Innovation in Chinese Writing Teaching Empowered by Digital Intelligence Operational Path, Classroom Practice, and Effectiveness Testing of Human Computer Co Writing Mode

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ABSTRACT To address major problems in Chinese writing instruction, including insufficient teacher guidance throughout the writing process, delayed personalized feedback, and weak externalization of students' writing thinking, this study constructs a human-computer collaborative writing teaching model empowered by digital intelligence. A three-level operational path is developed, consisting of collaborative brainstorming, segmented interactive writing, and multidimensional integrated evaluation and revision. Based on an intelligent writing platform, a 16-week classroom practice is conducted, and teaching effectiveness is examined through a quasi-experimental design from three dimensions: writing performance, thinking development, and learning engagement. The experimental results show that the post-test score of the experimental class is significantly higher than that of the control class, reaching 85.45 ± 5.15 compared with 78.18 ± 6.49 ($p < 0.001$). The adoption rate of AI suggestions reaches 53.12%, and the task completion rate reaches 92.96%. The findings confirm that the model can externalize the writing process, make writing thinking visible and iterative, and provide an operable solution for personalized guidance in large-scale writing teaching.

INDEX TERMS chinese writing instruction, human-computer collaboration, digital intelligence, writing feedback, teaching effectiveness

I. INTRODUCTION

In traditional Chinese writing instruction, three major dilemmas have long existed: separation of teaching and learning, delayed and homogenized feedback, and the invisibility of the writing thought process [1,2]. Teacher guidance is mostly focused on pre-writing review and post-writing correction, making it difficult to intervene in the complete dynamic process of students' brainstorming, writing, and revision; the correction cycle is long and the comments are general, failing to provide timely and precise intervention for each student's specific writing thought bottlenecks; students' writing relies heavily on intuition and lacks tools to make implicit thinking explicit and iterative [3]. These problems are particularly prominent in large-scale teaching situations and have become key bottlenecks restricting the improvement of writing instruction quality.

In response to the above problems, the academic community has explored from different perspectives. Xu analyzed the attitudes of Chinese university students towards written correction feedback and their use of self-learning strategies in online English writing during the COVID-19 pandemic through questionnaires and interviews [4]. Tsai explored the effectiveness of Google Translate as a cross-language auxiliary tool in English writing and the differences in the usage experience and writing performance of students with different English proficiency levels through experiments and questionnaire analysis [5]. Yang et al. developed a learning system based on spherical video virtual reality to address the problem of insufficient writing motivation among primary school students, and verified its effectiveness in improving writing interest and performance through experiments [6]. Jiang and Yu studied the process of English learners using automatic feedback based on multisource data, and found that it was affected by resources and strategies, showing different forms of feedback utilization [7]. Teng et al. verified the structural validity of the metacognitive academic writing strategy questionnaire through data analysis, and revealed the predictive role of various metacognitive strategies on English academic writing performance [8]. However, existing research mostly focuses on the single-point application of technical tools, or emphasizes the automation of post-writing review, and has not yet formed a systematic teaching model that runs through the entire process of "idea-writing-revision". Moreover, there is a lack of operational path design and empirical testing on how to embed artificial intelligence into the development process of students' writing thinking and achieve deep human-machine collaboration.

In recent years, some researchers have begun to try to introduce generative artificial intelligence into writing teaching and explore the classroom application of human-machine collaboration. For example, Evmenova et al. compared the writing suggestions generated by teacher feedback and different generative artificial intelligence tools to explore their application effects and differences in supporting students with writing difficulties [9]. Ironsi and Solomon explored the application effect of generative artificial intelligence in improving college students' writing ability through hybrid methods research and teaching experiments [10]. Bannister et al. pointed out through review and analysis that it is necessary to re-examine the application potential of artificial intelligence generative technology and its impact on education in the context of higher education, and provide reference directions for subsequent research [11]. These explorations have improved feedback efficiency to a certain extent, but there are still problems such as a lack of systematic operation path and classroom practice paradigm, which are difficult to replicate and promote in normal teaching. In view of the above limitations, this paper constructs a "human-computer co-writing" teaching model, positioning artificial intelligence as ta "co-evolutionary cognitive partner" that facilitates higher-order thinking through dialectical interaction. Through the three-stage operation path of "human-computer collaborative conception, segmented interactive writing, and multi-dimensional integrated evaluation and revision", AI is embedded in the entire writing process to realize the explicitness and iterative deepening of writing thinking.

