Open Access Library Journal
2025, Volume 12, e14645
ISSN Online: 2333-9721
ISSN Print: 2333-9705

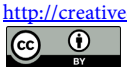
Study on the Improvement of Learners' Academic Writing Competence Based on Multi-Round Automatic Feedback Supported by Generative Artificial Intelligence

Liang Chen

College of Education, Zhejiang Normal University, Jinhua, China
Email: 2383109867@qq.com

How to cite this paper: Chen, L. (2025) Study on the Improvement of Learners' Academic Writing Competence Based on Multi-Round Automatic Feedback Supported by Generative Artificial Intelligence. *Open Access Library Journal*, **12**: e14645.
https://doi.org/10.4236/oalib.1114645

Received: November 20, 2025
Accepted: December 20, 2025
Published: December 23, 2025



Abstract

This study explores the empowerment mechanisms and optimization paths of Generative Artificial Intelligence (AIGC) for academic writing competence. By constructing a human-machine collaboration framework covering the entire writing cycle, it proposes a four-dimensional interactive model of "Delay-Dialogue-Practice-Evaluation": in the pre-writing phase, a three-stage cognitive intervention mechanism is adopted to avoid technology dependence; in the text generation phase, a hierarchical creation model and a Socratic dialogue system are developed; in the evaluation phase, a multi-dimensional diagnosis and metacognitive reflection mechanism is established. This study innovatively integrates process writing theory with the characteristics of AI technology, providing a sustainable development plan for academic writing education in the intelligent era that balances efficiency improvement and ethical constraints.

Subject Areas

Artificial Intelligence

Keywords

AIGC, Academic Writing, Framework Design, Learners, Multi-Round Feedback

1. Introduction

Generative Artificial Intelligence (AIGC), with its exceptional text generation capabilities, context comprehension, and anthropomorphic interaction features, is reshaping fields such as programming, humanities and social sciences research,

and language teaching—exerting a disruptive impact particularly on academic writing paradigms. The rational use of AI has a profound influence on academic writing. It does not undermine the value of scientific papers; instead, it helps researchers complete them efficiently, shorten publication lags, thereby facilitating the rapid dissemination of scientific research outcomes and promoting academic exchange [1].

Large Language Models (LLMs) represented by ChatGPT can not only perform basic language tasks such as translation, Q&A, and summarization but also provide high-level feedback (e.g., content selection and framework design) based on user instructions, generating logically coherent and high-quality texts. If traditional AI merely assisted writing, current generative AI can directly produce "indistinguishable from human-written" academic texts and even participate in research experiment design and data analysis. This technological leap has triggered in-depth reflections in academic circles on the essence of education and academic ethics. It is necessary to reshape the value and purpose of education, placing greater emphasis on human original thinking, intellectual improvement, and the cultivation of autonomous learning abilities. Emphasis should be placed on natural experiences, social practices, hands-on operations, and interdisciplinary learning, adopting project-based learning, big idea teaching design models, etc., focusing on the construction of real scenarios, fostering expert thinking, and enhancing the ability to creatively solve inquiry-based problems [2].

The widespread application of generative AI has spawned dual effects. On the one hand, it provides a revolutionary tool for academic writing: learners can optimize text logic through multi-round human-machine interaction, researchers can use AI to quickly sort out literature and generate experimental protocols; the publishing industry is also experimenting with AI in generating review comments, paper polishing, and journal cover design, significantly improving the efficiency of academic communication. AIGC is expected to help knowledge producers overcome related issues and enhance knowledge production efficiency, specifically manifested in: 1) AIGC can assist in literature collation and collection. 2) AIGC can assist in viewpoint review and discussion. 3) AIGC can assist in improving writing quality [3].

