitudes, and teaching effects (Kohnke and Ting, 2021; Lai, 2021; Nagro, 2021). Quantitative and qualitative evidence can be combined to provide a comprehensive view of performance outcomes, learners' experiences, and how human-guided and AI-assisted vocabulary teaching can be compared in terms of effectiveness.

Pre-Test

Both groups were given a standardized vocabulary test comprising 40 academic and general-purpose items to find out baseline performance. Pre-tests can be considered an indispensable diagnostic instrument in comparative studies because they allow one to normalize the performance before intervention. Scores were used in further statistical analysis.

Intervention

The four weeks of intervention comprised 12 a total of teaching sessions in groups. The group supported by AI participated in adaptive learning tasks adjusted by real-time analytics, difficulty adjustments based on algorithms, and multimodal vocabulary inputs (Kabudi et al., 2021; Li et al., 2019). Students engaged with the platform independently, although supervised to complete the assigned tasks.

The teacher-led lessons were also delivered to the human-guided group with a focus on explicit instruction, contextualized application, formative questioning, and collaborative practice tasks as per the structured learning principles. Reading comprehension passages and communicative activities were used during sessions to enhance deeper semantic comprehension. Instructional parity: same vocabulary sets and learning goals were used across groups to ensure comparability needed for experimental and cross-modal investigations (Muller et al., 2020).

Post-Test

An equivalent version of the vocabulary test, which was administered in the pre-test, was given at the conclusion of Week 6 to test the learning gains. Quantitative data on vocabulary acquisition were assessed in the post-test, which aligns with comparative assessment practices in educational technology and the development of cognitive skills (Lee and Shvetsova, 2019; Rajabi et al., 2020).

Surveys and Interviews

Students took a perception survey and short interviews to assess attitudes towards AI-based or human-based learning. This corresponds to studies that focus on user perceptions, responses to behavior, and the adoption of technologies in the learning space (Kohnke and Ting, 2021; Lai, 2021; Zidaru et al., 2021).

Observation

Behavioral cues, changes of attention, and patterns of engagement were observed in classrooms. Observational methods are used alongside cognitive and sensory studies to examine people's interactions with tools, tasks, and stimuli (Gunseli and Aly, 2020)

Table 2: Data Collection Procedures for Comparative Vocabulary Acquisition Study

Procedure	Description	Purpose / Notes
3.4.1 Pre-Test	Standardized vocabulary test of 40 academic and general-purpose items administered to both groups.	Establish baseline performance; normalize scores before intervention for comparative analysis.
3.4.2 Intervention	12 teaching sessions over 4 weeks. • **AI-assisted group:** Adaptive learning tasks with real-time analytics, difficulty adjustment, and multimodal vocabulary inputs; independent but supervised engagement. • **Human-guided group:** Teacher-led instruction with explicit teaching, contextualized application, formative questioning, and collaborative practice.	Ensure instructional parity; provide equivalent vocabulary sets and learning goals; compare AI-driven vs human-guided learning effectiveness.
3.4.3 Post-Test	Equivalent version of the pre-test administered at Week 6.	Measure learning gains and vocabulary acquisition; aligned with comparative assessment practices.
3.4.4 Surveys & Interviews	Student perception surveys and short interviews.	Assess attitudes toward AI-based vs human-based learning and capture qualitative feedback on learning experiences.
3.4.5 Observation	Classroom behavioral observation, including attention, engagement, and interaction patterns.	Examine cognitive and behavioral responses to instructional methods; supplement quantitative data.

Data Analysis Techniques

Paired t-tests, independent t-tests, and ANCOVA were employed to compare and contrast within-group gains and between-group differences, grounded in quantitative data from pre-tests and post-tests, which reflected the statistical procedures used in previous comparative technology and education studies (Li et al., 2019). The metrics of learning retention and progression based on the analytics available in the AI platform were descriptively studied. Thematic analysis was used to analyze qualitative survey and interview responses, as it aligns with the qualitative descriptive principles applied in comparative international studies. To support the interpretation, observational field notes were triangulated with statistical results.