The main innovative achievements of this paper can be summarized in the following three aspects: First, in terms of theoretical innovation, the conceptual framework of "human-computer co-writing" is constructed to redefine the position of AI from a "passive tool" to a "collaborative agent" that stimulates metacognitive awareness through structured prompts and logical scaffolding, rather than merely providing mechanical error correction; second, in terms of practice innovation, an operable three-tier teaching path and classroom implementation process are built to offer a visible teaching scenario for the front-line teachers; third, in terms of empirical innovation, a quasi-experimental research design is adopted to explore the teaching effect of the new writing teaching in three dimensions: improving students' writing performance, cultivating students' writing thinking and learning input and cognitive load from the perspective of learning.

II. BRAINSTORMING COLLABORATION LAYER: AI-ASSISTED EXTERNALIZATION OF THINKING

A. BRINGING BRAINSTORMING INTO PLAY

Writing begins with brainstorming, which is the most active but least externalized thinking stage for students, and in conventional teaching, teachers can only indirectly know students' brainstorming situations through simple guidance on topic analysis or checking writing outline, making it hard for them to deeply intervene in students' thinking and provide timely intervention for each student. This model explores using AI as a thinking guide during the brainstorming stage to make students' implicit brainstorming process explicit and visualized as a writing framework, and thus externalize students' thinking through human computer collaboration.

Specific operation includes three steps. After the teacher releases the writing task, students enter the "Brainstorming Collaboration" part of the intelligent writing platform according to the writing task and brainstorm. Students can enter key words, initial ideas or scattered materials. Based on the natural language processing technology, AI directly outputs multi-source writing framework suggestions in real time, including thematic perspective, structural arrangement, supporting arguments, etc. Secondly, students browse multi-framework schemes developed by AI and adjust them according to their own needs by dragging, adding, deleting and merging, so as to form an initial outline for their own writing intention. At this stage, the artificial intelligence does not substitute for the student's independent cognitive agency; rather, it functions as a heuristic catalyst designed to broaden the student's conceptual perspective. That is, providing multiple situations for students to solve problems, so as to make students overcome the dead end of ideas. In the third step, students submit their outlines after modifying them. AI will diagnose students' logical coherence and clarity of outline again, and give them optimization suggestions such as "there should be some transitional sentences between the second and third paragraphs" and "the logical relationship between central argument and subarguments should be further clarified." Students modify their outlines again according to these suggestions, so as to form more mature writing frameworks [12].

This design transforms the originally closed and vague ideation process into a visible and interactive collaborative construction process. Through repeated dialogues with AI, students gradually clarify their writing ideas, completing the transition from scattered thinking to structured expression. Simultaneously, the platform fully records students' ideation trajectory, providing a process basis for teachers' subsequent teaching interventions, enabling teachers to accurately identify students' thinking bottlenecks in the ideation stage and implement targeted guidance.

III. WRITING INTERACTION LAYER: SEGMENTED GENERATION AND REAL-TIME INTERVENTION

The writing stage is a crucial link in the transition of students' thinking from framework to concrete expression, and it is also the stage most prone to stumbles, deviations from the topic, or vague expressions. In traditional teaching, students often only discover problems after completing the entire essay, at which point revisions are costly and it is difficult to trace the source of their thinking. Therefore, this model adopts a "segmented writing, real-time feedback" strategy in the writing interaction layer, embedding AI into the dynamic process of students' writing.

