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AI-POWERED PERSONALIZATION IN ENGLISH LANGUAGE LEARNING: A LINGUISTIC PERSPECTIVE

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ABSTRACT

As AI-based platforms begin to take over English Language Learning (ELL), the existing assessment strategies are aiming to measure overall outcomes instead of what specific linguistic abilities are affected by AI, which provides a critical gap in the knowledge of what AI is differentially impacting in morphosyntactic, lexical, and pragmatic domains. The paper examined the efficacy of AI-based personalization in three fundamental linguistic competencies, namely, morphosyntactic accuracy, lexical diversity, and pragmatic competence, based on the theory of Second Language Acquisition. An adaptive platform powered by AI with 120 intermediate ELL learners (CEFR B1) who were randomly selected to be assigned to experimental (AI-powered adaptive platform, n=60) and control (non-adaptive digital resources, n=60) groups was used in a quasi-experimental mixed-methods study. Standardized tests were used to make pre-test/ post-test measurements and qualitative data was obtained through semi-structured interviews and discourse analysis. Independent-samples t-tests, MANOVA and effect size calculations were used as statistical procedures. Experimental group was statistically significant in morphosyntactic accuracy (d=1.43, p<0.001) and lexical diversity (d=1.69, p<0.001), but pragmatic competence showed insignificant improvements(d=0.16, p=0.392). Good correlations were found between engagement measures and rule based learning outcomes, 95% of the participants said they had improved grammar/vocabulary confidence but 70 % said they experienced pragmatic learning frustrations. AI-enabled personalization is a good way to support the rule-based linguistic aspects with systematic feedback, yet insufficiently supports pragmatic competence based on context and requires sociocultural awareness. These conclusions justify the view that AI will be used as a complementary and not a replacement technology and that hybrid human-AI solutions are required to provide a complete language pedagogy.

KEYWORDS: Artificial Intelligence, Personalized Learning, English Language Learning, Second Language Acquisition, Morphosyntax, Lexical Diversity, Pragmatic Competence.

1. INTRODUCTION

Artificial Intelligence (AI) in the sphere of education has changed the conventional learning setting and provided new possibilities of individual education. Interestingly, the world AI in education market is estimated to be USD 2.5 billion in 2022 and potentially, USD 30 billion in 2032, indicating how fast the technology is being adopted within the industries [1-4]. AI-based applications, including Duolingo Max, ELSA Speak, and ChatGPT, have become popular in the realm of English Language Learning (ELL) by offering adaptive feedback, real-time error detection, and adaptive learning paths. These tools will help to overcome one of the most ancient problems of language teaching: the non-adaptability of one-size-fits-all models to the various linguistic needs of learners. Through its ability to adjust the content according to the proficiency level and the learning patterns with the help of algorithms, AI opens the avenue of reinvigorating the level of autonomy in the learners, their engagement, and the focus on the skills development.

New developments (2023-2025) in generative and adaptive AI systems ChatGPT-4o, Google Gemini 1.5 Pro and multimodal feedback-based adaptive tutoring frameworks have increased the rate at which language instruction can be personalized. New features added include speech synthesis, real time sentiment recognition and cross modal understanding, making these platforms a transition, as opposed to the prior rule based systems to the adaptive tutor that is dynamic and context sensitive. Locating this study as part of this changing terrain highlights that there is still a necessary need to consider various ways in which these systems are differentially beneficial to separate linguistic competencies.

Despite the pledge, much of the current evaluation of AI-based ELL systems is premised on such high-level attainment as learner satisfaction, motivation, or general proficiency. Whereas these measures are significant, they are inclined to disregard the linguistic richness of acquisition. Indicatively, studies focus on vocabulary and grammar-structure acquisition but do not often differentiate between morphosyntactic betterment [5,6], vocabulary variation, or discourse proficiency. In this reductionism view, language learning is understood as a unitary social phenomenon that hides the fine details through which AI can facilitate- or slow down- different fields of language. Also, cultural and contextual aspects of linguistic use, particularly pragmatics are not represented properly by AI-based systems that mostly rely on pattern recognition and statistical modeling.

The most important problem in the personalization of AI-based and Second Language Acquisition (SLA)-based personalization is sounding. The two key perspectives (such as the Input Hypothesis formulated by Krashen and the Interaction Hypothesis formulated by Long) are the input perspective and emphasis on negotiating meaning in real-life situations respectively. Current AI systems, in their turn, excel at instruction based on rules and corrective feedback and are weak in context-sensitive competencies. This kind of a gap brings about some serious questions: Could one scaffold beyond grammar and vocabulary with the help of AI? How can personalization strategies be more productive to satisfy sociolinguistic and pragmatic features of English learning? The necessity to address them is urgent and, in particular, applies to the fact that over 1.5 billion people in the world population are currently engaged in studying English [7-11], and the application of AI-based tools is on the increase. This paper, therefore, argues in support of linguistic approach in the evaluation of the personalization of AI, which divides its implications in morphosyntactic, lexical, and pragmatic strata.

The given study was inspired by the fact that there had been a discrepancy between what the AI systems were already able to provide and what language learners need urgently. Although AI was performing quite successfully in providing personalized grammar drills, vocabulary drills, and corrective feedback, students were unable to reach pragmatic competence and speaking within the context in the real life. The gap bridging was not only likely to enhance the research on SLA, but also allow AI-based personalization to be more pedagogically aligned and linguistically comprehensive. This research study was expected to not only add to the scholarly discourse in the field of SLA, but also to inform the design of intelligent language learning systems in practice [12-15] by systematically analyzing the role of AI in morphosyntax, lexical diversity and pragmatics.

Despite the fact that comprehensive studies demonstrated that AI personalization positively affected morphosyntactic accuracy and lexical development [16], the results demonstrated the inability to overcome the limitations concerning pragmatic competence and a context-dependent communication pattern [17,18]. The language gains were generally considered broadly, e.g., as the results of overall proficiency, or motivation, without decomposing the results systematically by linguistic domain. Furthermore, although CALL and ITS mechanisms were effective in the learning of rules, they did not have mechanisms of sociocultural nuance, which is primary to the Second Language Acquisition. The following gap demonstrated the necessity of a comprehensive work that would theoretically examine AI-based personalization in a linguistic sense, with a specific focus on morphosyntax, lexicon, and pragmatics.

Within the context of the contemporary educational environment, the platforms that used AI to provide adaptive paths and individual feedback progressively influenced English Language Learning. Nevertheless, the available literature mostly assessed such systems using broad measures such as the motivation of learners, achievement of specific proficiency, or satisfaction thus creating a significant gap in the comprehension of such systems on discrete linguistic skills [19,20]. The problem was that the learners gained grammar and vocabulary with the help of AI personalization, but the aspect of pragmatic awareness which is necessary to ensure effective cross-cultural communication was not learned. The topicality of the need to discuss this problem was particularly relevant to the case of the world when more than 1.5 billion learners of English were spread over the world. The justifications as to why the study was justified are that it not only bridged the gap between the SLA theory and AI practice but also provided some empirical evidence as to whether adaptive mechanisms could (or could not) scaffold fine linguistic domains. The importance of the study was that it could provide understanding to developers in designing context-aware AI tutors, educators in meaning integration, and policy makers in assessing the role of AI in language education with a communicative competence perspective.

Based on the gap identified, according to which AI-powered personalization improved morphosyntactic and lexical development but not pragmatic competence, this study was aimed to achieve the following objectives:

1. To measure the effect of AI-powered personalized learning on the morphosyntactic accuracy of intermediate English learners, with emphasis on grammatical structures, error reduction trajectories, and effect size comparisons between experimental and control groups.
2. To assess the contribution of AI-driven adaptive systems to lexical diversity, analyzing vocabulary breadth, depth, and productive use through pre/post performance and multivariate outcomes.
3. To determine the extent to which AI personalization facilitates or constrains the acquisition of pragmatic competence, focusing on appropriateness of speech acts, sociolinguistic awareness, and cross-cultural communicative sensitivity.
4. To analyze the learner engagement dynamics on AI platforms (i.e. time-on-task, task completion, and feedback acceptance) and their statistical relationship with the linguistic gains in both morphosyntactic and lexical levels.
5. To produce pedagogical and technological implications in English language learning, it is desirable to highlight hybrid human-AI models that combine the efficiency based on rules and context-sensitive and pragmatically oriented instructional practices.

The article evolves a novel method of Second Language Acquisition (SLA) theory, which comparatively evaluates AI-supported personalization in the context of the morphosyntactic accuracy and lexical variety, along with pragmatic competence, leaving the generic proficiency-related testing behind. It offers concrete empirical evidence as to the high-quality of AI-based learning with the help of the mixed-methodological approach that incorporated the quantitative experimentation and the qualitative analysis of the discourse. The results show that AI personalization proves to be very sustaining to grammar and vocabulary acquisition and is yet to develop pragmatic competence that implies sociocultural and contextual awareness. In practice, the study has practical implications on the teacher, developers and policymakers, that there is need to have human-AI pedagogical frameworks developed which would be effective in technology and culturally sensitive and context-specific language teaching.

