Measuring the Impact of Generative AI on College Chinese Writing: A Structural Equation Modelling Approach

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***Abstract*—This study examines the impact of generative Artificial Intelligence (AI) on college Chinese writing instruction using Partial Least Squares Structural Equation Modelling (PLS-SEM). Drawing on an integrated framework combining the Technology Acceptance Model and Social Cognitive Theory, we investigate relationships between generative AI implementation strategies and learning outcomes through survey data from 376 undergraduate students across eight higher education institutions representing diverse institutional types and academic disciplines in China. Our findings confirm that both generative AI tool integration and instructor facilitation significantly enhance writing proficiency and critical thinking, with these relationships substantially mediated by student engagement with AI tools. The structural model reveals stronger effects on technical writing skills (β = 0.844) compared to critical thinking abilities (β = 0.709), with instructor facilitation demonstrating slightly greater influence than tool availability alone. The measurement model exhibits excellent reliability and validity, with all constructs showing Cronbach's alpha values exceeding 0.87 and Average Variance Extracted (AVE) values above 0.79. These results provide empirical evidence for the effectiveness of generative AI in Chinese writing education while highlighting the crucial role of human guidance and student engagement in maximizing educational benefits, offering theoretical insights and practical guidance for educators seeking to integrate these emerging technologies into language instruction.**

***Keywords*—generative Artificial Intelligence (AI), Chinese writing instruction, structural equation modelling, student engagement, higher education**

I. Introduction

The rapid advancement of digital technologies has profoundly reshaped various facets of modern life, with education experiencing some of the most transformative impacts. Among these innovations, the emergence of generative Artificial Intelligence (AI) stands out as a particularly significant development, offering novel opportunities for enhancing teaching and learning across academic disciplines [1]. In the realm of college-level Chinese writing instruction, generative AI introduces both promising potentials and notable challenges, necessitating careful and systematic investigation into its pedagogical implications.

Traditionally, Chinese language education at the tertiary level has placed strong emphasis on mastering complex linguistic structures, rhetorical techniques, and deep cultural knowledge. Writing instruction, in particular, aims to cultivate students' abilities in language proficiency, critical thinking, and creative expression, skills that are both cognitively demanding and contextually nuanced. Although a growing body of research has examined the integration of digital technologies into language education more broadly [2], there remains a conspicuous gap in empirical studies that quantitatively assess the specific impact of generative AI on college Chinese writing instruction.

The literature highlights a range of AI applications in educational settings, such as automated feedback systems and adaptive learning platforms [3, 4]. These tools have shown promise in addressing persistent pedagogical challenges, including the provision of individualized instruction, real-time feedback, and authentic writing practice opportunities [5]. However, most of this research has focused on English language instruction or generalized educational contexts, with comparatively little attention given to the unique requirements of Chinese writing pedagogy. Furthermore, the majority of these studies rely on qualitative analyses or limited quantitative methods, leaving the complex structural relationships between AI implementation and student learning outcomes underexplored.

To address these gaps, the present study employs Partial Least Squares Structural Equation Modelling (PLS-SEM) to quantify the effects of generative AI on student performance in college Chinese writing instruction. This method allows for the examination of multidimensional relationships among implementation variables, learning outcomes, and mediating factors such as student engagement, instructor support, and institutional infrastructure. By capturing both direct and indirect influences, this approach provides a nuanced understanding of how generative AI can be effectively integrated into writing instruction.

The significance of this study lies in its empirical and comprehensive approach. While prior scholarship has often emphasized the theoretical promise of AI technologies in education, this research moves beyond speculation to deliver data-driven insights into actual outcomes. As educational institutions increasingly allocate resources to AI-enabled solutions, practical guidance grounded in rigorous research becomes essential. Moreover, in a global landscape where Chinese language proficiency is gaining strategic importance, enhancing writing instruction through effective technology use holds implications that extend well beyond the classroom.