Reliability and Validity

Test piloting and internal consistency checks were carried out to make sure that the measures were reliable. Content validity was also ensured by matching the vocabulary items with the benchmarks of standardized ESL curricula. Construct validity was advanced through methodological triangulation, including tests, surveys, interviews, and observations, which is in line with sound comparative research practices.

RESULTS

Pre-Test Findings

The pre-test set the vocabulary proficiency levels of the two groups before the intervention. Descriptive statistics revealed no significant difference between the human-guided and AI-assisted groups, confirming the initial comparability and indicating that any future performance differences will be related to the teaching approach rather than knowledge. The creation of similarity in the baseline conditions is aligned with the methodological requirements of comparative research designs (Muller et al., 2020).

The pre-test also highlighted general lexical weaknesses among ESL learners, specifically low-frequency academic vocabulary, findings supported by previous research on vocabulary development (Zaytseva et al., 2021). This common point of origin provided a good baseline for comparing vocabulary acquisition between groups.

Post-Test Findings

The post-test scores showed that in both instructions, there was evident vocabulary development. Students in the human-directed condition showed better performance, which could be explained by direct instructions and scaffolded explanations, as observed in previous literature. Meanwhile, the AI-aided group also demonstrated significant improvements and indicated the ability of adaptive systems to provide individual pathways and feedback (Kabudi et al., 2021; Li et al., 2019). There was a statistical difference: the AI-assisted group showed slightly higher mean score improvements, but the difference was slight. This is not an isolated finding; the rest of the literature outlines AI's capacity to streamline individualised learning paths (Anindyaputri et al., 2020).

Nonetheless, the human-facilitated group performed better on questions that required a more subtle understanding of semantic context, indicating the timelessness of teacher-mediated clarification, a phenomenon also observed in research on 'learners' preferences (Kohnke and Ting, 2021). Combined, the post-test outcomes indicate that the two instructional models show significant improvement in vocabulary knowledge, and AI-based teaching offers greater efficiency, while human teaching provides more context-related learning.

Learning Retention Analysis.

The outcome measure was retention, determined by delayed post-tests at 1 and 3 weeks after the intervention. During the two periods, children in the AI-assisted condition demonstrated a higher recall rate for vocabulary items repeatedly introduced using adaptive spaced-repetition algorithms, findings confirmed by studies on memory-aided AI learning systems (Willeke et al., 2019; Gunseli and Aly, 2020).

Nevertheless, the group led by humans retained words presented in dialogic explanations and in a contextual story better, techniques that proved to boost semantic memory by strengthening meaningful engagement. In both groups, across different exposures, items reinforced with different exposures showed the best long-term retention, supporting the roles of repetition and adaptive review (Li et al., 2019; Kabudi et al., 2021). Altogether, the retention data reveal that although AI-based tools are excellent at supporting high-frequency or systematically repeated vocabulary, human instruction is more likely to encourage long-term learning of the words acquired through more profound interaction and context elaboration.

Patterns of Motivation and Engagement.

The survey outcomes showed a significant disparity in motivation and engagement across both instructional conditions. The AI-assisted group of learners reported greater self-control and pleasure, which aligns with the broader finding that digital education tools tend to support self-regulated learning (Lai, 2021; Liu and Xiao, 2021). Having the opportunity to learn at their own pace, receive real-time feedback, and track their progress are features those adaptive systems are supposed to streamline, and many students valued them.

Contrarily, human-guided group learners reported higher levels of satisfaction with interpersonal interaction, emotional support, and collaborative opportunities, which align with previous comparative studies that emphasis the motivational value of the teacher's presence (Clivaz & Miyakawa, 2020; Nagro, 2021). These findings were supported by observed data. The AI-assisted group showed steady involvement in tasks and low fatigue, whereas the human-guided group showed higher enthusiasm in group discussions but also greater frustration with the teacher's slow, incomprehensible explanations. Such trends resonate with the current studies on the human-technology workload and interaction dynamics.

