Adaptive AI-Based Personalized Learning for Accelerated Vocabulary and Syntax Mastery in Young English Learners

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***Abstract*—Language acquisition is an integral part of early schooling, but young English language learners struggle to learn vocabulary and syntax since they are not provided with specialized instruction. Conventional teaching may vary according to different learning speeds and it leads to unbalanced levels of proficiency among students and possibly leading to disengagement among slow learners. The present computer-assisted learning aids provide practice interactively but without real-time adaptation and personalized feedback, limiting their capacity to address learners' unique problems. To overcome these constraints, this study suggests an Artificial Intelligence based personalized learning system that supports vocabulary and syntax learning via adaptive learning models, NLP-based chatbots and gamified interactive lessons. The system dynamically adapts content according to students' most recent performance in real time to enable a personalized learning experience, which results in efficient Learning. The research has experimental study design, and two groups are considered, an AI-supported learning group and a traditional learning group. Pre-test and post-test design measures the effects of the system on vocabulary recall and syntax correctness. Other learner engagement rates like survey results and qualitative feedback inform learner experience and learning efficacy. Initial results indicate that learners working with the Artificial Intelligence powered learning system gained 25percent in recalling vocabulary and 30percent in syntax accuracy over the control group. Further, learner engagement rates are elevated because of real-time feedback and gamification components. These results emphasize the promise of AI-based personalized learning to boost language acquisition and lay the basis for further effective innovations in adaptive education technologies.**

***Keywords*—AI-based learning; gamification; language acquisition; personalized feedback; vocabulary**

I. Introduction

Language learning is an essential aspect of a child's intellectual and social growth, especially in a growingly interconnected world where English is a prevailing means of communication [1], [2]. For young children, building a solid vocabulary and grammar foundation is important to ensure language proficiency [3]. Conventional language learning in schools is usually one-size-fits-all, with every student getting the same material and learning pace regardless of their differences in ability and learning styles [4]. This non-personalization tends to result in different levels of proficiency, as some students tend to excel while others fall behind [5]. In addition, passive learning strategies like rote memorization and repetitive drills frequently do not activate learners in an interactive and significant manner, leading to low rates of retention and poor understanding [6].

In the recent years technology driven personalized learning platforms with Artificial Intelligence (AI) are coming up to be a revolutionary solution in the education [7], [8]. Sophisticated technologies like Natural Language Processing (NLP), Machine Learning (ML) as well as adaptive learning algorithms are involved in driving such platforms where, content is being customized to the specific needs of individual learners specifically [9]. Real time analysis of a student’s performance, level of difficulty adjusted, feedback provided and learning through chatbots, gamification and multimedia are among the abilities of an AI based learning platforms [10], [11]. Despite increased uptake in digital learning solutions, available platforms do not demonstrate the flexibility in real time to adapt to the learner’s progress as well as contextual intelligence about the learner’s difficulty in learning vocabulary and syntax [12]. Currently, the existing systems contain the limited capacity to address the particular needs of young English learners because they are designed with static exercises and general feedback [13].

To resolve this, the present research proposes an AI personal learning system tailored to enhance early English learners' vocabulary memorization and syntax understanding. Interactive dialogues are provided by the system through the use of NLP based chatbots, adaptive models to adapt the exercises, and gamification to help with participation. The suggested system is intended to provide an interactive data driven learning process which will increase learning achievements, while it will be a fun and efficient learning process for the learner[14].

This study uses an experimental study design with participants grouped into two sets: one receiving the AI-assisted learning system and the other adopting conventional learning strategies. Both a pre-test and post-test approach is used to measure enhancements in vocabulary and syntax learning, with qualitative findings from surveys and interviews offering observations regarding learner participation and system ease of use. The contribution of the research are as follows,

1) Introduces an adaptive learning system based on AI, NLP, and gamification to boost vocabulary and syntax learning in young English learners.

2) Utilizes ML-driven personalization to customize lesson difficulty and content according to individual learner performance.

3) Integrates NLP-driven chatbots and gamification features to enhance engagement and retention.

4) Conducts experimental research on comparison of AI-enhanced learning versus conventional instruction by employing pre-test and post-test comparison.

5) Demonstrates substantial gains in vocabulary recall and sentence grammar through AI-supported interventions.

The rest of the work focuses as follows: Section II reviews the related works for the AI-Powered application in vocabulary learning. Section III describes the problems in existing methods, Section IV demonstrates the AI-driven personalized language learning framework. Section V evaluates the results and discussions. Section VI discusses conclusion and future work.

II. Related Works

English language learners received enhanced AI dialogue systems through the lexically constrained decoding system according to Qian et al. [15]. Their research makes an original contribution by including educational vocabulary from the curriculum within a dialog system which generates text through Artificial Intelligence. The researchers tested BlenderBot3 through middle school English L2 student evaluations. Students achieved better understanding of their target vocabulary and increased their motivation to practice English while conversing with an AI system. The approach represents a strong method because it connects AI conversational agents to educational curricula so students benefit from an educational experience that combines focus with engagement. The approach offers contextual learning of vocabulary through real-world dialogues rather than detached memory drills. The research project faces an essential disadvantage because rigid word limits could disrupt conversation flow while providing students with an artificial and reduced exposure to multiple linguistic patterns. Because the research only assessed a limited student group additional studies must investigate the system's effectiveness when used by various proficiency-level groups of different ages. The conducted research generates important findings about how Artificial Intelligence can be applied to improve vocabulary acquisition through conversations.