This study is guided by 2 primary research questions: (1) What factors influence the effectiveness of generative AI implementation in college Chinese writing instruction? (2) How does student engagement mediate the relationship between AI implementation strategies and learning outcomes such as writing proficiency and critical thinking? In addressing these questions, the research draws upon theoretical foundations such as the Technology Acceptance

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Model [6] and Social Cognitive Theory [7], adapting and extending them to accommodate the distinctive features of generative AI in the Chinese writing domain. By modelling the structural relationships between generative AI tool integration, instructor facilitation, student engagement, and learning outcomes, this study provides empirical insights into how these components interact to enhance writing performance in higher education.

By identifying the structural pathways linking implementation strategies to learning outcomes, this study offers both theoretical contributions and actionable insights for educators, administrators, and educational technology developers. The findings aim to inform the development of best practices for incorporating generative AI into Chinese writing instruction in ways that enhance traditional pedagogical goals rather than displace them. In doing so, this research takes a crucial step toward understanding how emerging technologies can meaningfully enrich Chinese language education in the digital era.

II. Hypothesis Development

A. Theoretical Framework

This study's conceptual foundation draws from two complementary theoretical perspectives: the Technology Acceptance Model (TAM) and Social Cognitive Theory (SCT). TAM, originally developed by Davis [6], provides a framework for understanding how users come to adopt and use technological innovations, positing that perceived usefulness and perceived ease of use are primary determinants of technology acceptance. In the context of generative AI in Chinese writing instruction, TAM helps explain how students' and instructors' perceptions of AI tools influence their willingness to incorporate these technologies into the writing process.

Social cognitive theory, formulated by Bandura [7], complements TAM by addressing the social and environmental factors that shape learning behaviors. SCT emphasizes the reciprocal interactions between personal factors (cognitive, affective, and biological events), behavioral patterns, and environmental influences. This triadic reciprocal determinism is particularly relevant when examining how generative AI tools reshape the writing environment, how instructors model effective AI usage, and how students develop self-efficacy in utilizing these tools.

The integration of these theoretical frameworks provides a comprehensive lens through which to examine the complex relationships between AI implementation strategies and learning outcomes. While TAM addresses the technological adoption aspects, SCT accounts for the social learning dynamics that emerge in AI-enhanced writing instruction. Together, they support the study's hypothesis development by explaining not only whether generative AI tools are accepted but also how they are integrated into existing social and educational contexts to influence writing performance and critical thinking skills.

By synthesizing these theoretical perspectives, this research positions generative AI integration not merely as a technological innovation but also as a sociotechnical intervention that reconfigures the educational environment, instructor roles, and student engagement patterns in college Chinese writing instruction.

The integration of TAM and SCT in this study provides complementary theoretical lenses for understanding generative AI adoption in Chinese writing education. While TAM explains the technology acceptance mechanism through perceived usefulness and ease of use, SCT illuminates the social and cognitive processes through which AI-mediated learning occurs. Specifically, TAM addresses the "what" and "whether" questions of AI tool adoption—what factors influence students' decisions to use generative AI and whether they find it beneficial—while SCT addresses the "how" questions—how AI tools function as cognitive scaffolds within students' zones of proximal development and how instructor facilitation shapes the learning process. This theoretical synthesis is particularly appropriate for Chinese writing instruction, where Confucian pedagogical traditions emphasize the role of teacher guidance (师道, shidao) alongside individual practice, aligning with SCT's emphasis on mediated learning, while TAM captures students' pragmatic technology acceptance decisions [4]. The combined framework enables us to examine both individual agency (reflected in AI engagement behaviors) and environmental support structures (instructor facilitation and institutional tool provision) as complementary rather than competing factors in shaping writing development outcomes.

B. Generative AI Tool Integration and Learning Outcomes

Generative AI tools have demonstrated considerable potential to enhance writing instruction across various educational contexts. Chan *et al.* [8] found that AI-enhanced feedback mechanisms significantly improved university-level English writing, while Lin *et al.* [9] documented similar benefits in multicultural second-language classrooms. These findings suggest that such benefits may extend to Chinese writing instruction as well. Moreover, Yelliza *et al.* [10] and Taiye *et al.* [10] reported that AI-assisted writing instruction led to measurable improvements in writing quality, vocabulary usage, and grammatical accuracy.