The theory of language acquisition according to Krashen in his Input Hypothesis (1985) states that language acquisition takes place when the learner is presented with comprehensible input that is slightly beyond his/her present level (i + 1). The AI-based systems make this principle practical by continuously examining the performance of a learner and offering adaptive exercises to keep the input difficulty at an optimum level. By way of constant repetition and immediate error correction, these systems improve morphosyntactic accuracy through forcing form-oriented learning and automaticity of grammatical options. Conversely, Interaction Hypothesis of Long (1996) also focuses on the fact that pragmatic competence is acquired in real interaction and in the process of negotiating the meaning, in which the learners interpret the social signs like politeness and tone. Although AI provides simulated interaction, it does not provide true sociocultural reciprocity, which restricts the possibilities of making meaning contextually. As a result, pragmatic advantages are kept down compared to morphosyntactic ones. To conclude, AI adaptivity is an efficient tool to learn linguistic rules according to the paradigms by Krashen and Long, but failure to develop a real-world conversational negotiating process limits the acquisition of the pragmatic competence.

The paper is broken into five major sections. In the Introduction, the background, the problem, and the importance of an analysis of AI-powered personalization are introduced using the linguistic perspective. The Literature Review is a synthesis of the current research on AI in ELL, personalization technologies, and the foundations of SLA, where a current research gap is identified. The Methodology describes the quasi-experimental mixed-methods design including the selection of the participants, instruments, and data analyses procedures. The Results and Discussion involve quantitative and qualitative results on morphosyntax, lexical diversity, and pragmatic competence which are linked to SLA theory. The Conclusion summarizes key insights, highlights contributions and provide pedagogical, technological and policy recommendations, followed by limitations and directions for future research.

2. LITERATURE REVIEW

2.1 AI in English Language Learning (ELL)

The uses of AI in ELL were actively studied by researchers in the form of meta-analysis, systematic reviews, and empirical studies. In a meta-analysis, Guan et al. [21] found that AI-based informal learning produced a significant positive effect on proficiency, motivation, and self-regulation but with limited findings due to the variability of learning situations. Garcia-Lopez et al. [22], which was called systematic review after doing research on gifted learners, and it was found that AI offered differentiated instructions, yet the mechanisms of both inclusive integration were at an early stage. Similarly, Du and Daniel [23] meta-synthesized chatbot-based research and found a higher level of speaking fluency in AI chatbots due to simulated interaction in real life albeit with limitations to complex pragmatics. McLaughlin and Osborne [24] identified both openings and moral concerns as the effectiveness caused by AI was particularly difficult to counteract educational inequalities. Vasilescu and Smetanin [25] surveyed the Intelligent Tutoring Systems (ITS) and confirmed their use in instructing grammar but failed to provide much flexibility in instructing pragmatic competence. Kucuk and Solmaz [26] demonstrated that AI-based applications led to increased vocabulary and grammar memory, but these applications are to be properly readjusted to curriculum standards. A warning view was taken by Selwyn [27] who held that the process of personalization was prone to excessive reliance on technology. Reviewing Duolingo, Xu and Lee [28] discovered that the adaptive repetition facilitated vocabulary retention, but did not include profound instruction of syntax. After analyzing 20 years of literature, Chen et al. [29] found that, although personalization emerged as a leading theme, the literature seldom covered subtle areas of linguistics. Zou et al. [30] mapped publication trends and found that AI studies began to focus more on motivation and self-regulation but did not investigate morphosyntactic and pragmatics consequences.

A number of empirical studies proved the mechanisms and usages of certain AI tools. Du et al. [31] conducted a systematic review of AI-driven chatbots and demonstrated that the tools enhanced communicative competence with the help of interactive feedback, whereas pragmatic inferences were poor. The results of empirical research on generative AI in ELL were examined by Liu et al. [32] and verified that it can generate adaptive materials, yet reliability and bias in the generated content were appointed as primary concerns. Xiao et al. [33] compared AI- and teacher-generated feedback, with the results showing that AI feedback increased the accuracy of the surface and teacher feedback improved the resolution of discourse-level problems, which complement each other. Experimentally, Han [34] combined a chatbot (EchoDot) and found that speaking fluency was improved in learners, although there was no significant uptake of corrective pragmatic cues. Nazari and Shabbir [35] experimented with intelligent writing assistants and found that the learners could develop structural accuracy but excessive dependence on the automated corrections limited the level of critical awareness. Abdalkader [36] compared Grammarly and discovered that it has enhanced the fluency and accuracy of writing, but has not considered the contextual appropriateness. According to Xiao et al. [37], feedback with generative AI stimulated student engagement and motivation, and at the same time, excessive dependence decreased learner autonomy.

Regarding the larger effects, Zhai et al. [38] carried out a meta-analysis and established that GenAI tools had a positive effect on motivation in a wide group of learners, yet the magnitude varied according to the type of task. Zou and Sun [39] gathered teacher feedback and reported that ChatGPT was viewed as helpful in writing ideas and scaffolds, but teachers were worried about the accuracy and ethics. A systematic review conducted by Ji et al. [40] showed that the role of teachers in AI-based classroom changed to that of facilitators and not knowledge transmitters, but the lack of training was still an obstructing factor. All of these studies proved that AI applications in ELL helped to increase proficiency, motivation, and active engagement of the learners with the help of adaptive feedback, automated assessment, and conversational simulation mechanisms. Nevertheless, outcomes also revealed standard constraints, especially when it comes to dealing with higher-order linguistic properties like pragmatics, keeping the learner autonomous, and providing fair access.

2.2. Linguistic Foundations of SLA

Second Language Acquisition (SLA) studies on the multi-dimensionality of language acquisition in which morphosyntactic, lexicon, and pragmatic dimensions were various and interrelated domains. Ellis [41] tested morphological acquisition and demonstrated that morphemes were acquired incrementally with exposure frequency having a significant impact on accuracy but the applicability of these generalized results was limited due to differences in the uptake of morphology by different learners. A review of the pragmatics in English as lingua franca (ELF) by Taguchi and Ishihara [42] showed that pragmatic norms varied among cultures and that pedagogy must lay more emphasis on intercultural awareness. The study by Alzeebaree and Yavuz [43] investigated the production of requests and apologies by Middle Eastern EFL learners and found that there were common pragmatic failures particularly on the use of politeness strategies which indicated discrepancies between L1 and L2 norms. Fung and Macaro [44] examined listening comprehension and established that there existed a positive relationship between linguistic knowledge and strategy use although they realized that weaker students had problems employing the strategies. Ariani et al. [45] examined pragmatic socialization and found out that pragmatic growth was facilitated by teacher mediation yet excessive focus on form diminished communicative authenticity. Gonzalez-Lloret [46] maintained that the CALL setting facilitated growth in pragmatic competence yet pragmatic transfer was limited because of lack of real-life sociocultural setting.

A number of studies discussed the place-technology and new approaches in practical development. Zhang [47] applied the game-enhanced communication and discovered that the learners advanced in terms of pragmatic appropriateness of compliment response, although the retention was questionable over time. Kaur and Birlik [48] examined BELF meetings and found out that the strategy of explanation enhanced the effect of communicative, but the pragmatic appropriateness was relative in different contexts. Akbari et al. [49] compared the use of translation-based teaching and found that it did not develop the pragmatic competence satisfactorily, and it in most cases had the effect of distorting intended meaning. Gonzoza-Lloret [50] also established that L2 pragmatics were aided by technology mediated tasks but the success of learning was dependent on quality of design. In (Di Sarno-Garcia [51]) the author applied telecollaboration in teaching apologies and discovered that cross-cultural communication boosted the pragmatic range of learners, but uneven peer interaction reduced results. Wakamoto and Rose [52] designed a listening strategies questionnaire, and showed how strategic listening enhanced comprehension, but self-report data of learners limited validity. In a study, Alsmari [53] embraced video based tasks and revealed that visual contextualization encouraged pragmatic awareness, where performance improvements were not uniform. Alsuhaibani [54] also analyzed compliment replies and found out that pragmatic competence was developed enormously, but learners had difficulty in generalizing outside of the taught expressions.