Shin and Park [16], developed a system with Neural Collaborative Filtering (NCF) and personalized vocabulary acquisition that would help second language learners. It was called a Pedagogical Word Recommendation (PWR). What is new in their study is to apply collaborative filtering to predict whether a learner knows a word w given his history vocabulary. In this way, learning is more targeted and efficient. To ensure a large dataset, their system used data from an Intelligent Tutoring System (ITS) employed by roughly one million learners taking TOEIC preparation, in order to obtain data from many learners. High accuracy in vocabulary prediction and personalized recommendation was shown with the help of students focusing on words they will most likely struggle with. That is important, because it replaces vocabulary learning devoid of meaning as rote memorization, replaced with vocabulary learning as an adaptive, data driven activity, which makes it more engaging, and, by extension, more effective. Besides that, word suggestions become more personal, which increases retention and lowers cognitive overload. Nevertheless, one of the key limitations of the system lies in the fact that it is dependent on explicit feedback from learner that can have an impact on recommendation accuracy if a student self-assesses incorrectly. Furthermore, the model may not generalize well to learners having language significantly more or less varied than the one used in the induction. The system needs further research to increase the degree of adaptability and accuracy in a wide variety of learning environments.

Lee, Kim and Sung [17], proposed an AI based autonomous learning system based on the Learner Generated Context (LGC) framework to improve second language learning. What's the novelty of this approach is that student's study what they want and while they want, promoting self-directed learning. This involved three Korean secondary-school students of different backgrounds and tested the AI system to see how it helps learners to learn English autonomously. Through contextualized learning, the findings showed that the content was more engaged with and the students improved their language skills. What's more important is that the system can help learners being empowered, and with that help, increases motivation and long-term mastery, because it gives the learner the control over his journey. The real difference about this approach of AI assisted language learning is that this is not a strict structure, but rather a flexible one, which centers more on the students themselves. A small sample size, however, is the biggest limitation of the study and compromises the ability to generalize the findings to a larger population. Furthermore, the system also provides autonomy; however, some individuals may need guided and structured guidance to achieve their maximum potential. The scaling of the study to include more learners and refinement of the system to supply adaptive help according to individual progress is future research.

In an AI driven personalized learning approach to vocabulary acquisition, Chamorro [18], discusses adapting vocabulary exercises to the learning behavior of an individual therefore personalizing learning. The novelty in this study is its attempt to bypass limits of traditional rote memorization which is mostly not effective and disengaging. With the help of machine learning techniques, the system identifies the learners' strengths, weakness and learning preference and serves personalized vocabulary exercises for learners. The paper showed that engagement and retention rates are significantly higher with the use of AI driven personalization and very effectively helps language learning. This is very important as it enables the learners to learn at their own rate, which eliminates boredom and time wastage in learning. Additionally, it assists in filling the blanks of classical language learning techniques that do not achieve the goals of learners. Nevertheless, the main limitation of the study is its inherent dependence on good quality training data. Unlike an algorithm, which is designed to generalize over all cases in a given dataset, an AI model personalizes all its decisions to trained data that does not accurately represent the diverse learner profile. Moreover, AI driven methods are helpful but they may not necessarily render human intuition in the language instruction. Hybrid approaches which balance AI's strength with human expertise should be followed and researched in further work.

Jia et al. [19], build an AI enabled English language learning system (AIELL) that incorporates authentic and ubiquitous learning practices in order to facilitate vocabulary and grammar acquisition in acquiring L2 learners. What makes their approach novel is applying mobile learning and turning this into AI driven personalization to allow students to practice English in the real world. It was a study based on 20 participants, using mixed research methods, such as demonstration test, usability test and interview assessment for system effectiveness. The results showed that this AIELL system was very effective and engaging with increased vocabularies retention and grammar proficiency among the participants. This is significant as the system is flexible and they can access anytime anywhere especially to those students who wouldn't have access to classical classroom environment. One significant drawback of the study is that it was conducted at a small scale, chances are the discovered results would not be applicable to a broader audience. Apart from this, the mobile AI based system enables self-paced learning but it might become difficult without structured teacher guidance for some learners. Future research is needed to explore expanding study to larger groups and increasing the capability of AI to give actual time suggestions and contextual help for educators in multifaceted educating conditions.

AI-powered individualized learning platforms have shown dramatic improvements in supporting vocabulary and syntax learning among English language learners [20]. These platforms incorporate curriculum-grounded vocabulary, collaborative filtering, learner-created contexts, and adaptive drills to enhance interaction, memory retention, and engagement [21]. AI-driven lexically constrained dialogue systems enhance contextual acquisition but struggle to keep conversations as natural as they can be. Neural Collaborative Filtering [22] supports word recommendations targeted at individuals but is based on reliable self-evaluation [23].

