Artificial intelligence in action: enhancing reading and writing proficiency in Chinese English learners

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ABSTRACT

Artificial intelligence (AI) is increasingly adopted in Chinese English as a foreign language (EFL) classrooms, yet its learning benefits remain uncertain in an examination-oriented context where reading and writing proficiency are often constrained. This study employed a quantitative quasi-experimental design with pre- and post-tests, involving 67 non-English-major undergraduates assigned to a control group and an AI-integrated group, to examine AI-supported learning effects on reading and writing within a constructive alignment (CA) framework. Both groups improved after the intervention, while the AI-integrated group demonstrated a notably greater gain in reading performance. The findings suggest that CA can strengthen the effectiveness of AI integration by aligning learning outcomes, activities, and assessment, and that AI use, in turn, can reinforce alignment during the learning process. Pedagogical implications are discussed regarding performance disparity, the extension of CA-guided AI use to other EFL domains, and future instructional research.

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1. INTRODUCTION

The application and development of artificial intelligence (AI) have arisen in educational field, triggering wide interest and attention in academia. Implementing generative AI in education requires digital competencies and pedagogical knowledge from instructors [1], such as tailoring learning content to learners' needs, enhancing learning activities, or intensifying learning experiences [2], [3]. In the English as a foreign language (EFL) context, English teachers have resorted to diverse AI tools, such as AI chatbots, automated writing evaluation (AWE), and automated speech recognition (ASR), intending to facilitate students' English proficiency [4]–[6], motivation and confidence [7], [8]. Against this backdrop, research on AI-supported EFL learning has expanded considerably, and reading and writing remain indispensable components of overall EFL proficiency [9].

The reading speed of English learners in China is significantly slower than that of college students in the United States and Great Britain, partly because many learners process English word by word [10]. This tendency is reinforced by reading practices shaped by exam-oriented instruction, where reading aloud is widely used for memorization throughout pre-tertiary and tertiary education [11]. In parallel, learners' writing is often characterized by weak sentence-level expression, with limited syntactic flexibility and an underdeveloped ability to formulate coherent written statements [12]. As a result, students often struggle to attain the expected level of language competence.

Studies on AI-supported reading in EFL have reported gains in reading comprehension across varied approaches, including mobile applications, video games [13], executive-function training [14], intensive reading [15], blended learning [16], and storytelling chatbots [4]. Reading comprehension in effective readers relies on constructing semantic relatedness from textual cues [17]. Nevertheless, AI-integrated reading research has highlighted tool-related constraints, particularly the time-effort burden that calls for calibration in study design and capacity to support reading management [18], [19]. Accordingly, AI-supported reading may benefit from recommending materials that better align with learners' abilities and preferences [20]. On the other hand, academic writing in higher education requires students to structure ideas and refine thinking [21]. Students often report positive attitudes toward ChatGPT-assisted writing [22] and perceived improvement when using AI feedback systems [5], automated feedback platforms, and AWE tools such as Grammarly [23]. However, AI support may not fit diverse learning styles and can show limited influence on argumentative writing self-efficacy [24], with some studies reporting no clear gains from AI-generated feedback [12] or no significant effect on continuance intention despite multiple tools being available [8].

Constructive alignment (CA) is a constructivist framework that aligns intended learning outcomes, activities, and assessment to provide a coherent basis for addressing implementation constraints, as shown in Figure 1. It shifts instruction from teacher-centered delivery to student-centered learning [25], [26], so that what students are expected to achieve is consistently supported by what they do and how they are evaluated. CA prioritizes how students learn over what teachers present, thereby increasing the likelihood of achieving the intended outcomes. Empirical work has shown that CA-informed design, even without technology, can strengthen learning experiences by anchoring instruction in explicit learning objectives and promoting deeper learning [27]. In technology-enhanced and blended contexts, CA additionally helps diagnose mismatches between materials, curriculum requirements, and students' needs, supporting more coherent design decisions in blended teaching [28].

