

Article

Enhancing Sustainable English Writing Instruction Through a Generative AI-Based Virtual Teacher Within a Co-Regulated Learning Framework

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Abstract

English writing proficiency is pivotal to sustainable academic success and employability. In Chinese higher education, however, conventional instruction often constrains students' self-regulation and access to individualized feedback. Drawing on self-regulated learning (SRL) and co-regulated learning (CoRL), this study investigates whether a CoRL-guided generative AI virtual teacher (CoRL-VT), designed as a “more capable other,” is associated with enhanced undergraduate writing outcomes relative to standard AI support. Using a 12-week quasi-experimental design with two intact classes ($N = 61$) in Anhui, China, we compared a control condition (standard AI) with an intervention (CoRL-VT). Writing proficiency was assessed via IELTS Writing Task 2 at pre- and post-test; three certified examiners scored all scripts with strong agreement ($ICC = 0.87$). Analyses adjusting for baseline yielded an estimated group difference favoring CoRL-VT. Teacher interview testimony aligned with the quantitative pattern, noting clearer macro-organization, richer lexical choices, and more teacherly formative feedback among CoRL-VT students. Taken together, these findings offer exploratory, descriptive evidence consistent with the potential of structured, CoRL-informed AI scaffolding in sustainable writing pedagogy and outline design principles for replicable CoRL-VT implementations in resource-conscious contexts.

Keywords: co-regulated learning; self-regulated learning; generative AI; virtual teacher; English academic writing; technology-enhanced sustainable pedagogy



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1. Introduction

English proficiency strongly shapes students' sustainable academic and career trajectories, whether in further study or the job market. English writing skill is particularly vital: many scholarships demand proof of academic achievement through exams or written submissions, both of which require advanced writing skills [1,2]. Moreover, numerous studies report a significant positive link between students' English writing ability and their academic performance [3–5].

Due to the crucial importance of English writing proficiency, employing diverse strategies to enhance students' writing skills has long constituted a primary research focus in both educational practice and academic scholarship. Writing is now recognized as a

dynamic, non-linear cascade of cognitive operations rather than a simple linear task [6–8], which implies that instruction must cultivate students' strategic engagement and cognitive skills in text production. Empirical evidence indicates that stronger self-regulated learning (SRL) abilities significantly predict higher writing proficiency [9,10], underscoring the need to integrate cognitive and metacognitive strategies into English writing instruction.

SRL strategies (e.g., goalsetting and self-monitoring) have been shown to yield substantial gains in English writing performance [9–12]. Co-regulated learning (CoRL) frameworks further underscore the pivotal role of a “more capable other” in scaffolding learners' regulatory abilities through structured social interaction [13]. Beyond immediate performance, SRL has been conceptualized as a cornerstone of becoming a lifelong learner who can independently adapt strategies to future challenges, underscoring the sustainability dimension of cultivating regulatory skills in higher education [14]. In an empirical study with EFL learners found that the frequent use of self-regulation strategies correlated with higher performance in writing and overall language proficiency [15]. This indicates that SRL-oriented support can provide enduring benefits for second language writing development.

Although numerous empirical studies have demonstrated the effectiveness of SRL related strategies, their implementation in Chinese and other resource-constrained higher education contexts continues to face multiple challenges, thereby limiting their capacity to realize their full potential. In Chinese higher education, English writing instruction remains predominantly input-driven and teacher-textbook-centered, offering students limited opportunities for self-planning, monitoring, and reflection during the writing process [16]. Such approaches prioritize rote repetitive memorization over productive output and rely heavily on large class sizes, thereby reducing meaningful teacher–student interaction and constraining personalized feedback [17].

The rise of generative artificial intelligence (AI) presents significant opportunities for educational practice. By delivering real-time feedback and personalized guidance, AI systems can effectively enhance learners' cognitive development and learning outcomes. However, prior research has raised concerns that excessive reliance on AI may undermine students' cognitive abilities, leading to declines in certain learning outcomes [18,19]. Therefore, this study proposes leveraging AI as an effective extension of metacognitive strategy support by positioning it within a co-regulated learning (CoRL) framework as a “more capable other,” with the aim of assessing its potential to enhance students' English writing proficiency.

Addressing these gaps, this study examines whether a CoRL-guided generative AI virtual teacher (CoRL-VT) can enhance English writing proficiency in Chinese higher education contexts, and whether it delivers additional gains compared with standard generative AI.

2. Literature Review

2.1. Theoretical Background

2.1.1. Cognitive Process Theory of Writing

According to Flower and Hayes [6], academic writing is a complex cognitive task involving multiple concurrent mental processes, including planning, translating (drafting), and reviewing. These processes do not occur as simple linear stages but rather unfold simultaneously and interdependently. The cognitive model further emphasizes that writing is explicitly goal-directed; writers dynamically generate and adjust their goals based on an ongoing understanding of the writing task. Thus, this cognitive process framework portrays writing as a flexible and iterative activity, in which cognitive actions such as idea generation, organization, and goal-setting play crucial roles.

Over nearly half a century, numerous scholars, including Flower herself, have continued to refine and expand upon Flower and Hayes's [6] theory. Ni [20] conducted in-depth investigations into various affective factors influencing the writing process, such as emotions, motivation, confidence, and anxiety, highlighting their critical influence on writing quality. Graham and Harris [21] further emphasized the sociocultural dimensions of writing, suggesting that writing is not merely cognitive but profoundly influenced by social interactions, cultural backgrounds, and contextual factors. Hayes [7] also revised the earlier model to incorporate working memory and further specified the writing process into subprocesses closely related to metacognition, such as planning, generating, evaluating, and reproposing. Although the core of this updated model continues to focus on individual cognition and self-regulation, the introduction of "Collaborators & Critics" underscores the social nature of writing by highlighting the interactions and collaboration with others.