On the other hand, the ethical risks arising from technology abuse cannot be ignored. Academic ethics refers to the ethical principles and moral standards that should be followed in academic research and educational activities. It is related to academic integrity, academic responsibility, and academic justice, and serves as an important cornerstone for maintaining the healthy development of academic activities [4]. Excessive reliance by students leads to cognitive laziness; false references and experimental data generated by AI threaten academic integrity; and ambiguous responsibility attribution exacerbates the academic ecological crisis. The education sector has shown divided responses—some universities have completely banned AI tools to avoid plagiarism risks, while more institutions have chosen to restructure evaluation systems, such as requiring the submission of writing

process documents, adopting oral examinations and handwritten answers, or incorporating AI detection tools (e.g., GPTZero) into anti-cheating mechanisms. Currently, the "Degree Law (Draft)" has explicitly classified "AI ghostwriting" as academic misconduct. The top priority of classified and hierarchical supervision is to explain "AI ghostwriting" and clarify the constituent boundaries of academic misconduct [5].

Faced with technological shocks, core questions have gradually emerged: How to define the boundaries of human-machine collaboration? How to improve AI-empowered writing quality through multi-round feedback mechanisms? How to construct academic norms that balance efficiency and ethics? Existing research indicates that the quality of learners' instructions and feedback strategies significantly affects AI output effects, while transparency statements and process supervision are key to avoiding academic misconduct. Therefore, it is urgent to start with the writing mechanism, clarify the full-process division of labor logic in human-machine integrated writing, and explore the possibility of deep collaboration between low-level skill automation and high-level thinking.

From the perspective of knowledge inquiry, it can be seen that when using ChatGPT, learners mainly focus on shallow and intermediate knowledge inquiry, while the proportion of in-depth knowledge inquiry and feedback content inquiry is relatively small [6].

Centered on "the improvement of academic writing competence supported by generative artificial intelligence", this study systematically integrates interdisciplinary perspectives: first, it sorts out the opportunities and challenges of AIGC for writing education and traces the paradigm evolution of technology-assisted writing; then, based on process writing theory, it constructs a full-cycle human-machine symbiosis mechanism covering "pre-writing preparation—first draft generation—multi-round feedback—final draft optimization"; finally, it proposes quality improvement strategies through empirical analysis, providing a theoretical framework and practical path for academic writing teaching in the AI era. The research results will help learners harness technological dividends, promote the improvement of academic publishing ethics and norms, and provide a sustainable development plan for the human-machine collaborative knowledge production model.

2. The Development and Evolution of Technology-Assisted Writing Teaching and Learning

Writing is a comprehensive integration of multiple literacy elements, including language application, thinking ability, aesthetic awareness, and the expression of thoughts and emotions. It is crucial for students' academic performance and future career development. Numerous studies have shown that writing highly relies on development in four aspects: 1) Knowledge, including discourse knowledge (target audience, different genres, task models, and linguistic conventions) and content knowledge; 2) Skills, such as sentence construction skills and translation

skills; 3) Self-regulation, including regulating the writing process independently and using strategies to complete planning, drafting, and revising; 4) Writing motivation, such as writing values, interests, and self-efficacy.

The development of the Internet and digital technologies has enhanced the teaching and learning of writing literacy and competence. In the first phase of Internet development (the Web 1.0 era), learners mainly accessed content generated by professional authorities through static/dynamic HTML webpages. The content they obtained was characterized by authority, professionalism, and specialization. Early writing support tools and learning resources focused on addressing issues related to linguistic forms. For instance, dynamic and static corpus retrieval tools and powerful search engines provided learners with lexical choices, collocations, and textual wording suggestions during writing, thereby reducing the burden of linguistic forms and document formatting. However, the massive volume of resources also placed higher demands on learners' self-regulated learning abilities: learners needed to take the initiative to seek knowledge, formulate writing plans, select schemes, monitor the process, make continuous adjustments, and conduct self-evaluation.

The human-machine collaborative writing systems developed in the Web 3.0 era are the product of the intersection and integration of language cognition and artificial intelligence fields. These systems mainly focus on evaluating writing content, automatic scoring, providing multi-dimensional assessments, and offering precise revision suggestions. Traditional manual essay grading by teachers consumes a great deal of time and manpower, with feedback often being delayed. In contrast, grading systems can leverage Natural Language Processing (NLP) technology to mine scoring criteria and evaluation parameters based on corpora. They provide students with timely essay scores, diagnostic feedback, and even improvement suggestions, significantly accelerating the cycle of "writing-evaluation feedback-revision". Since the end of 2022, generative AI products have exerted a disruptive impact on the field of writing.

