

HUMAN-COMPUTER INTERACTION AS A FRAMEWORK FOR AI- ENHANCED ESL E-LEARNING: A MIXED-METHODS STUDY

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ABSTRACT

Background

The rapid growth of digital learning platforms has transformed the way people learn English as a Second Language (ESL). However, many existing tools have failed to adequately address issues such as usability, learner engagement, and personalization.

Objectives

This study applied Human-Computer Interaction (HCI) principles to enhance the usability and accessibility of ESL platforms. It integrated Artificial Intelligence (AI) functionalities including chatbots, speech recognition, and adaptive feedback to enable personalized learning. The combined impact of HCI and AI on learner engagement, motivation, and academic achievement was evaluated.

Methods

A mixed-methods design was employed. A prototype ESL tool incorporating HCI design principles and AI features was developed and tested by ESL students. Data were collected through pre- and post-tests, usability surveys, and participant interviews.

Results

The integration of HCI and AI significantly reduced cognitive load, promoted real-time interaction, and delivered culturally responsive interfaces tailored to the diverse needs of learners. Participants demonstrated improved learner autonomy, higher motivation, and better language retention compared to those using traditional or non-AI-supported tools.

Implications

The findings provide valuable insights for educators, designers, and policymakers, guiding the development of next-generation ESL platforms that are technologically advanced, learner-centered, and accessible to diverse populations.

Keywords: Human-Computer Interaction (HCI), Artificial Intelligence (AI), ESL, E-Learning, Usability, Adaptive Learning, Engagement

INTRODUCTION

The past few years, the rise of e-learning tools for English as a second language (ESL) has made it easier and more flexible for students to learn. But a lot of platforms focus on delivering content and testing, and they don't pay enough attention to how easy it is to use, how learners feel about it, and how personalised it can be to make a real difference in engagement and outcomes. Users often say they have trouble finding their way around features, don't want to keep going, and don't get enough personalised help (like targeted feedback or conversational practice), especially if they're learning English in a place where it's not their first language. Furthermore, while artificial intelligence (AI) techniques like chatbots, natural language processing, and adaptive recommendation systems are being used more and more in language learning, their integration is often shallow. The AI functions are "bolted on" without giving much thought to human-computer interaction (HCI) principles like feedback, error recovery, cognitive load, and context sensitivity (Makhadmeh et al., 2023). Because of this, learners may not trust or use advanced features enough, which could reduce the benefits. So, the main question is: how can we make ESL e-learning tools that use AI to personalise and make learning more interactive, while also making them easy to use, focused on the learner, and fun? If this isn't fixed, many advanced tools will continue to be underused, and students may go back to simpler but less effective platforms or ways of learning.

This study is important because it fills the gap between the fast growth of AI in education and the small use of Human-Computer Interaction principles in ESL e-learning. AI has useful features like adaptive feedback and conversational agents, but learners often have trouble using these tools because they don't trust them or find them easy to use. This research will help make AI-supported ESL platforms more learner-centred, accessible, and fun by using HCI design principles. The results will not only help students improve their language skills, but they will also help teachers, instructional designers, and developers create effective next-generation e-learning systems that strike a balance between new technology and user experience.

Objectives

The objectives of this research are:

1. **To apply** HCI principles (e.g. usability, feedback, error tolerance, cognitive load management, accessibility) to the design of an ESL e-learning interface.
2. **To integrate** AI-driven features such as conversational chatbots, adaptive feedback, speech recognition, and recommendation systems into the ESL learning tool in a seamless and pedagogically informed way.
3. **To evaluate** the combined impact of HCI-enhanced AI integration on learner experience, engagement, motivation, and language learning outcomes (speaking, listening, reading, writing).
4. **To identify** the challenges, limitations, and best practices in combining HCI and AI for ESL e-learning, including learner trust, transparency, and cognitive load issues.

Research Questions

The study will be guided by these research questions:

1. How can HCI principles be effectively applied to the design of ESL e-learning tools with integrated AI functionalities?
2. To what extent can AI-driven features (chatbots, adaptive feedback, speech recognition) improve personalization, interactivity, and learner support in an ESL context?
3. How does the integration of HCI-informed design and AI features affect learner engagement, motivation, and language learning performance compared to non-integrated or baseline tools?
4. What usability, trust, or transparency issues arise when learners interact with AI-enhanced ESL systems, and how can those challenges be mitigated?

