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Integrating Artificial Intelligence Tools into EFL Classrooms: Impacts on vocabulary acquisition, writing proficiency, and learner motivation among undergraduate students

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Abstract
Background: The rapid proliferation of Artificial Intelligence (AI) tools—particularly large language model-based applications—has created unprecedented opportunities for enhancing English as a Foreign Language (EFL) instruction. Despite growing enthusiasm, empirical evidence on their differential impact across key language competencies remains limited, particularly in South and Southeast Asian higher education contexts.
Objective: This study investigates the influence of AI-assisted language learning tools on EFL undergraduates' vocabulary acquisition, academic writing proficiency, and intrinsic motivation in a quasi-experimental university setting.
Method: A quasi-experimental pre-test/post-test design was adopted involving 120 undergraduate EFL students (60 experimental, 60 control) drawn from two intact sections of an English Communication Skills course. The experimental group used AI writing assistants and vocabulary applications (GPT-based and adaptive flashcard tools) over twelve weeks, while the control group followed traditional instruction. Data were collected through standardized vocabulary tests, analytical writing rubrics, and a validated motivation scale (MSLQ-adapted). SPSS v.26 was employed for independent samples t-tests and ANCOVA.
Key Results: The experimental group demonstrated significantly higher post-test scores in vocabulary breadth ($p < .001$, Cohen's $d = 0.84$) and academic writing quality ($p < .01$, $d = 0.72$). Intrinsic motivation showed a moderate but significant improvement ($p < .05$, $d = 0.51$). No significant gender-based differences were observed.
Conclusion: AI-assisted instruction meaningfully enhances core EFL competencies. Pedagogical integration frameworks and faculty digital literacy programs are recommended for sustainable implementation.

Keywords: Artificial intelligence, EFL instruction, vocabulary acquisition, academic writing, learner motivation, quasi-experimental

Introduction

The integration of digital technologies into language education has been a subject of sustained scholarly interest over the past two decades [1]. However, the emergence of sophisticated AI-powered tools particularly those leveraging large language models (LLMs) such as GPT-4 and its derivatives has fundamentally reconfigured the pedagogical landscape for English as a Foreign Language (EFL) educators and learners alike [2]. These tools offer real-time corrective feedback, contextually adaptive vocabulary exercises, and automated essay scoring, capabilities that were previously accessible only through intensive one-to-one human tutoring [3].

Vocabulary knowledge is widely acknowledged as the cornerstone of language proficiency [4]. Nation [5] established that a productive mastery of approximately 8,000 word families is necessary for unassisted comprehension of authentic English texts, a threshold that traditional EFL instruction has consistently struggled to help learners achieve within undergraduate program timelines. Concurrently, academic writing represents a high-stakes skill domain wherein EFL learners frequently demonstrate persistent difficulties with cohesion, argumentation, and lexical precision [6, 7].

Learner motivation occupies a central position in second language acquisition (SLA) theory. Self-Determination Theory (SDT) [8], as articulated by Deci and Ryan, distinguishes between intrinsic motivation—arising from genuine interest and perceived competence—and extrinsic motivation driven by external rewards or pressures. AI tools that provide immediate, non-judgmental feedback have been theorised to bolster learners' sense of autonomy and competence, thereby nurturing intrinsic motivation [9, 10].

Despite these theoretical promises, empirical research on AI integration in EFL contexts remains fragmented. The majority of available studies focus on chatbot-mediated speaking practice or automated writing evaluation (AWE) systems in isolation [11], leaving significant gaps in our understanding of how concurrent, multi-tool AI integration affects the interplay among vocabulary acquisition, writing proficiency, and motivational constructs. This lacuna is especially pronounced in South Asian higher education contexts, where resource constraints and large class sizes make personalised instruction particularly challenging [12].

The present study addresses these gaps by examining the comparative effects of a structured, twelve-week AI-assisted language learning programme against conventional instruction across three dependent variables: receptive and productive vocabulary, academic writing quality, and intrinsic motivation. Three research questions guide the inquiry:

RQ1: Do EFL undergraduates who receive AI-assisted instruction demonstrate significantly higher vocabulary acquisition gains than peers in traditional instruction?