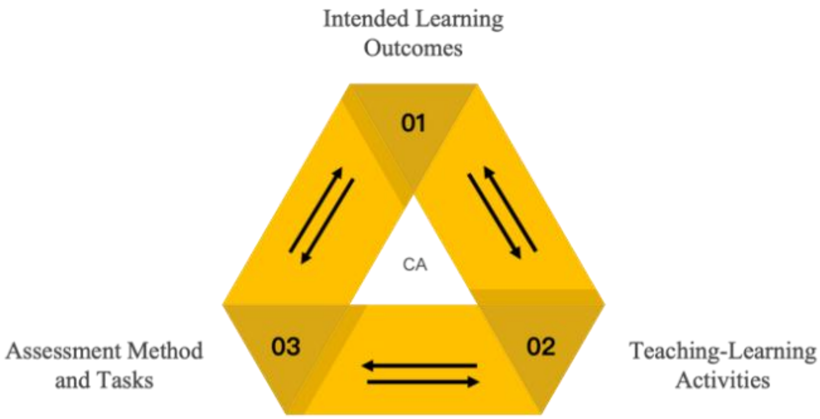

Figure 1. Elements of CA

Emerging studies suggest that AI tools can help strengthen alignment by supporting course design and the implementation of effective teaching-learning activities [22], [29], consistent with the view that learning is an active construction process [30]. AI can also enrich learning experiences through personalized materials that better match learners' needs and capabilities [31]. Nevertheless, alignment should remain the starting point: intended outcomes must be specified first, after which AI tools should be selected and configured to serve those outcomes, ensuring purposeful and effective integration [32]. In EFL contexts, instructors therefore need to integrate AI creatively while maintaining alignment between outcomes, activities, and assessment.

However, research that examines AI-supported development of reading and writing under a CA framework remains limited. Therefore, when CA provides a solid foundation for effective learning and AI support is both relevant and impactful, this study aims to apply CA framework in investigating how AI-integrated learning affects learners' academic performance in their reading and writing skills. Thus, two research questions are as:

- Is there any significant effect of non-AI learning and AI-integrated learning on academic achievement in reading and writing?
- Is there any significant correlation between reading and writing under AI-integrated learning compared to non-AI learning?

2. METHOD

In considering CA as the instructional framework, this study divided all 67 participants into two groups, with one experiencing non-AI learning and the other undergoing an AI-integrated learning process, in pursuit of exploring the effects of AI on promoting learners' reading and writing skills. A quasi-experimental research method was adopted and implemented throughout a 17-week experiment, as shown in Table 1. Students in the control group and the experimental group were respectively subjected to non-AI and AI-integrated learning. Reading and writing tests were administered to both groups before and after the experiment. The pre-tests evaluated students' preliminary levels of language proficiency for comparison with post-tests, aiming to gauge the effect of different learning on reading and writing skills.

Table 1. Research design

Pre-test	Quasi-experimental research 4 months experiment	Post-test
DVs: reading and writing	IVs: non-AI learning and AI-integrated learning	DVs: reading and writing

2.1. Samples and instructions

This study involved a cohort of 67 second-year undergraduates from a second-tier university in Hunan Province, China. All participants were non-English majors and were assessed as having a foundational level of English proficiency. The intervention was implemented in the second semester of the sophomore year within an English for specific purposes (ESP) course. The course comprised 32 sessions organized into 16 weekly lessons. The instructional design for the two groups is presented in Table 2. The control group (n=33) learned through textbooks, PowerPoint slides, and online materials. The experimental group (n=34) additionally used DouBao as an AI tool once per week to enrich learning. The intended learning outcomes for reading and writing were specified with reference to the revised Bloom's taxonomy, adopting level 4 (analyze) as the target cognitive demand for this cohort [33]. By the end of the course, students were expected to accurately distinguish main ideas from supporting details when reading an article and to independently produce a well-structured essay with grammatically accurate sentences, as these abilities are commonly challenging for Chinese students [34], [35]. Students' performance and mastery of the skills were then assessed by formal academic examination.