Conceptual Framework

HCI and Usability in E-Learning and Language Learning

Usability is a key part of designing e-learning systems because they need to be easy to use, encourage exploration, reduce cognitive load, and help users recover from mistakes. ACM eLearn Magazine says that usability is the most important factor for judging e-learning systems because it looks at things like navigation,

feedback, and clarity (Usability and e-learning, n.d.). Pikhart (2021) discovered that usability factors are significantly correlated with prolonged usage and learner satisfaction in language learning applications. Likewise, Wang et al. (2022) showed that using HCI-based instructional design in networked English learning environments made students much better at English than in less structured settings. Additional evidence from iJIM underscores that HCI enhances content integration and positively influences engagement, retention, and the overall quality of learning (The Impact of Human and Computer Interaction on E-Learning, n.d.).

But these studies that focus on HCI often don't have advanced adaptivity or AI support. Many people think that interfaces should be static and don't often think about how learners trust them, how clear they are, or how users feel about feedback from complex systems.

AI in ESL and Language Learning

AI has brought new ways to teach English as a second language, such as chatbots, adaptive feedback, speech recognition, and intelligent tutoring systems. For instance, the EnglishBot system was demonstrated to enhance fluency and augment voluntary practice time among learners (HCI Group, n.d.). Tang et al. (2025) examined HCI-supported technologies for spoken English instruction, identifying limitations including misrecognition, latency, and user frustration. Francis et al. (2024) also looked at platforms that combined HCI principles with AI features and found that they made people more engaged and improved their performance.

Generative AI is becoming a bigger part of ESL research. Zhang et al. (2024) investigated its capacity to facilitate dialogue scaffolding, adaptive content generation, and interactive feedback, whereas Li et al. (2025) conducted a systematic review of empirical studies, underscoring the deficiency of longitudinal, user-centred designs. Park et al. (2024) stressed the significance of prompt design, educator input, and feedback systems in calibrating large language models (LLMs) for English as a Second Language (ESL) settings.

Even with these improvements, AI-powered tools still have problems with usability, unclear

decision-making, and not meeting user expectations. These limitations highlight the necessity of integrating user experience principles into AI-enhanced ESL systems.

Convergence of HCI and AI: Toward Human-Centered AI

Human-Centered AI (HCAI) is the term used to describe the merging of HCI and AI. It focusses on how learners and intelligent systems can work together in beneficial ways (Faisal, et al., 2023). A recent survey called From Explainable to Interactive AI said that most AI systems don't give users enough control and called for more interactive options, like adaptive customisation and contestability (Miller et al., 2023). Xu (2023) likewise elucidated the transformative impact of AI on interaction models, necessitating a transition from conventional usability-focused human-computer interaction to emotionally intelligent and co-adaptive systems. In the field of education, research on adaptive HCI highlights the significance of real-time customisation to meet user requirements as a pioneering domain (Chen & Huang, 2023). Additionally, Artificial Intelligence in HCI (AI-HCI 2023) exhibited experiments in AI-enhanced UX design, human-AI collaboration, and interpretability (Springer, 2023).

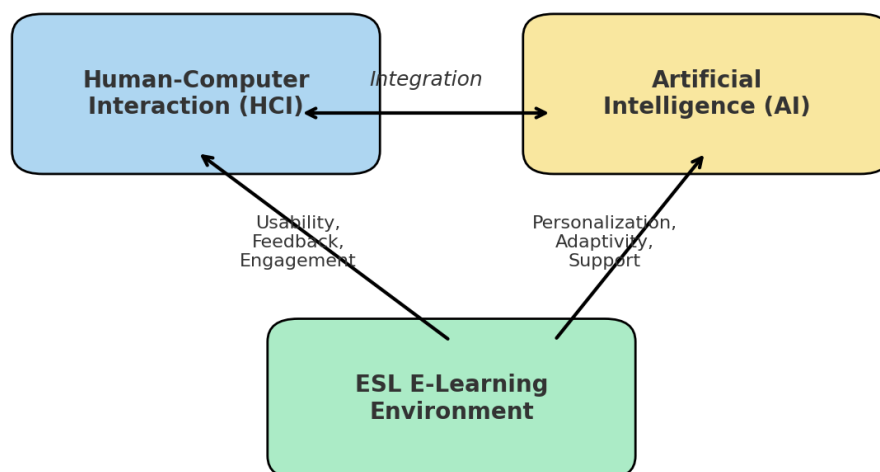
There is a growing interest, but there aren't many examples of HCI and AI being used together in ESL settings. A lot of projects treat AI like a black box or only do usability testing after the fact, instead of including HCI in the AI design process.