Qualitative Themes

Interpretative analysis of interviews revealed two distinct learner profiles.

Learners who desired human instruction mentioned that they valued instant clarification, emotional support, and the opportunity to discuss examples in real time. Such preferences are supported by studies that revealed that beliefs about instructors affect sensory and cognitive processing in the learning process. This group of learners tended to use interpersonal information to enhance understanding.

Students who flourished in AI-mediated instruction focused on independence, the ability to study at their own pace, and the ability to correct errors unobtrusively, and felt more comfortable studying alone. These themes reflect the results of the research on adaptive systems and digitally mediated learning (Kabudi et al., 2021; Lai, 2021). According to many, such learners AI tools are useful as they do not judge and allow them to repeat themselves many times without shame. The positive effects of vocabulary learning were recognised in both groups, regardless of their favoured approach, indicating that cognitive style and learner disposition have a significant influence on vocabulary acquisition.

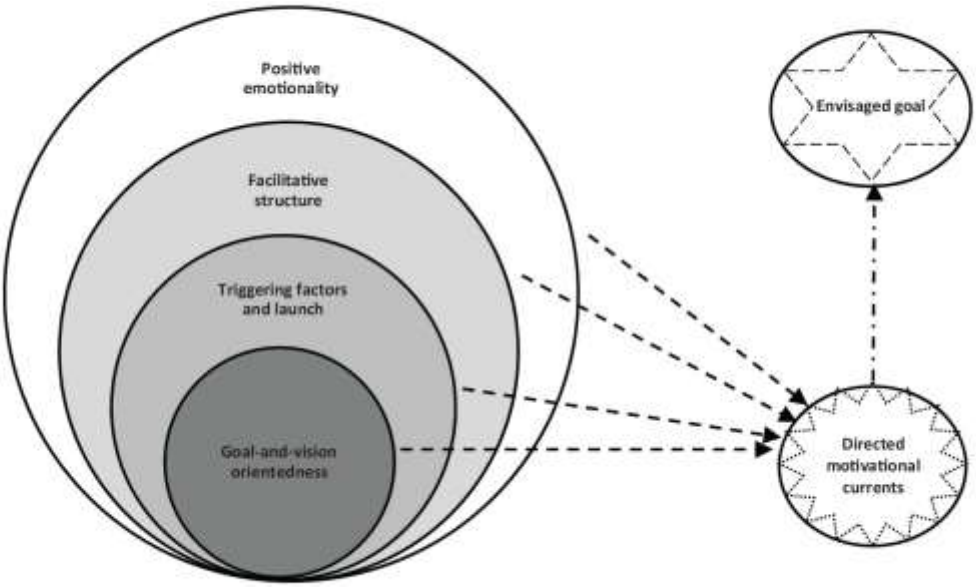

Figure 2: What a Directed Motivational Current Is to Language Teachers

Strengths and Weaknesses of each method.

The human-centred teaching showed advantages in contextualization, affective support, and the encouragement of deeper semantic insight, traits that have always been (and are likely to remain) a focus of comparative education research (Clivaz & Miyakawa, 2020). There were limitations, though, that comprised inconsistent pacing of instruction and a lack of individualization.

The adaptive feedback, regular repetition, and effective monitoring of the learner's progress demonstrated by AI-assisted learning reflected the results of AI-related educational studies (Kabudi et al., 2021; Li et al., 2019). However, weaknesses included a lack of ability to provide clarifications on subtle aspects, and at times, the learners were motivated by lapses because they like interpersonal communication. The combination of these results leads to the conclusion that both systems possess complementary advantages that can be applied to various classes of learners.