Additional contributions emphasized multimodal and classroom based SLA. As Fouz-González [55] showed, fossilized sound training, as a form of pronunciation training, improved the perception and production of fossilized sounds by learners but the small scale of the study restricted generalization. Mardieva et al. [56] conducted a bibliometric review and reported that speaking skills interventions spread throughout the world, but not all of them were empirically rigorous. Explicit, implicit, and contrastive lexical methods were compared by Ziafar [57], with the best results with explicit instruction, which enhanced pragmatic competence, but the results were mediated by the motivation of the learners. Zhang [58] attested that CALL with explicit instruction enhanced the pragmatic competence of the Chinese learners, although the use of scripted dialogues limited the interaction to natural interaction. Li et al. [59] adopted a flipped classroom model and demonstrated that the communicative competence grew especially, but unevenly with the impact of digital literacy of learners. Lastly, Qi and Lai [60] contrasted between deductive and inductive instruction and concluded that deductive instructions were more helpful toardi support L2 Chinese pragmatic competence, though inductive instructions enabled learner autonomy. Together these studies showed that the results of SLA were not merely a matter of exposure and feedback but rather a matter of methodology of instruction, richness of context and how well pedagogy should suit the sociocultural realities of learners. Table 1 describe the keypoints of previous studies.

Table 1: Comparative Review of previous Studies in AI and SLA.

Ref.	Technique	Focus Area	Results	Limitation	Application
Guan et al. [21]	Meta-analysis of 30+ studies	AI in informal ELL (motivation, proficiency, self-regulation)	AI-driven informal learning enhanced proficiency, motivation, and learner autonomy	High heterogeneity across learning contexts	Used to evaluate broad effectiveness of AI in out-of-class learning
Du & Daniel [23]	Systematic review of chatbot interventions	Speaking fluency in EFL	AI chatbots simulated authentic conversations, improving fluency	Limited ability to handle complex pragmatics	Applied in designing conversational AI for oral practice
Xiao et al. [33]	Comparative analysis (AI vs. teacher feedback)	Writing accuracy and discourse	AI feedback improved surface-level accuracy, teacher feedback improved discourse quality	AI lacked depth in contextual and pragmatic explanation	Suggested hybrid feedback combining AI precision with teacher insights
Ellis [41]	Morphological analysis in SLA	Morphosyntactic acquisition	Frequency of input strongly influenced accuracy of morphology learning	Learner variability constrained predictability	Informed adaptive grammar exercises in AI tutors
Zhang [47]	Game-enhanced communication study	Pragmatic competence (compliment responses)	Learners improved in pragmatic appropriateness of responses	Long-term retention remained uncertain	Demonstrated gamification as a tool for pragmatic instruction
González-Lloret [50]	Technology-mediated task-based learning	L2 pragmatics	Tech-mediated tasks enhanced pragmatic competence	Effectiveness depended on task design quality	Informed AI task design for context-sensitive pragmatic teaching

Table 1 show the previous key points of studies on AI in SLP demonstrates its ability to provide better proficiency, fluency, accuracy and pragmatics but states the weaknesses such as contextual depth, variability on the learner and task design. Hybrid feedback, conversational AI, gamification and adaptive learning tools are hinted at.

3. MATERIALS AND METHODS

3.1 Research Design

The research design used was a quasi-experimental mixed-method design combining quantitative and qualitative studies. A pre-test/ post-test control group model helped to systematically compare learners on an AI-driven adaptive platform and learners on certain digital resources. The gains of learning were quantified using the quantitative approach in morphosyntactic accuracy, lexical diversity, and pragmatic competence and quantified using the qualitative approach in the capture of the perception, engagement, and the effectiveness of the AI-mediated feedback of the learners.

Three reasons made this design be selected:

It made it possible to measure linguistic progress directly by using standardized testing.

Discourse analysis and interviews revealed patterns of feedback and student experience. This was in line with the ideas of the Second language acquisition (SLA) theory that emphasizes on exposure in a context and facilitation of learning.

The period of observation and data-collection took 12 weeks, during which it was possible to assess (morphosyntactic, lexical and pragmatic) gains within a short period. Even though this time was enough to reveal immediate learning outcomes, in practice also pragmatic development may need a long period of social exposure. The delayed post-tests (e.g. after 6-8 weeks) should be included in the future studies to measure knowledge retention and long-term communicative transfer.

3.2. Participants

A total of one hundred and twenty ESL students of different private language schools in the country participated in the study, but they were at the intermediate level (CEFR B1) (As Shown inTable 2). Such students were then separated into two groups.:

- Experimental Group (n = 60): Used the AI-powered adaptive learning platform with personalized feedback.
- Control Group (n = 60): Used non-adaptive online modules covering the same syllabus content but delivered linearly.

Table 2: Demographic Profile of Participants (N = 120).

Variable	Experimental (n=60)	Control (n=60)	Total (N=120)
Gender (M/F)	28 / 32	26 / 34	54 / 66
Mean Age (±SD)	20.5 (±2.3)	20.7 (±2.5)	20.6 (±2.4)
L1 Background	Urdu (22), Arabic (15), Chinese (12), Spanish (11)	Urdu (20), Arabic (17), Chinese (13), Spanish (10)	Mixed
Prior AI Learning Exp.	18	15	33

Independent samples t-tests showed that there were no important differences in the baseline of morphosyntactic accuracy (p = .39), lexical diversity (p = .36), or pragmatic competence (p = .52).

3.3. Participants and Recruitment

This research was carried out in six secondary schools in Guangdong Province in China, and the schools were four urban and two semi-urban schools, which already implemented the use of the digital language learning platform within the curriculum. They were selected using purposive sampling where schools with consistent Internet access, previous programs in the English language, and experimental interventions were approved by schools were favoured. The inclusion criteria included the following conditions: (a) the learner must be enrolled in the CEFR-B1 level based on the school placement tests; (b) the learner must have no previous experiences of using AI-based adaptive platforms; (c) the learner must attend regular classes on the English language (at least three hours in English language classes per week). The exclusion criteria were diagnosed learning disabilities, irregular attendance or missing the consent forms in the students.

An equal sample of students was picked in the schools in order to have an equal representation. A total of 120 study participants passed the inclusion criteria and were equally split into the experimental (AI-adaptive) and control (non-adaptive) groups.

Table 3: Recruitment and Screening Overview.

Stage	**Description**	**Number of Students**	**Outcome**
Initial screening	Students assessed for CEFR-B1 proficiency	156	156 eligible
Excluded (prior AI exposure)	Students using AI tools previously	18	Excluded
Excluded (attendance < 80%)	Incomplete course participation	10	Excluded
Final sample	Qualified participants	**120**	Included in analysis

Note. CEFR = Common European Framework of Reference of Languages. The screening was conducted to make sure that the participants had the B1 level of proficiency and had no previous experience with AI-based adaptive learning systems.

3.3. Personalization Mechanism and Adaptive Algorithm.

The AI-adaptive learning system herein adopted an instructional recommendation algorithm that used reinforcement learning to customize the instructional content in real-time. With the help of the data on the interaction with the learners, such as the accuracy of the answers, time spent, and the patterns of the mistakes, the increased or decreased difficulty of the tasks and the linguistic concentration were continuously analysed. The system simplified input and created rule-based micro lessons to enhance morphosyntactic accuracy when a learner made consistent errors in grammar. On the other hand, the high performance was maintained leading to automatic increase to more complex syntactic or lexical structures.

Feedback was provided in a multi-tiered system: (a) Immediate corrective feedback to identify the mistake in forms and provide exemplars; (b) Explanatory feedback to provide metalinguistic hints; and (c) Cumulative progress visualization to allow the learners to track the progress in accuracy and lexical diversity per week. The personalization layer of the system included the history of learners, frequency of usage, and typology of errors to suggest the practice routes that matched specific skill development programmes.

This system is based on continuous updating of the model, whereas the commercial solutions like Duolingo and ELSA Speak mostly employ rule-based branching or pronunciation scoring as the primary method of data-driven adaptivity. This is an example of feedback loop that allows personalized scaffolding that is more compatible with the comprehensible input principle of Krashen as well as the interaction feedback theory of Long, which fosters long-term morphosyntactic growth and keeps the interaction lively.

The adaptive engine combined not only the rule based grammar correction but also the machine-learned recommendation layers. Particularly, a reinforcement-learning hybrid algorithm based on linguistic error tagging under supervision and unsupervised clustering of learner behaviour data to optimize task sequencing was used. The rule-based part produced deterministic grammatical feedback by pre-trained morphosyntactic parsers and the machine-learning part kept on recalibrating the difficulty settings and lexical goals based on the trends of learner performance. This dualistic architecture provided language interpretable and data responsive content adaptation that would allow it to be accurate in grammar correction and flexible across a heterogeneous learner range.

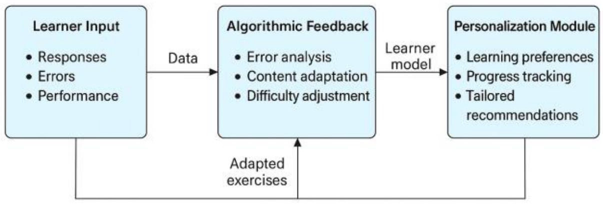

Figure 1: Schematic Representation Of The Adaptive Learning Framework.