Notably, the evolved cognitive process theory of writing aligns closely with the principles of self-regulated learning (SRL) and its derivative theories. Writing research papers or essay sections inherently exemplifies a self-regulatory cycle: writers proactively plan content and strategies, monitor their progress (e.g., evaluating coherence of arguments or sufficiency of evidence), and revise their methods or text based on feedback or self-assessment. Hayes's [7] emphasis on the writer's active control over planning, drafting, and revising has laid a robust theoretical foundation for applying SRL theory in writing instruction. This perspective not only underpins interventions designed to enhance writing through SRL principles but also provides a basis for supporting co-regulated learning (CoRL), where guidance from others—such as teachers or intelligent technological tools—serves as scaffolding for students' writing processes.

2.1.2. Co-Regulated Learning

To effectively support students' academic writing through AI-enhanced instruction, the present study draws on the theoretical foundation of self-regulated learning (SRL) and its socially extended forms, particularly co-regulated learning (CoRL). Self-regulated learning (SRL) refers to learners' active engagement in their own learning processes through goal setting, strategic enactment, progress monitoring, and reflective adjustment [10,22]. In the context of academic writing, SRL manifests as an iterative cycle in which writers plan the content and structure of their texts, monitor coherence and the adequacy of supporting evidence during composition, and revise their work based on self-evaluation or external feedback [23,24]. Specific SRL skills—such as setting subgoals, monitoring textual coherence, and evaluating draft quality—have been found to positively correlate with writing proficiency [25]. Accordingly, writing instruction informed by SRL principles encourages students to approach writing tasks with intentional planning, periodic self-assessment, and strategic adjustment based on rhetorical goals.

Although SRL emphasizes individual agency, regulation frequently occurs within social contexts [13]. Co-regulated learning (CoRL) refers to a transitional interpersonal process in which a "more capable other"—such as a teacher, tutor, or peer—scaffolds a learner's regulatory behaviors by modeling the use of strategies, posing metacognitive questions, or providing targeted feedback. In CoRL, the learner and the supporter operate on a shared problem-solving plane, with the supporter intervening to assist the learner in generating subgoals, monitoring progress, and reorganizing writing strategies until the learner internalizes effective self-regulatory routines. This dynamic is grounded in Vygotsky's [26] concept of the zone of proximal development, which posits that interaction with a more knowledgeable other enables learners to accomplish tasks beyond their current independent capabilities. Empirical studies have shown that CoRL-

based interventions—such as teacher-guided demonstrations of planning or peer-mediated metacognitive prompting—significantly enhance students’ strategic engagement [27].

By applying CoRL principles to guide the AI, it can strengthen students’ SRL-related cognitive skills. Combined with immediate feedback on their English writing, this approach further promotes improvements in their English writing proficiency. To this end, the study introduces a Generative AI-based Virtual Teacher (CoRL-VT) as a digital co-regulator for academic writing instruction. CoRL-VT functions as a virtual tutor capable of interacting with students in real time: it prompts learners to outline argument structures (supporting planning), identifies ambiguous passages for reconsideration (guiding monitoring), and offers revision strategies aligned with rhetorical goals (facilitating self-evaluation). By emulating the scaffolding role of a human instructor, CoRL-VT supports students’ iterative cycles of goal setting, strategic implementation, and self-reflection throughout the writing process. Its ultimate objective is to enhance learners’ metacognitive capacities and improve their overall English writing proficiency.

2.2. Empirical Studies

2.2.1. SRL and English Writing Outcomes

Integrating SRL with English writing instruction has shown great potential and has been proven effective through nearly two decades of empirical research. The three components of SRL—goal setting and planning, self-monitoring, and self-assessment—have been particularly effective in enhancing English writing skills [9,28,29].

Seker [8] conducted an empirical study demonstrating that the level of students’ SRL ability is a significant predictor of their achievements in acquiring English as a second language. The study’s sample consisted of 222 undergraduate students from a state university in Turkey who were learning English as a second language. Using a five-point Likert scale and the university’s English achievement exam, the quantitative analysis revealed that SRL is a significant predictor of English as a second language achievement and is significantly correlated with students’ English language proficiency. Furthermore, through observational methods and semi-structured interviews, the author found that despite the researcher’s recommendations and encouragement for teachers to develop students’ SRL, most teachers had not fully integrated SRL into their instructional plans and classroom practices.

Sun and Wang [30] employed a modified version of the Questionnaire of English Self-Regulated Learning Strategies (QEWSRLS) [31] to measure the SRL strategies used by students during the English writing process. The study sample comprised 319 sophomore students from two public universities in Northwest China, with 65.2% male and 33.2% female participants, evenly distributed across humanities and sciences. Utilizing descriptive statistics, Pearson correlation analysis, and other methods, the authors concluded that the extent of SRL strategies usage significantly predicted students’ English writing proficiency. This finding aligns with previous research outcomes [32–34].

2.2.2. Interrelations Between CoRL and SRL Abilities

As early as the late 20th century, researchers proposed theories emphasizing the role of collaborative learning processes in enhancing students’ various abilities. Over the subsequent two decades, these theories have been gradually substantiated through empirical research, with some of their components becoming integral to the framework of CoRL. Studies have shown that learners often benefit from working collaboratively with more capable others, as it provides opportunities for sharing ideas, receiving feedback, and engaging in meaningful discussions about learning goals and strategies [26]. In addition, collaboration facilitates the sharing of diverse perspectives and ideas, critical thinking, and problem-solving skills. Slavin [35] argues that cooperative learning methods,

which involve students working in small groups to accomplish a common learning goal, significantly enhance student achievement and motivation to learn. Some studies have also demonstrated the significance of collaborative writing in enhancing the quality of students' writing and deepening their understanding of the writing process [11,12]. Some research also suggests that carefully designed computer-supported writing environments not only foster effective social interactions among learners but also exhibit positive correlations with outcomes achieved by individuals and collectives through collaborative efforts [36].