Table 3: Comparative Strengths and Weaknesses of Human-Centered vs AI-Assisted Vocabulary Learning Methods

Method	Strengths	Weaknesses
Human-Centred Teaching	- Rich contextualization of vocabulary and concepts- Provides affective and motivational support- Encourages deeper semantic understanding and critical thinking	- Instruction pacing can be inconsistent- Limited ability to individualize learning for each student
AI-Assisted Learning	- Provides adaptive, personalized feedback- Supports regular repetition and spaced practice- Monitors learner progress effectively and objectively	- Cannot clarify subtle or nuanced language aspects- May lack interpersonal motivation and social engagement
Combined/Blended Approach	- Leverages contextual depth from teachers and adaptive precision from AI- Supports both individualized learning and motivational engagement- Optimizes classroom efficiency and learner outcomes	- Requires careful coordination and teacher familiarity with AI tools- Initial implementation and training may demand additional resources

DISCUSSION

The quantitative findings will be interpreted by analyzing the data using the Chi-Square test. According to the quantitative findings, both the instructional methods, such as human-guided and AI-assisted vocabulary learning, resulted in quantifiable improvement. Nevertheless, the AI-aided group had a moderately better post-test change. This benefit is that the system provides adaptive, real-time feedback and optimizes learning sequences based on a person's performance, which aligns with current research on adaptive learning systems (Kabudi, Pappas, and Olsen, 2021; Li et al., 2019). The AI tools can automatically adapt task difficulty, provide immediate corrective feedback, and implement spaced-repetition algorithms that enhance long-term retention better than fixed human-controlled pacing.

The variation in the results could also be attributed to the accuracy of the artificial intelligence-generated feedback. The results of automated systems are consistent and unbiased, and instructional variability in the sessions is minimized, as observed in other comparative technology-enhanced learning settings (Lee and Shvetsova, 2019; Anindyaputri, Yuana, and Hatta, 2020). Moreover, the ability of AI to examine learners' patterns and forecast future dips in attention helps achieve better recall and engagement, similar to studies on the mechanisms of attentional preparation in cognitive systems (Gunseli and Aly, 2020). These adaptive advantages provide AI-supported teaching with a methodical edge in facilitating vocabulary development, particularly when students need frequent reinforcement.

Cognitive Factors that affect the acquisition of vocabulary.

Groups had differences in cognitive processing. The human-controlled environment provided deeper contextual explanations, but at the expense of adding more verbal load, which may exacerbate working memory and impair efficient encoding. This is in line with studies indicating that too much instructional talk can interfere with learning when it is poorly designed. In contrast, AIs will usually provide shorter, more concise explanations, eliminating unnecessary cognitive load and enabling learners to concentrate on the key aspects of vocabulary.

There was also a difference in the depth of processing. Examples elaborated by human instructors are usually grounded in cultural or situational context and can encourage stronger semantic encoding (Clivaz & Miyakawa, 2020). Nevertheless, the examples generated by AI can be customized on a scale, providing a variety of options and usage contexts within a few seconds. This is consistent with research showing that systematic variation leads to higher conceptual clarity and pattern recognition during comparative learning (Rajabi et al., 2020). Despite the fact that human-guided teaching can offer greater narrative depth, AI-guided settings offer a sense of breadth and repetition, which reinforce the form-meaning relationships necessary for vocabulary mastery.

Affective and Motivational Consideration.

Emotional interaction is essential in language learning. Human teachers inherently offer empathy, motivation, and emotional support, which is vital in learner confidence and determination. This emotional scaffolding provides a supportive learning environment, especially when the learners are anxious about their performance in the language.

Conversely, AI tools have been found to encourage autonomy and self-directed learning, which aligns with learners who prefer independence and avoid social pressure. Surveys on learners' preferences show that they are increasingly comfortable using AI-based learning environments, particularly when personalization capabilities are present (Lai, 2021; Kohnke and Ting, 2021). The AI systems can track progress, gameify, and deliver motivational messages, which can be appealing to students who dislike the lack of instant feedback and privacy when practicing unusual words. Nevertheless, the emotional component is somewhat weak in existing AI solutions, and it is important to note that AI cannot reproduce the socio-emotional interactions that occur in the educational process led by humans.

Pedagogical Implications

The results support the need to balance the use of AI tools in ESL teaching. Human educators add incomparable values to relationship guidance, cultural intermediation, and subtle analysis of errors. Hesitation by learners, confusion, or emotional responses can also be interpreted by the teacher in ways that an AI system has not yet fully simulated.