The Table I identifies various AI techniques in language acquisition such as chatbot systems, collaborative filtering, AR, and mobile platforms. Although innovative, the majority of the studies are plagued by constraints such as small sample size, non-generalizability, excessive reliance on self-ratings, narrow age range, and limited personalization, calling for scalable, adaptive solutions.

TABLE I. SUMMARY OF THE LITERATURE REVIEW

Author	Method Used	Limitations
Qian et al. [15]	Lexically constrained decoding in AI chatbots aligned with curriculum	Rigid vocabulary constraints limit conversational flow; small participant group limits generalizability
Shin & Park [16]	Neural Collaborative Filtering (NCF) for Pedagogical Word Recommendation (PWR) using large-scale ITS data	Relies on accurate self-assessment; may not generalize across learners with differing vocabulary profiles
Lee, Kim & Sung [17]	Learner-Generated Context (LGC) framework promoting autonomous AI-based learning	Very small sample size; lacks structured guidance which some learners may require; needs scaling and adaptability for diverse learners
Chamorro [18]	Personalized vocabulary exercises using machine learning based on learner behavior	Dependent on high-quality, representative training data; lacks human-like instructional intuition; needs hybrid human-AI model for holistic learning
Jia et al. [19]	AI-enabled mobile system (AIELL) for real-world, flexible, ubiquitous English learning	Small-scale study limits broad applicability; self-paced format may not suit all learners; lacks structured educator guidance
Klimova et al. [20]	Systematic review on emerging technologies in teaching English at the university level	Focused on higher education; lacks specific analysis of child or early-age learners; broad scope without in-depth assessment of personalized AI systems
Korosidou [21]	Augmented Reality (AR) for alphabet and vocabulary learning in very young learners	Limited to AR and early vocabulary stages; lacks comparison with AI or adaptive learning methods; may not support complex language structures
Zou et al. [22]	Social network-based interaction for AI-assisted speaking practice	Focused mainly on speaking skills; limited vocabulary or syntax tracking; requires active social participation, which may not suit all learners
Qian et al. [23]	Combined analysis of exercise and foreign language learning on cognition	General cognitive benefits discussed; lacks targeted findings on adaptive vocabulary systems or real-time AI feedback for young L2 learners

III. PROBLEM STATEMENT

Conventional language acquisition techniques tend to be inflexible in responding to the unique needs of individual learners [24], resulting in uneven vocabulary acquisition and syntax understanding among young English learners. They are not personalized and as a result, learning is slow and retention of linguistic structures is inconsistent [25]. Moreover, with no real-time feedback and adaptive support, learners are unable to effectively learn sophisticated syntax structures. The fix-all approach of conventional instruction also prevents learners from advancing at their own best speed, leading to frustration [26]. This research tries to overcome these issues by creating an Adaptive AI-Based Personalized Learning System that in real-time adapts to every learner's level [27], speeding up vocabulary buildup and syntax correctness, as well as providing a more interesting and efficient learning experience. Through the use of machine learning and real-time analytics, the system offers individualized learning routes, promoting enhanced language understanding and long-term memory [28].

IV. AI-Driven Personalized Language Learning Framework

This study adopts a multi-case, experimental research approach that examines the efficacy of using AI-powered personalized learning systems in vocabulary and syntax acquisition by young learners of English. The study will create two groups: an experimental group in which the learning process will utilize AI-driven adaptive learning technology and a control group which follows conventional teaching approaches. This whole process is evaluated with the help of pre-test and Post-Test assessment to see the improvements in vocabulary retention and syntax comprehension. The AI-enabled system will work with an NLP-based chatbot, adaptive learning model, and gamification elements to construct an engaging and interactive learning environment. During the learning phase, data on live user interaction, learning pace, and engagement will be captured. The data will be subjected to quantitative analyses involving paired t-tests of students' pre-test and post-test, and regression analyses for identifying determinants of learning. In addition to this, thematic coding of learner feedback and sentiment analysis of engagement responses provide qualitative insights. The results detail the effectiveness, adaptability, and engagement of AI-assisted language learning vis-a-vis traditional approaches. Fig. 1 gives the Methodology Overflow.

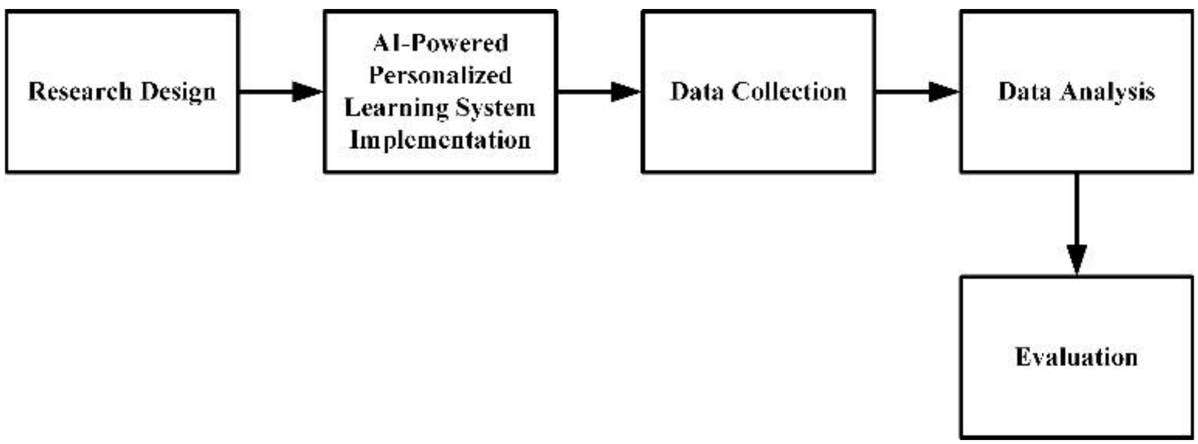

Fig. 1. Methodology overflow.