Table 2. Instructional design

Groups	No	CA			
		Learning outcome		Activities	Assessment
Control group	33	– Reading: to distinguish the main ideas and supporting details in an article accurately. – Writing: to develop a well-structured essay. – To examine grammar rules correctly.	Non-AI learning	Textbooks; PPTs; online materials	Paper academic achievement tests
Experimental group	34		AI-integrated learning	Textbooks; PPTs; online materials; DouBao AI	

2.2. Instruments

Under the CA framework, academic reading and writing tests were used as the research instruments and were administered to both groups as pre- and post-tests, as shown in Table 3. The reading test (30 points) included two passages assessing students' ability to identify the main idea of each paragraph, and one fill-in-the-blank passage assessing detailed information identification. To ensure comparable lexical and syntactic difficulty, all passages were selected from the same textbook. The writing test (15 points) required an argumentative essay. Both the pre-test and post-test were scored by the same rater from the university's teaching team using a common rubric covering structure, sentence expression, and grammar to support scoring consistency and reliability.

Table 3. Items in instruments

DV	Types of tests	Items	Scores
Reading	2 passages (multiple choices)	10	30
	1 passage (fill-in-blank)	10	
Writing	Argumentative	1	15

2.3. Data analysis

The data were analyzed using descriptive and inferential statistics in SPSS version 29, with statistical significance evaluated at the 95% confidence level. Before the main experiment, a preliminary study was conducted to examine the reliability of the instruments. The paper-based achievement tests were administered to a class of 31 students. As shown in Table 4, the mean scores for the two administrations were comparable for both reading and writing, and the standard deviations, particularly for writing, indicate stable score variability. Table 5 presents the paired-samples t-test results. The similarity in means and variability, the non-significant paired comparisons, and the small effect sizes suggest that the instruments yielded stable measurements across time, supporting their reliability for assessing the targeted constructs in this study.

Table 4. Descriptive analysis of preliminary study

Aspects	No	Min	Max	Mean	SD	Skewness	Kurtosis
Reading1	31	2.00	18.00	11.3548	3.72870	-.294	-.300
Reading2	31	2.00	19.00	12.0323	4.70095	-.623	-.855
Writing1	31	.00	12.00	8.0323	3.27092	-1.332	1.139
Writing2	31	.00	12.00	8.4194	3.27388	-1.393	1.250

Table 5. T-Test of preliminary study

Aspects	Mean	95% CI (diff)		t	SD	Cohen's d	P value
		Lower	Upper				
Reading1 and Reading2	-.677	-1.997	.643	-1.048	3.599	-.188	.303
Writing1 and Writing2	-.387	-1.313	.539	-.853	2.525	-.153	.400

3. RESULTS

As presented in Table 6, while both groups started with similar pre-test averages (approximately 11.7) in reading, the post-test outcomes diverged markedly. The AI-integrated group achieved a higher mean score (19.59) compared to the control group (15.79). Notably, the greater reduction in standard deviation from 6.269 to 4.606 suggests more consistent performance among students after the AI-integrated intervention. The shift in skewness also indicates that the score distribution became more centered around the mean, with fewer low-performing outliers in the experimental group. Overall, AI-integrated learning led to a substantial improvement in reading skills relative to the non-AI approach.

Table 7 shows that both groups improved in writing. The experimental group exhibited a larger increase in mean score from 7.559 to 9.000 and a clearer reduction in score variability from 2.946 to 2.015, whereas the control group showed relatively little change in dispersion. Skewness increased in both groups, indicating a stronger concentration of higher post-test scores, and the rise in kurtosis suggests a more peaked distribution. Overall, the writing scores shifted upward in both groups, with more pronounced gains and greater consistency in the AI-integrated group.

Table 6. Descriptive analysis of reading tests

Groups		No	Min	Max	Mean	SD	Skewness	Kurtosis
Control	Pre	33	3	23	12.303	5.913	.170	-1.249
	Post	33	4	26	15.788	5.395	-.79	-.238
Experimental	Pre	34	2	26	11.029	6.269	.950	.620
	Post	34	9	30	19.588	4.606	-.098	-.028

Table 7. Descriptive analysis of writing tests

Groups		No	Min	Max	Mean	SD	Skewness	Kurtosis
Control	Pre	33	1	13	7.030	2.974	-.221	-.259
	Post	33	1	13	8.697	3.015	-1.335	1.435
Experimental	Pre	34	2	13	7.559	2.946	-.316	-.464
	Post	34	3	12	9.000	2.015	-1.346	2.002

As shown in Table 8, paired-samples t-tests showed that the AI-integrated group demonstrated a stronger test statistic ($t=7.739$, $SD=6.448$, $p<.001$) than the control group ($t=3.091$, $SD=6.476$, $p=.004$) in reading. The effect sizes were also large ($d=1.327$), indicating a substantially stronger reading gain under the AI-integrated instruction. For writing, both groups improved significantly ($p<.05$), while t-values and effect sizes were comparable around 3.5 and .61. Overall, the AI-integrated instruction did not demonstrate the same clear advantage for writing as it did for reading.