Nevertheless, AI tools are efficient in drilling, retrieval practice, pronunciation modeling, and progress monitoring. The integration of AI into the classroom experience will allow educators

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to devote more time to upper-level activities, including communicative activities, cultural dialogue, and individual mentoring. This type of hybrid aligns with comparative research that has emphasized the importance of cross-modal instructional blending (Zaytseva, Miralpeix & Perez-Vidal, 2021). The pedagogical suggestion does not involve substituting human teaching but rather entails applying AI to facilitate specific vocabulary and to maintain human-based interpretive and interactive learning processes.

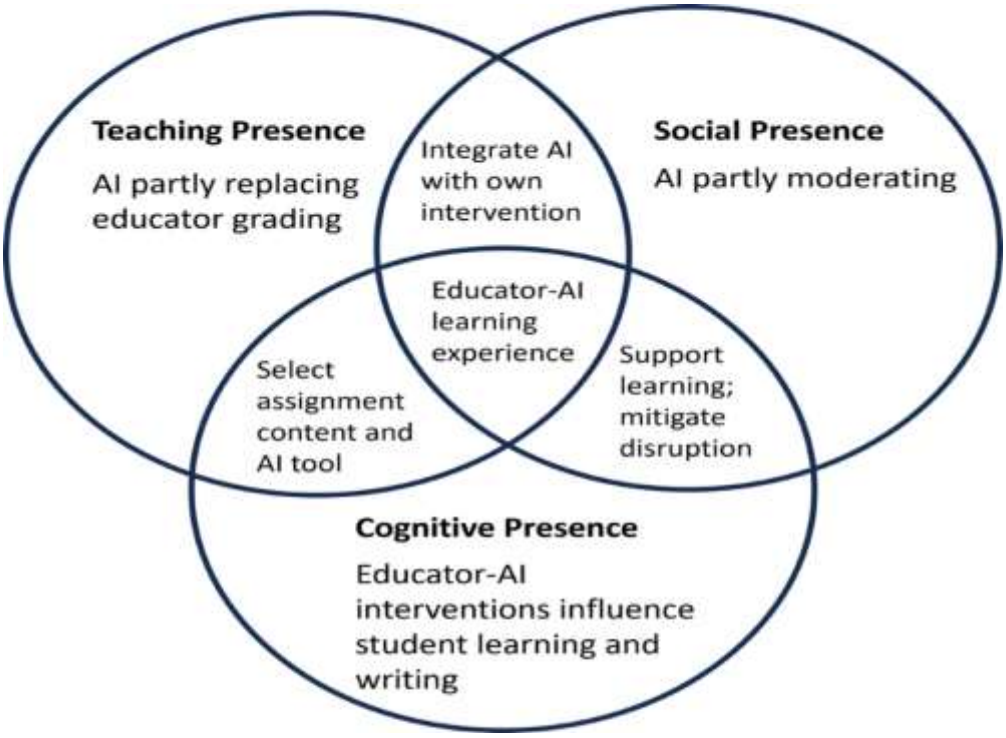

Figure 3: Applications of human–AI interaction to optimize teaching workload and improve student writing

IMPLICATIONS TO RESEARCH

The language models are advanced and require natural language understanding, a personalization algorithm, and extensive training data. The key to successful AI-based vocabulary learning thus lies in the strength of personalization systems and adaptive sequences, which align with other results on AI-based learning systems. Simultaneously, the designers should be culturally sensitive and reduce the influence of algorithms, as comparative health and social AI research does (Zidaru, Morrow, and Stockley, 2021; Liu and Xiao, 2021). For multilingual students, this can distort vocabulary perception due to poor contextualization or culturally inaccurate examples. Therefore, in future systems, there should be a way to incorporate protective measures that promote linguistic competence, cultural compatibility, and ethical clarity.