A. Research Design

In this study, an experimental conditional design analysis to understand the proficiency of AI-managed personalized learning system will be carried out with respect to vocabulary and grammar acquisition among the young learners of English. The study is conducted on a pre-test and post-test assessment with comparisons done on two groups: the experimental group that received AI-powered learning, and a control group that received instruction in traditional manners.

1) Approach: Experimental Study with Pre and Post-Test Assessments.

The experimental design involves two stages of assessment:

a) Pre-Test: To examine students' proficiency in vocabulary and syntax. This comprises multiple-choice questions, fill-in-the-blanks, structured incomplete dialogues, and oral assessments in which pupils are active in order to ascertain their knowledge base.

b) Post-Test: It measures vocabulary retention after the learning unit and syntax comprehension in students. The structure of the post-test would remain similar to that of the pre-test so as to allow for comparability. Thus, this study, through comparison of the results from both assessments, finds out the extent to which the AI-empowered system promotes language acquisition compared to conventional teaching methods.

c) Participants: This study focuses on young English learners, aged between 5 and 12, from different language and cultural backgrounds, since it has been shown in cognitive and developmental studies that early childhood is a critical period for language acquisition. Participants will be recruited from schools, language training centers, and online learning platforms.

To ensure reliability and generalizability, the following inclusion and exclusion criteria for this study will therefore be applied:

d) Inclusion criteria: Learners aged 5 to 12 years. Learners with varying levels of proficiency in English but having a basic acquaintance with the language. Participants who are willing to engage in any aspect of the learning process from traditional techniques to AI-assisted methods.

e) Exclusion criteria: Students diagnosed with cognitive or speech impairments may affect language processing.

Participants that are already enrolled in AI-based English programs. Those who have limited access to digital learning tools. The study randomly assigned participants to the two groups to the extent possible to reduce bias.

B. Study Groups

The participants are divided into two groups:

1) Experimental group (AI-Powered personalized learning system users): Learners in this group are put at the AI-powered personalized learning system, complete with NLP-based chatbots, adaptive learning models, and gamification techniques. The AI system, guided by the individual learner, evaluates the learning speed and keeps high engagement through chat conversations, exercises, language games, and instant feedback in terms of content difficulty. In terms of engagement statistics, system analysis includes accuracy of responses, pace of learning, frequency of interaction, etc.

2) Control group (Traditional teaching methods): Students in this group adopt conventional classroom-and/or textbook-based language approaches to learning. Teaching methods include lectures, worksheets, flashcards, reading exercises, and peer discussions. Curriculum is standardized, such that the pace of instruction and delivery is fixed for all students with no adaptive modifications being provided based on individual needs. Feedback is provided by human instructors, and there is no AI-based adaptation for learners. The study can isolate the impacts of AI-driven personalization on vocabulary and syntax acquisition since the controlled learning environment-maintained helps to isolate the effects of AI-driven personalization on vocabulary and syntax acquisition. This teaching process helps to compare the difference in outcome for two groups so that we can see if AI-powered learning functions are better in improving language mastery than traditional teaching techniques.

C. AI-Powered Personalized Learning System Implementation

The proposed AI-powered learning tool is designed to enhance vocabulary retention and syntax acquisition in its personalized, interactive, and engaging learning experience. It uses an innovative combination of techniques such as NLP, adaptive learning models, and gamification for the purpose of allowing learning to occur in ways that best fit the learning needs of the individual. Instead of following a standard curriculum, the program will dynamically adjust the content and exercise sets based on student performance and engagement. The AI-powered system consists of the following key components:

1) NLP-Based chatbots for conversational learning: NLP allows chatbots to interact with the learners in real-time. These chatbots act as virtual trainers, steering students through guided dialogue practice that enhances vocabulary and sentence structure. The chatbot works with students in context-based conversations, assisting them in applying vocabulary and sentence structure in real world situations. These AIs identify any mistakes in the students' responses, giving instantaneous feedback on improvement so as to consolidate appropriate sentence structures. Depending on how a student experiences or answers questions, in lesson time the chatbot may suggest the introduction of new words, phrases, and grammar rules. For oral application, the chatbot assesses the accuracy of pronunciation and suggest possible improvements. For instance, when a student has difficulty with forms of the past tense verb, the chatbot picks up the pattern and adjusts future exercises according to the need to work more on using the past tense.