Hadwin, Wozney and Pontin [27] investigated changes in SRL levels over a year using a sample of ten graduate students. The students were instructed to create learning portfolios based on course objectives and engage in multiple meetings and dialogues with teachers, guided by the CoRL framework. The content of these meetings and dialogues was recorded and analyzed. The results indicated a significant increase in students' self-regulation abilities over the year, and a notable shift in the content of student-teacher interactions: discussions related to learning tasks decreased, while those related to SRL strategies increased. The author suggested that during this process, students achieved a crucial transition from CoRL to SRL, and the CoRL framework can effectively guide students in enhancing their SRL ability.

Similarly, DiDonato [37] examined the use of collaborative interdisciplinary authentic tasks as a context in which learners develop and use SRL processes. Participants included sixty-four students from a U.S. middle school predominantly composed of residents from low-income families. Over a nine-week period, students worked in groups to design and carry out an authentic, interdisciplinary project. A Hierarchical Linear Modeling (HLM) analysis suggested that students' individual SRL increased over the course of the project and that CoRL moderated this relationship. Students' improvement in SRL during the project is not solely dependent on their individual efforts but is significantly influenced by the CoRL process. Furthermore, one group was selected as an exemplar case to provide an explanation of how co-regulation occurred and influenced SRL within this collaborative group. The study's findings highlight the theoretical and practical implications of incorporating CoRL strategies to enhance SRL in collaborative learning environments. Although the impact of CoRL on students' SRL has been empirically validated, its application and effectiveness within the context of artificial intelligence-driven learning environments remain unexplored.

2.2.3. Computer-Supported Collaborative Learning (CSCL) Environments and CoRL Practices

Although previous research has robustly demonstrated that self-regulated learning (SRL) strategies significantly predict English writing achievement, these self-regulatory capacities often require external support to be effectively internalized and applied. Through the guidance of a "more capable other", such as a teacher or peer, the co-regulated learning (CoRL) process provides a critical social scaffold for students' SRL abilities [11,13,37]. With the advancement of computer technology, this co-regulatory framework has been extended within computer-supported collaborative learning (CSCL) environments, creating additional technology-supported collaborative learning opportunities and thereby further promoting the integration and application of SRL at higher levels.

The paradigm of Computer-Supported Collaborative Learning (CSCL) represents a significant advancement in leveraging technology to enhance educational outcomes, particularly by utilizing the power of collective intelligence, collaboration, and interactivity. Within this context, CoRL has emerged as critical a construct that potentially address how learners regulate their learning processes within both social and human-AI interactive environments. The integration of pedagogical strategies into CSCL environments has been identified as a vital factor influencing both the learning process and outcomes [38,39].

According to Boud and Soler [40], assessment practices should not only certify current achievement but also equip students with the evaluative capacities required for future learning. Framing AI within this sustainable assessment perspective highlights its role in fostering transferable self-monitoring skills. In CSCL environments, Co-regulated Learning (CoRL) may provide learners with scaffolding through AI-based tools, such as generative AI virtual tutors. These tools can deliver real-time adaptive feedback, personalized guidance, and problem-solving support, functioning as assessment-informed scaffolds and a “more capable other” to help learners maintain their learning pace and more effectively address complex tasks. Moreover, CSCL environments offer researchers a unique opportunity to capture and analyze CoRL data derived from human–AI interactions: by leveraging the technological infrastructure of digital platforms, researchers can record detailed exchanges between virtual tutors and learners, thereby extracting regulatory behaviors associated with CoRL. This study specifically investigates how a generative AI virtual tutor, embedded in a CSCL platform, influences learners’ cognitive abilities and their English writing development.

2.2.4. Applications of Generative AI in Learning Support

With the technological breakthroughs in Generative AI, numerous researchers have endeavored to apply it within the educational sector. In recent years, several studies have demonstrated the substantial potential of Generative AI in assisting students to acquire subject knowledge efficiently and in enhancing their cognitive abilities [41–43]. The revolutionary breakthrough in Generative AI can be traced to the introduction of the ‘Transformer’ model architecture by Ashish Vaswani [44] and colleagues in 2017. This transformer architecture subsequently underpinned later large language model families, including OpenAI’s GPT series and Hangzhou DeepSeek AI’s DeepSeek series (<https://www.deepseek.com/> accessed on 25 September 2025). Through Self-Attention mechanism, these models offer transformative approaches to language processing, closely mirroring human cognition and enhancing educational methods. During pre-training, GPT learns general language patterns from large corpora; fine-tuning then adapts it with task-specific data to optimize performance for particular applications [45]. The foregoing findings provide the theoretical and technological foundation for the research design of the present study.

Generative AI can support the learning process through immediate, personalized feedback, offering suggestions, and evaluating academic works, which aids learners in developing their writing skills. Kohnke [46] investigated the application of generative artificial intelligence (GenAI) tools, specifically Grammarly and Quillbot, within a first-year English for Academic Purposes (EAP) course by employing a mixed-methods design that combined questionnaire data with semi-structured interviews. The study revealed that 66.7% of participants reported frequent use of GenAI tools, primarily to enhance grammar accuracy, vocabulary selection, writing style, and reading comprehension. Existing empirical studies have demonstrated that Generative AI can simultaneously promote students’ acquisition of scientific knowledge and enhance their cognitive abilities [42]. Research by Chan and Hu [47] indicates that Generative AI significantly supports personalized learning, brainstorming, and writing processes among students from various disciplines in Hong Kong, who generally hold a positive view towards these technologies. Similarly, Salvagno [43] contend that Generative AI can significantly aid the writing process, including aspects such as formatting and language review.