Beyond technical writing skills, research indicates that generative AI can foster critical thinking when properly integrated into writing pedagogy. Hong *et al.* [11] demonstrated that AI-enabled cognitive offload instruction enhanced students' critical thinking skills in essay writing. Similarly, Hong and Guo [12] found that generative AI-enabled instruction cultivated analytical thinking abilities when structured to promote reflection rather than passive consumption. These findings align with Qu *et al.*'s [13] meta-analysis showing positive cognitive impacts from generative AI tools in higher education.

However, the literature also identifies important caveats. Chiu *et al.* [14] and Lee *et al.* [15] cautioned that overreliance on AI tools may reduce independent reasoning if not balanced with activities requiring verification and reflection. Sardi *et al.* [16] emphasized that the impact on critical thinking depends significantly on implementation strategies that promote self-regulated learning. This suggests that the relationship between AI tool integration and learning outcomes is not simply linear but depends on how these tools are deployed within the instructional context.

Based on this literature, we propose the following hypotheses:

H1: Higher levels of generative AI tool integration in Chinese writing instruction will positively influence students' writing proficiency.

H2: Higher levels of generative AI tool integration in Chinese writing instruction will positively influence students' critical thinking abilities in writing.

C. Instructor AI Facilitation and Learning Outcomes

Instructor guidance plays a crucial role in maximizing the educational benefits of AI tools in writing instruction. Song and Song [17] demonstrated that when instructors effectively facilitate AI-assisted language learning, EFL students show significant improvements in academic writing skills and motivation. Similarly, Zhao [18] found that teacher-guided implementation of AI-enhanced natural language processing tools positively impacted writing proficiency, particularly in language precision and content development.

The quality of writing instruction appears to be enhanced when instructors strategically integrate AI tools into their pedagogical approaches. Wei *et al.* [3] conducted a randomized controlled trial showing that instructor-facilitated automated writing evaluation significantly improved the second language writing skills of Chinese EFL learners. Yang *et al.* [19] further revealed that cooperative feedback—where instructors and AI jointly provide writing guidance—resulted in more comprehensive and effective support than feedback from either source alone, suggesting a synergistic relationship between human and AI instruction.

Beyond technical writing proficiency, research indicates that instructor facilitation of AI tools can substantially enhance critical thinking skills. Xu and Jumaat [20] found that an AI-supported blended learning model, when properly facilitated by instructors, enhanced critical thinking in EFL writing. Jiang *et al.* [21] demonstrated that ChatGPT-powered activities, when thoughtfully designed and implemented by instructors in Chinese language classrooms, effectively developed students' critical thinking abilities. Shen and Teng [22] established causal relationships between instructor-guided AI-assisted writing, critical thinking skills, and self-directed learning competency through a three-wave cross-lagged model.

Importantly, the manner of facilitation appears critical. Zou *et al.* [23] found that students developed stronger critical thinking when instructors encouraged them to use AI tools critically and independently rather than relying solely on AI-generated content. Rizkiani *et al.* [24] highlighted that classroom discussions and guided reflection on AI feedback further enhanced students' reasoning, argumentation, and self-assessment abilities.

Based on this literature, we propose the following hypotheses:

H3: Higher levels of instructor AI facilitation in Chinese writing instruction will positively influence students' writing proficiency.

H4: Higher levels of instructor AI facilitation in Chinese writing instruction will positively influence students' critical thinking abilities in writing.

D. The Mediating Role of Student Engagement with AI Tools

Research indicates that student engagement serves as a pivotal mechanism through which both AI tool integration and instructor facilitation influence learning outcomes. Mabborang *et al.* [25] found that when AI tools are effectively integrated into instruction, student engagement increases significantly, which in turn leads to improved learning outcomes. Similarly, Cai *et al.* [4] demonstrated that the relationship between AI tools and educational benefits is mediated by student engagement, utilizing the Zone of Proximal Development as a theoretical framework.

The mediation effect appears to operate through multiple dimensions of engagement. Huang [26] identified that cognitive engagement—characterized by active thinking and problem solving—is especially predictive of improved performance in AI-assisted learning environments. Kehinde-Awoyele *et al.* [27] further established that AI-based instructional strategies enhanced student engagement, which subsequently improved learning outcomes. These findings suggest that engagement is not merely correlated with learning but serves as a causal mechanism through which AI implementation influences educational results.