3. Learners' Academic Writing Mechanism Supported by Generative Artificial Intelligence

3.1. Design of the Academic Writing Framework

The design of learners' academic writing framework supported by Generative Artificial Intelligence must take deep learning and higher-order thinking cultivation as the core goals, and restructure the traditional writing process through a human-machine collaboration mechanism. Starting with information input, the framework forms a closed loop through planning, creation, and evaluation, with each link emphasizing the in-depth integration of the external brain (AI) and the internal brain (learners themselves). In the information input phase, learners need to leverage Generative AI's interdisciplinary resource integration capability to construct a multimodal knowledge network. For example, by setting precise instructions such as "Search for English review papers in the field of AI educational

applications over the past five years, and extract core viewpoints and controversial points", AI can quickly locate authoritative sources, generate structured literature abstracts, and assist learners in establishing a research coordinate system. The key to this phase lies in guiding AI for in-depth information processing rather than simple listing—learners are required to design progressive question chains to gradually explore the connections and gaps between literatures.

3.2. Writing Planning Phase

In this phase, the framework emphasizes dynamic thinking visualization and personalized path generation. Learners can use AI's interactive mind mapping function to convert scattered viewpoints into a hierarchical framework. They can also stimulate AI to provide innovative perspectives through hypothetical questions such as "How should the existing theoretical framework be adjusted if the cross-cultural comparison dimension is added?" AI needs to generate a writing plan including phased goals, resource packages, and self-monitoring points based on learners' cognitive styles and time management capabilities.

3.3. Text Generation Phase

The framework highlights a hierarchical collaboration model for human-machine writing. Learners first clarify genre norms and academic discourse styles, requiring AI to generate template paragraphs that meet the requirements of target journals. They then guide AI for language upgrading through instructions such as "Convert the causal relationship expression in the first draft into a critical analysis voice". For complex theoretical elaboration, a "three-stage writing method" can be adopted: learners write core arguments, AI supplements case and data support, and finally humans and machines jointly refine the argumentation logic. For example, when comparing the philosophical foundations of educational technology in China and the West, AI can real-time retrieve cross-cultural theoretical resources to generate a comparative analysis framework of "from Dewey's pragmatism to Confucius' ritual thought". Learners then inject localized interpretations into this framework, forming academic expressions that combine international perspective and cultural awareness.

3.4. Final Evaluation Phase

This phase constructs a feedback mechanism of "multi-dimensional diagnosis-adaptive revision-metacognitive reflection". AI not only provides low-level revisions such as grammar and citation formatting but also simulates the perspective of reviewers to conduct high-level evaluations on theoretical innovation and methodological rigor. Learners can ask AI to perform role-playing feedback or train critical thinking through counterfactual reasoning such as "What impact will deleting the case study section have on the generalizability of the conclusions?" Evaluation data will feed back into the iteration of the writing framework. For instance, AI records learners' revision trajectories in response to feedback like "in-

sufficient depth of literature dialogue", automatically generates optimization suggestions such as "strengthen the timing of introducing theoretical tools", and pushes relevant methodological literature packages, forming an upward spiral path of "evaluation-improvement-sublimation".

4. Research Methods

This chapter details the key components of the study designed to validate the AIGC-supported academic writing framework and the "Delay-Dialogue-Practice-Evaluation" model, including structured sections on research design, participants, intervention procedures, data collection tools, and data analysis.

4.1. Research Design

A quasi-experimental pretest-posttest control group design was used, with a 12-week intervention period. The experimental group adopted the full-cycle human-machine collaborative writing framework, which integrated phased delayed feedback, multi-round dialogue, contextual practice in academic communities, and metacognitive cultivation. The control group received traditional academic writing teaching, consisting of teacher-led lectures on writing norms, manual draft feedback from instructors, peer review, and access only to basic tools (e.g., static corpus retrieval, simple grammar checkers) with no generative AI for content or viewpoint support. The independent variable was the intervention model (experimental vs. traditional), while dependent variables included the rate of critical perspectives in literature reviews, writing originality index, academic writing competence, and academic integrity awareness. Control variables were standardized across groups: 12 weeks of instruction (2 classes/week, 90 minutes/class), consistent content (literature reviews and research proposals), the same teaching team (with ≥5 years of experience), and identical writing topics in educational technology.