Ng [42] employed an evaluative case study design to explore the integration patterns of Generative AI in educational settings, with a focus on how AI enhances students’ learning of computer programming languages and their SRL abilities. The authors utilized validated specific prompts to elicit responses from ChatGPT-3 related to instructional

content (knowledge of programming languages) and SRL strategies (monitoring, feedback, planning, etc.). The findings indicate that Generative AI excels in providing personalized guidance and integrating various information sources into comprehensive explanations, which is crucial for learning programming languages. Additionally, the results demonstrate that Generative AI potentially support students' SRL strategies.

Taken together, the empirical studies reveal three converging strands: decades of robust evidence for SRL's impact on writing, well-theorized frameworks for CoRL as an amplification of SRL via social scaffolds, and the recent breakthroughs in Generative AI that enable it to act as a "more capable other." However, empirical investigations remain scarce on the additional gains in English writing performance afforded by a CoRL-guided AI intervention compared with standard generative AI. Accordingly, this study deploys and fine-tunes a generative AI virtual teacher (CoRL-VT) within a CoRL framework to evaluate its effect on English writing outcomes among Chinese university students, thereby forging new empirical links between established educational theory and cutting-edge AI technology.

3. Method

To fill these empirical and theoretical voids, the present study is guided by the following research questions: Compared to standard AI support, how does CoRL-VT affect pre-post gains in IELTS writing score?

3.1. Quantitative Experimental Research Design

This study employs a 12-week, parallel-group, pretest-posttest quasi-experimental design to assess English writing proficiency (IELTS Writing Task 2), using a primarily quantitative approach complemented by qualitative insights. Two intact classes (clusters) served as the units of assignment. Classes were formed administratively via Gaokao-based streaming; no researcher-implemented randomization was used. Class 8 was assigned to the control condition (standard AI) and Class 9 to the intervention (CoRL-VT) at the class level. The baseline balance analysis (Results, Section 4.1.1) confirms comparability between groups, with no attrition observed.

3.2. Participants

This study was approved by the Academic Research Ethics Committee, School of Education, City University of Macau (protocol SOE-09-03-2425-05-06-DEDCF; approval date 25 March 2025). Participants were 61 undergraduate non-English majors from a public university in Anhui Province, China. Following Gaokao admission, students were administratively streamed by the university into two intact classes; the two classes were comparable in overall Gaokao scores and were taught by the same instructor using the same syllabus. All participants attended one compulsory public English class per week, and there were no other mandatory English examinations during the semester. The control group ($n = 31$; 74.2% female, 25.8% male; mean age = 18.74 years, $SD = 0.63$) used the platform's built-in DeepSeek AI, whereas the experimental group ($n = 30$; 70% female, 30% male; mean age = 18.83 years, $SD = 0.65$) used a version of DeepSeek AI fine-tuned according to CoRL principles (CoRL-VT). A detailed demographic profile is reported in Supplementary Material S3.

In addition, the public English course for both classes was taught by one instructor (Teacher A, pseudonym), a 45-year-old male with 20 years of university-level English teaching experience. Teacher A conducted one session per week for each class and had no prior experience using AI as part of instruction.

3.3. Intervention Materials

Both the control and experimental groups used AI systems based on DeepSeek-R1. A knowledge base containing 1436 high-quality IELTS essays scored by experienced IELTS examiners, together with the official IELTS scoring criteria, was uploaded for retrieval by the AI to enhance the accuracy and consistency of its scoring and feedback. The AI employed by the experimental group (CoRL-VT) was further fine-tuned in accordance with the CoRL principles outlined in Table 1, Figure 1. Detailed fine-tuning procedures, following the prompt-engineering framework of Ingley and Pack [48], are provided in Supplementary Material S1.

Table 1. Components of CoRL-VT fine-tuning.

Component	Description
Description	Defines CoRL-VT as a virtual teacher simulating a “more capable other” to enhance students’ SRL abilities specifically in English writing tasks.
Classification	“Instruction”(other possible categories include “learning”, “course creation”, “instructional evaluation,” etc.)
Prompt Words	Structured prompts that guide the AI model to facilitate goal-setting, provide tailored strategy recommendations, monitor progress, foster collaborative interactions.
Dedicated Knowledge Base	IELTS official scoring materials, IELTS Writing Samples Dataset (Kaggle), and academic literature on SRL and CoRL.
Function Calls	Includes capabilities such as image generation, speech synthesis, oral proficiency assessment, Bing search, and web crawling.
Opening Remarks	Standardized initial greeting in Chinese, inviting students to define their English proficiency level and clarify learning goals.
Publication Permissions	Initially set to private; may later be configured for public access and broader community use.