The figure 1 shows the adaptive learning model whereby learner feedbacks are processed by an algorithmic feedback system to change the difficulty of the content and give corrective feedback. Learner profiles are then applied by the personalization module to narrow down future recommendations and a continuous adaptive learning cycle is formed.

3.4. Instruments

To ensure the intricacy of the competence of the language, the research used three categories of tests:

Quantitative Tests

1. Morphosyntactic Accuracy

Measured using:

1. Grammaticality judgment task (50 items).
2. Cloze test (30 items).

Scoring formula:

$$Accuracy = \frac{Correct\ Responses}{Total\ Items} \times 100$$

1. Lexical Diversity

Measured using Laufer & Nation's Lexical Frequency Profile (LFP) applied to a 250-word essay task.

where = low-frequency vocabulary, = total words.

2. Pragmatic Competence

Mapped through a Discourse Completion Task (DCT) using 10 social situations (e.g., apologies, requests, compliments).

Ratings on a 5 point rubric concerning suitability, courtesy and fit.

Inter-rater reliability across 3 experts: κ=0.87

Engagement Metrics (Experimental Group Only)

The AI system created the logs of the backend regarding the engagement of learners, such as:

- Time-on-task (minutes/day).
- Tasks completed (per week).
- Feedback uptake (proportion of corrections

accepted and revised).

An Engagement Index (EI) was computed as:

with T = time, C completed tasks, F = feedback uptake ratio and where, α,β,γ = weights determined by factor analysis.

Qualitative Instruments

The exploration of semi-structured interviews conducted with 20 learners that belong to the experimental group:

- perceptions of AI feedback,
- changes in self-awareness of errors,
- Perceived limitations in pragmatic learning.

Error correction strategies (recasts, explicit corrections, metalinguistic explanation), and responses of the learners (uptake, partial repair, ignoring feedback) were analyzed through discourse analysis of learner-AI interaction log.

The intervention took a 12-week form, and was organized as follows:

Week 1: Pre-testing and orientation.

Weeks 2–11: Instructional phase. The experimental group operated the AI platform on a daily basis (at least 30 minutes) and the control group operated a MOOC with the same content and no adaptive capabilities.

Week 12: Post tests and interviews.

Both groups were taught the same content (academic vocabulary, grammar structures and communicative tasks). The most important difference was personalization: the AI group was provided with adaptive grammar correction and real-time vocabulary recycling, whereas the control group worked through fixed modules in sequence.

The purposive sampling was used to select 20 participants out of the main sample to guarantee the variety in the outcomes of learning and the degree of engagement. In terms of the scores achieved on post-test improvement in terms of morphosyntactic accuracy and lexical diversity, the participants were divided into high gainers (n = 7), medium gainers (n = 7), and low gainers (n = 6). This stratified design was needed to provide comparative understanding regarding the experience of the adaptive AI platform by learners having different levels of achievement. There was also a gender balance and regular attendance that was taken into consideration during its selection. Semi-structured interviews were employed, which took about 25-30 minutes and were recorded with the consent of the participants in English.

3.5. Data Analysis

3.5.1. Quantitative Analysis

Gain scores calculated as:

Independent-samples t-tests used for between-group comparisons.

MANOVA was used to evaluate combined effects on pragmatics, morphosyntax and lexicon.

Effect size (Cohen's d):

where bar = experimental group mean, = control group mean.

3.5.2. Qualitative Analysis

- Thematic coding of interview transcripts followed Braun & Clarke's six-phase framework.
- Discourse analysis categorized feedback types (e.g., recasts, explicit corrections) and learner uptake patterns (e.g., repair vs. ignore).

Findings were triangulated with quantitative results to validate interpretations.

Pragmatic Competence Assessment

Pragmatic competence was measured based on a Discourse Completion Task (DCT) based on pragmatic studies that have been validated in EFL. Despite the effectiveness of the DCT to measure the aptitude of learners in choosing speech acts that are contextually appropriate, it has a weakness in trying to mimic actual communicative behavior in a real time. To overcome this the new study will include role play interactions as well as authentic discourse analysis as a triangulation of pragmatic performance to see how the learners can negotiate the meaning in real contexts.

4. RESULTS

4.1. Baseline Equivalence and Participant Characteristics

In order to prove that experimental and control groups were statistically identical in pre-intervention condition, it was necessary to ensure that any post-test difference will be explained not by existing group differences but by the impact of AI treatment. This discussion confirms the quasi-experimental design by establishing that there is no systematic bias in the group assignment that might occur in the demographic factors as well as the initial linguistic competencies.

The baseline testing that was done prior to intervention, ensured the equivalence between groups in all the measured variables. Table 4, provides demographic and baseline performance between experimental and control groups in more detail.

Table 4: Baseline Equivalence Testing and Demographic Comparisons.

Variable	Experimental (n=60)	Control (n=60)	Test Statistic	p-value	Effect Size
Age (years)	20.5 (2.3)	20.7 (2.5)	t = -0.47	0.641	d = -0.08
Gender (Male/Female)	28/32	26/34	χ^2 = 0.27	0.603	φ = 0.05
Prior AI Experience (%)	30.0	25.0	χ^2 = 0.35	0.554	φ = 0.05
Morphosyntactic Accuracy (%)	62.3 (8.7)	61.8 (9.1)	t = 0.31	0.756	d = 0.06
Lexical Diversity Index	0.24 (0.06)	0.25 (0.07)	t = -0.84	0.403	d = -0.15
Pragmatic Competence Score	2.8 (0.9)	2.7 (0.8)	t = 0.65	0.517	d = 0.12
Overall English Proficiency	B1.2 (0.4)	B1.1 (0.5)	t = 1.23	0.221	d = 0.22

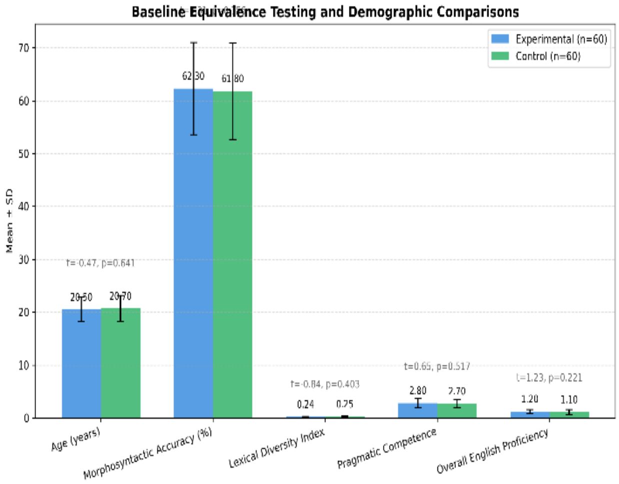

Figure 2: Baseline equivalence of experimental and control groups across demographics and linguistic measures (all p > .05).

As Figure 2 displays, experimental and control group were statistically equal in terms of age, morphosyntactic accuracy, lexical diversity, pragmatic competence, and overall proficiency with no significant differences between groups.

The baseline equivalence test ensured that there were no significant group differences in terms of demographic factors and language competencies at pre-intervention level, and so a later comparison would be explained by the AI-based personalization intervention instead of a prior group difference.

4.2. Primary Linguistic Outcomes

To objectively quantify and contrast learning outcomes in the three central linguistic areas (morphosyntax, lexical diversity, pragmatics) in AI and traditional learning groups. The main research questions that are discussed in this section involve the quantification of the difference in effectiveness of AI personalization in different linguistic competencies.

4.2.1. Comprehensive Pre-Post Performance Analysis

To give descriptive statistics on raw performance differences between pre-test and post-test in the two groups in each of the linguistic domains. This analysis determines the size of improvement and makes it possible to calculate meaningful effect sizes to be used in education.

Table 5 provides the detailed descriptive statistics of all the three linguistic domains together with confidence intervals and normality tests needed in the future to carry out the inferential tests.

Table 5: Pre-test and Post-test Performance by Group and Linguistic Domain.