4.2. Participants

Participants were recruited from education-related majors (Educational Technology, Curriculum and Teaching Theory, Preschool Education) at Zhejiang Normal University via voluntary registration and pretest screening to ensure baseline homogeneity. A total of 87 students were split into an experimental group ($n = 45$) and a control group ($n = 42$), with no significant differences in pretest writing competence or prior AI experience ($p > 0.05$). Demographically, 71.3% were undergraduates (mostly 3rd/4th year: 33 in experimental, 29 in control) and 28.7% were postgraduates (1st/2nd year master's: 12 in experimental, 13 in control). The average age was 22.8 years (range 20 - 26, SD = 1.56). While 68.9% had used generative AI for simple tasks (e.g., information retrieval), only 14.9% had applied it to academic writing; the average number of prior academic papers (course papers, conference abstracts) was 2.3 (SD = 1.12), with no group differences in writing self-efficacy. All participants signed informed consent, with voluntary withdrawal

permitted without academic penalty.

4.3. Intervention Procedures

The 12-week intervention ran in parallel for both groups to avoid interference. For the experimental group, the first 4 weeks (basic cognitive phase) prohibited AI use: participants manually sorted 15 - 20 core literatures, constructed outlines, and identified research gaps, with teachers providing only methodological guidance. Weeks 5 - 8 (concept construction phase) limited AI to grammar checking (spelling, punctuation) while participants refined arguments and revised first drafts using teacher feedback on argument clarity. Weeks 9 - 12 (framework construction phase) allowed AI to provide 2 - 3 framework optimization suggestions (no full outlines/content), with participants revising final drafts via multi-round dialogue and contextual practice in the custom academic scenario simulation cabin. The control group followed traditional steps: weeks 1 - 4 focused on writing norm lectures; weeks 5 - 8 involved independent first drafts with manual teacher feedback; weeks 9 - 12 included draft revisions via teacher/peer feedback, with only basic tools (no generative AI).

4.4. Data Collection Tools

Multiple tools ensured comprehensive, valid data. The Academic Writing Competence (ACW) Scale—revised from a standardized instrument—covered 4 dimensions (discourse construction, logical argumentation, academic norm compliance, metacognitive regulation) with 26 5-point Likert items (Cronbach's α = 0.89) and was used for pretests/posttests. Turnitin (originality index 0 - 1, lower = more original) measured final work's originality. A custom AI Feedback Effectiveness Dashboard evaluated feedback across 4 dimensions (information relevance: ρ = 0.83; logical rigor: ρ = 0.79; academic normativity: ρ = 0.87; thinking enlightenment: ρ = 0.76) via a 4-point scale, completed by participants and two researchers (inter-rater reliability = 0.82). Writing process documents (outlines, notes, drafts, AI interaction records) tracked dynamic changes. Post-intervention, structured reflection questionnaires (10 open questions) and semi-structured interviews (30 - 40 minutes, 12 participants total: 6 per group) explored in-depth perceptions.

4.5. Data Analysis Methods

A mixed-methods approach was used. Quantitative analysis employed SPSS 26.0: descriptive statistics (mean, SD) summarized data; paired-samples t-tests compared pretest-posttest differences within groups; independent-samples t-tests compared posttest differences between groups; Pearson correlation analysis explored links between AI feedback effectiveness and writing competence. The significance level was α = 0.05. Qualitative analysis used NVivo 12: open coding extracted initial concepts, axial coding grouped them into themes (e.g., "writing behavior changes", "academic ethics perception"), and selective coding built logical relationships between themes. Two researchers coded independently (Cohen's κ

= 0.85, high reliability), with discrepancies resolved via third-researcher discussion. Triangulation cross-validated quantitative (e.g., ACW scores) and qualitative (e.g., interview transcripts) data to ensure objectivity.