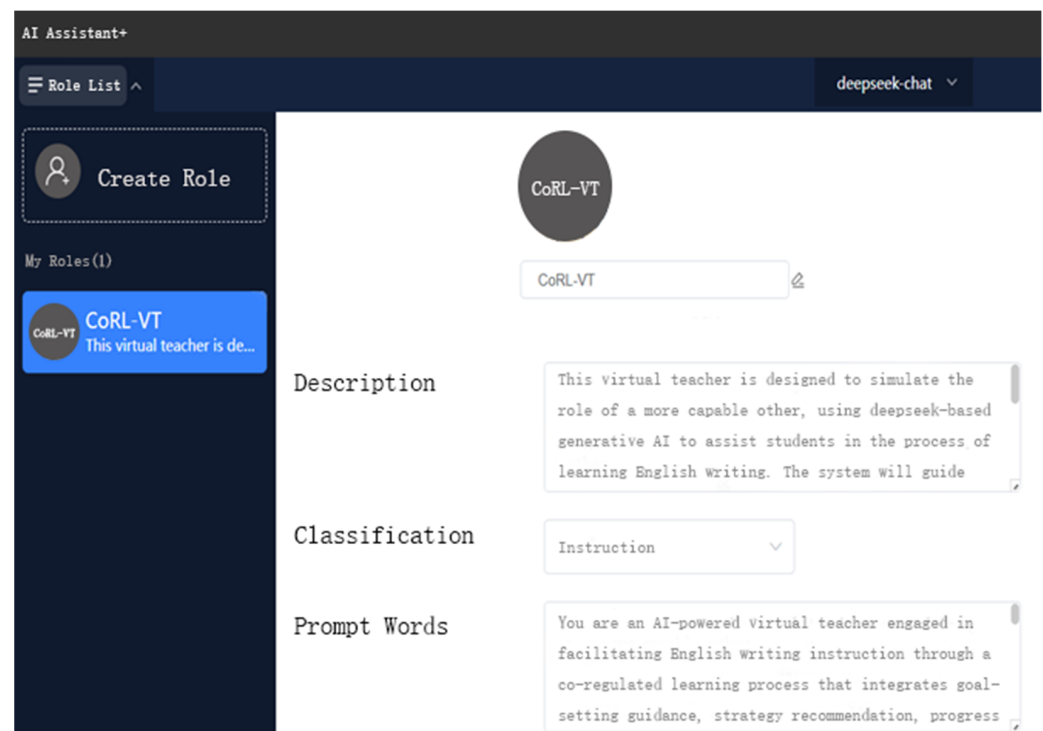


Figure 1. Illustration of CoRL-VT fine-tuning.

After fine-tuning, CoRL-VT is capable of providing professional evaluations of students' writing essays by identifying both deficiencies and areas for improvement. Moreover, it offers timely assistance to help students set objectives, refine learning strategies, and promote group collaboration, mutual review, and other such approaches to enhance their cognitive abilities and English writing proficiency.

Operationalization of Co-Regulation in Human–AI Interaction

Guided by Winne and Hadwin's [24,49] phase model of self-regulated learning and the COPES architecture, we define co-regulation in CoRL-VT as the scripted orchestration of planning, monitoring, and reflection across the SRL cycle. Prior to drafting, CoRL-VT clarifies task conditions and standards by unpacking IELTS descriptors and drawing on representative exemplars from the dedicated knowledge base; it elicits explicit performance targets aligned to the rubric and prompts an outline of claim, reason, and evidence to establish a workable plan. During composing, periodic prompts elicit rubric-referenced self-checks on task response, coherence and cohesion, lexical resource, and grammatical range and accuracy, together with metacognitive probes that help locate weak warrants or missing evidence; learners briefly annotate planned revisions. Following feedback, learners synthesize actionable revisions and identify a strategy intended for transfer to the next task, recording a brief plan for enactment; alignment with standards can then be revisited in subsequent cycles. In contrast to a standard large-language-model that offers generic, post hoc suggestions from the same knowledge base, CoRL-VT organizes a structured SRL cycle enacted through pedagogically scripted dialogue moves. Full prompt schemas and example interaction turns are provided in Supplementary Material S1 to support replication.

3.4. Instruments

For the assessment of students' English writing proficiency, the Academic IELTS Writing Task 2 was used as the primary instrument to measure changes in writing performance before and after the intervention. This task requires students to write an essay in response to an academic question and is scored based on four criteria: Task Response, Coherence and Cohesion, Lexical Resource, and Grammatical Range and Accuracy. The task was administered at both the pre-intervention and post-intervention stages to evaluate the development of students' English writing skills.

To ensure consistency in the difficulty level of the writing tasks, three professional IELTS instructors were invited to review both the pre-test and post-test prompts. The pre-test writing prompt was: "Some people believe that technology has made our lives more complicated, while others think it has improved our quality of life. Discuss both views and give your own opinion." The post-test writing prompt was: "Some people argue that online education is as effective as traditional classroom teaching, while others believe it cannot replace face-to-face instruction. Discuss both views and give your own opinion."

Both prompts are standard IELTS Academic Writing Task 2 argumentative questions ("Discuss both views and give your own opinion") that address widely familiar, non-specialized topics (technology; online education). As such, they require a comparable argumentative structure (two-sided discussion plus personal stance) and draw on similar levels of background knowledge, thereby imposing similar cognitive and linguistic demands under the same rubric dimensions. The three independent expert reviews concurred that the two prompts are equivalent in difficulty. This provides convergent design evidence of prompt comparability, thereby supporting the interpretation that pre–post differences primarily reflect learning gains rather than prompt effects.

In addition, a semi-structured interview was conducted with Teacher A one week after the post-intervention test to gather his perspectives on AI integration, student engagement and differences in writing quality between groups.

3.5. Procedure

All participants attended a 45 min preparatory induction, beginning with a 20 min module on AI prompt engineering and usage techniques followed by a 25 min module on IELTS Writing Task 2 scoring criteria and writing guidelines. Immediately after this induction (pre-intervention, T1), participants completed the Academic IELTS Writing Task 2 test in class.

The 12-week intervention then began. During this period, students learned English writing with AI assistance on the CocoClass platform. Control-group participants used the DeepSeek-R1 model without further modification, drawing solely upon the uploaded knowledge base containing 1436 expert-scored IELTS essays and official scoring criteria. In contrast, the experimental group used CoRL-VT, which, beyond accessing the same knowledge base as the control group, underwent additional fine-tuning aligned with CoRL principles (see Table 1). Detailed fine-tuning procedures are presented in Supplement Material S1.

At the end of the 12 weeks (post-intervention, T2), participants again completed the in-class Academic IELTS Writing Task 2 test in class.

One week after the post-intervention assessment (T2), Teacher A took part in a 30 min semi-structured interview conducted in his office. The session was audio-recorded and transcribed verbatim; the complete transcript is provided in Supplement Material S2.