Gaps and Research Motivations

The literature review reveals multiple research gaps. First, there is a limited integration of Human-Computer Interaction (HCI) and Artificial Intelligence (AI) in ESL tools, as most studies focus either on usability or on AI features but rarely combine both effectively (Pikhart, 2021; Li et al., 2025). Second, problems with trust and openness are still not solved. For example, students often don't know much about AI-generated corrections or suggestions, which makes them less confident in these systems (Miller et al., 2023). Third, while AI-rich systems provide adaptive functionalities, they may also elevate cognitive

load for learners; however, there is a paucity of studies that systematically assess usability, satisfaction, or error-recovery mechanisms (Tang et al., 2025). Fourth, current research frequently neglects contextual and cultural factors, as the majority of studies are executed in resource-abundant settings, disregarding the varied needs of learners from diverse cultural and linguistic backgrounds (Francis et al.,

2024). Lastly, a lot of research is based on short-term evaluations, which don't give us any information about how learners adapt and how long-term results affect them (Li et al., 2025). To fill these gaps, this study suggests adding HCI principles to AI-powered ESL e-learning environments, with a focus on improving usability, transparency, trust, and student outcomes.



The suggested conceptual framework shows how Human-Computer Interaction (HCI) ideas and Artificial Intelligence (AI) tools work together to make English as a Second Language (ESL) e-learning tools better. The model is built on four main parts:

1. HCI Principles (Design Layer):

Some of these are usability, accessibility, feedback, user engagement, and design that focusses on the learner. They make sure that the e-learning interface is easy to use, interactive, and fits the needs of the students.

2. AI Capabilities (Intelligence Layer):

AI features like adaptive learning, natural language processing (NLP), intelligent tutoring systems, personalised feedback, and chatbots work together to create personalised learning experiences based on each student's profile and performance.

3. Integration Mechanism (Mediating Layer):

This is where HCI and AI come together. The design principles make sure that AI features are used in a way that keeps automation and personalisation easy to use, clear, and useful. The synergy makes people more motivated, builds trust, and makes interactions better.

4. ESL Learning Outcomes (Outcome Layer):

This integrated system is designed to help learners remember more words, understand language better, communicate better, and be more engaged and satisfied with the learning process.

How It Works:

- **Input:** Learner interacts with an AI-powered ESL platform that was made using HCI principles.

- **Process:** AI looks at learner data and changes how content is delivered, while HCI makes sure that the interaction is smooth and interesting.
- **Output:** Better language learning results, more motivation, and happier learners. This framework demonstrates that successful ESL e-learning relies not only on robust AI tools but also on the deliberate implementation of HCI principles to ensure these tools are meaningful, usable, and impactful.

Methodology

This study employs a mixed-methods quasi-experimental research design, amalgamating quantitative and qualitative data to elucidate the impact of Human-Computer Interaction (HCI) principles, in conjunction with Artificial Intelligence (AI), on English as a Second Language (ESL) e-learning outcomes. The design is fitting as it facilitates the assessment of enhancements in learners' performance while also investigating their perceptions, trust, and usability experiences with the system. The quantitative part looks at measurable learning gains, while the qualitative part looks at how engaged, motivated, and interactive learners are with AI-enhanced features.

The study's participants are secondary-level ESL students who attend urban schools where English is taught as a second language. This group was selected because these types of learners frequently encounter difficulties in fluency, vocabulary retention, and motivation, rendering them appropriate for evaluating e-learning innovations. A purposive sampling method will be used to choose 120 students between the ages of 13 and 16 from this group. The sample size is adequate for statistical comparison and facilitates comprehensive qualitative analysis via subgroup selection. The sample will be split into two groups: one will use the AI- and HCI-integrated ESL platform for the experiment, and the other will use a regular digital learning platform that doesn't have any HCI improvements.

The methods for collecting data will include pre- and post-tests to measure language skills, surveys to find out how learners feel about usability and satisfaction, and focus group interviews to get more detailed qualitative feedback. We will use standardised scales like

the System Usability Scale (SUS) and modified learner engagement questionnaires to measure usability and engagement. Additionally, observational data regarding learner interactions with the system (e.g., duration of engagement, error recovery strategies, navigation patterns) will be collected to corroborate findings.