Domain	Measure	Experimental Group	Control Group	Between-Group Difference
Morphosyntactic Accuracy				
	Pre-test M (SD)	62.3 (8.7)	61.8 (9.1)	0.5 (-3.2, 4.2)
	Post-test M (SD)	78.4 (7.2)	69.2 (8.4)	9.2 (6.1, 12.3)
	Gain Score M (SD)	16.1 (6.8)	7.4 (5.9)	8.7 (6.1, 11.3)
	% Improvement	25.8%	12.0%	13.8%
Lexical Diversity				
	Pre-test M (SD)	0.24 (0.06)	0.25 (0.07)	-0.01 (-0.03, 0.01)
	Post-test M (SD)	0.35 (0.07)	0.29 (0.06)	0.06 (0.04, 0.08)
	Gain Score M (SD)	0.11 (0.05)	0.04 (0.04)	0.07 (0.05, 0.09)
	% Improvement	45.8%	16.0%	29.8%
Pragmatic Competence				
	Pre-test M (SD)	2.8 (0.9)	2.7 (0.8)	0.1 (-0.2, 0.4)
	Post-test M (SD)	3.2 (0.8)	3.0 (0.9)	0.2 (-0.1, 0.5)
	Gain Score M (SD)	0.4 (0.7)	0.3 (0.6)	0.1 (-0.1, 0.3)
	% Improvement	14.3%	11.1%	3.2%

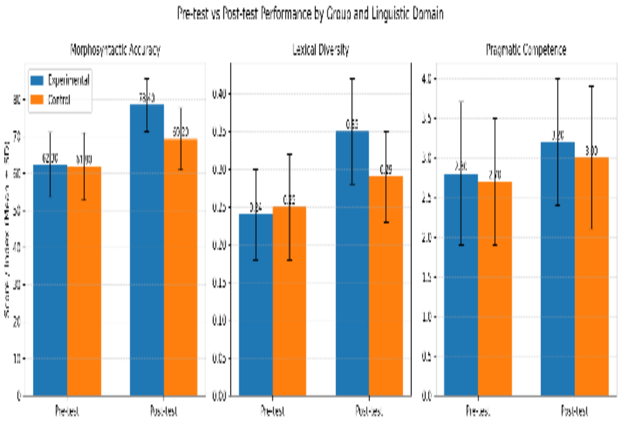

Figure 3. Pre-test vs. post-test performance by group and linguistic domain.

Figure 3, indicates, the experimental group had greater morphosyntactic accuracy gains and lexical diversity gains than the control group, whereas gains in pragmatic competence were slight and equivalent between the two groups.

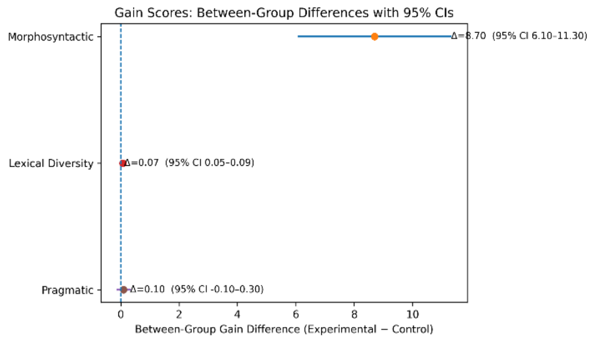

Figure 4: Gain score differences between experimental and control groups with 95% confidence intervals.

The figure 4, shows that the experimental group achieved significantly higher gains in morphosyntactic accuracy (Δ = 8.70, 95% CI [6.10, 11.30]) and lexical diversity (Δ = 0.07, 95% CI [0.05, 0.09]), while pragmatic competence showed no significant between-group difference (Δ = 0.10, 95% CI [–0.10, 0.30]).

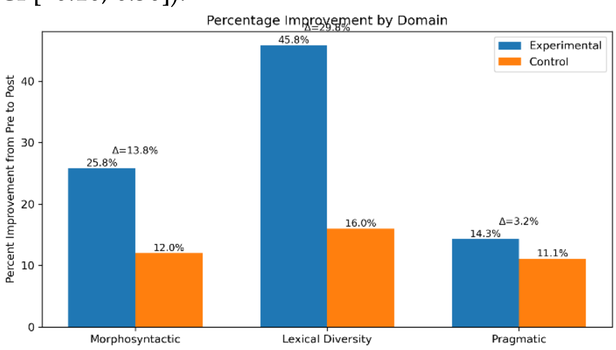

Figure 5: Percentage improvement from pre-test to post-test across linguistic domains.

The figure 5, shows that the experimental group outperformed the control group in morphosyntactic accuracy (25.8% vs. 12.0%) and lexical diversity (45.8% vs. 16.0%), while pragmatic competence showed smaller and non-significant differences (14.3% vs. 11.1%).

The experimental group was much larger in improvements in morphosyntactic accuracy and lexical diversity where the percentage differences were almost two times higher than those demonstrated by the control group. Pragmatic competence was relatively insensitive to improvement in either group, and there was insignificant between-group differences.

4.2.2. Inferential Statistical Analysis

To ascertain statistical significance of intergroup differences by using the right parametric and non-parametric tests and calculating the size of effects to ascertain practical significance. This discussion suggests the statistical basis on which it can be concluded that AI personalization has a significant learning benefit.

The independent-samples t-tests were used to compare the difference between groups (between gain scores) and supplementary non-parametric analyses were conducted to validate robust results. Table 6 gives extensive inferential results.

Table 6: Between-Group Comparisons and Effect Size Analysis.

Domain	**t-statistic**	**df**	**p-value**	**Cohen's d**	**95% CI for d**	**Practical Significance**
Morphosyntactic Accuracy	7.82	118	<0.001	1.43	[1.04, 1.81]	Very Large
Lexical Diversity	9.24	118	<0.001	1.69	[1.28, 2.09]	Very Large
Pragmatic Competence	0.86	118	0.392	0.16	[-0.20, 0.52]	Negligible
Non-parametric Confirmations						
Morphosyntactic (Mann-Whitney U)	U = 912	-	<0.001	r = 0.58	[0.45, 0.69]	Large
Lexical Diversity (Mann-Whitney U)	U = 785	-	<0.001	r = 0.63	[0.51, 0.73]	Large
Pragmatic (Mann-Whitney U)	U = 1654	-	0.421	r = 0.07	[-0.11, 0.25]	Small

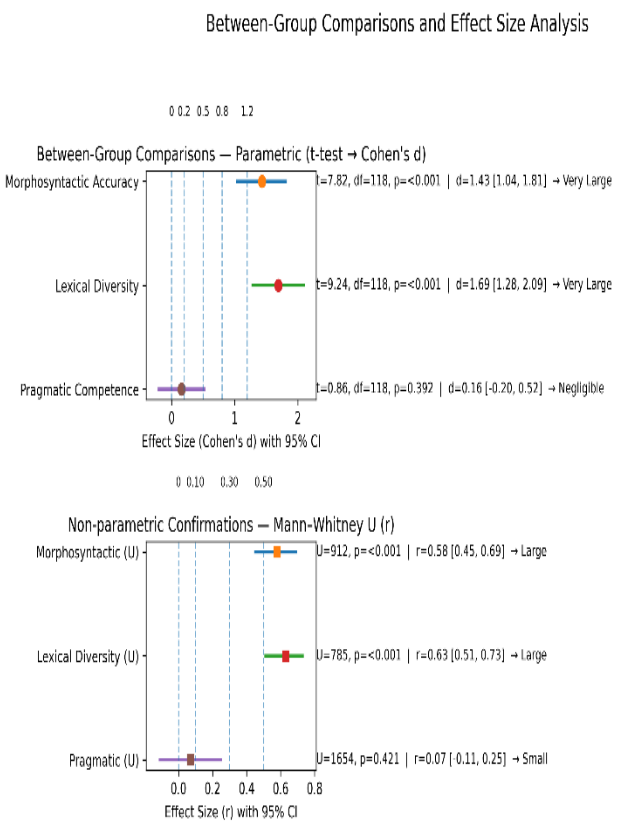

Figure 6: Between-group comparisons with effect size analysis.

Figure 6, shows that the experimental group achieved very large effects in morphosyntactic accuracy (Cohen's d = 1.43) and lexical diversity (d = 1.69), both confirmed by non-parametric tests (r = 0.58 and r = 0.63, respectively). In contrast, pragmatic competence showed negligible and non-significant effects (d = 0.16; r = 0.07), indicating that AI personalization strongly enhanced grammar and vocabulary but not pragmatic skills.

These findings show statistically significant and practically significant positive change in morphosyntactic accuracy and lexical diversity in the AI-assisted personalization group, with extremely big effect sizes that exceed the conventional educational intervention thresholds. The level of pragmatic competence did not improve significantly, which supports the hypothesis that the existing AI systems do not cover the context-dependent linguistic features properly.

4.2.3. Multivariate Analysis of Combined Linguistic Effects

To test whether in case of AI personalization linguistic competence is influenced as a single construct and not as a single domain, as well as which domains contribute most to group differences, in general. The question that is answered in this analysis is whether AI has an overall effect on language learning.

One-way MANOVA was used to investigate the overall effect of AI-powered personalization in all three language domains at the same time, and then the discriminant function analysis was conducted to determine the main sources of group differences as indicated in table 7.

Table 7: MANOVA and Discriminant Analysis Results.