3.6. Data Analysis

After both pre- and post-tests were completed, all scripts were pooled, anonymized, and randomized across time and class; three senior IELTS examiners independently scored each script blind to group and time. Interrater reliability was assessed using the intraclass correlation coefficient (ICC [3, k]; two-way mixed-effects model for average measures), with $ICC [3, k] \geq 0.80$ indicating acceptable reliability. Final scores for each essay were calculated as the mean of the three examiners' ratings.

With regard to the qualitative materials, one researcher conducted the initial line-by-line coding and theme development following Braun and Clarke's [50] six-phase thematic analysis framework to the verbatim transcripts in order to generate qualitative insights that complement the quantitative findings. To enhance the credibility and auditability of the analysis, the coding framework, representative extracts, and theme definitions were subsequently reviewed and discussed by the research team. Discrepancies in interpretation were resolved through group discussion, and refinements were made until consensus was reached. Themes are presented with anchoring quotations, and interpretations are advanced as descriptive and contextual, given the small sample of one teacher and two classes.

4. Results

4.1. Quantitative Results

All computations were performed in Python 3.12. Inter-rater agreement among the three examiners was excellent, $ICC [3, k] = 0.87$, 95% CI [0.84, 0.91]. Based on the detailed scoring results of the three senior IELTS examiners presented in Supplementary Material S3, the specific results of the data analyses are presented below.

4.1.1. Baseline Characteristics, Equivalence, and Audit Checks

Table 2 summarizes baseline comparability between the control (Class 8) and intervention (Class 9) on pre-test writing, gender, and age; Welch *t*-tests (continuous) and χ^2 (gender) were used, and SMDs are reported to aid auditability. Attrition was zero.

Table 2. Baseline characteristics and equivalence checks.

Variable	Control (Class 8, <i>n</i> = 31)	Intervention (Class 9, <i>n</i> = 30)	Test (<i>df</i>)	<i>p</i>	SMD
Pre-test writing (<i>M</i> , <i>SD</i>)	5.500 (0.392)	5.483 (0.364)	Welch <i>t</i> (58.91) = −0.17	0.864	−0.04
Female% (<i>n</i> / <i>N</i>)	74.2% (23/31)	70.0% (21/30)	χ^2 (1) = 0.01	0.937	−0.09
Age (years, <i>M</i> , <i>SD</i>)	18.74 (0.63)	18.83 (0.65)	Welch <i>t</i> (58.79) = 0.56	0.579	0.14

Taken together, the two classes were comparable at baseline on observed covariates (pre-test writing, gender, and age), with small standardized mean differences ($|SMD| \leq 0.14$) and non-significant tests (all $p \geq 0.579$).

4.1.2. Descriptive Statistics

Pre- and post-intervention means and standard deviations for each class are summarized in Table 3.

Table 3. Descriptive statistics of IELTS writing performance.

Group	<i>n</i>	Pretest <i>M</i>	Pretest <i>SD</i>	Posttest <i>M</i>	Posttest <i>SD</i>
Class 8	31	5.500	0.392	5.618	0.328
Class 9	30	5.483	0.364	5.867	0.402

4.1.3. Within-Group Paired-Samples *t*-Tests

Each class exhibited a statistically significant increase from pretest to posttest (Table 4).

Table 4. Paired-samples *t*-Test results.

Group	<i>t</i>	<i>df</i>	<i>p</i>	Cohen's <i>d</i>
Class 8	2.182	30	0.037	0.392
Class 9	5.358	29	<0.01	0.978

4.1.4. Homogeneity of Regression Slopes

The interaction between pretest score and group was non-significant, confirming the assumption of homogeneity of regression slopes (Table 5).

Table 5. Test of homogeneity of regression slopes.

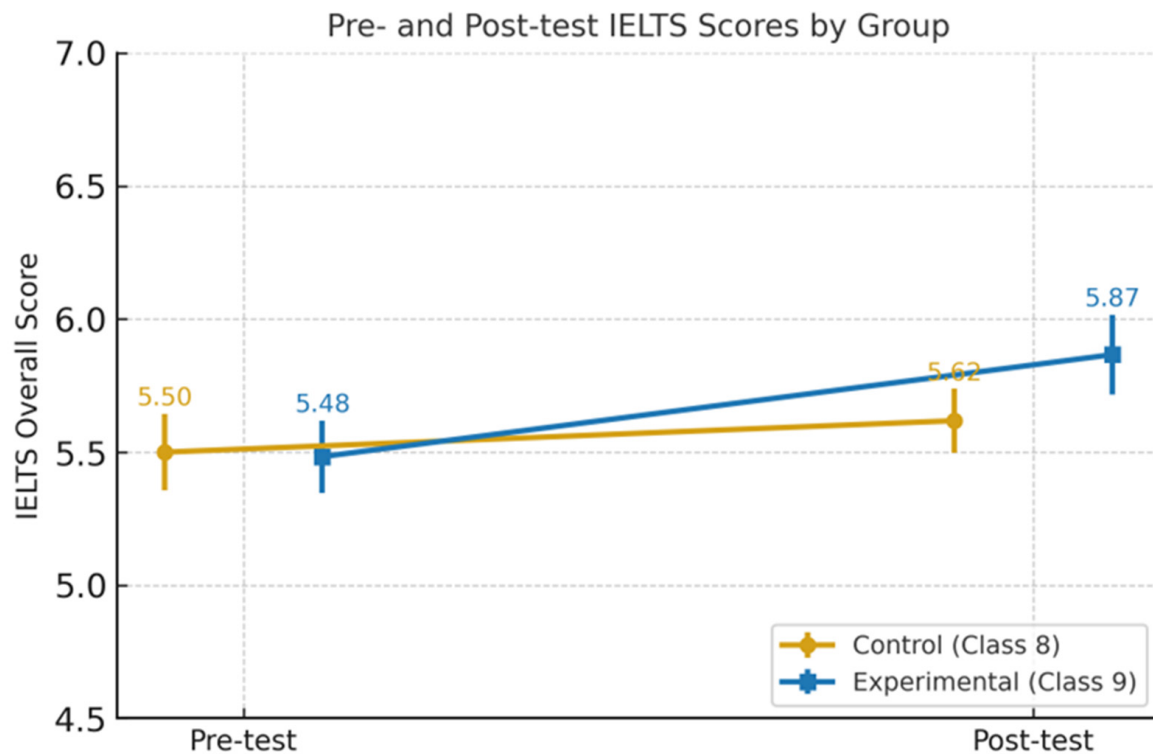
Interaction	Sum of Squares	<i>df</i>	<i>F</i>	<i>p</i>
Pretest × Group	0.00117	1	0.012	0.912