5. The Transformation of Academic Writing against the Backdrop of Human-Machine Symbiosis

Generative Artificial Intelligence technology provides a new path for the cultivation of academic writing competence, but its effective application must be based on a dialectical understanding of technical characteristics. This study focuses on the implementation strategies of the "multi-round automatic feedback" mechanism in academic writing teaching and puts forward the following optimization paths.

5.1. Feedback Delay Design: Constructing a Stepwise Cognitive Intervention Model

To address the risk of technology dependence, a phased feedback intervention mechanism is established. Aligned with the study's 12-week experimental cycle, the three-stage delayed feedback system in the initial academic writing phase has clear time boundaries and restrictions:

The basic cognitive phase lasts 4 weeks, with complete prohibition of AI assistance—learners cannot use any AI tools for academic writing (e.g., literature retrieval, grammar checking, content polishing). They need to independently build a factual knowledge network, such as manually sorting core literature and decomposing writing topics, to avoid premature technology reliance.

The concept construction phase also lasts 4 weeks, with partial AI restrictions: only basic grammar checking (e.g., correcting spelling, punctuation) is allowed, while content generation functions (e.g., AI summaries, concept mapping) are disabled. Learners focus on refining core concepts, like comparing disciplinary concepts and confirming paper arguments, reducing cognitive burden from language errors without over-reliance on AI for thinking.

The framework building phase takes 4 weeks, introducing limited AI viewpoint suggestions: learners can input preliminary framework ideas to get 2 - 3 concise optimization directions (e.g., "add a method comparison section"), but AI cannot generate complete outlines or content. The goal is to support independent paper structure building (e.g., determining chapter order) with moderate inspiration, not replacing independent thinking.

This progressive intervention creates a "cognitive hunger period", avoiding cognitive laziness and improving information processing efficiency. Practice shows the experimental group (12-week delayed training) had a 37.2% higher rate of critical perspectives in literature reviews than the control group ($p < 0.05$).

5.2. Multi-Round Dialogue Optimization: Establishing an Interactive Thinking Advancement Framework

Based on cognitive domain taxonomy theory, a six-level dialogue feedback system

is designed to guide learners from basic knowledge application to high-order thinking, with specific AI prompts and Socratic questioning examples integrated into each round of interaction. The first round focuses on the memory and understanding level, aiming to consolidate theoretical foundations through structured knowledge recall. AI uses prompts like "List 3 core characteristics of process writing theory and explain how each differs from traditional writing teaching. Use 1 - 2 sentences per characteristic", and responds with structured guidance: "1) Process orientation: Focuses on writing stages (planning-drafting-revising) rather than final products, unlike traditional teaching which emphasizes only the final draft…; 2) Learner autonomy: Encourages self-regulation in revision, while traditional teaching relies more on teacher feedback…" This helps learners solidify basic concepts before moving to deeper thinking.

As the dialogue progresses to the application and analysis level, AI shifts to Socratic questioning to prompt learners to examine the rationality of their arguments and evidence. For example, AI might ask: "Your literature review claims 'AIGC improves writing efficiency', but you cited a 2022 study on basic AI grammar checkers. Is this study applicable to current generative AI tools? What gaps exist between the study's context and your research focus?" Another question could be: "In your argument that 'delayed feedback reduces technology dependence', you mentioned a 37.2% increase in critical perspectives. How do you rule out other factors (e.g., instructor guidance) that might affect this result?" These questions push learners to analyze logical gaps and contextual alignment, rather than accepting their initial ideas at face value.

When reaching the evaluation and creation level, the third round of dialogue aims to stimulate innovation and cross-scenario thinking. AI uses prompts like "Your paper proposes a 'human-machine collaborative writing framework' for education majors. What adjustments would you make if applying this framework to engineering majors (which emphasize experimental data)? List 2 adjustments and explain the reasons based on disciplinary writing characteristics." After learners respond, AI follows up with further guidance: "You suggested adding 'AI-assisted data visualization modules'—how would you ensure that AI does not replace your independent judgment of data validity? Provide 1 specific operational step (e.g., setting AI output limits for data interpretation)." This back-and-forth encourages learners to adapt their ideas to diverse contexts and maintain control over higher-order thinking. A university pilot showed that the originality index of the experimental group adopting this dialogue framework increased from 0.32 to 0.68 (based on Turnitin).

