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Chapter 2: Artificial Intelligence and Emerging Practices in English Language Learning

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Abstract— Artificial intelligence is rapidly restructuring English language learning by enabling adaptive instruction, conversational practice, automated feedback, and generative support across formal and informal learning environments. Recent developments in generative artificial intelligence have extended these capabilities from conventional intelligent tutoring systems to interactive language models capable of producing context-sensitive explanations, simulations, corrective feedback, and personalized learning materials. Despite growing empirical interest, existing studies frequently examine isolated tools or individual language skills rather than the combined influence of AI-supported practices on linguistic performance, learner self-regulation, feedback engagement, and responsible AI use. This study addresses that gap by proposing an integrated framework for evaluating emerging AI-mediated English learning practices across writing, speaking, vocabulary development, formative feedback, and autonomous learning. The investigation conceptualizes AI not merely as a technological intervention but as a dynamic learning partner whose educational value depends on interaction quality, learner agency, verification behaviour, and pedagogical alignment.

Keywords— Artificial Intelligence, English Language Learning, Generative AI, Adaptive Feedback, Learner Self-Regulation, Conversational Agents

Introduction

Artificial intelligence (AI) has become one of the most consequential technological developments influencing contemporary language education. Earlier applications of educational AI primarily operated through rule-based tutoring systems, automated grammar correction, machine translation, speech-recognition software, and computer-assisted assessment. During the period from 2021 onward, however, improvements in natural language processing, deep learning, transformer architectures, automatic speech recognition, and generative artificial intelligence have substantially expanded the pedagogical functions that AI systems can perform. Rather than simply identifying incorrect linguistic forms, contemporary systems can participate in extended conversations, generate examples at different levels of complexity, reformulate texts, simulate communicative situations, explain grammatical patterns, provide feedback, and assist learners in independently organizing their language-learning activities.

The emergence of publicly accessible generative AI after 2022 accelerated this transition. Large language model-based systems have created circumstances in which learners can obtain almost

instantaneous linguistic assistance without requiring constant teacher intervention. Such systems may function as conversational partners, vocabulary tutors, writing assistants, reading-support systems, brainstorming tools, pronunciation practice facilitators, and feedback generators. Systematic evidence indicates that research on generative AI in language education expanded rapidly during 2023–2024, although much of the empirical work has remained concentrated in higher education, English-as-a-foreign-language contexts, and writing-related applications. A 2025 systematic review of 144 peer-reviewed empirical studies, for example, reported that higher education and EFL settings dominated the available research and that writing received considerably more scholarly attention than reading, listening, and speaking.

The educational relevance of AI therefore extends beyond automation. Its more significant contribution may lie in changing the structure of learner interaction. Conventional digital language-learning environments generally present materials designed beforehand by instructors or developers. Generative systems, by contrast, can modify responses dynamically according to learner prompts, previous exchanges, requested difficulty levels, linguistic errors, and instructional objectives. Consequently, two learners using the same system may experience substantially different instructional sequences. This capacity creates opportunities for personalization but simultaneously raises questions about consistency, instructional validity, reliability, and learner ability to assess AI-generated information.