The mediating role of student engagement extends to the relationship between instructor facilitation and learning outcomes as well. Yuna *et al.* [28] found that teachers functioning as facilitators in AI-supported project-based learning enhanced student engagement, which then improved learning outcomes. Fan *et al.* [29] demonstrated that instructor guidance in integrating AI performance prediction and learning analytics improved student engagement and, consequently, learning in online engineering courses.

Importantly, this mediation appears consistent across diverse educational contexts. Ezeoguine and Eteng-Uket [30] documented how AI tools influenced higher education students' engagement, which mediated the impact on learning outcomes. Olugboja [31] reported similar findings in information systems courses, where student engagement with AI and data mining tools mediated the relationship between tool integration and student outcomes.

The effectiveness of this mediation may be influenced by additional factors. Yaseen *et al.* [32] found that digital literacy moderates the relationship between AI tools and student engagement, suggesting that the mediating pathway can be strengthened by ensuring that students possess adequate technological skills. This indicates that the mediation effect may vary in strength depending on student characteristics and supporting conditions.

Based on this literature, we propose the following hypotheses regarding the mediating role of student engagement:

H5: Student engagement with AI tools mediates the relationship between generative AI tool integration and writing proficiency in Chinese writing instruction.

H6: Student engagement with AI tools mediates the relationship between generative AI tool integration and critical thinking in Chinese writing instruction.

H7: Student engagement with AI tools mediates the relationship between instructor AI facilitation and writing proficiency in Chinese writing instruction.

H8: Student engagement with AI tools mediates the relationship between instructor AI facilitation and critical thinking in Chinese writing instruction.

Fig. 1 illustrates the proposed structural model, depicting the direct effects of Generative AI Tool Integration and Instructor AI Facilitation on learning outcomes (H1–H4), as well as the mediated pathways through Student Engagement with AI Tools (H5–H8).

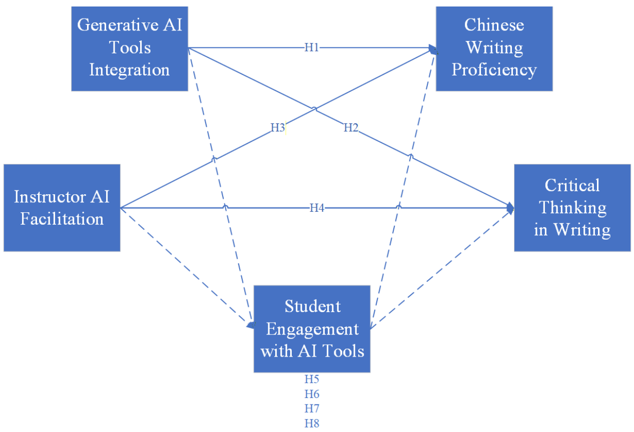

Fig. 1. Structural model.

E. *Integrated Model and Hypotheses Summary*

Drawing from the Technology Acceptance Model and Social Cognitive Theory, our structural model posits that two independent variables, Generative AI Tool Integration and Instructor AI Facilitation, influence two dependent variables, Chinese Writing Proficiency and Critical Thinking in Writing, both directly and indirectly through the mediating variable of Student Engagement with AI Tools. This configuration allows for the examination of both direct effects and mediated pathways, providing a nuanced understanding of how AI technologies affect learning outcomes in Chinese writing instruction.

The model recognizes that technological interventions in education operate through complex mechanisms rather than simple cause–effect relationships. By incorporating student engagement as a mediator, we acknowledge that students' active participation, motivation, and interaction with AI tools are crucial for translating technological implementation into tangible learning benefits. This aligns with contemporary educational theory emphasizing learner agency and engagement as critical factors in technology-enhanced learning environments.