RQ2: Does AI-assisted instruction significantly improve academic writing proficiency as measured by a validated analytical rubric?

RQ3: What is the effect of AI-assisted instruction on EFL learners' intrinsic motivation?

By addressing these questions within a controlled quasi-experimental design, this study contributes to both theoretical understandings of technology-enhanced language learning (TELL) and practical frameworks for pedagogical AI integration in EFL tertiary contexts.

Literature review

1. AI and technology-enhanced language learning (TELL)

Technology-Enhanced Language Learning has evolved through successive waves: computer-assisted language learning (CALL) of the 1980s and 1990s, web-based collaborative platforms of the 2000s, and the current AI-driven paradigm [13]. Godwin-Jones [14] characterised this evolution as a shift from static, drill-based applications toward dynamic, learner-responsive systems capable of modelling communicative competence. Contemporary AI tools distinguish themselves through natural language processing (NLP) capabilities that allow them to parse learner-produced text, identify morphosyntactic errors, and generate contextually appropriate suggestions a functionality that approximates, though does not replicate, the pedagogical sensitivity of expert human feedback [15].

2. AI-assisted vocabulary acquisition

Vocabulary acquisition research within CALL frameworks has consistently demonstrated advantages for spaced repetition systems (SRS) over massed practice [16]. AI-enhanced SRS applications such as Anki and Quizlet have been shown to increase vocabulary retention rates by up to 30% in controlled studies [17]. More recently, LLM-integrated vocabulary tools provide learners with rich contextual examples generated on demand, addressing a key limitation of traditional word lists that present target items in isolation. Webb and Nation [18] have argued that deep lexical processing—engaging with words across multiple dimensions of form, meaning, and use—is essential for durable retention, a condition that AI-generated contextual scaffolding is particularly well-positioned to ful fill.

3. Automated writing evaluation and EFL writing development

Automated Writing Evaluation (AWE) systems such as Turnitin Revision Assistant, Grammarly, and GPT-based essay coaches have been extensively studied in the context of L2 writing [19]. Meta-analytic evidence suggests that AWE feedback, when used iteratively in revision cycles, produces effect sizes comparable to (d = 0.60-0.75) or slightly below those of expert human feedback (d = 0.82-0.95) [20]. Crucially, the formative value of AI feedback appears contingent upon learner engagement with suggested revisions; passive reception of automated corrections yields minimal gains [6]. This finding underscores the importance of pedagogical scaffolding that encourages critical evaluation of AI-generated suggestions.

4. Motivation in AI-mediated EFL contexts

Motivational dynamics in technology-mediated learning have been theorised through multiple frameworks, including SDT [8], the Technology Acceptance Model (TAM) [21], and Dörnyei's L2 Motivational Self System (L2MSS) [22]. Empirical studies report largely positive motivational outcomes from AI tool use, particularly regarding perceived competence and autonomy [9]. However, Golonka et al [23]. caution against uncritical optimism, noting that novelty effects—whereby learners exhibit heightened engagement with new technologies that diminishes over time may inflate short-term motivational measurements. This methodological concern is partially addressed in the present study through the use of a twelve-week intervention period, sufficient to attenuate initial novelty effects while remaining pedagogically representative of a semester-long course.

5. Research gap

The foregoing review reveals three intersecting gaps: (a) Most studies examine AI's impact on a single language skill rather than their interconnection; (b) South Asian EFL higher education contexts remain underrepresented in empirical TELL research; and (c) Methodologically rigorous quasi-experimental designs with adequate sample sizes and validated instruments are scarce. The present investigation responds to all three gaps.

Methodology

1. Research design

A quasi-experimental pre-test/post-test control group design was employed [24]. This design was selected because random assignment of individual participants to conditions was not feasible within the institutional constraints of intact classroom groups; instead, two equivalent sections of an English Communication Skills course were randomly assigned (at the class level) to experimental and control conditions.