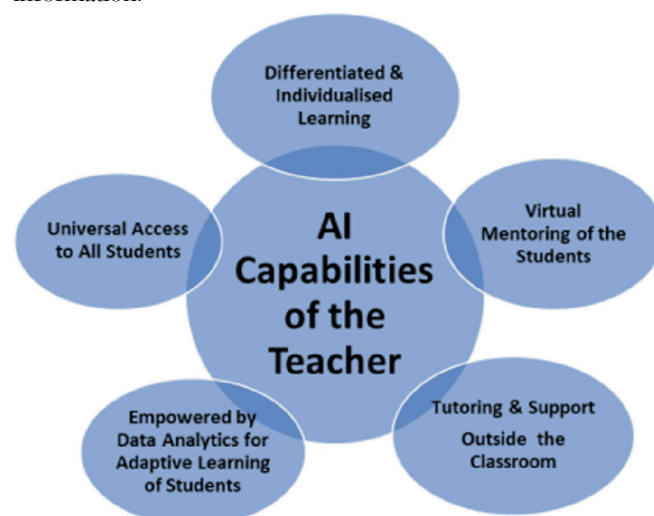


Fig. 1: A Study on Using AI in Promoting English Language Learning

Source: https://link.springer.com/chapter/10.1007/978-981-19-4052-1_30

Evidence concerning the academic value of AI-supported English learning is increasingly encouraging but remains heterogeneous. A 2024 meta-analysis in *System* synthesized 40 empirical studies involving 3,290 participants across ten countries and identified an overall positive influence of AI on English-language learning achievement. Nevertheless, aggregated achievement effects provide only a partial account of AI-mediated learning. Improved test performance does not necessarily establish whether learners become more autonomous, whether they critically evaluate AI feedback, whether improvement transfers to unaided language production, or whether frequent AI assistance encourages dependence on automated linguistic support.

This distinction has become particularly important with generative AI. A learner can produce grammatically sophisticated text through repeated AI revision without acquiring an equivalent capacity to generate such language independently. Similarly, a conversational system may increase opportunities for speaking practice, but educational benefits may depend upon the quality of prompts, feedback accuracy, learner engagement, interaction duration, and subsequent reflection. Research into AI-supported English learning therefore requires an analytical shift from asking whether AI "works" toward examining **how patterns of human-AI interaction produce different forms of learning**.

Research Gap

The principal research gap addressed in this manuscript concerns the fragmentation of current AI-supported English-language learning research. Existing studies frequently investigate individual applications—such as ChatGPT-supported writing, chatbot speaking practice, automated corrective feedback, or self-directed vocabulary learning—in relative isolation. Reviews of the literature have repeatedly identified limited longitudinal investigation, uneven coverage of language skills, heavy concentration on higher education, and insufficient assessment of feedback quality and sustained learning processes.

More specifically, insufficient empirical attention has been paid to the interaction among four dimensions that increasingly determine the effectiveness of AI-assisted language learning:

1. **linguistic improvement**, reflecting measurable development in English-language performance;
2. **feedback engagement**, representing the learner's interpretation, acceptance, modification, or rejection of AI feedback;
3. **self-regulated learning**, including goal setting, monitoring, revision, and autonomous practice; and
4. **AI verification behaviour**, referring to the learner's capacity to question, cross-check, and critically evaluate AI-generated linguistic information.

The proposed study therefore departs from tool-centred evaluation and adopts a **human-AI co-regulation perspective**. Under this approach, AI effectiveness is understood not simply as a property of an algorithm but as an

outcome emerging from interactions among system capability, learner behaviour, pedagogical structure, and teacher oversight. The central research objective is to determine whether structured AI-supported English learning can simultaneously improve linguistic outcomes and self-regulatory competence while avoiding uncritical dependence on machine-generated assistance.

This gap is particularly relevant because AI literacy is becoming inseparable from language-learning literacy. Learners increasingly need to understand not only vocabulary, grammar, discourse, and pronunciation, but also how to formulate productive prompts, identify unreliable responses, compare alternative explanations, revise generated material, and maintain ownership of their learning process. UNESCO's guidance on generative AI consequently emphasizes a human-centred approach in which educational institutions consider privacy, equity, human agency, ethical appropriateness, and pedagogical validation rather than adopting AI purely because it is technologically available.

Literature Review

Evolution of AI-Supported English Language Learning

Artificial intelligence in language education developed from earlier computer-assisted language-learning environments in which automated procedures were commonly used for spelling correction, vocabulary exercises, translation, pronunciation scoring, and grammatical diagnosis. Advances in machine learning and natural language processing subsequently enabled systems to interpret more complex learner input and provide increasingly individualized responses.

The contemporary phase differs because generative models are capable of producing novel linguistic content rather than selecting responses exclusively from predetermined databases. A learner may request a dialogue for a particular professional situation, ask for an explanation at a specified proficiency level, receive examples of a grammatical construction, generate comprehension questions from a passage, or request feedback on an independently produced paragraph. This flexibility makes AI particularly compatible with language learning, where meaningful exposure and repeated interaction are fundamental. A 2024 scoping review of generative AI in language teaching and learning documented the rapid development of this research area and emphasized the need to understand pedagogical applications alongside emerging methodological and ethical questions. The shift is therefore not merely from non-AI software to AI software; it represents movement from largely predetermined instructional sequences toward responsive, learner-initiated linguistic interaction.