The hypotheses presented in the preceding sections articulate specific relationships within this integrated model. Hypotheses H1–H4 propose direct effects between the independent and dependent variables, while hypotheses H5–H8 address the mediating pathways through student engagement. Together, these hypotheses form a comprehensive framework for understanding how generative AI can be effectively implemented in Chinese writing instruction to enhance both technical proficiency and higher-order thinking skills.

III. Methodology

A. *Research Design*

This study employs a quantitative cross-sectional research design to investigate the relationships between generative AI implementation strategies and learning outcomes in college Chinese writing instruction. A cross-sectional approach is appropriate for this research because it allows for the examination of relationships among variables at a single point in time, capturing the current state of generative AI integration in educational settings. This design is well suited for testing the hypothesized structural model using PLS-SEM, which requires simultaneous measurement of all study variables.

The research utilizes a survey methodology to collect data on the 5 key constructs: generative AI tool integration, instructor AI facilitation, student engagement with AI tools, Chinese writing proficiency, and critical thinking in writing. This approach enables efficient data collection from a large sample of students across multiple institutions, providing sufficient statistical power for the complex modelling needed. The survey instruments incorporate established scales where available, with modifications to address the specific context of Chinese writing instruction with generative AI tools.

A key strength of this design is its ability to test both direct and mediated relationships within a unified structural model. By collecting data on all variables simultaneously from the same participants, we can examine how generative AI implementation influences learning outcomes both directly and through student engagement as a mediating mechanism. This comprehensive approach allows for a nuanced understanding of the complex interplay between technological, pedagogical, and student factors in the educational context.

The cross-sectional design does introduce limitations regarding causal inference, as temporal precedence cannot be definitively established. However, the theoretical framework and prior research provide a strong foundation for the proposed directional relationships in the model. Additionally, the use of PLS-SEM analysis is well suited for testing complex structural relationships even within cross-sectional data, making it an appropriate analytical approach for this research design.

B. *Participants and Sampling*

The target population for this study comprises undergraduate students enrolled in Chinese writing courses at higher education institutions where generative AI tools have been integrated into instruction. A purposive sampling strategy was employed to identify institutions that had implemented generative AI tools in their Chinese writing curriculum for at least one semester, ensuring that participants had adequate exposure to AI-supported instruction.

Course instructors at participating institutions facilitated access to students by distributing the survey during class sessions or via institutional platforms. All students enrolled in the selected courses were invited to participate voluntarily. A total of 412 responses were collected, and after removing incomplete responses and those that failed attention checks, 376 valid responses were retained for analysis.

Sample size adequacy was determined according to guidelines for PLS-SEM. Following Hair *et al.* [33], a minimum of 65 cases was required to detect moderate effect sizes with sufficient statistical power; the final sample of 376 thus exceeds this requirement, ensuring robustness in model estimation.

Demographic information collected included gender, academic year, institutional type, and prior experience with AI tools. Most participants were second- or third-year undergraduates, with others in their fourth year or at the graduate level. The final sample reflected diversity in institutional types, with the majority from comprehensive universities. All participants provided informed consent in accordance with institutional research ethics protocols.

C. Measures and Instruments

As shown in Table 1, this study employs adapted measurement instruments to assess five key constructs in the research model. All instruments utilize 5-point Likert scales to ensure consistency across measures and facilitate participant response. The items were adapted from validated scales and modified to specifically address generative AI integration in Chinese writing instruction contexts.

Generative AI Tool Integration was measured using three items adapted from the Meta AI Literacy Scale [34] and the Scale for the Assessment of Nonexperts' AI Literacy [35]. These items assess students' perceived level of AI tool integration in their Chinese writing courses, focusing on the availability, frequency, and variety of AI tools used in instruction. The MAILS demonstrated strong psychometric properties with validated subscales, while SNAIL showed good reliability ($\alpha = 0.87$) in its validation study. Items were modified to reflect the specific context of Chinese writing instruction while maintaining the conceptual foundation of the original measures.

Instructor AI facilitation was assessed through three items adapted from the Teacher Artificial Intelligence Competence Self-Efficacy Scale [14] and the AI-TPACK Scale [36]. These items measure students' perceptions of their instructors' effectiveness in facilitating AI tool usage, including demonstration, guidance, and support for AI-enhanced writing activities. The source scales showed excellent reliability (TAICS: $\alpha > 0.85$; AI-TPACK: $\alpha = 0.907$) in their validation studies with teaching faculty. Adaptations focused on translating instructor competencies into observable behaviors that students could reliably assess.