Limitations of the Study

The research was limited in several ways. The sample size is limited, and the brief intervention period does not allow for a conclusion about long-term retention. Technological uncertainty, such as disparities in device functionality or web connectivity, might have affected learners' AI-supported experiences, as noted in previous comparative system research (Muller et al., 2020). Future studies should use larger samples, be longitudinal, and include different ESL settings to yield more conclusive results. Also, scholars ought to investigate the concept of hybrid teaching and examine learners' responses with varying cognitive and affective characteristics to different levels of AI integration.

CONCLUSION

Summary of Main Findings

This comparative analysis shows that AI-assisted vocabulary learning offers quantifiable benefits in efficiency, personalization, and learner engagement, whereas human-guided instruction offers a better scaffolding approach, contextual explanation, and cognitive load reduction. As with other adaptive and intelligent learning settings, AI-modified adaptive systems perform better at setting and adjusting the level of difficulty and creating custom learning courses (Kabudi, Pappas & Olsen, 2021; Li et al., 2019). Nevertheless, instructional leadership, guided by a human, still provides motivational support and socio-cognitive interaction, which are similar to findings from comparative studies across various educational areas (Clivaz & Miyakawa, 2020)

ESL Practitioner Recommendations.

Teachers would be advised to adopt AI tools as supplementary tools rather than substitutes, using them to support spaced practice, diagnostic feedback, and multimodal exposure to vocabulary, while maintaining teacher-directed discourse to ensure more profound semantic growth (Kohnke & Ting, 2021). Designers are advised to incorporate culturally responsive information, open-adaptive reasoning, and cognitive load-sensitive interfaces, based on emerging research on AI-assisted learning and user behavior (Lai, 2021; Nagro, 2021).

FUTURE RESEARCH DIRECTIONS

Future research should consider hybrid human-AI systems, evaluate long-term vocabulary memory, and assess the ability of various AI structures to effectively work with multilingual learners, as other technical methods are compared (Li et al., 2019; Li et al., 2019; Rajabi et al., 2020).

REFERENCES

1. Adnan, N. H., Norman, H., & Nordin, N. M. (2020). Instructor-generated Hand-drawn 2D Animations for ESL Vocabulary Learning in Secondary Education. Asian ESP Journal, 16(1–2), 67–81.

2. Alissa, K., Almubairik, N. A., Alsaleem, L., Alotaibi, D., Aldakheel, M., Alqhtani, S., … Alshahrani, M. (2019). A comparative study of WhatsApp forensics tools. SN Applied Sciences, 1(11). https://doi.org/10.1007/s42452-019-1312-8
3. Almoselhy, R. I. M. (2021). Comparative study of vegetable oils oxidative stability using dsc and rancimat methods. Egyptian Journal of Chemistry, 64(1), 299–312. https://doi.org/10.21608/EJCHEM.2021.51238.3051
4. Anindyaputri, N. A., Yuana, R. A., & Hatta, P. (2020, January 1). Enhancing Students' Ability in Learning Process of Programming Language using Adaptive Learning Systems: A Literature Review. Open Engineering. De Gruyter Open Ltd. https://doi.org/10.1515/eng-2020-0092
5. Barua, P. D., Vicnesh, J., Gururajan, R., Oh, S. L., Palmer, E., Azizan, M. M., … Acharya, U. R. (2022, February 1). Artificial Intelligence Enabled Personalised Assistive Tools to Enhance Education of Children with Neurodevelopmental Disorders—A Review. International Journal of Environmental Research and Public Health. MDPI. https://doi.org/10.3390/ijerph19031192
6. Chaaban, Y., Arar, K., Sawalhi, R., Alhouti, I., & Zohri, A. (2021). Exploring teachers' professional agency within shifting educational contexts: A comparative study of Lebanon, Qatar, Kuwait, and Morocco. Teaching and Teacher Education, 106. https://doi.org/10.1016/j.tate.2021.103451
7. Clivaz, S., & Miyakawa, T. (2020). The effects of culture on mathematics lessons: an international comparative study of a collaboratively designed lesson. Educational Studies in Mathematics, 105(1), 53–70. https://doi.org/10.1007/s10649-020-09980-1
8. Co-Reyes, J. D., Gupta, A., Sanjeev, S., Altieri, N., Andreas, J., DeNero, J., … Levine, S. (2019). Guiding policies with language via meta-learning. In 7th International Conference on Learning Representations, ICLR 2019. International Conference on Learning Representations, ICLR.
9. Gao, X., Gao, Q., Gong, R., Lin, K., Thattai, G., & Sukhatme, G. S. (2022). DialFRED: Dialogue-Enabled Agents for Embodied Instruction Following. IEEE Robotics and Automation Letters, 7(4), 10049–10056. https://doi.org/10.1109/LRA.2022.3193254
10. Gunseli, E., & Aly, M. (2020). Preparation for upcoming attentional states in the hippocampus and medial prefrontal cortex. ELife, 9. https://doi.org/10.7554/eLife.53191
11. 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. https://doi.org/10.1016/j.caeai.2021.100017
12. Kohnke, L., & Ting, A. (2021). ESL students' perceptions of mobile applications for discipline-specific vocabulary acquisition for academic purposes. Knowledge Management and E-Learning, 13(1), 102–117. https://doi.org/10.34105/j.kmel.2021.13.006