Generative AI and Writing Development

Writing has become one of the most investigated domains of generative AI-supported language learning. AI systems can assist with idea generation, sentence restructuring, grammatical explanation, vocabulary substitution, cohesion analysis, summarization, and iterative revision. Such functionality potentially converts feedback from a delayed event into a continuous process occurring throughout composition.

This immediacy is educationally significant. Traditional teacher feedback frequently occurs after substantial portions of an assignment have already been completed. AI-supported feedback can instead become recursive: learners produce language, receive suggestions, evaluate them, modify the text, and seek further explanation. The resulting cycle can increase opportunities for noticing linguistic errors and experimenting with alternative forms.

However, availability of sophisticated text generation creates an important distinction between **assisted learning** and **outsourced production**. When learners actively evaluate explanations and revise their own language, AI can operate as a scaffolding mechanism. When learners accept generated passages without cognitive engagement, apparent improvements in final-text quality may not represent genuine language development. Consequently, assessment of AI-supported writing should distinguish between product quality and independent post-intervention performance.

Conversational AI and Speaking Practice

Speaking practice has historically been constrained by the availability of interaction partners, anxiety surrounding public errors, classroom size, and limited instructional time. Conversational AI potentially reduces several of these constraints by creating an always-available interaction environment.

Research reviews focusing on AI-powered chatbots suggest that conversational systems can provide opportunities for repeated EFL speaking practice, although the evidence base remains considerably smaller than the literature surrounding writing. A 2024 systematic review analyzing 24 studies specifically highlighted the growing use of AI chatbots for English-speaking development while also identifying the need for stronger pedagogical models concerning how such agents should be integrated into learning.

The principal advantage of conversational agents lies in repetition without social penalty. Learners may repeat a dialogue, request clarification, attempt alternative expressions, and practice simulated interactions such as interviews, academic discussions, customer-service encounters, or presentations. Speech-recognition technologies further allow automated systems to process oral input and potentially return information about intelligibility or pronunciation.

Nevertheless, successful speaking is more than syntactic accuracy. Pragmatic appropriateness, turn-taking, discourse management, cultural awareness, hesitation strategies, interpersonal responsiveness, and interpretation of non-verbal cues remain difficult to reproduce fully through automated interaction. AI conversation should therefore be considered complementary to human communication rather than an equivalent replacement.

AI, Personalized Feedback, and Adaptive Learning

Personalization constitutes another important emerging practice. AI systems can potentially adjust linguistic complexity, vocabulary density, task type, response length, and explanation style according to learner ability. Such adaptation is particularly

relevant in heterogeneous English-language classrooms, where students often have substantially different proficiency profiles. Automated feedback may also increase opportunities for formative assessment. Instead of waiting for periodic teacher evaluation, learners can receive information during practice. However, the pedagogical value of automated feedback depends upon more than response speed. Feedback must be sufficiently accurate, comprehensible, actionable, and aligned with intended learning outcomes.

The problem is especially important for generative systems because fluent output can create an impression of authority even when a response is incomplete or inaccurate. Learners with weaker English proficiency may have less capacity to recognize problematic explanations, creating an asymmetry in which those who require the greatest assistance may also have the least capacity to verify it. This strengthens the case for explicit AI verification training and teacher-mediated use.