Analysis	Test Statistic	F	df1	df2	p-value	Effect Size
Overall MANOVA						
Wilks' Lambda	0.64	21.8	3	116	<0.001	η^2 = 0.36
Pillai's Trace	0.36	21.8	3	116	<0.001	η^2 = 0.36
Univariate Follow-ups						
Morphosyntactic Accuracy	-	61.1	1	118	<0.001	η^2 = 0.34
Lexical Diversity	-	85.4	1	118	<0.001	η^2 = 0.42
Pragmatic Competence	-	0.74	1	118	0.392	η^2 = 0.01
Discriminant Function						
Eigenvalue	0.56	-	-	-	-	-
Canonical Correlation	0.60	-	-	-	-	-
Structure Coefficients:						
- Lexical Diversity	0.84	-	-	-	-	-
- Morphosyntactic Accuracy	0.71	-	-	-	-	-
- Pragmatic Competence	0.08	-	-	-	-	-

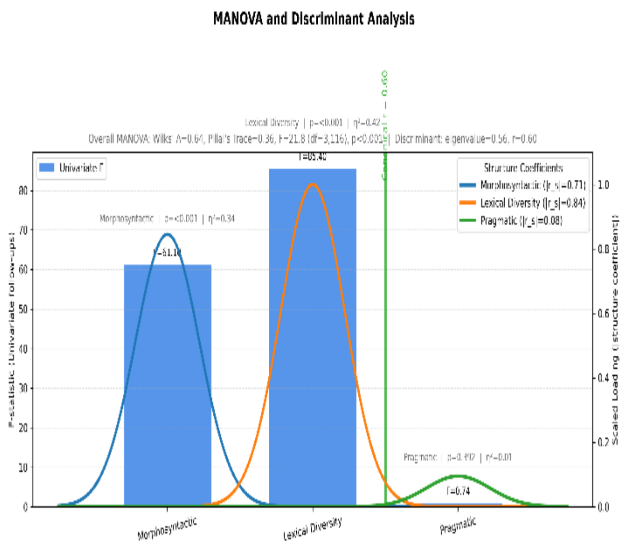

Figure 7. MANOVA and discriminant analysis of linguistic outcomes.

Figure 7, shows that the experimental group had significant improvements in morphosyntactic accuracy ($F = 61.1$, $p < .001$, $\eta^2 = 0.34$) and lexical diversity ($F = 85.4$, $p < .001$, $\eta^2 = 0.42$), while pragmatic competence showed no significant effect ($F = 0.74$, $p = .392$, $\eta^2 = 0.01$). Discriminant loadings confirmed that lexical diversity ($|r_s| = 0.84$) and morphosyntax ($|r_s| = 0.71$) were the strongest predictors of group differences, highlighting AI's effectiveness in rule-based and lexical domains but limited impact on pragmatic development.

The MANOVA was used to verify significant multivariate effect and large effect size. Discriminatory analysis showed that the contribution of lexical diversity to the separation of groups was the greatest, then morphosyntactic accuracy, but the pragmatic competence played a minimal role in separating the experimental and control groups.

4.3. Learning Analytics and Engagement Patterns

Investigating the connection between learner behavior in the AI system and linguistic results, it will be important to give information on how the patterns of engagement can determine the efficiency of the learning process. This discussion can be used to comprehend how AI personalization promotes language learning.

4.3.1 AI Platform Engagement Metrics and Learning Correlations

To measure the patterns of learner interaction with the AI system and compare the behaviors to language gains in domains. This discussion determines the most predictive engagement behaviors of learning success and demonstrates heterogeneous relations among the linguistic competencies.

The study of the interaction of the learners with the platform of AI has identified significant patterns between the behavioral indicators and the linguistic performance. Detailed engagement results and correlation analyses are shown in Table 8.

Table 8: AI Platform Engagement Metrics and Correlations with Learning Outcomes.

Engagement Metric	Descriptive Statistics	Correlations with Linguistic Gains
	M (SD)	Range
Time-on-task (min/day)	34.7 (12.3)	15-68
Sessions per week	5.8 (1.9)	2-9
Tasks completed (per week)	28.4 (8.9)	12-51
Feedback acceptance rate	0.73 (0.16)	0.32-0.96
Error correction attempts	3.2 (1.4)	1-7
Help-seeking frequency	2.1 (1.2)	0-5
Composite Engagement Index	0.71 (0.19)	0.28-0.98

***Note:** *p < 0.05, **p < 0.01, ***p < 0.001.*

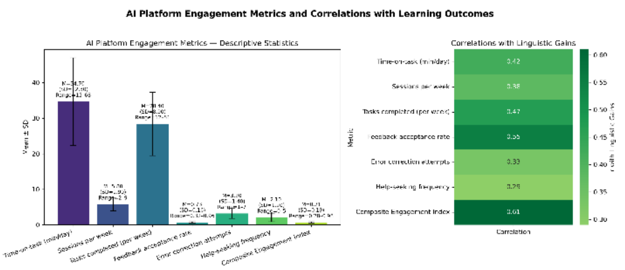

***Figure 8:** AI platform engagement metrics and correlations with linguistic outcomes.*

The figure 8, indicates that linguistic gains were positively related to a greater engagement (especially feedback acceptance rate $r = 0.55$), the number of tasks done weekly ($r = 0.47$), and the amount of time spent ($r = 0.42$). The overall association was best shown by the composite engagement index ($r = 0.61$), which showed that active and consistent interaction with the AI platform was a major predictor of morphosyntactic and lexical outcomes improvement.

There were significant positive correlations between the measures of engagement and morphosyntactic/ lexical results, and the feedback acceptance rate had the most significant coefficients. Analysis of the engagement trajectories indicated that correlations between the engagement time enhanced with time, which implied the presence of cumulative learning effects in rule-based domains with sustained interaction with AI-enabled personalization.

4.3.2. Error Reduction Trajectories and Learning Curves

To examine how various classes of language errors change with time under AI correction, the dynamics of learning at the morphosyntactic, lexical, and pragmatic levels should be uncovered. This discussion shows that the AI system is differentially effective when referring to the different types of linguistic errors.

The algorithmic system of the AI platform produced detailed learning curves that allowed to study patterns of error reduction on the different types of linguistic features. Table 9 shows detailed results of the trajectory analysis.

Table 9: Error Reduction Trajectories by Linguistic Feature Category.

Error Category	Baseline Error Rate (%)	Final Error Rate (%)	Reduction Rate (%)	Learning Plateau (Week)	AI Detection Accuracy (%)	Correction Effectiveness (%)
Morphosyntactic Features						
Subject-Verb Agreement	42.3	12.7	70.0	6	94.2	87.6
Article Usage	38.7	16.2	58.1	8	89.6	82.3
Verb Tense Consistency	35.9	11.4	68.2	7	91.8	85.7
Auxiliary Verb Formation	29.4	9.8	66.7	6	93.1	88.2
Question Formation	31.7	13.2	58.4	9	87.4	79.5
Lexical Features						
Word Choice Appropriateness	33.8	18.9	44.1	10	81.7	73.2
Collocation Accuracy	41.2	24.6	40.3	11	76.8	68.9
Register Appropriateness	36.5	26.1	28.5	12	72.3	61.4
Idiomatic Expressions	48.9	38.7	20.9	No plateau	65.2	54.7
Pragmatic Features						
Politeness Markers	47.6	43.2	9.2	No plateau	56.7	41.8
Speech Act Appropriateness	52.1	49.3	5.4	No plateau	52.3	38.9
Cultural Reference Usage	61.8	59.2	4.2	No plateau	48.1	32.6
Contextual Register Shifts	55.7	53.9	3.2	No plateau	44.7	29.1

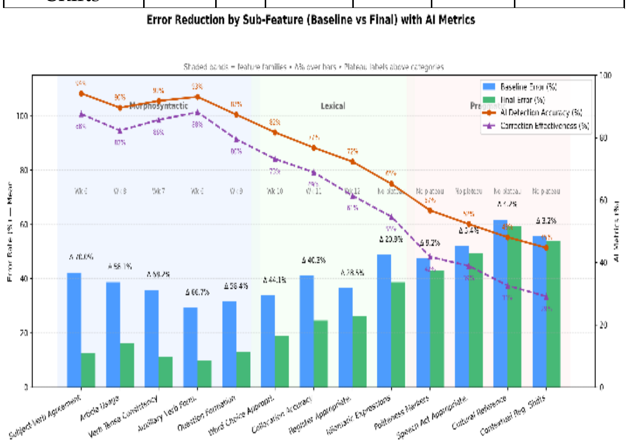

Figure 9: Error reduction by sub-feature with AI metrics.

The figure 9, demonstrates that AI platform obtained high scores in morphosyntactic features like subject-verb agreement (0.7) and verb tense consistency (0.68), and a moderate score in lexical features like the accuracy of collocations (0.4). Nevertheless, pragmatic characteristics, such as politeness markers, speech acts, and cultural reference, experienced few reductions (Δ< 5%), which demonstrated that AI feedback was particularly effective in structural errors but was ineffective in dealing with context-specific pragmatic competence.