4.1.5. Analysis of Covariance (ANCOVA)

An ANCOVA controlling for pretest performance indicated an estimated group effect on posttest scores, $F(1, 58) = 10.804$, $p < 0.01$, partial $\eta^2 = 0.157$, Cohen's $f = 0.432$ (Table 6, Figure 2).

Table 6. ANCOVA on posttest IELTS scores (controlling for pretest).

Source	Sum of Squares	df	F	p	Partial η^2	Cohen's <i>f</i>
Group	1.010	1	10.804	<0.01	0.157	0.432
Pretest (cov)	2.500	1	26.744	<0.01	-	-
Residual	5.422	58	-	-	-	-

**Figure 2.** Mean IELTS Writing Task 2 Scores at Pre-test and Post-test by Group. Note: Error bars represent 95% confidence intervals. Points are horizontally offset (jittered) for visual clarity; both groups were measured at the same two time points.

In summary, both cohorts demonstrated significant gains in IELTS writing performance from pretest to posttest (Class 8: $t(30) = 2.182$, $p = 0.037$, $d = 0.392$; Class 9: $t(29) = 5.358$, $p < 0.01$, $d = 0.978$). Moreover, ANCOVA controlling for baseline scores revealed an estimated group effect on posttest outcomes ($F(1, 58) = 10.804$, $p < 0.01$, partial $\eta^2 = 0.157$, $f = 0.432$). Adjusted means (95% CI) at the grand mean of the pre-test were: Control = 5.614 [5.504, 5.724]; Intervention = 5.871 [5.760, 5.983]. These results provide preliminary, descriptive evidence that, after accounting for initial ability, the CoRL-VT intervention yielded greater improvement in writing scores than standard AI support.

4.1.6. Robustness and Sensitivity Analyses

We assessed robustness using gain scores (post–pre) and conducted sensitivity ANCOVAs controlling for gender and age to probe potential composition effects (Table 7).

Both robustness checks converged on a treatment advantage: the intervention class exhibited larger gains (Cohen's $d = 0.76$), and the group effect remained significant in ANCOVAs adjusting for pre-test alone and additionally for gender and age (all $p < 0.01$); neither gender nor age predicted post-test performance ($p \geq 0.243$).

Table 7. Robustness (gain-score) and sensitivity (gender- and age-controlled ANCOVA) analyses.

Analysis	Control (<i>M, SD</i>)	Intervention (<i>M, SD</i>)	Test (<i>df</i>)	<i>p</i>	Effect Size
Gain-score (post–pre)	0.118 (0.302)	0.383 (0.392)	Welch <i>t</i> (≈ 54.50) = 2.95	<0.01	Cohen’s <i>d</i> = 0.76
ANCOVA: Post ~ Pre + Group + Gender	-	-	Group: <i>F</i> (1, 57) = 10.793	<0.01	partial η^2 = 0.159
			Gender: <i>F</i> (1, 57) = 0.254	0.616	-
ANCOVA: Post ~ Pre + Group + Gender + Age	-	-	Group: <i>F</i> (1, 56) = 11.35	<0.01	partial η^2 = 0.168
			Gender: <i>F</i> (1, 56) = 0.10	0.750	-
			Age: <i>F</i> (1, 56) = 1.39	0.243	-

4.2. Qualitative Findings

The verbatim interview transcript is provided in Supplementary Material S2; all quotations below have been translated into English. Following Braun and Clarke’s [50] six-phase thematic analysis, four overarching themes emerged. Each theme is illustrated with exemplar quotes and serves as an illustrative complement to the ANCOVA findings.

- Theme 1: AI as Supplementary Support with Occasional In-Class Demonstrations

Teacher A explained that both AI systems were used primarily as after-class aids, with only occasional in-class demonstrations, partly because strict school regulations limit teachers’ motivation to innovate instructional formats: “Our classes are somewhat strict—if students use AI or play on their phones, we might get in trouble. . . AI can only serve as an after-class aid for the two groups. . . however, I do sometimes demonstrate it on my laptop in class, letting the AI interact with them—it really catches their attention.” This aligns with our finding that both groups improved, suggesting that the observed improvements in both classes’ English writing performance were attributable mainly to the after-class AI feedback, rather than the occasional in-class demonstrations.

- Theme 2: Enhanced Writing Organization and Student Agency

Teacher A noted that students in the CoRL-VT group (Class 9) demonstrated clearer structure and an expanded vocabulary: “Class 9 was noticeably better—at least their vocabulary improved, grammar was fine in both classes, and Class 9’s writing showed some clear organization.” This qualitative insight is consistent with the ANCOVA: after adjusting for pre-test scores, we observed an estimated between-group difference in writing gains, Class 9 (CoRL-VT) showed larger improvements than the control class.

- Theme 3: Perceived Quality of AI Feedback

According to Teacher A, students in the experimental group described CoRL-VT’s feedback as more “teacher-like” and actionable, whereas control-group students felt standard DeepSeek feedback was generic: “The AI for Class 9 was pretty good—it at least gave feedback like a real teacher. . . As for the one in Class 8, students didn’t have any strong reaction; they said Doubao was still more useful.” This underscores how systematic fine-tuning endows CoRL-VT with greater potential as a virtual teacher and as a “more capable other” compared to standard AI.