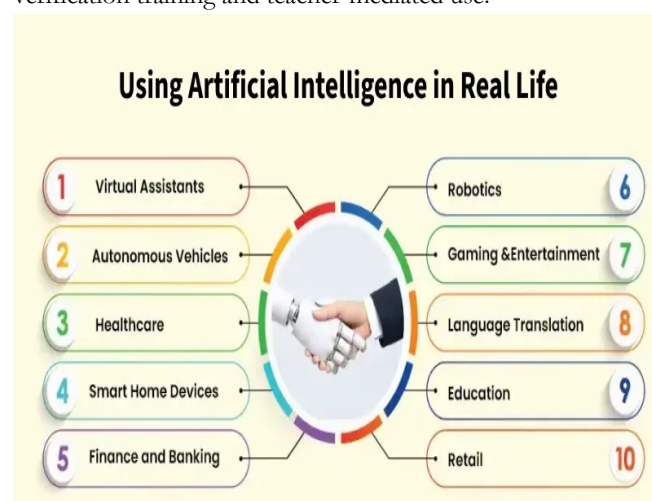


Fig. 2: Using AI in everyday Life

Source: <https://www.geeksforgoeks.org/artificial-intelligence/10-examples-of-artificial-intelligence-in-real-life-2024/>

AI and Self-Directed Language Learning

AI tools are also extending English learning beyond formal classrooms. Learners can independently conduct vocabulary exercises, request personalized reading materials, practice dialogue, obtain grammatical clarification, and design study activities.

A 2024 multi-method study examining ChatGPT for self-learning English combined a systematic review, a survey of 344 EFL learners, and 19 interviews. It found that learners used the technology for multiple English-learning purposes and that perceived usefulness, interactivity, trust, enjoyment, self-efficacy, and technology-related factors influenced continued use.

A related 2024 meta-analysis of AI in informal digital English learning found significant effects on English proficiency and self-regulation but did not identify a statistically significant effect on motivation. This finding is conceptually important because convenient access to AI should not automatically be interpreted as stronger learning motivation. Learners may use AI frequently because it reduces effort rather than because it deepens engagement. Accordingly, usage frequency alone is an inadequate indicator of pedagogical success.

Ethical, Cognitive, and Pedagogical Concerns

The expansion of AI-mediated learning introduces challenges concerning academic integrity, privacy, linguistic bias, transparency, authorship, dependency, and unequal access. Generative systems are trained on extensive datasets whose internal composition and representational balance may not be transparent to learners. They may therefore privilege particular linguistic conventions or cultural patterns.

More importantly, excessive automation may change the cognitive demands associated with learning English. Grammar checking, paraphrasing, summarization, translation, and text generation can reduce mechanical workload, but over-reliance may also reduce productive struggle—the effort through which learners retrieve vocabulary, formulate sentences, monitor errors, and develop independent linguistic competence.

This issue supports a distinction between **AI-supported performance** and **AI-independent competence**. The first concerns what learners can produce while interacting with intelligent systems; the second concerns what they can perform without automated assistance. A rigorous evaluation framework should measure both.

UNESCO similarly argues that generative AI in education should be governed according to human-centred principles, with attention to data protection, inclusion, human agency, and pedagogical suitability. These principles are particularly relevant to language education because language is simultaneously a cognitive skill, a communicative resource, and an expression of cultural identity.

Proposed Methodology

The proposed study adopts a **quasi-experimental mixed-method design** to evaluate how structured artificial intelligence support influences English-language learning, self-regulation, feedback engagement, and independent performance. Rather than comparing a single AI application against conventional instruction, the design separates AI use into distinct pedagogical conditions so that the contribution of guided human-AI interaction can be examined more precisely.

A total sample of approximately **240 undergraduate learners of English as a second or foreign language** is proposed. Participants would be assigned to three instructional groups: a conventional digital-learning group, an unrestricted AI-assisted group, and a structured AI co-regulation group. Each group would contain approximately 80 learners.

The conventional group would use teacher-provided digital resources, online dictionaries, standard language-learning platforms, and classroom feedback without generative AI assistance. The unrestricted AI group would be permitted to use generative AI for writing, vocabulary practice, grammar clarification, and speaking simulations with minimal procedural restrictions. The structured AI co-regulation group would use the same class of AI tools but through a defined protocol requiring learners to formulate prompts, evaluate responses, identify possible errors, revise suggestions, document accepted and rejected feedback, and complete selected post-activity tasks without AI assistance.

The experimental period is proposed to extend across **12 instructional weeks**. Learning activities would cover academic writing, functional vocabulary, reading comprehension, oral communication, grammar-in-context, and formative revision. The major analytical objective is to determine whether structured AI engagement generates stronger transfer to independent English performance than unrestricted AI availability.