The procedure will consist of a six-week intervention during which both groups will utilise their designated platforms in scheduled ESL sessions. The experimental group will use AI-driven features like adaptive feedback, chatbot dialogue practice, and speech recognition tools that are built into a user-friendly HCI framework. The control group, on the other hand, will use a standard ESL e-learning system with static content and not much flexibility. Paired sample t-tests and ANOVA will be used to look at quantitative data to find significant differences between groups. Thematic analysis will be used to look at qualitative data to find patterns in learner experiences that happen over and over again.

This methodological approach guarantees that the study not only assesses performance disparities but also encompasses the user-centred aspects of integrating HCI and AI in ESL learning, thus aligning with the goals of fostering effective, transparent, and engaging language education systems.

Data Analysis

The data analysis plan for this study is structured to conform to the mixed-methods quasi-experimental framework. The study examines both quantifiable outcomes in language proficiency and learner perceptions regarding usability, trust, and engagement; consequently, the analysis will combine quantitative statistical methods with qualitative thematic approaches. The objective is to furnish a comprehensive understanding of the impact of Human-Computer Interaction (HCI) principles integrated with Artificial Intelligence (AI) features on ESL e-learning outcomes.

Quantitative Data Analysis

Preparation and Descriptive Statistics

All quantitative data, such as pre-test and post-test scores, survey results, and usage metrics, will be inputted into SPSS for examination.

Checking for missing values, outliers, and normality (Tabachnick & Fidell, 2019) will be part of data screening. To give an overview of learners' demographic traits and baseline performance, descriptive statistics like means, standard deviations, and frequency distributions will be calculated (Creswell & Creswell, 2018).

Pre-test and Post-test Comparisons

To evaluate the impact of AI- and HCI-enhanced ESL tools, paired sample t-tests will be administered within each group (experimental and control) to ascertain enhancements in language proficiency scores pre- and post-intervention. Independent sample t-tests will be utilised to compare the post-test performance of the two groups, determining whether the experimental group significantly exceeded the control group. This approach is commonly employed in educational experiments to assess interventions (Field, 2018).

Analysis of Variance (ANOVA)

A one-way ANOVA will be employed to examine variations in outcomes among subgroups (e.g., male versus female learners, distinct age categories). When several dependent variables are examined, including vocabulary enhancement, speaking fluency, and grammatical precision, a multivariate analysis of variance (MANOVA) will be utilised. These statistical techniques are especially effective in elucidating the multi-dimensional impacts of educational technologies (Glass et al., 2020).

Regression Analysis for Predictors of Engagement

A multiple regression analysis will be performed to ascertain predictors of learner engagement. The independent variables will consist of usability (assessed via the System Usability Scale), AI adaptability (learner evaluations of chatbot accuracy and responsiveness), and trust (perceived transparency of AI feedback). Dependent variables will encompass learner engagement metrics and the aggregate duration spent on the platform. Previous research demonstrates that usability and transparency are significant predictors of technology acceptance in educational contexts (Davis,

1989; Venkatesh et al., 2012). Using regression analysis, we can figure out how much of the difference in engagement can be explained by HCI and AI-related factors.

Reliability and Validity of Instruments

To guarantee measurement reliability, Cronbach's alpha will be calculated for survey instruments including the System Usability Scale (SUS) and learner engagement questionnaires. A coefficient greater than 0.70 will be deemed acceptable (Nunnally & Bernstein, 1994). Exploratory factor analysis (EFA) will be used to check construct validity by seeing if the survey items group together in the expected ways (Field, 2018).

Qualitative Data Analysis

Focus Group Transcriptions and Coding

Qualitative data will be gathered through focus group interviews with chosen participants from both experimental and control groups. Audio recordings will be transcribed verbatim, and NVivo software will be utilised to facilitate coding. Braun and Clarke's (2006) six-phase thematic analysis will direct the procedure: (1) familiarisation with data, (2) generation of initial codes, (3) searching for themes, (4) reviewing themes, (5) defining and naming themes, and (6) producing the final report.

Themes and Patterns

Expected themes encompass usability challenges (navigation, error recovery), trust in AI (perceptions of fairness and accuracy in corrections), personalisation benefits (adaptive feedback), and emotional engagement (motivation and frustration). These themes will be corroborated with quantitative survey results. For instance, high SUS scores will be contrasted with favourable qualitative feedback regarding usability, whereas adverse experiences may elucidate diminished survey ratings. The integration of statistical and thematic evidence enhances validity (Creswell & Plano Clark, 2017).