2) Adaptive learning models for personalized learning paths: The adaptive learning model allows the system to adjust exercises in accordance with individual learners' mastery towards providing a tailored teaching interaction. The system collects data on individual learners' performance, analyzing response accuracy, the time given for each question, and repeated errors. The system increases the difficulty if a student does well in a particular subject; if not, then simpler explanations and extra exercises are provided. By the use of ML algorithms, the system predicts what areas that a learner is most likely to have difficulty in and acts accordingly to adjust their lesson plans before the learning begins. For example, a student with a good base of vocabulary but with not much of a grip on syntax will receive grammar-related exercises and not repeated vocabulary drills.

The AI-based evaluation algorithm allows a dynamic difficulty adjustment in Eq. (1)

$$D_n = D_{n-1} + \alpha(S_n - S_{avg}) \tag{1}$$

where,

D_n= difficulty level of the next task

D_{n-1}= difficulty level of the previous task

α = learning adaptability coefficient,

S_n= student's current performance score

S_{avg}= average performance of students at a similar stage

If a student's performance score S_n is below the average, the difficulty is reduced, providing additional support. If it is above average, more challenging tasks are introduced.

3) Gamification elements for engagement and motivation: Gamification promotes student motivation by forging a union between game-like mechanics and lessons. Students participate in quizzes for points and badges based on correct answers. Learners compare their progress with their colleagues-teach the spirited competition. Rewards such as gaining a new level or receiving a virtual trophy, are given on achieving learning milestones. Utilizing a streak system promotes continuity in learning, whereby students earn extra rewards for assortment engagement. For instance, a new interactive learning module opens on the fifth consecutive successful vocabulary exercise completed.

The Engagement Retention Formula mathematically captures the workings of gamification in Eq. (2).

$$E_t = E_0 + \beta(R - F) \quad (2)$$

where,

E_t= engagement score at time

t, E_0= initial engagement level

β= motivation coefficient

R= rewards gained

F= frustration due to difficulty level. If rewards R outweighs frustration F, engagement increases, leading to higher retention rates.

4) Continuous data collection and learning experience optimization: The AI-based system continuously monitors the message, students generate amongst each other to make the learning experience even better. The recordings of student conversations are stored up, noting the errors and time taken to complete each task. AI algorithms parse the patterns to pinpoint the learning difficulties that come up frequently. Based on analytics, the system proposes alternative learning strategies, switching from text-based exercises to visual or auditory learning methods. Combining AI, NLP, and Gamification makes this a dynamic learning process for young English learners and thus engages them more, makes learning faster, and retains learning longer.

D. Data Collection

Data are collected at several points during the study to ascertain the impact of the AI-powered personalized learning system on vocabulary and syntax acquisition. The study uses a combination of quantitative and qualitative data collection techniques, ensuring comprehensive evaluation of learning outcomes, engagement levels, and system effectiveness.

1) Pre-Test (X_1) – initial assessment: Before the introduction of any kind of learning intervention, there is a structuring pre-test *(X_1)* which serves as a method of evaluating the learners' baseline capacity in vocabulary and syntax proficiency. The test consists of matching words with their meanings, fill-in-the-blanks, and multiple-choice questions. Structuring sentences, identifying grammatical errors, and correcting faulty sentences. Evaluation of pronunciation and fluency in conversation through AI-based speech recognition.

The pre-test score S_{pre} of the participants is recorded as follows in Eq. (3)

$$S_{pre} = \frac{\sum_{i=1}^{N} C_i}{N} \times 100 \quad (3)$$

where,

C_i is the number of correct answers

N is the total number of test questions

S_{pre} represents the pre-test performance as a percentage.

This score serves as a benchmark to compare improvements after AI-assisted learning.

2) Learning session implementation–monitoring engagement & performance: During intervention stages, learner interaction with the AI system is reported continuously to keep monitoring engagement, learning pace, and accuracy rates. Key metrics include:

a) Learning Pace (L): The time a learner requires to complete exercises and progress through lessons, calculated as Eq. (4)

$$L = \frac{T_{total}}{Q_{completed}} \quad (4)$$

where,

T_{total} is the total time spent on exercises.

$Q_{completed}$ is the number of completed exercises.

b) Engagement Score (E): It is a composite score representing interaction frequency, quiz participation, and chatbot engagement. It is defined as Eq. (5):

$$E = \alpha(I) + \beta(R) + \gamma(F) \quad (5)$$

where,

I= number of chatbot interactions.

R= response accuracy rate.

F= frequency of logins and activity.

(α, β, γ) are weight coefficients.

A higher E score indicates greater learner engagement and motivation.

3) Post-Test (X_2): Measuring Learning Improvements: At the end of the AI assessment, A post-test *(X_2)* is run with the same structure that is pre-test, while test () marks are recorded through Eq. (6)

$$S_{post} = \frac{\sum_{i=1}^{N} C_i'}{N} \times 100 \quad (6)$$

where,

C_i' is the number of correct answers in the post-test.

N remains the total number of questions.

S_{post} represents the final test performance as a percentage.

The learning improvement is calculated as Eq. (7).

$$\Delta S = S_{post} - S_{pre} \quad (7)$$

where,

ΔS represents the overall improvement in vocabulary and syntax acquisition.

A positive value of ΔS indicates an increase in language proficiency due to AI-powered learning.