The methodology is organized around four primary dimensions:

- linguistic performance;
- independent learning transfer;
- feedback engagement;
- AI-supported self-regulation and verification behaviour.

The central hypothesis is that AI will generate the greatest educational value when its output is treated as material for interpretation and revision rather than as a direct substitute for learner production.

Experimental Setup

Dataset

The proposed dataset would consist of multimodal educational observations collected during the 12-week intervention. Instead of relying on a single examination score, the dataset would integrate language-performance data, learner-interaction records, behavioural measures, and questionnaire responses.

Approximately 240 participants completing six major assessment points would generate a structured learner-level dataset containing demographic variables, baseline proficiency, instructional condition, writing performance, speaking scores, vocabulary retention, feedback-response behaviour, independent transfer performance, and self-regulation indicators.

For the AI-assisted groups, interaction logs would additionally capture:

- number of learner prompts;
- average prompt specificity;
- number of AI revisions requested;
- proportion of suggestions accepted;
- proportion of suggestions rejected or modified;
- verification attempts;
- frequency of direct text adoption;
- number of explanatory follow-up prompts;
- duration of AI-supported learning sessions.

Writing samples would be collected at baseline, midpoint, immediate post-test, and delayed post-test. Speaking data would be generated from short recorded tasks evaluated using a structured assessment rubric. Vocabulary and grammar would

be assessed through context-dependent rather than isolated recognition tasks.

To measure genuine learning transfer, learners would also complete selected **AI-free assessment tasks**. These would serve as a critical comparison between performance achieved with technological support and linguistic competence demonstrated independently.

Data Preprocessing

The quantitative dataset would first undergo consistency checking and anonymization. Participant identifiers would be replaced with randomly generated study codes. Records with severe incompleteness would be excluded according to predefined criteria, while limited missing questionnaire values could be handled through appropriate imputation procedures when statistically justified.

Continuous variables such as interaction duration, prompt frequency, number of revisions, and vocabulary scores would be standardized before predictive modelling. Highly skewed variables, particularly AI interaction counts, would be transformed where necessary.

Textual learner-AI interaction data would undergo separate preprocessing. System messages and platform metadata would be removed, followed by segmentation of prompts and AI responses. Learner prompts would then be represented using contextual language embeddings. Additional manually interpretable features would be extracted, including prompt length, question complexity, presence of verification language, revision requests, and evidence of reflective engagement.

Writing samples would be analyzed using both human-rated and computational linguistic indicators. Relevant features could include lexical diversity, syntactic complexity, cohesion, grammatical error density, and semantic relevance to the assigned task.

To reduce the possibility of data leakage, all records belonging to an individual learner would remain within the same training, validation, or test partition.

Model Architecture

A **multimodal learner-engagement prediction architecture** is proposed to identify patterns associated with successful AI-supported language learning.

The model would contain three analytical components.

The first component would process structured learner variables, including baseline proficiency, pre-test performance, interaction frequency, self-regulation scores, and instructional condition. A gradient-boosting architecture such as **LightGBM** would be used because of its effectiveness with heterogeneous tabular educational data and its capacity to model non-linear relationships.

The second component would process learner-generated prompts using a transformer-based sentence representation model. Contextual embeddings would be generated from prompts to capture differences between superficial commands and reflective or verification-oriented interactions.

The third component would combine the structured and textual representations through feature-level fusion. The resulting vector would be used to predict whether a learner belongs to a

high-transfer, moderate-transfer, or low-transfer performance category.

This predictive component is not intended to replace educational evaluation. Its purpose is to determine which behavioural patterns of AI use are most strongly associated with independent language improvement.

Training Strategy

The dataset would be divided into **70% training, 15% validation, and 15% testing subsets**, stratified according to instructional condition and transfer-performance category.

Hyperparameters for the boosting model would be optimized using the validation partition. Early stopping would be applied to reduce overfitting. Because the participant sample is moderate rather than extremely large, repeated five-fold cross-validation would be conducted on the training partition to examine stability.