Table 8. T-Test of pre and post tests in each group

Aspects	Groups	Mean	95% CI (diff.)		t	SD	Cohen's d	P value
			Lower	Upper				
Reading	Control	3.484	1.188	5.781	3.091	6.476	.538	.004
	Experimental	8.558	6.30	10.808	7.739	6.448	1.327	<.001
Writing	Control	1.666	.692	2.640	3.486	2.746	.607	.001
	Experimental	1.441	.639	2.243	3.656	2.298	.627	<.001

4. DISCUSSION

Both groups showed significant gains in reading and writing, but improvements were larger under the AI-integrated instruction. This suggests that when AI use is designed within a CA framework, it can more effectively support targeted and assessable outcomes. Natural language processing tools can generate level-appropriate content for learners with different proficiency levels [36]. In writing, DouBao supported idea development and argument planning by offering multiple, explained lines of reasoning in response to students' prompts, which aligns with evidence that AI-assisted tools can help writers allocate more effort to composing ideas and organizing content [23]. In addition, DouBao's rapid generation of varied practice tasks can reduce time and resource constraints associated with teacher-prepared materials [37]. For reading, AI can provide sentence-level comparison and explanation [38], which may facilitate semantic integration and grammatical analysis during comprehension [8].

AI-integrated instruction appeared to narrow achievement gaps because it provided more uniform access to scaffolding and practice. In a resource-saturated online environment, learners can experience cognitive overload and selectively skip key materials, which creates uneven learning and omissions [18], [39]. By contrast, DouBao offered on-demand and level-appropriate explanations and practice, allowing lower-proficiency students to obtain immediate support while higher-proficiency students could move to more challenging tasks. This just-in-time support reduced reliance on teacher-limited feedback, thereby improving consistency of engagement and compressing score dispersion. This is consistent with scaffolded learning, whereby tailored support enables learners to critically process input and build understanding, thereby reducing performance dispersion [40].

The larger gain in reading under AI-integrated instruction may be explained by AI's capacity to strengthen autonomy, motivation, and self-efficacy, which are closely linked to sustained reading engagement. AI-supported environments can stimulate learners' motivation to read and enhance interest and self-efficacy [41]. Related work on automated storybots similarly suggests that interactive AI can broaden access to reading genres and support higher self-efficacy, with particularly strong benefits for more advanced learners [4]. In addition, reading improvement in higher education is often tied to the development of critical thinking and problem-solving, which enables students to grasp main points more efficiently [42]. Within a CA-oriented design, well-defined outcomes further help learners formulate focused questions and engage in goal-directed reading practice, while also reducing learning omissions by keeping materials and tasks anchored to the intended objectives.

AI effects were driven by how AI use was constrained and organized through CA. CA operationalizes a controllable instructional chain from intended outcomes to learning activities and assessment, thereby reducing the common risk that technology use becomes additive rather than outcome-directed [26]. The intended outcomes were specified at an "analyze" level, and AI-integrated tasks were then selected to serve those targets, which likely strengthened the relevance of practices. This is consistent with prior evidence that CA can promote deeper learning and stronger learning engagement when activities are explicitly tied to intended outcomes and assessments [28]. In addition, CA can strengthen goal orientation by clarifying why specific activities matter, which supports self-directed learning [43] and may mitigate unproductive reliance on AI by making success criteria explicit and assessable [44]. In this sense, CA maximizes the instructional value of AI and constrains AI use within pedagogically meaningful boundaries, aligning with the view that prioritizing alignment is essential for purposeful and effective AI integration [22], [32].