13. Koutsantonis, D., Koutsantonis, K., Bakas, N. P., Plevris, V., Langousis, A., & Chatzichristofis, S. A. (2022). Bibliometric Literature Review of Adaptive Learning Systems. Sustainability (Switzerland), 14(19). https://doi.org/10.3390/su141912684
14. Lai, C. L. (2021). Exploring University Students' Preferences for AI-Assisted Learning Environment: A Drawing Analysis with Activity Theory Framework. Educational Technology and Society, 24(4), 1–15.
15. Lee, B. C., Pandian, A., Rethinasamy, S., & Tan, D. A. L. (2019). Effects of PWIM in the ESL classroom: Vocabulary knowledge development among primary Malaysian learners. 3L: Language, Linguistics, Literature, 25(4), 179–197. https://doi.org/10.17576/3L-2019-2504-11
16. Lee, J. H., & Shvetsova, O. A. (2019). The impact of VR application on student's competency development: A comparative study of regular and VR engineering classes with similar competency scope. Sustainability (Switzerland), 11(8). https://doi.org/10.3390/su11082221
17. Li, B., & Peng, M. (2022). Integration of an AI-Based Platform and Flipped Classroom Instructional Model. Scientific Programming, 2022. https://doi.org/10.1155/2022/2536382
18. Li, M., Shang, X. F., Liu, N., Pan, X., & Han, F. (2022). Knowledge Management in Relationship Among Abusive Management, Self-efficacy, and Corporate Performance Under Artificial Intelligence. Journal of Global Information Management, 30(11). https://doi.org/10.4018/JGIM.307067
19. Li, Y., Shao, Z., Wang, X., Zhao, X., & Guo, Y. (2019). A Concept Map-Based Learning Paths Automatic Generation Algorithm for Adaptive Learning Systems. IEEE Access, 7, 245–255. https://doi.org/10.1109/ACCESS.2018.2885339
20. Li, Z., Zou, D., Tang, J., Zhang, Z., Sun, M., & Jin, H. (2019). A comparative study of deep learning-based vulnerability detection system. IEEE Access, 7, 103184–103197. https://doi.org/10.1109/ACCESS.2019.2930578
21. Lim, L., Lim, S. H., & Lim, R. W. Y. (2022). Measuring Learner Satisfaction of an Adaptive Learning System. Behavioral Sciences, 12(8). https://doi.org/10.3390/bs12080264
22. Liu, T., & Xiao, X. (2021, November 30). A Framework of AI-Based Approaches to Improving eHealth Literacy and Combating Infodemic. Frontiers in Public Health. Frontiers Media S.A. https://doi.org/10.3389/fpubh.2021.755808
23. Lynch, C., & Sermanet, P. (2021). Language Conditioned Imitation Learning over Unstructured Data. In Robotics: Science and Systems. MIT Press Journals. https://doi.org/10.15607/RSS.2021.XVII.047
24. Müller, Y. K., Wernicke, T., Pittroff, M., Witzig, C. S., Storck, F. R., Klinger, J., & Zumbülte, N. (2020). Microplastic analysis—are we measuring the same? Results on the first global comparative study for microplastic analysis in a water sample. Analytical and Bioanalytical Chemistry, 412(3), 555–560. https://doi.org/10.1007/s00216-019-02311-1