In specific operation, the entire writing task is broken down into four relatively independent paragraph modules: "Introduction—Main Development—Climax—Conclusion." After each module is completed, the platform automatically triggers AI analysis, generating real-time diagnostic comments from three dimensions: language fluency, richness of detail, and logical coherence. Language fluency mainly checks whether the syntactic structure is complete and the vocabulary is appropriate; richness of detail focuses on whether the description is specific and whether there are supporting details; logical coherence assesses whether the paragraph flows naturally and smoothly within itself and connects with the preceding text. In addition to providing quantitative scores, AI also offers specific suggestions for revision, such as "This paragraph lacks a transition sentence, it is recommended to add one to connect with the preceding text" and "The description can be enhanced with sensory details, such as visual and auditory descriptions" [13]. Faced with AI feedback, students have full autonomy and can choose to "adopt" the suggestion to revise directly, "refute" the suggestion to retain the original expression, or perform secondary processing based on the AI suggestion. Every human-computer interaction is fully recorded by the platform, forming a visualized revision trajectory. Teachers can view each student's writing progress and AI interaction records in real time in the background, organize centralized explanations for common problems, or provide precise intervention for individual students. For example, when a student repeatedly exhibits logical gaps, the teacher can retrieve their revision records and provide targeted guidance on-site.

IV. EVALUATION AND REVISION INTEGRATION LAYER: MULTI-DIMENSIONAL FEEDBACK AND FINAL DRAFT ITERATION

After finishing the whole essay, the main task for students are to combine all the paragraphs into a whole and get better understanding and expression at higher level. In the traditional correction, teacher's correction are usually on overall score and general comment. Students know clearly their final score, but they have no idea about what's their specific problem and they have no systematic direction to revise. So this model build the "AI aid diagnosis—peer review—teacher explanation" three-pronged multi-dimensional feedback layer at evaluation and revision integration layer to guide students to revise in depth from the first draft to the final draft.

The specific operation consists of four stages. First, AI outputs a complete analysis report. After students submit their complete essays, the platform automatically generates two analysis reports: one is a structural diagram, which visually presents the logical relationships between paragraphs and identifies issues such as paragraph breaks, disorganized structure, or disconnected beginnings and endings; the other is a language analysis report, which marks high-frequency vocabulary, sentence structure uniformity, punctuation usage, and other language features, and provides optimization suggestions, such as "The word 'then' is repeated 8 times in the text; it is suggested to replace it with conjunctions such as 'in addition' or 'at the same time'." Second, peer review is organized in groups of 4 to 6 students. Using the analysis results in the AI report, students conduct peer reviews based on three dimensions: "clarity of structure," "sufficiency of argumentation," and "vividness of language." Each student writes a peer review of no less than 50 words. During the peer review process, students need to explain the basis of their evaluation and verify it against the AI report, cultivating critical thinking. Third, teachers provide focused in-person feedback. Teachers review the AI reports and peer review records of all students in the class, select common problems or typical cases, and provide concentrated explanations in class, such as "how to avoid abrupt paragraph transitions" and "how to enhance vividness through detailed descriptions." For individual students struggling with writing, teachers retrieve their revision records and provide one-on-one feedback to address persistent thinking difficulties. F ourth, s tudents u ndergo m ultiple rounds of iterative revisions. Students revise their essays at least twice, incorporating AI suggestions, peer feedback, and teacher guidance. Each revision is accompanied by a brief explanation of the changes and reasons on the platform. The platform automatically saves all historical versions, creating a complete iterative trajectory for teachers to use for process evaluation.