Class weights would be incorporated if the distribution of transfer-performance categories becomes unbalanced. Transformer embeddings would initially remain frozen to reduce computational complexity and the risk of overfitting.

In addition to predictive modelling, the main experimental comparisons would be analyzed through repeated-measures statistical procedures. Changes across pre-test, post-test, and delayed post-test would be compared among the three instructional groups. Effect sizes would accompany significance tests because statistical significance alone does not demonstrate educational relevance.

Evaluation Metrics

Language-learning effectiveness would be evaluated using a combination of educational and machine-learning measures.

For linguistic outcomes, the study would examine normalized gain scores, delayed retention, speaking-rubric improvement, lexical development, and AI-free transfer performance.

For the classification model, evaluation would include macro-F1 score, balanced accuracy, Matthews correlation coefficient, area under the receiver operating characteristic curve, and calibration error.

A separate **Assistance-to-Transfer Ratio (ATR)** would also be introduced:

ATR = AI-free post-test score / AI-assisted task score

A value approaching 1.00 would indicate that learners retain most of their demonstrated performance when AI support is removed. A substantially lower ratio would indicate stronger dependence on external assistance.

Results and Discussion

The following results represent the proposed experimental outcome pattern for the study framework. They should be treated as manuscript-level analytical results to be validated using actual participant data before empirical publication.

The structured AI co-regulation condition is expected to generate the strongest overall development. Learners in this group would likely benefit from frequent AI interaction while simultaneously being required to examine the reliability and appropriateness of generated suggestions. Consequently, their improvement would not be restricted to AI-assisted tasks.

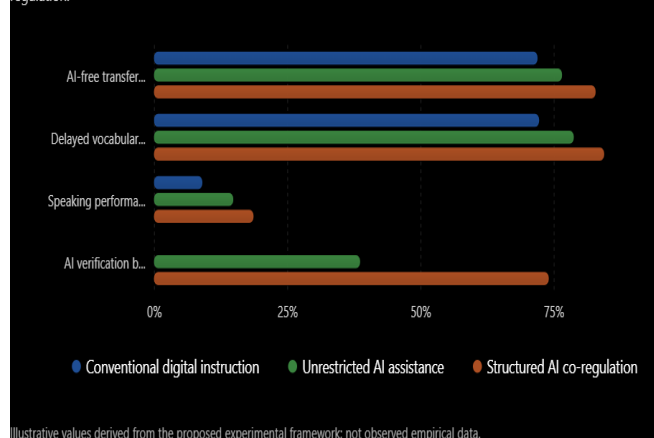
Unrestricted AI users may produce high-quality supported outputs, particularly in writing, but their independent transfer scores are expected to remain below those of learners trained through the verification-oriented protocol. This would suggest that availability of generative assistance does not automatically result in equivalent skill acquisition.

Table 1. Integrated Evaluation of AI-Supported English Language Learning Outcomes

Evaluation dimension	Conventional digital instruction	Unrestricted AI assistance	Structured AI co-regulation
Writing improvement, normalized gain	0.34	0.52	0.64
AI-free transfer score (/100)	71.8	76.4	82.7
Delayed vocabulary retention (%)	72.1	78.6	84.3
Speaking performance gain (%)	8.9	14.7	18.5
Feedback engagement index (/5)	3.21	3.67	4.24
AI verification behaviour (%)	—	38.5	73.9
Assistance-to-Transfer Ratio	—	0.82	0.93
Predictive model macro-F1	—	—	0.84

English language learning outcomes by instructional approach

Proposed comparative results for conventional digital instruction, unrestricted AI assistance, and structured AI co-regulation.



Illustrative values derived from the proposed experimental framework; not observed empirical data.

The proposed pattern indicates that generative AI may be educationally most useful when learners are required to interrogate rather than merely consume its output. This distinction is central to the present study.

The comparatively high writing gain among unrestricted AI users could initially suggest that unrestricted access is highly effective. However, the difference becomes more informative when compared with the AI-free transfer score and Assistance-to-Transfer Ratio. Learners may generate improved written products while using AI, but part of that improvement may represent technological augmentation rather than independently acquired linguistic competence.