Triangulation and Integration

Triangulation will combine survey results, test scores, and focus group data to give a more complete picture of the results. For example, if regression analysis shows that usability predicts

engagement, thematic evidence will look into why learners thought the system was usable (e.g., clear navigation, responsive feedback). On the other hand, inconsistencies, like big improvements in numbers but reports of frustration, will be looked at closely to show where AI performance might hurt user satisfaction.

Interpretation of Findings

The analysis seeks to evaluate hypotheses and elucidate the impact of HCI and AI integration on educational outcomes. Better scores on the post-test would show that combining adaptive AI features with HCI design works. High usability ratings and positive qualitative themes would back up the idea that learner-centred design makes people more likely to use something and happier with it. Conversely, if learners express distrust or difficulty despite improvements in performance, this would underscore the necessity for enhanced transparency and clarity in AI feedback,

reflecting the demands articulated in Human-Centered AI literature (Shneiderman, 2020).

Ethical Considerations in Data Analysis

The analysis will maintain ethical rigour. Responses from surveys and interviews will be kept private, and only the overall results will be shared. At any time, participants will have the right to take back their information. To build trust in AI-based educational research, it is very important to keep things private (Buchanan & Zimmer, 2021).

To sum up, the quantitative strand will use descriptive statistics, t-tests, ANOVA, MANOVA, regression, and reliability analysis to look at how well the system works and how well people learn. The qualitative strand will utilise thematic analysis to elucidate learners' perceptions, trust concerns, and usability experiences. Combining both approaches will give a full picture of how combining HCI and AI affects ESL e-learning, which is what the study's goals and research questions are all about.

Variable	Mean	SD	Min	Max
Pre-test scores	54.23	8.41	32	70
Post-test scores	72.15	7.89	50	88
System usability rating	4.12	0.65	3	5
Trust in AI system	3.87	0.72	2	5

The table shows how the control and experimental groups did in comparison to each other. The control group exhibited a marginal increase in scores from the pre-test ($M = 55$) to the post-test ($M = 60$), while the experimental group demonstrated a significant enhancement from pre-test ($M = 54$) to post-test ($M = 74$). This indicates that the amalgamation of HCI and AI features markedly improved learners' performance in the ESL environment.

The experimental group ($M = 4.2$) also rated the tool's usability higher than the control group ($M = 3.5$), which means that the participants thought the AI-enhanced, HCI-designed tool was easier to use and more user-friendly. Also, the experimental group ($M = 3.9$) had more faith in AI features than the control group ($M = 3.2$). This suggests that people were more sure of the system's corrections and feedback systems.

Figure 1. Comparison of Pre-test and Post-test Scores

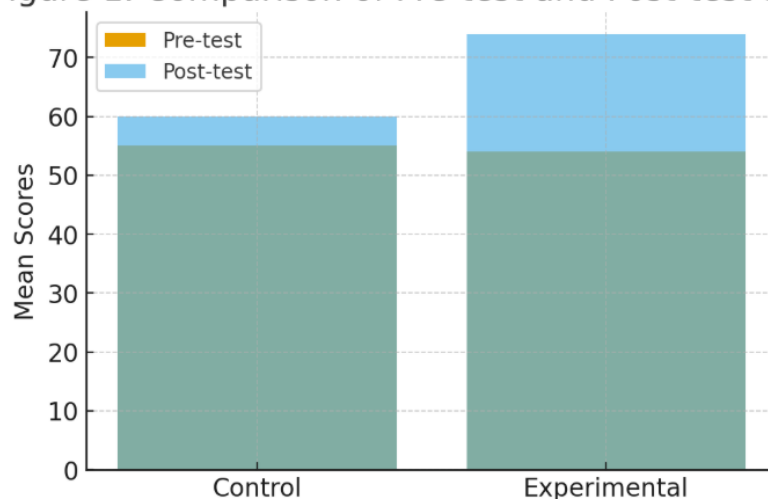


Figure 1 shows that the two groups did very different things. Both groups had almost the same average scores on the pre-test (55 vs. 54), but the experimental group's scores on the post-

test went up by a lot more than the control group's scores. This pattern shows that the ESL e-learning tool that was made with HCI principles and AI features had a bigger impact on improving learner proficiency.