25. Nagro, S. A. (2021). THE ROLE OF ARTIFICIAL INTELLIGENCE TECHNIQIES IN IMPROVING THE BEHAVIOR AND PRACTICES OF FACULTY MEMBERS WHEN SWITCHING TO ELEARNING IN LIGHT OF THE COVID-19 CRISIS. International Journal of Education and Practice, 9(4), 687–714. https://doi.org/10.18488/JOURNAL.61.2021.94.687.714
26. Rajabi, A., Eskandari, M., Ghadi, M. J., Li, L., Zhang, J., & Siano, P. (2020). A comparative study of clustering techniques for electrical load pattern segmentation. Renewable and Sustainable Energy Reviews, 120. https://doi.org/10.1016/j.rser.2019.109628
27. Sein Minn. (2022). AI-assisted knowledge assessment techniques for adaptive learning environments. Computers and Education: Artificial Intelligence, 3. https://doi.org/10.1016/j.caeai.2022.100050
28. Vedadi, S., Abdullah, Z. B., & Cheok, A. D. (2019). The effects of multi-sensory augmented reality on students' motivation in english language learning. In IEEE Global Engineering Education Conference, EDUCON (Vol. April-2019, pp. 1079–1086). IEEE Computer Society. https://doi.org/10.1109/EDUCON.2019.8725096
29. Wang, S., Hou, Y., Li, X., Meng, X., Zhang, Y., & Wang, X. (2021, December 23). Practical Implementation of Artificial Intelligence-Based Deep Learning and Cloud Computing on the Application of Traditional Medicine and Western Medicine in the Diagnosis and Treatment of Rheumatoid Arthritis. Frontiers in Pharmacology. Frontiers Media S.A. https://doi.org/10.3389/fphar.2021.765435
30. Wang, S., Hou, Y., Li, X., Meng, X., Zhang, Y., & Wang, X. (2021, December 23). Practical Implementation of Artificial Intelligence-Based Deep Learning and Cloud Computing on the Application of Traditional Medicine and Western Medicine in the Diagnosis and Treatment of Rheumatoid Arthritis. Frontiers in Pharmacology. Frontiers Media S.A. https://doi.org/10.3389/fphar.2021.765435
31. Willeke, K. F., Tian, X., Buonocore, A., Bellet, J., Ramirez-Cardenas, A., & Hafed, Z. M. (2019). Memory-guided microsaccades. Nature Communications, 10(1). https://doi.org/10.1038/s41467-019-11711-x
32. Xie, H., Zou, D., Zhang, R., Wang, M., & Kwan, R. (2019). Personalized word learning for university students: a profile-based method for e-learning systems. Journal of Computing in Higher Education, 31(2), 273–289. https://doi.org/10.1007/s12528-019-09215-0
33. Yang, J., & Zhang, B. (2019, May 1). Artificial intelligence in intelligent tutoring robots: A systematic review and design guidelines. Applied Sciences (Switzerland). MDPI AG. https://doi.org/10.3390/app9102078
34. Zaytseva, V., Miralpeix, I., & Pérez-Vidal, C. (2021). Because words matter: Investigating vocabulary development across contexts and modalities. Language Teaching Research, 25(2), 162–184. https://doi.org/10.1177/1362168819852976
35. Zidaru, T., Morrow, E. M., & Stockley, R. (2021, August 1). Ensuring patient and public involvement in the transition to AI-assisted mental health care: A systematic

scoping review and agenda for design justice. Health Expectations. John Wiley and Sons Inc. https://doi.org/10.1111/hex.13299