V. MULTIDIMENSIONAL TESTING DESIGN OF TEACHING EFFECTIVENESS

A. TESTING THE EFFECT OF WRITING SCORE IMPROVEMENT

To empirically validate the pedagogical utility of the proposed framework, a structured evaluation was conducted. This study used quasi-experimental design to examine the influence of the human-computer collaborative writing mode on writing scores. The experimental class adopted human-computer collaborative writing approach, while control class used the traditional teaching mode. There were 45 students in both Figure 1 (a-b). Distribution and mean difference of the writing scores of experimental class and control class before and after test Quasi-experimental results revealed that the post-test writ-ing score of experimental class was 85.45 ± 5.15 points, which was significantly higher than that of control class (78.18 ± 6.49 points) ($t = 6.81$, $p < 0.001$). Experi-mental class increased 10.33 points before and after tests ($p < 0.001$), while control class only increased 2.37 points;

there was no significant difference between two classes ($p = 0.080$). It means that the human computer collaborative writing model can improve the students' writing performance and its advantages are especially reflected in structural logic and creative expression dimension.

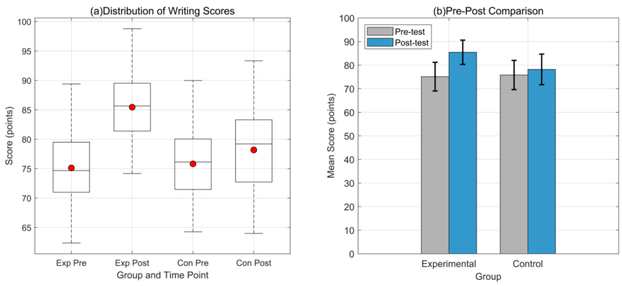

FIGURE 1. Comparison of Writing Score Improvement

B. EXAMINATION OF THE DEVELOPMENT PROCESS OF WRITING THINKING

To study the promoting effect of human–computer collaborative writing on the development of writing thinking, this study randomly selected 45 students in the experimental class as the research objects and collected all the writing process data of 16 weeks teaching process based on the intelligent writing platform. This study was approved by the Ethics Committee of Jinzhong Normal College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. Through analyzing students' AI interaction record, text modification trajectory and version iteration, an objective development process of writing thinking was clearly displayed in the four dimensions of interaction activity, feedback adoption rate, modification depth and iteration frequency, as shown in Table 1.

TABLE 1. Comparison of Writing Thinking Development Process

Indicator	High-Level Group (n=15)	Medium-Level Group (n=15)	Low-Level Group (n=15)	Overall (n=45)
AI Suggestion Adoption Rate (%)	68.42 ± 8.15	52.36 ± 9.23	38.57 ± 10.41	53.12 ± 13.56
Average Revision Rounds per Student	4.27 ± 0.89	3.12 ± 0.76	2.08 ± 0.64	3.16 ± 1.07
Revision Depth Index	2.84 ± 0.62	2.03 ± 0.55	1.47 ± 0.48	2.11 ± 0.74
Average AI Interactions per Student	18.73 ± 4.21	13.45 ± 3.86	9.21 ± 3.02	13.80 ± 5.17

Note: The revision depth index is assigned a score of 1–4 based on "word replacement—sentence restructuring—paragraph reconstruction—theme adjustment," with higher scores indicating deeper revision levels.

During the 16-week teaching cycle, students in the experimental class interacted with AI an average of 13.80 times, with an AI suggestion adoption rate of 53.12% and an average of 3.16 revision rounds. In terms of revision depth, the average revision depth index for all students was 2.11, placing them at the "sentence restructuring" level. Grouping by post-test scores showed that the high-level group significantly outperformed the low-level group in adoption rate (68.42%), revision rounds (4.27 rounds), and revision depth (2.84), suggesting a high level of engagement with the iterative process; however, it is essential to distinguish between active cognitive externalization and potential AI dependency. While the higher revision depth in high-achieving groups points toward a more sophisticated integration of feedback, future research must further investigate whether these interaction frequencies represent a genuine internalizing of writing logic or a strategic reliance on algorithmic suggestions to meet task requirements.