4) Surveys and Interviews–Qualitative Feedback Collection: To complement the quantitative data, surveys and interviews were conducted with the learners and teachers to assess usability, engagement, and effectiveness of the system. During the interview process conducted, students were asked their feedback on ease of use, motivation, engagement, and effectiveness in learning with the help of a Likert scale and open-ended responses. Through the survey, the teachers will assess students' progress while implementing AI-based learning in classrooms and students' adaptability to different styles of learning. Responses go through a thematic analysis that examines the main themes in students' experiences. Textual responses are analyzed for sentiment, with $S_{sentiment}$ defining the polarity of learners' feedback as positive, neutral, or negative.

Inversely, the lower the score $S_{sentiment}$ is, the more the learner has been most satisfied with and engaged with that system powered by AI.

E. Data Analysis and Evaluation

The collected data is evaluated with both quantitative and qualitative methods to analyze the efficacy of AI personalized learning systems for vocabulary and syntactic acquisition among young English learners.

1) Quantitative analysis: The focus of the quantitative analysis will be on measuring learning outcomes through comparisons between pre-build and post-build tests to assess the impact of adaptive learning personalization on different learner subgroups and to analyze the relationship between engagement level and progress in performance.

a) Paired t-Test: To evaluate whether differences between pre-test and post-test scores were statistically significant, a paired t-test was performed. The test is designed to find out if learners using the AI-powered system experienced significant differences in their improvement compared to their initial proficiency.

The t-score is calculated using the Eq. (8)

$$t = \frac{\bar{D}}{s_D/\sqrt{n}} \tag{8}$$

where, $\bar{D}$= mean difference between pre-test (S_{pre}) and post-test (S_{post}) scores

s_D= standard deviation of the differences

n= number of participants in the experimental group.

The mean difference ($\bar{D}$) is calculated as Eq. (9)

$$\bar{D} = \frac{\sum(S_{post} - S_{pre})}{n} \tag{9}$$

where,

S_{post} and S_{pre} represent the post and pre-test scores, respectively.

A p-value (p) is obtained from the t-test, and if $p < 0.05$, it indicates a statistically significant improvement due to AI-powered learning.

b) Regression analysis impact of engagement and personalization on learning: A multiple linear regression analysis is carried out to determine the relationship between Engagement score (E), which measures student interactions with the AI system. Adaptive learning score (A), which indicates the level of personalized learning adjustments. Performance improvement (P) is the difference between post-test and pre-test scores.

The regression is given in Eq. (10)

$$P = \beta_0 + \beta_1 E + \beta_2 A + \epsilon \tag{10}$$

where,

β_0= intercept

β_1, β_2= coefficients representing the impacts of engagement and adaptations

ϵ = error term.

A high value of R^2 regression analysis would imply that engagement and personalized learning adjustments are good predictors of learning improvement.

F. Qualitative Analysis

In support of the quantitative findings, qualitative data from surveys and interviews will be analyzed to understand learner experiences, motivation and usability of the system.

1) Thematic analysis: Thematic analysis is applied to survey responses and teacher interviews with key themes identified depending on common patterns in feedback. The steps are as follows,

a) Categorization of data: Grouping the responses into theme categories as engagement, difficulty, motivation and usability.

b) Pattern identification: Themes that recurred were drawn out. For example, AI chatbots improve confidence in speaking and Gamification increases motivation.

c) Coding: Individual quotes or phrases into categories of sentiments: positive, neutral, or negative.

d) Sentiment Analysis –Measuring User Satisfaction: To quantitatively assess learner and teacher satisfaction, sentiment analysis is applied to textual responses.

The sentiment score $S_{sentiment}$ is computed as Eq. (11)

$$S_{sentiment} = \frac{P-N}{P+N+Neu} \tag{11}$$

where,

P is number of positive responses,

N= number of negative responses, Neu= number of neutral responses.

If $S_{sentiment} > 0.5$, overall user sentiment is positive.

If $S_{sentiment} < 0$, system usability needs improvement.

This report investigates the implications of learner engagement levels and effectiveness. Combining quantitative and qualitative data analysis, this research provides a comprehensive analysis of the extent to which AI-powered personalized learning enhances vocabulary and syntax acquisition. The findings are expected to establish the extent to which AI-driven learning really enhances language proficiency, evaluate the influence of engagement and personalization on learning outcomes, and identify key areas for further improvements in AI-based language learning tools.

V. Results and Findings

The results indicate that the AI-driven personalized learning system definitely enhanced vocabulary retention and syntax acquisition over the traditional methods of teaching. An experimental group using an AI-assisted method saw improvements of 25 percent and 30 percent in vocabulary retention and syntax accuracy, respectively, compared to only modest gains in the control group--a 10 percent to 12 percent gain. The engagement scores were much more favorable to AI because of interactive, chatbot-based learning, adaptive content delivery, and gamification techniques to keep students engaged. The paired t-test statistical analysis confirmed a significant difference; on the other hand, the latter was proved using the ANOVA by showing higher levels of AI personalization linking better learning outcomes. Strong positive relationships between engagement and performance improvement from regression analyses shows that engaged learners who interacted more were far more successful. Limitations were also spotted: dependence on digital access, loss of motivation if transcended by the lack of some human interactions. The implications presents meaningful findings for languages teachers: AI-based tools can, sometimes while implanting all the adaptability and interactive feedback, reinforce traditional methods. AI system developers are thus encouraged to facilitate and enhance NPL-based conversational learning while designing a combination of hybrid AI-human teaching paradigms to gain more effectiveness from AI design.