2. Participants and setting

One hundred and twenty undergraduate students (N = 120) enrolled in a first-year English Communication Skills course at [University Name] participated. The experimental group comprised 60 students (33 female, 27 male; mean age = 19.3 years), and the control group comprised 60 students (31 female, 29 male; mean age = 19.1 years). All participants shared L1 backgrounds in [Regional Language] and had completed secondary education through English-medium instruction. Institutional Review Board approval was obtained prior to data collection.

3. Data collection instruments

Vocabulary Test: The Vocabulary Levels Test (VLT) [25], adapted to reflect academic word families relevant to the course curriculum, assessed receptive vocabulary. A 50-item productive vocabulary test was also administered.

Writing Rubric: A six-dimension analytical rubric adapted from the IELTS Academic Writing Task 2 scoring criteria assessed: task achievement, coherence and cohesion, lexical resource, grammatical range and accuracy, use of evidence, and overall argument quality. Inter-rater reliability was established at κ =.87 (Cohen's kappa).

Motivation Scale: The Motivated Strategies for Learning Questionnaire (MSLQ), adapted for EFL contexts [26], provided intrinsic motivation subscale scores on a 7-point Likert scale.

4. Intervention

Over twelve weeks, the experimental group supplemented regular instruction with: (a) a GPT-4-based academic writing assistant for drafting and revision cycles, and (b) an AI-enhanced spaced repetition vocabulary application providing contextualised example sentences. The control group received equivalent instructional time using conventional textbook-based activities and teacher feedback. Both groups were taught by the same instructor to control for teacher effect.

5. Data Analysis

Pre-test equivalence was confirmed via independent samples t-tests. Post-test comparisons utilised ANCOVA with pre-test scores as covariates to control for initial differences. Effect sizes were calculated using Cohen's d. All analyses were conducted in SPSS v.26. Alpha was set at.05.

Results and Discussion

1. Pre-Test Equivalence

Independent samples t-tests confirmed no significant pre-test differences between groups on vocabulary (t^{118} = 0.43, p =.67), writing (t^{118} = 0.61, p =.54), or motivation ($t1^{18}$ = 0.29, p =.77), establishing baseline equivalence.

Table 1: Descriptive Statistics Pre-test and Post-test Scores by Group (Simulated Data)

Variable	EXP Pre M (SD)	EXP Post M (SD)	CON Pre M (SD)	CON Post M (SD)	F (ANCOVA)	p
Receptive Vocab (/ 100)	51.3 (8.2)	72.6 (7.4)	50.8 (7.9)	58.1 (8.6)	48.73	<.001
Productive Vocab (/ 50)	19.4 (4.1)	32.7 (5.2)	19.8 (4.4)	24.3 (4.8)	37.61	<.001
Writing Score (/ 60)	28.4 (5.8)	43.2 (6.1)	28.9 (5.5)	34.7 (5.9)	29.84	<.01
Intrinsic Motivation (/ 49)	27.6 (6.3)	35.8 (6.0)	27.1 (6.1)	30.4 (6.4)	14.22	<.05

Note. EXP = Experimental group; CON = Control group; M = Mean; SD = Standard Deviation. All data simulated.

2. Vocabulary acquisition (RQ1)

ANCOVA results (Table 1) revealed a highly significant between-group difference in both receptive (F(1, 117)= 48.73, p <.001, d = 0.84) and productive vocabulary gains ($F^{1, 117}$ = 37.61, p <.001, d = 0.79) after controlling for pre-test scores.

These large effect sizes suggest that the AI-assisted spaced repetition tool, by providing contextually rich, on-demand exemplar sentences and immediate retrieval practice, created conditions highly conducive to deep lexical encoding. These findings are consistent with Webb and Nation's [18] framework of deep lexical processing and extend the empirical base established by Nation [5] and Schmitt [16] in CALL contexts.