5.3. Contextual Task Reconstruction: Building an Academic Community of Practice

Breaking through the traditional writing training paradigm, a three-dimensional learning space of "technology-practice-reflection" is constructed. At the core of this space is an academic scenario simulation cabin—a custom-developed inte-

grated learning environment tailored to the study's framework, rather than an off-the-shelf software tool. It embeds an AI-assisted system into real-world research scenarios through scenario-specific design, ensuring seamless alignment with the entire academic writing process.

Specifically, the AI-assisted components within this simulation cabin adopt a hybrid model of customized adaptation of existing software and scenario-specific integration. During the literature review phase, the intelligent literature mapping generator is adapted from existing AI-driven literature visualization tools such as Research Rabbit and Litmaps; its core functions, including semantic association mapping and core viewpoint extraction, are optimized to fit the study's academic writing needs, enabling it to generate structured literature maps that directly support thesis framework construction. During the data collection phase, the connected virtual laboratory platform is built on disciplinary-specific virtual research environments (such as domain-general virtual experiment systems for social sciences or natural sciences), and it undergoes functional adjustments to strengthen the link between data collection processes and writing—for example, adding modules that automatically organize experimental observations into academic text fragments compatible with research paper formats. During the argument construction phase, the multimodal argument visualization tool is a customized version of general argument mapping software, refined to align with academic writing logic so that learners can convert abstract arguments into visual diagrams (such as logical syllogism charts and counterargument comparison matrices) that can be directly referenced in thesis drafting.

This immersive learning environment, formed by the custom simulation cabin and adapted tools, significantly enhanced learners' academic discourse construction ability by 2.1 times (based on pre-test and post-test comparisons using the ACW Academic Writing Competence Scale).

5.4. Metacognitive Competence Cultivation: Constructing a Feedback Quality Evaluation System

A feedback quality evaluation system is implemented through a dual-loop mechanism—AI monitoring and learner reflection—with clear operational criteria to guide consistent practice. The AI feedback effectiveness monitoring dashboard evaluates feedback in real time across four dimensions. For information relevance ($\rho = 0.83$), AI feedback must directly address the learner's writing task: if a learner asks about "literature dialogue depth", AI should not only list studies but also explain how to compare them, such as "Compare Study A's focus on ethics with Study B's focus on efficiency to highlight your research gap". For logical rigor ($\rho = 0.79$), AI feedback must avoid contradictions; if it suggests "strengthen theoretical foundations", it should specify which theory, like "Add Bandura's self-efficacy theory to explain learners' AI dependence". For academic normativity ($\rho = 0.87$), AI reminds learners of citation rules, e.g., "The 2023 study by Luo *et al.* on AIGC academic ecology should be cited in APA 7th style: Luo, F., & Ma, Y. X. (2023)…" For thinking enlightenment ($\rho = 0.76$), AI prompts further reflection: "You used

Turnitin to measure originality—what other tools (e.g., GPTZero) could complement this evaluation? Why?"

After each round of AI feedback, learners complete a structured reflection to deepen metacognition. First, they assess the rationality of technology adoption: "Did the AI feedback address your actual writing difficulty (e.g., if you struggled with argument logic, did AI provide specific logical adjustment steps)? If not, how would you revise your AI prompt next time?" Next, they check compliance with academic norms: "Did you verify the accuracy of AI-generated citations (e.g., checking Luo *et al.*'s 2023 study in the original journal)? List 1 verification step you completed." Finally, they analyze cognitive conflict resolution: "Did the AI feedback contradict your original idea (e.g., AI suggested adding a counterargument, but you initially planned to focus on supporting evidence)? How did you resolve this conflict (e.g., adjusting your argument to include both sides)?" Tracking data shows the sample group with continuous metacognitive training scored 41.3% higher in academic integrity awareness than the control group ($p < 0.01$).