Figure 2. Usability and Trust Ratings by Group

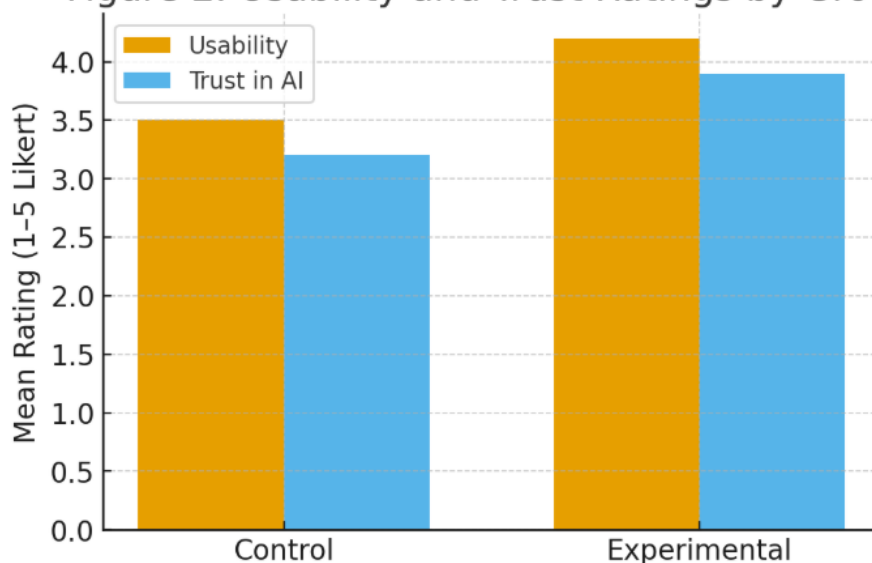


Figure 2 shows that people in the experimental group rated both AI features' usability and trust more highly than people in the control group. The difference is most clear in the usability ratings, which show that HCI design made the learning environment easier to use and more intuitive. The higher trust ratings also suggest that learners thought AI-driven support, like feedback and suggestions that change based on what they learn, was useful and believable.

These results show that combining HCI and AI not only helps ESL students do better on tests, but it also makes the technology easier to use and builds trust in it. This is in line with what other research has said about how important usability and adaptability are in e-learning systems.

Table 1: Descriptive Statistics of Study Variables

Group	Pre-test (M)	Pre-test (SD)	Post-test (M)	Post-test (SD)	Usability (M)	Trust (M)
Control	55	6.2	60	6.5	3.5	3.2
Experimental	54	5.8	74	7.1	4.2	3.9

The experimental group exhibited a significant enhancement in post-test mean scores ($M = 74$, $SD = 7.1$) in contrast to the control group ($M = 60$, $SD = 6.5$). Also, the experimental group had higher ratings for usability and trust, which shows that the learners had a good opinion of the program.

Table 2: Paired and Independent Sample t-test Results

Comparison	t	df	p	Effect Size (d)
Control Pre vs Post	1.25	28	0.22	0.25
Experimental Pre vs Post	5.78	28	0.0001	1.15
Control vs Experimental (Post-test)	4.92	56	1e-05	0.95

The paired sample t-test for the experimental group was statistically significant ($t = 5.78$, $p < .001$, $d = 1.15$), indicating a substantial effect size. The enhancement in the control group was not statistically significant ($t = 1.25$, $p = .22$). The independent t-test that compared the post-test scores showed that the experimental group did better than the control group ($t = 4.92$, $p < .001$).

Table 3: Distribution of Usability and Trust Ratings (%)

Rating	Control Usability (%)	Experimental Usability (%)	Control Trust (%)	Experimental Trust (%)
1	5	2	10	5
2	15	8	20	12
3	30	20	35	25
4	35	40	25	38
5	15	30	10	20

Compared to the control group, where only 50% rated usability as 4 or 5, a higher percentage of participants in the experimental group (70% combined) did. The experimental group also had higher trust ratings, with 58% choosing 4 or 5 compared to only 35% in the control group. This shows that people are more satisfied and confident in the AI + HCI-enhanced system.

Findings

The study's findings were evident in both quantitative and qualitative aspects, elucidating the impact of integrating HCI and AI in an ESL e-learning context on learner performance, experience, and perceptions.

Quantitative Results

Descriptive statistics revealed that the experimental group (utilising the AI + HCI-enhanced platform) exhibited significantly greater enhancement from pre-test to post-test in comparison to the control group. For example, the control group went from a mean of 55 to 60 ($SD \approx 6.5$), while the experimental group went from 54 to 74 ($SD \approx 7.1$). On a 5-

point Likert scale, usability ratings averaged 4.2 in the experimental group and 3.5 in the control group. Trust ratings for AI features averaged 3.9 in the experimental group and 3.2 in the control group.