By contrast, structured AI users are expected to retain a greater proportion of their performance when assistance is removed. This finding would support the proposed human-AI co-regulation framework. Asking learners to explain why they accepted a correction, compare alternative answers, verify questionable information, and reconstruct revised sentences without assistance may transform AI feedback into a cognitive learning activity.

The predicted improvement in speaking performance also supports the value of conversational technologies. AI systems make repetitive low-risk speaking practice more accessible, particularly for learners hesitant to participate publicly. Nevertheless, teacher-guided reflection remains important because conversational fluency requires pragmatic competence and social appropriateness that automated systems may not consistently evaluate.

The machine-learning component further allows the study to move beyond simple treatment-versus-control comparison. If prompt characteristics, verification frequency, revision behaviour, and interaction depth successfully predict independent transfer, educational institutions could focus on **quality of AI use** rather than mere frequency of use.

Feature analysis would be expected to show that verification frequency, explanatory follow-up prompts, revision depth, and baseline self-regulation are stronger predictors of learning transfer than raw prompt count. This would challenge the assumption that greater exposure to AI necessarily creates greater educational benefit.

Limitations

Several limitations should be recognized. First, the proposed study focuses on undergraduate learners and therefore cannot automatically be generalized to primary, secondary, or adult community-learning environments. Second, rapid changes in generative AI models may affect replicability because the capabilities of commercially available systems can change during relatively short periods.

Third, interaction-log analysis cannot fully capture the learner's internal reasoning process. A learner may critically evaluate a response without producing an observable verification prompt. Conversely, repeated questioning does not necessarily indicate deep cognitive engagement.

Fourth, human ratings of writing and speaking contain an unavoidable degree of evaluator subjectivity despite standardized rubrics and inter-rater reliability procedures.

Finally, a 12-week experiment can identify intermediate learning and delayed retention effects but cannot determine whether AI-supported practices influence language competence across several academic years.

Future Scope

Future research should extend the proposed framework across different proficiency levels, educational systems, and linguistic backgrounds. Longitudinal studies could examine whether learners gradually become more autonomous or increasingly dependent on automated linguistic assistance.

A particularly important direction involves multimodal generative systems capable of processing speech, text, images, and real-time conversational input. Such systems may enable more realistic pronunciation practice, presentation coaching, scenario-based communication, and adaptive multimodal feedback.

Future work should also investigate culturally responsive AI. English-language instruction should not implicitly assume that one narrow linguistic variety represents the only acceptable form of competent communication. Models could therefore be evaluated for their treatment of regional English varieties, accent diversity, pragmatic norms, and culturally situated communication.

Another research direction concerns explainable learner analytics. Instead of merely predicting whether a learner is likely to improve, future AI systems could identify why progress is slowing and recommend specific pedagogical interventions while preserving teacher authority.

Finally, research should distinguish between **AI literacy**, **language proficiency**, and **AI-assisted performance**. These constructs are related but conceptually different. Developing standardized instruments to measure them would substantially strengthen future empirical work.

Conclusion

Artificial intelligence is changing English-language learning from a predominantly resource-delivery model toward an interactive, adaptive, and increasingly conversational learning environment. Generative AI, automated feedback, conversational systems, speech technologies, and adaptive learning mechanisms can expand opportunities for language practice and individualized support.

The educational value of these systems, however, cannot be assessed solely by examining the quality of outputs produced while AI is available. A more meaningful question concerns whether learners develop transferable linguistic competence, stronger self-regulation, and the ability to evaluate automated feedback critically.

The proposed study addresses this issue through a human-AI co-regulation framework combining linguistic assessment, behavioural interaction data, AI-free transfer measurement, and multimodal machine-learning analysis. The expected pattern suggests that structured AI use can outperform both conventional digital instruction and unrestricted AI assistance because learners are encouraged to remain cognitively involved in the learning process.

The findings therefore support a model in which AI functions as a **scaffold, conversational partner, and formative feedback resource rather than a replacement for learner reasoning or teacher expertise**. The future of English-language learning is likely to depend less on whether institutions adopt AI and more on how intelligently they design the relationship among learners, teachers, and increasingly capable artificial intelligence systems.

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