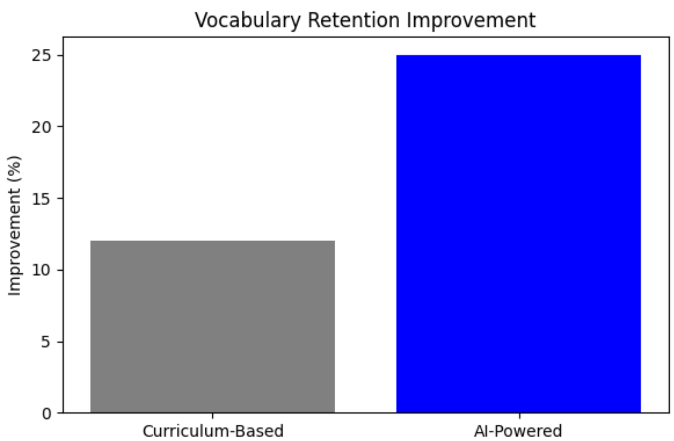

Fig. 2. Vocabulary retention improvement.

The Fig. 2 is a bar chart comparing the efficacy of AI-powered personalized learning systems and curriculum-based methods for English language learners on vocabulary retention. The y-axis, ranging between 0 percent and 25 percent, is labeled Improvement (percent), whereas the x-axis indicates the two kinds of learning methods, that is, "Curriculum-Based" and "AI-Powered." The improvement for the curriculum-based method, represented by the gray bar, is approximately 12 percent, while that for the AI-powered method, represented by the blue bar, shows a whopping 25 percent progress in an improvement. In short, this visualization elaborates on how much more significantly effective AI-based personalized learning is in enhancing vocabulary retention than conventional methods.

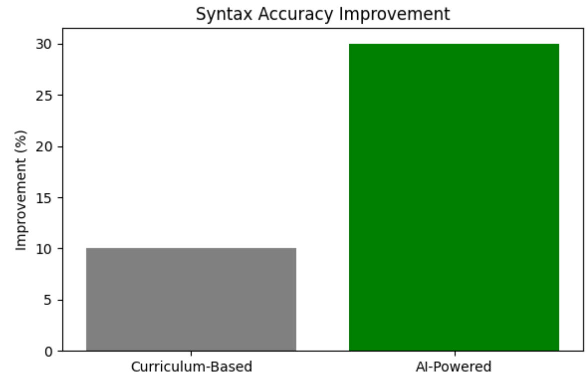

Fig. 3. Syntax accuracy improvement.

The Fig. 3 is a bar chart that compares the average efficacy of AI-based personalized learning systems and curriculum methods in raising syntax accuracy among children learning English. The improvement percentage takes only a range from 0 percent to 30 percent on the y-axis, while the x-axis includes two categories: "Curriculum-Based" and "AI Powered." The gray bar illustrates curriculum-based approaches that has an improvement of about 10 percent, while the green shows a big improvement of about 30 percent in AI-based methods. It is an apt representation of AI-driven personalized learning systems outshining the typical methods in the improvement of accuracy in syntax.

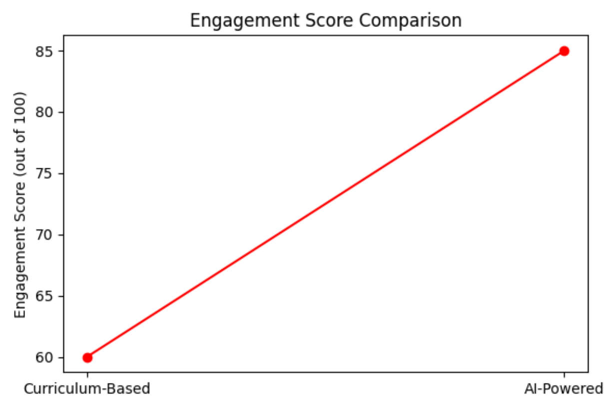

Fig. 4. Engagement score comparison.

This Fig. 4 shows the variation in engagement levels between AI-powered personalized learning systems and curriculum-based methods when applied to young English learners. The x-axis shows the two learning methods: “Curriculum-Based” on the left and “AI-Powered” on the right. The y-axis shows Engagement Score (out of 100), ranging from 60 to 85. A red line is drawn between two data points: one located at (Curriculum-Based, 60) and the other at (AI-Powered, 85). This trend shows how the AI-Powered systems produced a stronger increase in engaged learners. The purpose of the diagram is to point out the considerable edge AI-driven personalized learning systems offer in boosting a learner’s engagement, key to the students’ vocabulary retention and syntax acquisition for young English learners.