C. LEARNING ENGAGEMENT AND COGNITIVE LOAD ASSESSMENT

To understand students' learning engagement and cognitive load during human-computer collaborative writing, this study randomly selected 45 students in an experimental class and collected their objective behavioral data for 16 weeks during teaching through the log system of intelligent writing platform. Two dimensions, learning engagement and behavioral indicators of cognitive demand, were evaluated for the teaching model by analyzing active usage frequency, task completion rate, continuous writing time per session, operation interval, and number of version rollbacks. The specific data is shown in Table 2:

TABLE 2. Comparison of Learning Input and Cognitive Load

Dimension	Indicator	High-Level Group (n=15)	Medium-Level Group (n=15)	Low-Level Group (n=15)	Overall (n=45)
Learning Engagement	Active Usage Frequency (times/week)	3.87 ± 1.21	2.45 ± 0.98	1.62 ± 0.74	2.65 ± 1.25
Learning Engagement	Task Completion Rate (%)	98.33 ± 3.15	93.89 ± 6.23	86.67 ± 9.87	92.96 ± 8.04
Learning Engagement	Early Completion Rate (%)	35.56 ± 12.34	21.48 ± 10.56	12.59 ± 8.21	23.21 ± 13.07
Cognitive Load	Continuous Writing Duration per Session (min)	28.45 ± 6.78	24.32 ± 7.12	19.87 ± 8.03	24.21 ± 7.67
Cognitive Load	Average Operation Interval (sec)	8.23 ± 2.45	10.56 ± 3.21	14.38 ± 4.56	11.06 ± 4.01
Cognitive Load	Version Revert Count (times/essay)	1.23 ± 0.56	1.87 ± 0.72	2.64 ± 0.98	1.91 ± 0.89

The experimental class students actively used the platform an average of 2.65 times per week, achieving a task completion rate of 92.96%, with an advanced completion rate of 23.21%, indicating a high level of overall learning engagement. In terms of cognitive load, the average continuous writing time for all students was 24.21 minutes, with an average operation interval of 11.06 seconds and 1.91 version rollbacks per essay. Grouping by post-test scores showed that the high-achieving group significantly outperformed the low-achieving group in active usage frequency (3.87 times) and advanced completion rate (35.56%), while also showing better average operation intervals (8.23 seconds) and version rollbacks (1.23 times). The data suggests that the human-computer collaborative writing mode facilitated a relatively fluid workflow for high-achieving students. However, it is important to note that while behavioral metrics like operation intervals provide insight into task fluency, they serve as indirect proxies for cognitive load. Future studies should incorporate standardized psychological instruments, such as the NASA-TLX scale, to provide a more direct assessment of the mental effort required by the model. While the data suggests a high level of proficiency among high-achieving students, the observed variation in operation intervals and version rollbacks across groups indicates that cognitive load is closely moderated by individual student competency. Rather than a universal low cognitive load, the model appears to offer a navigable framework where high-achieving students can maintain fluid workflows, whereas the higher rollback rates in the low-level group suggest that the cognitive demand remains significant for students with lower baseline writing proficiency.

VI. CONCLUSION

This study built and validated the effectiveness of human-computer collaborative writing mode in Chinese writing instruction. This model embeds artificial intelligence into whole writing process through the three-stage operational path of "human-computer collaborative brainstorming—segmented interactive writing—multi-dimensional integrated evaluation and revision", opens up a closed teaching loop from brainstorming to revision in an explicit way, and promotes students' writing thinking to be developed step by step. The study proves that this model has good acceptability and sustainability, and achieves a good balance between students' learning input and cognitive load. This study also has some limitations. Firstly, the experimental period was relatively short, and the sample only came from one middle school. The validity of experimental results should be further tested in a larger sample. Secondly, the influence of design of platform function on student behavior and the differences of adaptability to this model in students of different grade levels still need to be explored deeply. In the future, we could enlarge the sample, extend experimental period, explore the applicability of this model in teaching different grade levels and different genres, and further improve the interactive design of intelligent platform.

AUTHOR CONTRIBUTIONS

Xiang Li designed, collected and analyzed the data, and drafted the manuscript. Xiang Li conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiang Li participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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