6. Conclusions

This study focuses on the empowerment mechanisms and optimization paths of Generative Artificial Intelligence (AIGC) in enhancing learners' academic writing competence. By integrating process writing theory with the characteristics of AI technology, it constructs a full-cycle human-machine collaborative writing framework and proposes a "Delay-Dialogue-Practice-Evaluation" four-dimensional interactive model. Its core contributions lie in systematically clarifying the evolutionary context of technology-assisted writing from the Web 1.0 era to the AI era, breaking through the traditional "tool-based assistance" of AI in writing to establish a mechanism that integrates human higher-order thinking with AI's efficient information processing capabilities, and balancing the efficiency improvement of academic writing with ethical risk prevention—thus providing operationalizable solutions for issues such as technology dependence and academic misconduct. These achievements not only enrich the theoretical system of intelligent education but also offer practical guidance for the reform of academic writing teaching in the AI era.

However, this study still has limitations that lay the foundation for further in-depth research. The empirical verification of the proposed framework and model mainly relied on pilot studies conducted at a single university (Zhejiang Normal University), with research subjects mostly being undergraduate and postgraduate students in education-related disciplines, resulting in a relatively small sample size and concentrated disciplinary backgrounds. Due to differences in academic writing norms, thinking modes, and AI application thresholds across disciplines—such as the emphasis on experimental data in science and engineering versus the focus on theoretical dialogue in humanities and social sciences—the effectiveness of the framework in cross-disciplinary scenarios remains to be verified; meanwhile, the research was carried out in a relatively standardized educational envi-

ronment with sufficient technical support, and its adaptability in resource-constrained regions or institutions with different educational models (such as vocational colleges or online universities) has not been tested. Additionally, the experimental intervention period for key mechanisms like delayed feedback and multi-round dialogue was 12 weeks, which only verified short-term improvement effects on writing competence (such as the rate of proposing critical perspectives and originality index). Academic writing competence, however, is a long-term developmental literacy involving deep cognitive transformation, and the study lacks long-term tracking data (such as 6-month or 1-year follow-ups) to confirm whether the framework can promote sustained improvement in learners' metacognitive abilities and academic thinking; at the same time, the research did not fully consider the dynamic evolution of AI technology itself—with the continuous upgrading of Large Language Models (LLMs), changes in functions such as context comprehension and feedback accuracy may affect the implementation effect of the proposed framework, requiring continuous adjustment and optimization. Furthermore, in the empirical research, the evaluation of writing competence mainly relied on quantitative indicators such as originality detection (Turnitin index) and academic writing competence scales (ACW Scale), supplemented by qualitative analysis of revision trajectories. Yet academic writing competence involves multiple connotative dimensions including creative thinking, disciplinary discourse construction, and academic ethics awareness, which are difficult to fully measure through existing indicators—for example, the "thinking enlightenment" dimension in the feedback quality evaluation system ($\rho = 0.76$) lacks more refined qualitative evaluation tools. In addition, the study did not fully control for individual differences among learners, such as prior writing experience, AI literacy, and self-regulated learning ability, which may have potential impacts on the implementation effect of the framework but were not analyzed as intervening variables.

A dialectical perspective is needed to evaluate the universality of the proposed framework. The core logic of the framework has universal value: the four-dimensional interactive model takes "cultivating deep learning and higher-order thinking" as its core goal, and its design adheres to the inherent laws of academic writing (from planning to creation to evaluation) and the cognitive development characteristics of learners. Mechanisms such as stepwise cognitive intervention, Socratic dialogue-driven reflection, and contextualized practice are not limited to specific disciplines or educational stages—they can be flexibly adjusted and applied to undergraduate thesis writing, postgraduate dissertation research, and even academic paper creation by young scholars. For instance, the delayed feedback mechanism can be adapted to different educational stages: stricter AI use restrictions can be adopted for junior undergraduates to consolidate basic writing skills, while more flexible AI collaboration modes can be provided for postgraduates focusing on innovative research. That said, the framework still requires localized adjustments based on specific scenarios to achieve effective application. For

disciplinary adaptation, science and engineering writing—which emphasizes experimental design and data analysis—should strengthen AI's ability to assist in data visualization and experimental protocol optimization, while humanities and social sciences writing—which focuses on theoretical construction and logical argumentation—should optimize the multi-round dialogue system to enhance critical thinking guidance. For language and cultural adaptation, when applying the framework to non-native English writing scenarios, it is necessary to enhance AI's functions in academic English expression norms and cross-cultural discourse adaptation, and for regions with different academic norms (such as differences in citation formats and academic ethics standards), the evaluation phase should be adjusted to align with local academic requirements. For technical condition adaptation, institutions with limited access to advanced AI tools can simplify the framework—for example, retaining core mechanisms such as delayed feedback and metacognitive reflection—and match them with lightweight AI tools (such as basic grammar checkers and literature sorting tools) to ensure practicality.