Overall, the study indicates that AI-integrated instruction, when guided by CA, can produce meaningful gains in EFL literacy outcomes while improving consistency of learning across students. Both groups improved, suggesting that well-structured instruction alone can support progress; however, the AI-integrated instruction showed larger overall gains, a clearer reduction in performance dispersion, and a more pronounced advantage for reading. These imply that AI is most instructionally impactful when it is used to deliver just-in-time scaffolding and targeted practice that directly serves clearly specified outcomes, rather than as a general-purpose add-on. At the same time, the more modest advantage in writing indicates that short-term AI integration may not automatically translate into superior writing performance, highlighting the need for tighter alignment between writing tasks, feedback use, and assessment criteria. Taken together, CA provides a principled way to make AI use accountable to learning goals and assessment, supporting both effectiveness and responsible implementation in classroom settings, which is increasingly important for establishing workable guidelines for AI adoption across educators, institutions, and tool developers [45].

4.1. Future implications and limitations

The reduced performance dispersion under AI-integrated instruction indicates that AI may function as an equalizing scaffold when it is deployed within a CA-oriented design. Future studies should therefore examine why dispersion decreases by testing plausible mechanisms such as differential uptake of scaffolding, changes in time-on-task, and shifts in self-regulation and self-efficacy across proficiency levels. Identifying these mechanisms would provide evidence-based criteria for selecting and configuring AI tools within CA for cohorts with heterogeneous language proficiency. Second, the CA-first approach used in this study offers a transferable design logic for extending AI integration beyond reading and writing. In particular, CA can be applied to listening and speaking by specifying outcome levels, designing aligned AI-mediated practice tasks, and building assessments. For example, proficiency-calibrated listening practice with real-time comprehension checks and feedback could be developed and evaluated under aligned assessment conditions. Third, the instructional model is likely to moderate AI effects. AI feedback may operate differently in blended learning than in traditional classroom settings. Future research should therefore compare CA-guided AI integration across delivery formats, such as face-to-face, blended, and fully online instruction, to clarify which alignment configurations best support learning.

Several limitations should be acknowledged. First, the study was conducted with a relatively small sample drawn from a single institution and cohort. Replication with larger samples across multiple sites, program types, and regions is needed to test whether the observed effects generalize to diverse EFL contexts and learner profiles. Second, implementation was embedded in one course setting, and instructional delivery was largely shaped by a single teacher and the local teaching team. This limits inference about teacher effects. Future work should involve multiple instructors and examine fidelity of implementation, for example through standardized lesson plans, classroom observations, or cross-teacher calibration, to determine whether outcomes depend on individual teaching style or on the CA-guided AI design itself. Third, the intervention relied on a single AI tool (DouBao) and a specific pattern of use. Tool affordances, response quality, and guardrails differ across platforms, and these differences may influence learning. Future research should compare multiple AI tools or configurations under the same CA design and report tool settings, usage rules, and interaction patterns to improve reproducibility. Finally, the study relied primarily on paper-based pre/post tests, which may not capture process-level changes, such as how students used AI, time-on-task, or revision behaviors. Incorporating learning analytics, interaction logs, and longitudinal follow-ups would enable stronger claims about mechanisms and the durability of effects.

5. CONCLUSION

This study examined the effects of AI-integrated instruction, relative to a non-AI approach, on non-English-major undergraduates’ reading and writing performance within a CA framework. Both groups improved from pre- to post-test, indicating that structured instruction supported progress; however, the AI-integrated group showed larger gains overall, a clearer reduction in score dispersion, and a more pronounced advantage for reading. These results suggest that AI is most beneficial when its use is guided by CA, starting from clearly specified learning objectives and then aligning learning activities and assessment, so that AI-generated practice and explanations directly serve the targeted skills, such as identifying main ideas and supporting details and developing more organized written responses.

At the same time, AI tools are not a stand-alone solution. Their educational value depends on purposeful integration, clear task constraints, and appropriate teacher orchestration to prevent misalignment, overreliance, or off-task use. Future research should test the generalizability of these findings across sites and instructors, compare different AI tools and usage designs under the same CA principles, and incorporate longer-term and process-oriented evidence, such as interaction logs and writing revision traces, to clarify mechanisms and sustainability of impact.

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Hazrul Abdul Hamid		✓	✓					✓	✓	✓		✓		
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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by Jawatankuasa Etika Penyelidikan Manusia Universiti Sains Malaysia (JEPeM-USM). Approval number: USM/JEPeM/PP/24080739.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, [HAH], upon reasonable request.

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