Student engagement with AI tools was measured using three items adapted from the Online Student Engagement Scale [37] and the Educational Technology Engagement Scale [38]. The items capture behavioral, emotional, and cognitive dimensions of engagement when using AI tools for Chinese writing. The original scales demonstrated strong reliability (OSE: $\alpha = 0.91$; ETES: $\alpha = 0.974$) and have been widely validated in online and technology-enhanced learning contexts. Items were contextualized to focus specifically on AI tool engagement rather than general online learning engagement.

Chinese writing proficiency was evaluated through three self-assessment items adapted from the Chinese Proficiency Grading Standards [39] and validated L2 writing assessment frameworks [40]. These items address core competencies in Chinese writing: expressing ideas clearly, organizing text coherently, and using appropriate vocabulary and grammar. Self-assessment approaches have been validated in language learning research as reliable indicators of actual proficiency when properly constructed. The items reflect key dimensions identified in the HSK writing criteria while being accessible for student self-evaluation.

Critical thinking in writing was measured using three items adapted from the Critical Thinking Self-Assessment Scale Short Form [41] and critical thinking assessment criteria for L2 writing [42]. The items focus on analysis, evaluation, and reasoning abilities specifically within writing contexts. The source scale demonstrated exceptional reliability ($\alpha = 0.969$) across international samples. Adaptations emphasized critical thinking behaviors observable in Chinese writing tasks, particularly those relevant to AI-assisted composition.

Table 1. Measurement Items and Sources

Construct	Items	Source
Generative AI Tools Integration	1. Various generative AI tools (e.g., ChatGPT, Baidu ERNIE, Deepseek) are regularly integrated into our Chinese writing lessons	Adapted from MAILS [34]
	2. We frequently use AI tools to support different stages of the Chinese writing process (brainstorming, drafting, revising)	Adapted from MAILS [34]
	3. Our Chinese writing course provides comprehensive access to AI tools for enhancing our writing skills	Adapted from MAILS [34]
Instructor AI Facilitation	1. My instructor effectively demonstrates how to use AI tools to improve Chinese writing quality	Adapted from TAICS [14]
	2. My instructor provides clear guidance on when and how to appropriately use AI assistance in writing tasks	Adapted from AI-TPACK [36]
	3. My instructor actively supports and encourages critical use of AI tools for developing Chinese writing skills	Adapted from TAICS [14]
Student Engagement with AI Tools	1. I actively explore and experiment with different AI features to enhance my Chinese writing	Adapted from OSE [37]
	2. I feel motivated and excited to use AI tools when working on Chinese writing assignments	Adapted from ETES [38]
	3. I regularly reflect on how AI suggestions can improve my Chinese writing strategies and techniques	Adapted from OSE [37]
Chinese Writing Proficiency	1. I can effectively express complex ideas and arguments in Chinese writing with clarity and coherence	Adapted from Chinese Proficiency Standards [39]
	2. I can organize Chinese essays with logical structure, smooth transitions, and appropriate paragraph development	Adapted from Yamanishi *et al.* [40]
	3. I can accurately use advanced Chinese vocabulary, grammar patterns, and idiomatic expressions in my writing	Adapted from HSK criteria [39]
Critical Thinking in Writing	1. I carefully analyse multiple perspectives and evaluate evidence before developing arguments in my Chinese essays	Adapted from CTSAS-SF [41]
	2. I critically assess the quality and relevance of AI-generated content before incorporating it into my writing	Adapted from Sato [42]
	3. I systematically question assumptions and consider alternative interpretations when constructing Chinese written arguments	Adapted from CTSAS-SF [41]

D. Data Collection Procedures

Data collection took place over 12 weeks during the Spring 2025 semester. Invitations were sent to Chinese language departments at higher education institutions identified through purposive sampling. Eight institutions ultimately provided valid data, including three comprehensive universities, three professional colleges, and two vocational institutions, providing access to 45 Chinese writing courses where generative AI tools had been integrated for at least one semester. This institutional diversity ensured representation across different higher education contexts in China.