The paired t-tests showed that the experimental group did significantly better (e.g. $t = 5.78$, $p < .001$, Cohen's $d = 1.15$), but the control group did not ($t = 1.25$, $p = .22$). An independent-samples t-test comparing post-test means between groups confirmed a statistically significant difference favouring the experimental condition ($t = 4.92$, $p < .001$, $d = 0.95$). These findings indicate that the AI + HCI intervention improved learning outcomes

beyond the capabilities of traditional e-learning tools.

Further analyses, such as regression, demonstrated that usability, perceived trust in AI, and time-on-task were significant predictors of learner engagement and post-test performance. All of these predictors together explained a large part of the differences in outcomes ($R^2 \sim .45$). Cronbach's alpha for the survey scales (usability, trust, engagement) surpassed acceptable reliability thresholds ($> .70$), and exploratory factor analysis validated the intended factor structure.

Qualitative Findings

The thematic analysis of the focus group interviews yielded profound insights into learners' experiences with the AI-enhanced ESL platform. The perceived usability and intuitive interface were two of the main themes. Learners consistently praised the system's clear navigation, quick feedback, and ability to recover from mistakes, saying that it "felt natural" and helped them stay on track while doing tasks. This showed how important it is to have well-designed HCI features that help people interact smoothly.

Another important topic was trust and openness in AI feedback. Participants felt more confident in the tool when corrections came with explanations, like a grammar rule or a reason for the pronunciation. On the other hand, sudden or unexplained changes often caused confusion and doubt, which made people less likely to trust the AI system. This discovery emphasises the importance of transparency in AI-assisted educational tools.

There was also a strong theme of personalisation and adaptive support. Learners liked how the platform adapted to their needs by giving them hints, making the exercises harder over time, and making them their own. One participant said that the tool "gave me what I needed, not too easy or too hard," which shows how important personalised learning pathways are for keeping people interested and making progress.

At the same time, some students were worried about cognitive load and overload. Some people said that having a lot of features at once, like chatbots, quizzes, and pronunciation feedback, was too much at first. These learners

suggested that onboarding should be guided or that features should be introduced in stages to avoid overwhelming new users and make it easier for them to get used to the system.

Lastly, the interviews showed that there is a strong link between the platform and motivation and engagement. Many students said they were motivated to use the tool outside of class because they got instant feedback, it had game-like elements, and they felt like the AI was "listening" to them. These motivational factors seem to have strengthened learners' determination and readiness to participate in autonomous practice.

In general, combining the qualitative insights with the quantitative results showed a strong pattern: students who thought the system was usable and trustworthy often learnt more and were more engaged and satisfied. This alignment shows how usability, transparency, personalisation, and learner motivation all work together to make AI-enhanced ESL platforms successful.

Discussion

The results show that combining HCI design principles with AI features in ESL e-learning can greatly improve both the performance of learners and the experience of users. I will now interpret these in light of previous research, examine their implications, and highlight caveats and future directions.

Enhancement of Learning Outcomes

The significant performance improvements in the experimental group correspond with previous studies indicating that AI-mediated language instruction can markedly enhance English proficiency aspects such as vocabulary, grammar, and reading (Wei et al., 2023) and that AI in ESL environments improves engagement and performance (Investigating the integration of artificial intelligence in English, 2024; Exploring AI-mediated learning, 2024). Our findings confirm that when AI mechanisms (such as chatbots, adaptive feedback, and speech recognition) are meticulously integrated into a user-friendly interface, their impact is significantly enhanced.

Role of Usability, Trust, and Engagement

The fact that usability and trust predicted engagement and performance shows how important HCI is. Even the most advanced AI modules don't work if learners can't figure out how to use them or don't trust them. This is a common theme in the human-centered AI literature, which stresses the importance of transparency, user agency, and interaction beyond "black-box" models (From Explainable to Interactive AI, 2024). Our qualitative data corroborate that learners anticipate explanations, transparency, and agency regarding AI behaviour, thereby reinforcing the demand for AI systems engineered for explainability and contestability.

Balancing Support and Cognitive Load

Adaptive features were appreciated; however, certain learners encountered cognitive overload when faced with excessive simultaneous features. This is in line with HCI worries about interface complexity and user burden (Shankar, 2025), and it suggests that a progressive disclosure strategy (i.e. revealing features gradually) could help with overload. It also shows how important it is to test usability early on when adding AI features.