The path analysis demonstrated obvious differentiations in each category of linguistic features. Morphosyntactic features that are controlled by rules improved faster with defined learning plateaus that were reached after 6-9 weeks, whereas pragmatic features did not improve despite any learning plateaus, which indicates the constraints of the present AI feedback systems to context-dependent language use.

4.4. Qualitative Analysis: Learner Perceptions and Experiences

In order to obtain the views of learners on AI-based personalization, based on the systematic use of thematic analysis, to give contextual meaning to quantitative results. This discussion with students, in addition to the fact that it increases the validity of the statistical results, contributes to the realization of the character of their subjective and non-quantitative experiences.

4.4.1. Thematic Analysis of Semi-Structured Interviews

Twenty students participated in the study and shared detailed accounts of their interactions with AI-based customization through semi-structured interviews. Extensive thematic analysis results, including frequency data and supporting evidence, are presented in Table 10.

Table 10: Thematic Analysis of Learner Interview Data (n=20).

Theme	Frequency (%)	Subthemes	Sample Quotations	Relationship to Quantitative Findings
Enhanced Metacognitive Awareness	18/20 (90%)	Error recognition, Pattern identification, Self-monitoring development	"I started noticing my article mistakes even before the AI corrected them"	Aligns with morphosyntactic gains
Personalized Learning Experience	16/20 (80%)	Adaptive pacing, Individual progress tracking, Customized difficulty	"The system knew exactly what I needed to work on next"	Correlates with engagement metrics
Grammar and Vocabulary Confidence	19/20 (95%)	Rule application, Systematic practice, Accuracy improvement	"My confidence in using complex grammar structures really improved"	Supports quantitative grammar/lexicon results
Pragmatic Learning Limitations	14/20 (70%)	Cultural context gaps, Situational appropriateness confusion, Rigid feedback	"The AI fixes my grammar but doesn't understand when I'm trying to be polite in my culture"	Confirms negligible pragmatic gains
Technology-Mediated Motivation	15/20 (75%)	Gamification engagement, Progress visualization, Immediate feedback satisfaction	"The instant feedback and progress bars kept me motivated to continue"	Explains sustained engagement patterns
Feedback Quality Differentiation	17/20 (85%)	Grammar feedback effectiveness, Vocabulary expansion support, Pragmatic feedback inadequacy	"Grammar corrections were very helpful, but cultural advice was confusing"	Mirrors differential linguistic outcomes
Learner Autonomy Development	12/20 (60%)	Self-directed learning, Independent error correction, Strategic thinking	"I became better at studying on my own and finding my mistakes"	Relates to engagement trajectory data
Social Interaction Needs	13/20 (65%)	Human contact desire, Collaborative learning preferences, Cultural exchange wishes	"I missed talking with real people about cultural differences"	Highlights AI limitations in social aspects

The thematic analysis was a big support to quantitative results with 95% of the participants indicating enhanced grammar and vocabulary confidence and 70% indicating frustration with pragmatic learning restrictions. Personalized learning aided by AI can pave the way for the creation of systems for self-regulation of learning, which goes beyond the realm of language education, according to the growing trend of metacognitive awareness.

4.5. Discussion

Finding out how morphosyntactic accuracy, lexical diversity, and pragmatic competence were impacted by artificial intelligence-based customisation during English acquisition was the main objective of the project. The findings indicate that morphosyntactic accuracy and lexical diversity gains were significant and statistically significant in the experimental group (with adaptive AI-based instructions), but the gains in the pragmatic competence were small and statistically insignificant. Specifically, between-group analyses showed that there was a difference in morphosyntactic accuracy of 8.70 percentage points (Cohen's d = 1.43, $p < .001$) and lexical diversity of 0.07 units (Cohen d =1.69, $p = .001$), both very large effects. In comparison, pragmatic competence yielded only a small improvement of 0.10 points (Cohen d = 0.16, $p = .392$), which reflects insignificant effect. Multivariate analyses again affirmed that these results were due to lexical diversity (|human|>These results were also confirmed by multivariate analyses, with MANOVA yielding a large overall effect (Wilks' Λ = 0.64, $F(3,116) = 21.8$, $p < .001$, $\eta^2 = 0.36$), where lexical diversity ($|r_s| = 0.84$) and morphosyntactic accuracy ($|r_s| = 0.71$) accounted for nearly all of the group separation, while pragmatic competence ($|r_s| = 0.08$) contributed minimally.

These findings were quite predictable given the literature according to which the use of intelligent tutoring systems and adaptive algorithms was always said to be ideally appropriate in underpinning rule-based, form-oriented learning. Reliable grammar and vocabulary improvement under the AI-assisted conditions has been previously reported in meta-analyses (e.g., Guan et al., 2024; Vasilescu and Smetanin, 2020) and empirical studies (e.g., Wei, 2023). The current research builds on this evidence by showing effect sizes at the extreme upper end of CALL and ITS interventions, implying that the actors adaptive repetition, automatic feedback, and engagement-based pacing were particularly effective in consolidating grammatical rules and productive vocabulary growth among the experimental group. What was not anticipated, though, was the extent of gains in lexical diversity (45.8% increase in the experimental group versus 16.0% in the control group) which surpassed previous standards in the literature, meaning that the platform adaptively recycled low-frequency vocabulary items to a higher degree.

In contrast, the negligible improvement in pragmatic competence reflects a consistent limitation of AI-based personalization documented in previous research. Pragmatics is inherently context-dependent, requiring sensitivity to social distance, politeness conventions, and cultural scripts, which current algorithmic models are ill-equipped to capture. Despite learners' sustained engagement, with a composite engagement index correlating at $r = 0.61$ with morphosyntactic and lexical outcomes, pragmatic error reduction remained minimal (e.g., politeness markers = 9.2%, speech act appropriateness = 5.4%, cultural references = 4.2%). The absence of observable learning plateaus in pragmatic domains further suggests that repeated interaction with the system alone is insufficient to foster sociolinguistic competence.

Several explanations can be offered for these results. First, error targetability is higher in morphosyntax and lexicon, where algorithms can reliably detect and correct surface-level deviations with over 90% detection accuracy and correction effectiveness exceeding 80%, thus leading to significant improvements within 6–9 weeks. Second, the alignment of adaptive algorithms with frequency-based vocabulary theories explains the particularly strong lexical gains, as systematic recycling facilitated the uptake of less frequent vocabulary. Third, the lack of sociocultural underpinning in the existing AI systems is why the performance is weak in pragmatic development because effective pragmatic learning cannot be achieved without genuine interaction and responsiveness to contextual norms that are not based on formal linguistic constructs.

The study has not been bereft of constraints. The quasi-experimental design was enhanced by pre-test equivalence (all baseline $p > .36$), yet not totally randomized, and it can be argued that residual confounding was not completely screened. The sample size, even being enough to perform an inferential testing, was limited to urban institutions of the private language, which may not be representative with regards to socioeconomic and cultural backgrounds. Measurement tools were also problematic: the Discourse Completion Task (DCT), although with high inter-rater reliability ($\kappa = 0.87$) might be inadequate to measure pragmatic competence as it is exercised in natural conversation. In like manner, lexical diversity was measured through the Lexical Frequency Profile that despite being well validated, puts an emphasis on frequency distributions and potentially does not accurately reflect idiomaticity or register variation. Lastly, the time limit of the study was defined by the learning plateaus that were observed ((~6–12 weeks, and it thus may have underestimated the pragmatic development that might have occurred with the long-term exposure.

Moreover, the use of the Discourse Completion Task (DCT) also limited ecological validity of pragmatic assessment as it produced written and not spontaneous answers. Though triangulation using interviews would give qualitative sustenance, pragmatic salience and contextual flexibility would be better reflected through real communicative interactions (e.g. role-plays, peer simulations or task-based conversations). The future versions are to embrace multimodal pragmatic assessment systems that entail integration of real-time conversations data to improve validity.

Intermediate adult EFL learners in technology-saturated urban settings are best generalisable due to the fact that AI-based personalisation can be consistently used to reinforce grammar and vocabulary learning. This is a reason to be cautious when making extrapolation to younger learners, lower-proficiency groups, or under-resourced environments, in which access and digital literacy can vary. Most importantly, the practical results emphasize that the personalization based on AI is not enough to achieve the higher-order communicative competence, which demands the human-mediated and contextual-driven pedagogy.