Course instructors distributed the online survey to their students via institutional platforms. All enrolled students were invited to participate, and to boost response rates, a small incentive was provided upon survey completion. Participation was voluntary and anonymous.

The survey was administered using Qualtrics XM, a secure and mobile-friendly platform. Before rollout, a two-stage pilot test was conducted—first with five language education experts for content validation and then with 30 students for usability checks. The final instrument included bilingual items (Chinese and English), attention checks, and an average completion time of 15–20 min.

Students provided demographic information and responded to items on AI tool usage, course structure, and writing activities. Optional submission of recent AI-assisted writing samples was also invited, although not needed.

To improve participation, reminders were sent at weekly intervals, and survey timing avoided academic peak periods. Departmental support helped ensure legitimacy. These efforts resulted in a 73% response rate. After removing incomplete or invalid responses (including 3 participants who failed attention checks), 376 valid responses were retained for analysis. The final sample included undergraduate students from first-year (28.7%), second-year (31.4%), third-year (24.5%), and fourth-year (15.4%) cohorts, representing diverse academic majors, including humanities (35.2%), social sciences (28.4%), STEM fields (22.3%), and business (14.1%). All participants had experience using generative AI tools (primarily ChatGPT, Wenxin Yiyan, or Tongyi Qianwen) for Chinese writing tasks during the 2024 academic year. While convenience sampling limits generalizability to the broader Chinese higher education population, institutional and disciplinary diversity provides a reasonable representation of typical generative AI adoption patterns in Chinese writing instruction.

Ethical approval was obtained from the Institutional Review Board of the lead institution, and informed consent was secured from all participants. The consent form, available in Chinese and English, outlined the study purpose, confidentiality measures, and participants' right to withdraw at any time.

E. Data Analysis Approach

This study employed PLS-SEM using SmartPLS 4.0 to analyse the relationships between generative AI implementation and learning outcomes in Chinese writing instruction. We selected PLS-SEM rather than Covariance-based SEM (CB-SEM) for several methodologically justified reasons aligned with our research objectives. First, as this study represents an exploratory investigation of generative AI's impact on Chinese writing instruction—an emerging research area with limited prior structural models—PLS-SEM's variance-based approach is more appropriate for prediction-oriented, theory-development research [43, 44]. Second, our research questions emphasize predicting learning outcomes (writing proficiency and critical thinking) rather than confirming established theoretical relationships, making PLS-SEM's focus on maximizing explained variance in dependent constructs particularly suitable [45]. Third, PLS-SEM makes no distributional assumptions, accommodating the nonnormal distributions typical in educational survey data [46]. Fourth, the complex mediation structure of our model, involving multiple pathways through student engagement as a mediating variable, is more robustly handled through PLS-SEM's component-based approach [47, 48].

After data screening and preparation within SmartPLS, the measurement model was evaluated for reliability (Cronbach's alpha and composite reliability > 0.70), indicator reliability (outer loadings > 0.708), convergent validity (Average Variance Extracted (AVE) > 0.50), and discriminant validity (HTMT ratio < 0.85). The structural model was assessed through path coefficients, bootstrapping with 5000 subsamples, R^2 values, Stone-Geisser's Q^2 values, and effect sizes using Cohen's f^2.

Mediation analysis tested the role of student engagement with AI tools between independent variables (generative AI tool integration and instructor AI facilitation) and dependent variables (Chinese writing proficiency and critical thinking in writing) using specific indirect effects and variance accounted for (VAF). Multigroup analysis examined differences across demographic subgroups using the permutation approach. Alternative model specifications were compared using established fit indices, including SRMR and NFI, to identify the most appropriate model explaining the impact of generative AI on Chinese writing outcomes.