Table 2: Writing Rubric Dimension Scores — Post-test Comparison (Simulated Data)

Writing Dimension (/ 10 each)	EXP Post M	CON Post M	t-value	Cohen's d
Task Achievement	7.8 (1.1)	6.1 (1.3)	7.29**	0.88
Coherence & Cohesion	7.4 (1.2)	5.9 (1.4)	6.01**	0.77
Lexical Resource	7.6 (1.0)	5.7 (1.2)	8.93***	1.02
Grammatical Accuracy	7.1 (1.3)	5.8 (1.4)	5.04**	0.61
Use of Evidence	6.9 (1.4)	5.5 (1.5)	5.12**	0.62
Argument Quality	6.4 (1.5)	5.7 (1.6)	2.40*	0.45

Note. * p <.05; ** p <.01; *** p <.001. Data simulated for training purposes.

3. Writing Proficiency (RQ2)

The experimental group's writing scores improved significantly across all six rubric dimensions (Table 2), with the largest effects observed in Lexical Resource (d = 1.02) and Task Achievement (d = 0.88). These results are noteworthy: lexical richness gains are likely mediated by the concurrent vocabulary intervention, supporting an integrative view of language skills as mutually reinforcing rather than independent. The relatively smaller (though still significant) effect for Argument Quality (d = 0.45) suggests that higher-order critical thinking skills require more time or additional pedagogical scaffolding to develop through AI-assisted tools, consistent with Warschauer and Grimes' [19] observations on the bounded scope of AWE systems.

Table 3: MSLQ Intrinsic Motivation Subscale Items — Mean Scores Post-test (Simulated Data)

Item (7-point Likert scale)	EXP M (SD)	CON M (SD)	p
I prefer course material that arouses my curiosity	5.8 (0.9)	4.9 (1.1)	.002
I enjoy activities that challenge me linguistically	5.6 (1.0)	4.7 (1.2)	.001
Understanding language deeply is important to me	5.9 (0.8)	5.3 (1.0)	.024
I feel competent when using digital language tools	5.7 (1.1)	4.4 (1.3)	<.001
Overall Intrinsic Motivation Subscale Mean	5.75 (0.95)	4.83 (1.15)	<.05

Note: Data simulated for training purposes. N = 120 total.

4. Intrinsic Motivation (RQ3)

Motivational outcomes (Table 3) indicate that the AI-assisted group reported meaningfully higher intrinsic motivation scores across all four subscale items, with the most pronounced difference on the digital competence item (M = 5.7 vs. 4.4, p <.001). This pattern is consistent with SDT's predictions: as learners experience increasing competence—facilitated by timely, non-punitive AI feedback—their self-determination in learning activities strengthens [8]. The moderate overall effect size (d = 0.51) underlines that motivational effects, while real, are secondary to competency gains and require longer interventions or supplementary affective support strategies to fully materialise.

Conclusion

This study provides robust quasi-experimental evidence that structured AI-assisted language learning, when integrated systematically over a twelve-week period, produces significant and educationally meaningful gains in EFL undergraduates' vocabulary acquisition, academic writing proficiency, and intrinsic motivation. The magnitude of effects particularly for receptive vocabulary and lexical resource in writing suggests that AI tools offer genuine pedagogical value beyond novelty, functioning as scalable, personalised instructors capable of addressing the individualisation deficit endemic to large EFL classes.

Practically, EFL programme coordinators are encouraged to develop structured AI integration frameworks that train learners to engage critically with AI feedback rather than accept it passively. Faculty professional development in digital pedagogy is equally essential. Ethically, instructors must address academic integrity concerns proactively by distinguishing AI-as-tutor from AI-as-ghostwriter.

This study is subject to several limitations. The single-institution sample limits generalizability; the twelve-week timeline may not capture long-term retention effects; and the quasi-experimental design, while appropriate, precludes causal inference as definitively as randomised controlled trials. Future research should employ multi-site randomized designs, longitudinal follow-ups beyond the instructional period, and mixed-methods components to capture the qualitative nuances of AI-mediated EFL learning experiences.

Ethical Statement

This article was written entirely originally for academic formatting and training purposes. No real human participant data are reported. All statistical values, means, and outcomes are simulated for illustrative purposes and are clearly labelled as such throughout the manuscript. No real author identities, institutional affiliations, or previously published datasets are misrepresented. References are provided in APA format; DOI numbers have been omitted where they cannot be verified. This manuscript must not be submitted to any journal without replacement of all placeholders and simulated data with authentic research evidence.

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