- Theme 4: Pedagogical Benefits and Implementation Challenges

Teacher A noted that AI significantly reduced his lesson-planning workload and drafting materials. At the same time, he cautioned that, without proper safeguards, some students might become overly dependent on the AI for writing tasks, underscoring the need for clear usage policies, vigilant monitoring, and targeted teacher training: “I use DeepSeek to draft lesson plans and such—it does lighten my workload a bit. . . I think the

more serious issue is that some kids might use it to help write their essays; it really depends on their own self-discipline”.

5. Discussion

Consistent with sustainability goals in higher education, these exploratory findings suggest that pedagogically guided AI may provide a scalable, resource-conscious complement to English writing instruction. Although the mean gain difference was modest in absolute terms (0.38 vs. 0.12 band points), it may still hold preliminary pedagogical relevance. Specifically, the CoRL-VT group’s mean score rose from 5.48 to 5.87, approaching the IELTS 6.0 threshold that is often required for scholarship eligibility or entry to English-medium degree programs. In contrast, the control group’s mean remained around the mid–5 range. While these short-term gains from a 12-week intervention should be interpreted cautiously due to the small number of clusters, they tentatively suggest that structured AI scaffolding could accelerate students’ trajectory toward meaningful proficiency benchmarks.

Our results provide exploratory, descriptive evidence that digital agents designed with pedagogical intelligence have the potential to scaffold higher-order writing skills. Teacher A’s interview provided qualitative support: he observed that CoRL-VT students produced essays with clearer argumentative structure and richer vocabulary, whereas the control group’s improvements were more superficial. He also noted that CoRL-VT’s feedback felt more “teacher-like” and actionable compared to the standard AI’s generic comments.

This perceptual difference likely motivated deeper engagement in the revision process and reinforced strategic writing behaviors in the experimental group. From a practical standpoint, CoRL-VT offered efficiency benefits: the instructor reported a marked reduction in time spent on lesson planning and draft feedback, as routine evaluative tasks were delegated to the AI. However, he cautioned that some students might become overly reliant on AI suggestions if usage is not properly monitored. This risk echoes concerns that generative AI can encourage cognitive offloading without clear guidelines and AI-literacy training. To mitigate this, educators should require students to draft independently before consulting the AI and to critically evaluate AI-generated revisions.

However, due to limited available resources, this study has several limitations. First, the sample was restricted to two classes at a single institution, and only one English teacher was interviewed. Future research should replicate this design with a larger and more diverse population, and ideally incorporate an additional control group receiving only traditional instruction to assess the absolute gains attributable to the experimental intervention. Additionally, process-focused measurement instruments, such as writing process logs captured via keystroke logging software (e.g., Inputlog or Scriptlog), should be incorporated to provide fine-grained data for evaluating how AI scaffolding influences students’ writing behaviors and overall language learning processes. Like most AI software, CoRL-VT is web-based and device-agnostic, accessible through a standard browser on a smartphone or a laptop. Precisely because the AI’s access is so low-friction, potential risks such as overreliance and cognitive offloading and concerns about authorship transparency and academic integrity require attention; future studies should prioritize pre-specified usage policies and AI literacy guidance, autonomy-preserving “fading” scaffolds with basic audit logging, and delayed post-tests to assess durability.

6. Conclusions

Our student-level analyses provide preliminary, descriptive evidence consistent with greater gains under CoRL-VT than standard AI. Both groups exhibited statistically significant pre-to-post gains (Class 8: $t(30) = 2.182$, $p = 0.037$, $d = 0.392$; Class 9: $t(29) = 5.358$,

$p < 0.01$, $d = 0.978$), and ANCOVA controlling for baseline scores indicated an estimated group difference on post-test outcomes ($F(1, 58) = 10.804$, $p < 0.01$, partial $\eta^2 = 0.157$). In practical terms, the CoRL-VT class improved by an average of 0.38 band points, compared to 0.12 in the control class. This moderate-to-large effect underscores the value of embedding metacognitive scaffolds within AI feedback.

This study provides exploratory evidence that a CoRL-informed AI tutor has potential to enhance L2 writing outcomes beyond standard AI support. By acting as a virtual “more capable other,” CoRL-VT delivered corrective feedback and fostered students’ metacognitive engagement, resulting in larger gains in overall English writing proficiency. Theoretically, these findings extend SRL and CoRL theory into AI-mediated contexts by demonstrating that digital agents can scaffold learning processes in ways akin to human tutors. Practically, they suggest that pedagogically designed AI tools have the potential to augment teacher capacity and provide individualized support at scale, provided that institutions establish clear usage policies and train both students and instructors in effective AI integration.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su17198770/s1>, Figure S1. Fine-Tuning of CoRL-VT—Part 1; Figure S2. Fine-Tuning of CoRL-VT—Part 2; Figure S3. Interaction Scenario Example 1; Figure S4. Interaction Scenario Example 2; Supplementary Material S1: Detailed Introduction to CoRL-VT; Supplementary Material S2: Interview; Supplementary Material S3: Pre- and Post-test IELTS Overall Scores; Supplementary Material S4: Official Approval Letter for Academic Ethics Review Application; Supplementary Material S5: Informed Consent Form.

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Data Availability Statement: The original datasets, coding framework, and scoring rubrics used in this study are provided in Supplementary Materials S1–S3. The datasets and analysis code generated and used in this study are available from the corresponding author on reasonable request for research purposes, subject to institutional data-sharing agreements and ethics approval. Public benchmark resources used to build the AI knowledge base are cited in the manuscript and can be accessed from their original repositories.

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