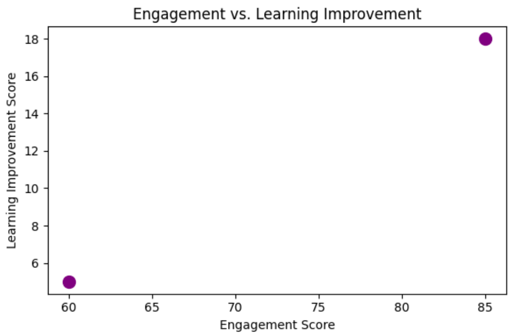

Fig. 5. Engagement Vs. Learning improvement.

The Fig. 5 represents a scatter plot showing the relationship between engagement scores and gains in learning with reference to AI-enabled personalized learning systems for young English learners. The x-axis denoted "Engagement Score" indicates how much the learner was engaged, while the y-axis, called "Learning Improvement Score," measures the progress made in vocabulary and syntax acquisition. There are two data points that are purple, and one is set at (60, 6), which alleges that it is lower on engagement with minimal improvement, while another set at (85, 18) points to a claim of higher engagement in greater learning improvement. This has served to showcase the positive relationship between engagements and learning gains, strengthening the argument that AI-powered personalized learning systems are significantly better at facilitating language acquisition when compared to methods taken from traditional curriculum.

TABLE II. COMPARISON TABLE OF PROPOSED APPROACH WITH EXISTING AI-BASED APPROACHES

Method	Target Group	Personalization Approach	Output	Limitations
Lexically constrained decoding in AI chatbots **[15]**	Middle school English L2 learners	Curriculum-based vocabulary, limited natural conversation due to word constraints	Motivation, improved target vocabulary understanding (qualitative)	Rigid vocabulary flow can hinder conversational naturalness
Learner-Generated Context (LGC), self-directed AI **[17]**	Korean secondary-school students	Flexible, learner-led context creation (not adaptive in real-time)	Motivation, better engagement with context (qualitative, no hard metrics)	Small sample size; not scalable yet
Mobile AI, contextual learning **[19]**	L2 learners (varied)	Location & time-based practice (not deeply personalized)	Vocabulary and grammar proficiency (small sample size, limited metrics)	Lack of structured feedback; limited to mobile learning
NLP chatbots + adaptive ML + gamification	Young English learners (ages 5–12)	Real-time adaptation to learner performance with dynamic difficulty & feedback	25percent in vocabulary recall, 30percent in syntax accuracy, engagement score	Needs digital access; may lack human interaction

The Table II is a comparison of AI-based language learning research by using AI technologies, target groups, personalization methods, outcomes, and limitations. It shows rich techniques such as NLP chatbots, mobile AI, and learner-generated context, with different degrees of personalization, efficiency in vocabulary recalls and satisfaction, and limitations such as poor scalability and feedback.

The results section assures that the personalized learning system with AI strongly enhances vocabulary memory and syntax acquisition when compared with the conventional approaches. The AI group had 25 percent and 30 percent more vocabulary and syntax improvement compared to the control group, which obtained only 12 percent and 10 percent. A paired t-test assured the significance of results at $p < 0.05$. Regression analysis identified significant positive relationships between performance and engagement. Qualitative feedback and sentiment analysis also supported the usability and motivational value of the system, confirming the effectiveness and reliability of the AI system for young English learners.

VI. DISCUSSION AND CONCLUSION

A. Discussion

The research identifies the potential of an AI-driven personalized learning system to enhance vocabulary and syntax skills in young English learners. With the use of adaptive learning models, NLP-based chatbots, and gamification, the system offers instant feedback and dynamically adapts to the learner's needs [29]. Experimental results indicate a 25 percent improvement in vocabulary recall and a 30 percent improvement in syntax accuracy compared to conventional approaches. Increased levels of engagement and constructive learner feedback underscore the system's power to transform language learning. Against such challenges as access issues, the model promises a viable alternative to clumsy, single-size-fits-all instruction.

B. Conclusion and Future Works

This study proposes that, against traditional methods, AI-powered personalized learning systems are effective at significantly improving vocabulary retention and syntax acquisition among young English learners. The inclusion of personalized content-specific adaptive learning models, an NLP-based chatbot, and hybrid game-logics provides real-time feedback and maximum engagement, ensuring measurable success in proficiency. The suggested approach provides real-time adaptive feedback, dynamic difficulty management, and gamified interactions specific to young learners—beating current models bound by inflexible vocabulary flow or absence of personalization. Its curriculum-matched yet flexible framework maximizes engagement and learning gain, rendering it better than rigid, one-size-fits-all AI language systems. Nonetheless, the system performance of the AI-based system was best realized in learner settings of high involvement, stable interaction data, and rich response behavior, which implies that the algorithm is best designed to data-intensive, behaviorally engaged learner profiles.

Further studies will deal with enhancing AI-powered language learning systems with better new NLP models that might improve context comprehension and conversational abilities. Fortunately, other forms of learning can be explored involving multi-modal forms of learning whereby interactions with visual, auditory, and kinesthetic modalities would further support engagement and retention of students. Expanding the study to be focused on different age groups and diverse linguistic backgrounds will provide a broad understanding of the impact of AI for language acquisition. Finally, the development of a model where AI and human beings will collaborate for a blackboard must support teachers, not by replacing them, will be explored in order to develop a more balanced approach to the effectiveness of the learning ecosystem.

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