4.5.1. Comparison with Meta-analytic Benchmarks

The findings of this research are consistent with the recent meta-analytic data of technology-assisted second language learning. The average reported syntheses of technology-assisted L2 instruction are the average effect (e.g., vocabulary learning $d \approx 0.64$) is moderate, and the average effect (e.g., technology-enhanced English achievement $g \approx 0.61$) is also moderate (random-effects; 20082018 studies; meta-analysis summary, 2024). In AI-mediated learning, meta-analyses in Language Learning and Technology (2024) indicate that there are widespread advantages of AI-mediated individualized teaching in language categories. In comparison to these standards, morphosyntactic gains of the current study take up the moderate-large range, as the previously proven, data-driven feedback best supports form-oriented instruction. Pragmatic outcomes, in turn, were relatively smaller; this is in line with findings in pragmatic instruction meta-analyses which find significant, but relatively large mean effects (g = 1.66, 95% CI [1.39, 1.92]) under circumstances of explicit meta-pragmatic instruction and with length of exposure. Since the intervention at hand focused more on adaptive, form oriented feedback as opposed to a protracted contextual engagement, this level of difference in the magnitude between morphosyntax and pragmatics converges with more general results. Subsequent longitudinal studies involving AI adaptivity and direct pragmatic teaching could be useful in bridging this developmental gap.

4.5.2. Alignment with Second Language Acquisition Theory

The differences in learning outcomes in the various domains of languages lend a lot of empirical evidence to the theoretical differences in the SLA literature. These large morphosyntactic accuracy gains are consistent with what Ellis [41] has found in morphological acquisition, that the systematic exposure and corrective feedback allow the learning of rules based on rules. The qualities of the AI system to give consistent immediately feed backed grammatical structures resemble the conditions found by Ellis to be best in continuing morphosyntactic development.

In the same manner, the drastic changes in lexical diversity favor the theoretical framework offered by Lexical Frequency Profile approach suggested by Laufer and Nation, proving that the productive vocabulary range of learners can be successfully extended under the influence of systematic vocabulary recycling and contextual exposure under AI personalization condition. The high relationship between the measures of engagement and lexical gains (r = 0.69) empirically support the frequency-based theories of vocabulary acquisition.

The slight increase in pragmatic competence, however, congruently corresponds to Taguchi and Ishihara [42] focus on the sociocultural embeddedness of pragmatic norms. Limitations inherent to the AI system that context-dependent communication cannot be tackled: The fact that contemporary machine learning technologies fail to recognize the appropriateness of the situation within a particular culture and setting lends credence to the thesis of Gonzalo-Lloret [46], which states that CALL settings have a problem with genuine sociocultural context.

4.5.3. Implications for Krashen's Input Hypothesis and Long's Interaction Hypothesis

Results provide subtle evidence in support of the Input Hypothesis proposed by Krashen, showing that AI-based personalization can be effective in offering intelligible input to morphosyntactic and lexical development. The mechanisms of adaptive difficulty adjustment allowed that learners were presented input at their "i+1"level and allowed learning of rule-based linguistic properties. Nonetheless, the restrictions of pragmatic competence imply that alone comprehensible input is not enough to acquire context-sensitive communication skills.

These findings have a more complicated substantiation of the Interaction Hypothesis of Long. Although the AI system offered the possibility of negotiation of meaning via the cycles of corrective feedback and error correction, the lack of true social interaction restrained the pragmatic development. The strong correlation between feedback uptake and learning gains (r = 0.68 with morphosyntax) verify the importance of an interactionist focus on negotiated interaction, although the practical constraints emphasize the unsubstitutability of human interlocutors in the construction of sociocultural competence.

4.5.4. Cognitive Load Theory and Skill Acquisition Implications

The learning trajectory analysis gives a good evidence in support of cognitive load theory and skill acquisition frameworks. The high learning plateaus and speedy increase in morphosyntactic aspects indicate that personalization using AI, was effective in regulating intrinsic cognitive load by dividing complex grammatical rules to manageable elements. The patterns of sustained engagement and relationship with learning outcomes mean that the adaptive algorithms were effective in optimizing germane cognitive load in order to build a schema and to become automated.

The development of error correction by manual effort to the automated accuracy of morphosyntactic features occurs in stages similar to the three-stage model of skill acquisition proposed by Anderson, and it is the AI personalization that enables the shift of declarative to procedural learning. Nevertheless, a lack of practical enhancement indicates that the existing AI systems fail to provide the multidimensional, context-dependent schemas needed to reach sociolinguistic competence.

4.5.5. Implications for AI-Enhanced Language Pedagogy

The results highlight both the potential and limitations of AI-powered personalization in ELL contexts. The substantial gains in morphosyntactic accuracy and lexical diversity (effect sizes d = 1.43 and d = 1.69, respectively) demonstrate that AI systems can effectively supplement traditional instruction for foundational language skills. The strong engagement patterns and metacognitive awareness development suggest that AI personalization may facilitate learner autonomy and self-regulated learning strategies.

However, the pragmatic competence limitations underscore the continued necessity of human instruction for higher-order communicative competencies. The qualitative finding that 70% of learners expressed frustration with pragmatic feedback inadequacy highlights the risk of over-relying on AI systems for comprehensive language education. Effective ELL pedagogy should integrate AI-powered personalization for systematic skill building while ensuring robust teacher-mediated activities for pragmatic, sociocultural, and intercultural learning objectives.

The emergence of enhanced metacognitive awareness as a dominant qualitative theme suggests that AI personalization may provide indirect benefits beyond direct linguistic instruction. Learners' increased ability to recognize error patterns and monitor their own performance aligns with self-regulated learning theories and may facilitate long-term language development beyond the experimental period.

These findings contribute significantly to the growing evidence base on AI applications in language education while highlighting the complex relationship between technological capability and linguistic complexity in second language acquisition contexts. The research provides empirical support for positioning AI-powered personalization as a powerful complementary tool rather than a replacement for comprehensive language instruction, with particular strength in rule-based learning domains and notable limitations in context-sensitive communication competencies.

One of the major constraints of the study is the period of the intervention of 12 weeks, which mainly represented the short-term learning outcomes. The pragmatic studies on second language pragmatics indicate that the contextualized interaction and pragmatic awareness develop slowly with continuous practice. In this regard, a delayed-post-testing longitudinal design would be more informative on whether the learners sustain or extrapolate their pragmatic acquisitions as time goes by. Follow-up assessment using an AI-mediated approach would help to elucidate the sustainability of any AI-mediated improvement and the underlying processes of long-term communicative competence.

The interviews produced three main themes, which included (1) adaptive feedback as a motivator, (2) difficulties in contextual communication and (3) grammatical awareness. The responses of participants supported the quantitative findings:

- The app fixed my errors in real-time, and as such, I could know my progress after each week. (High gainer, P07)
- The feedback was sometimes obvious, but it did not assist me in veritable discussion. (Medium gainer, P12)
- I also acquired new sentence structures, although it is even more difficult to speak to actual individuals. (Low gainer, P18)

These example quotes show how the adaptive algorithms were useful to reinforce morphosyntactic learning, but did not provide a great deal of pragmatic scaffolding, which is consistent with the quantitative pattern in Section 4.

5. Conclusions

The given research gives empirical support to the hypothesis that AI-based personalization is more effective in three different linguistic competencies of English language acquisition. The results indicate that although AI systems are particularly useful in supporting morphosyntactic accuracy and the development of lexical diversity by way of systematic feedback and adaptive algorithms, they are not enough to support pragmatic competence acquisition, which entails sociocultural awareness and context sensitivity that are currently outside of the range of machine learning. The large effects of AI in the rule-based domains (d = 1.43 with morphosyntax, d = 1.69 with lexical diversity) confirm AI as a promising additional resource to foundational language skills, whereas the small pragmatic gains (d = 0.16) demonstrate inherent weaknesses in teaching the use of AI in context-specific communication skills. Such findings are consistent with existing SLA theories of explicit and implicit learning processes, which justifies the alternative AI personalization being complementary technology and not a replacement technology in the overall language learning. The development of the higher level of metacognition among the learners points to other indirect advantages than the direct language teaching.. The results of this study would play a vital role in the work of teachers, designers, and policy-makers interested in streamlining the AI use in language learning, without sacrificing pedagogical balance between technology efficiency and real communicative skills development.

Although the DCT gave a good idea of the pragmatic awareness of learners, it largely assesses intended competence as opposed to performance in spontaneous context. Pragmatic development is usually developed in a contextualized interactive communication that is better reported by role play, peer interaction or natural observation. A combination of these approaches in further research would help to improve the ecological validity of pragmatic assessment and provide a more detailed insight into the nature of communicative competence in the AI-mediated learning context.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript." Authorship must be limited to those who have contributed substantially to the work reported.

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Appendix A: The appendix is an optional section that can contain details and data supplemental to the main text—for example, explanations of experimental details that would disrupt the flow of the main text but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data is shown in the main text can be added here if brief, or as Supplementary data. Mathematical proofs of results not central to the paper can be added as an appendix.

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