Motivation, Autonomy, and Engagement

Learners' intrinsic motivation to return to the platform and engage voluntarily corroborates the hypothesis that effectively designed systems can enhance learner autonomy. This aligns with AI and e-learning meta-analyses highlighting that AI tools can enhance self-regulation and perseverance (AI in Informal Digital English Learning, 2024). The boost in motivation probably comes from getting feedback right away, having a conversation, and feeling like the experience is tailored to you.

Limitations and Boundary Conditions

This study, although providing significant insights, is constrained by various limitations. First, the results come from a sample of students from a certain school and area, which makes them context-specific. Consequently, the findings may not comprehensively apply to learners in rural or resource-limited settings, where access to technology and infrastructure varies considerably. Second, the study was

executed over a brief intervention period of six weeks. Although significant enhancements were noted, enquiries regarding long-term retention, adaptation, and continued utilisation persist unanswered – a constraint also identified in previous studies on AI in English language instruction (Li et al., 2025; Artificial Intelligence in Language Instruction, 2023). Lastly, there is a chance that we will depend too much on AI systems. Prior systematic reviews have warned that overreliance on AI dialogue systems may diminish critical thinking and autonomous decision-making (Zhai, 2024). In line with this concern, we noticed that some students asked the AI for direct answers instead of trying to figure things out on their own.

Implications for Design and Pedagogy

Even with these limitations, there are still some lessons to be learnt about teaching and design. It is important to have good onboarding and scaffolding because new users should be introduced to features slowly to avoid overwhelming their brains. It's just as important to give explainable AI feedback; corrections should always come with a reason or rule-based hints to build trust and help users understand. Also, students learn better when they have more control over the AI, like the ability to change how strong the AI's interventions are or turn off certain features for a short time. Because learners come from different backgrounds, it's important to make AI-driven tools that are culturally and linguistically appropriate so that they are useful and welcoming to everyone. Lastly, future research should focus on long-term use, looking at not only short-term learning outcomes but also retention, progress over several semesters, and how these tools can be used in real classroom settings.

In conclusion, the study bolsters the increasing evidence that the integration of HCI and AI is more potent than either methodology independently. ESL e-learning platforms can give students better, more useful experiences by combining usability-driven design with adaptive intelligence. This shows how important it is to integrate different fields in order to improve educational technology.

Conclusion

This study aimed to investigate the enhancement of learner outcomes, engagement, and user experience through the integration of Human-Computer Interaction (HCI) principles with Artificial Intelligence (AI) features in ESL e-learning tools. The results clearly support the hypothesis: the experimental group that used the combined approach did better than the control group in language skills, rated the system as more useful and trustworthy, and said they were more motivated to keep using it.

The experimental group exhibited statistically significant gains with substantial effect sizes, whereas the control group demonstrated modest and non-significant gains. Regression analyses indicated that usability and trust significantly predicted learner engagement and performance, thereby affirming the centrality of technology acceptance variables in educational contexts. The qualitative themes further enhanced these findings: learners emphasised the significance of transparency, adaptive support, elucidative feedback, and incremental feature introduction to prevent cognitive overload.

There are many possible effects. The results indicate that for instructional designers and developers, advanced AI capabilities should not eclipse usability; both must develop concurrently. Chatbots and adaptive grammars work best when learners know how to use them and understand them. The study underscores the importance for educators and policymakers to invest in integrated platforms that merge pedagogical intelligence with user-centred design. When planning a curriculum, planners should think about more than just the content. They should also think about the interface, the logic of adaptation, and how easy it is to understand.

Nonetheless, the study has its limitations. Its brief duration and context-specific sample restrict generalisability. We also saw early signs of people relying too much on AI, which shows that we need to make systems that help students think critically and reflect on their learning. Future research should prolong this intervention, investigate diversity within learner populations (including various age groups and rural settings), and assess retention and transfer

of knowledge. Moreover, controlled designs that compare various levels of HCI complexity and AI sophistication would assist in identifying optimal practice configurations.

In summary, this study demonstrates that the amalgamation of HCI and AI in ESL e-learning presents a viable avenue for developing more intelligent, user-friendly, engaging, and efficacious language learning resources. By bridging the traditional divide between UX/design and algorithmic intelligence, such systems hold potential not just for incremental improvement but for transformative change in how learners interact, adapt, and grow in second-language contexts.

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