Future research can be further expanded in multiple directions to make up for the limitations of this study and improve the framework's maturity and applicability. It can expand the research scope by conducting cross-disciplinary, cross-institutional, and cross-regional empirical studies—increasing the sample size, covering disciplines such as science, engineering, agriculture, medicine, literature, and law, and involving different types of institutions (including research universities, applied universities, and vocational colleges) and regions—to verify the framework's cross-scenario adaptability and revise it based on empirical results. It can also strengthen long-term effect tracking and dynamic adjustment of the framework: conducting follow-up surveys on research subjects to analyze the long-term impact of the framework on learners' academic writing habits, innovative thinking, and academic ethics awareness, while tracking the iterative upgrading of AI technology to update the human-machine interaction logic in the framework and ensure its synchronization with technological development. Additionally, it can improve the evaluation system and deepen research on key mechanisms: developing a more comprehensive academic writing competence evaluation index system that integrates quantitative and qualitative methods and incorporates dimensions such as creative thinking and disciplinary discourse competence, while conducting in-depth research on core mechanisms such as multi-round dialogue optimization and metacognitive cultivation to clarify the influence paths and boundary conditions of different mechanisms on learners with different characteristics. Finally, it can pay attention to the integration of ethical education and framework application: further exploring how to more effectively embed academic ethics education into each link of the framework—such as strengthening AI's prompts on academic integrity in the feedback phase—and establishing a more complete AI use traceability and responsibility identification mechanism to address ethical risks such as "AI ghostwriting" and false references at the source.

As an emerging technology that reshapes the academic production model,

AIGC's impact on academic writing is profound and far-reaching. This study is only a preliminary exploration of AI-assisted improvement of academic writing competence. With the continuous development of technology and in-depth research, it is expected to build a more mature, comprehensive, and universally applicable human-machine collaborative academic writing system, providing strong support for the high-quality development of academic education in the intelligent era.

Funding

This work was supported by the 26th phase university-level research project of Zhejiang Normal University for Chen Liang.

Conflicts of Interest

The author declares no conflicts of interest.

References

[1] Xu, L.Q. (2024) Construction of a Collaborative Prevention System for Scientific and Technological Academic Ecological Risks under the Background of AIGC. *Journal of Jingchu University of Technology*, **39**, 81-90.

[2] Wang, J., Mierwaiti, K.M. and Yang, Y.Q. (2023) The Hybrid Brain of Human-Machine Symbiosis: Application Development and Model Innovation of Generative AI-Assisted Writing Teaching. *Journal of Distance Education*, **41**, 37-44.

[3] Luo, F. and Ma, Y.X. (2023) The Impact of AI-Generated Content on the Academic Ecology and Its Responses—Discussion and Analysis Based on ChatGPT. *Modern Educational Technology*, **33**, 15-25.

[4] Sun, D., Zhu, C.C., Xu, Z.D., *et al.* (2024) Research on College Students' Programming Learning Behavior Analysis Based on Generative Artificial Intelligence. *E-Education Research*, **45**, 113-120.

[5] Li, Z.K. and Zhang, X. (2024) Research on Legal Issues of Applying AI-Generated-Content (AIGC) to Dissertation Writing. *Academic Degrees & Graduate Education*, No. 4, 84-93.

[6] Ding, J.H., Fan, Z.H. and Liu, H.Z. (2024) Visualization and Correlation Analysis of Learning Engagement Based on Multimodal Data of Collaborative Programming—Understanding the Interaction Between Behavior, Cognition, Society, and Emotion and Its Impact on Learning. *Journal of Distance Education*, **42**, 40-49.