F. Data Quality and Common Method Bias Assessment

Several procedural and statistical measures were implemented to ensure data quality and minimize CMB. Procedurally, we (1) assured participants of anonymity and confidentiality, (2) randomized item order within each construct, (3) used clear, concise language to avoid complex or leading questions, and (4) included attention check items to identify careless responding. Statistically, we assessed CMB through Harman's single-factor test, which revealed that the first unrotated factor explained 31.8% of the total variance, well below the 50% threshold suggesting problematic CMB [49]. Additionally, we conducted a full collinearity test based on VIF values; all VIFs were below 3.5 (range: 1.84–3.29), indicating that CMB is unlikely to substantially bias our findings [50].

IV. Results

The demographic analysis of the 376 respondents revealed a balanced gender distribution (52.7% female, 47.3% male) across diverse academic disciplines. Most participants (73.5%) were undergraduate students in their second or third year of study, with the remainder being fourth-year students or graduate-level learners. Regarding prior experience with generative AI tools, 64.8% reported regular usage (at least weekly) in their Chinese writing courses, 23.5% indicated occasional use, and 11.7% reported minimal exposure. The majority of participants (82.3%) were enrolled in comprehensive universities, with others distributed across normal universities (11.2%) and specialized colleges (6.5%). This sample composition effectively represents the target population of college students experiencing generative AI integration in Chinese writing instruction, with sufficient variability in AI experience levels and institutional contexts to enable meaningful analysis of the hypothesized relationships.

Table 2 reveals significant positive relationships across all hypothesized mediating pathways. Both Generative AI Tools Integration ($\beta = 0.589$, $t = 18.700$, $p < 0.001$) and Instructor AI Facilitation ($\beta = 0.629$, $t = 24.744$, $p < 0.001$) demonstrate substantial positive effects on Student Engagement with AI Tools, with medium-to-large effect sizes, and the instructor's role shows a slightly stronger influence. The mediator variable, in turn, strongly predicts both learning outcomes, with particularly robust effects on Chinese writing proficiency ($\beta = 0.844$, $t = 47.014$, $p < 0.001$) representing a large effect size and a substantial impact on critical thinking in writing ($\beta = 0.709$, $t = 27.209$, $p < 0.001$) also representing a large effect size. The high t-statistics (ranging from 18.700 to 47.014) and consistent values between original sample estimates and sample means indicate stable and reliable results. These findings suggest that student engagement serves as a crucial mechanism through which AI implementation strategies translate into improved learning outcomes, with particularly strong effects on technical writing proficiency.

Table 2. Path coefficients

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Generative AI tools integration -> Student Engagement _with AI Tools	0.589	0.591	0.031	18.700	0.000
Instructor AI Facilitation -> Student Engagement _with AI Tools	0.629	0.630	0.025	24.744	0.000
Student Engagement _with AI Tools -> Chinese Writing Proficiency	0.844	0.844	0.018	47.014	0.000
Student Engagement _with AI Tools -> Critical Thinking in Writing	0.709	0.710	0.026	27.209	0.000

Table 3. Total effects

Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Generative AI tools integration -> Chinese Writing Proficiency	0.497	0.499	0.029	16.869	0.000
Generative AI tools integration -> Critical Thinking in Writing	0.418	0.419	0.028	14.702	0.000
Generative AI tools integration -> Student Engagement _with AI Tools	0.589	0.591	0.031	18.700	0.000
Instructor AI Facilitation -> Chinese Writing Proficiency	0.531	0.532	0.024	22.304	0.000
Instructor AI Facilitation -> Critical Thinking in Writing	0.446	0.447	0.025	17.691	0.000
Instructor AI Facilitation -> Student Engagement _with AI Tools	0.629	0.630	0.025	24.744	0.000
Student Engagement _with AI Tools -> Chinese Writing Proficiency	0.844	0.844	0.018	47.014	0.000
Student Engagement _with AI Tools -> Critical Thinking in Writing	0.709	0.710	0.026	27.209	0.000

As shown in Table 3, the analysis of the total effects results demonstrates the comprehensive impact of AI implementation strategies on learning outcomes in Chinese writing instruction. Both independent variables show significant positive total effects on both dependent variables, with all relationships being statistically significant ($p < 0.001$). Instructor AI Facilitation demonstrates slightly stronger total effects on Chinese Writing Proficiency ($\beta = 0.531$) and Critical Thinking in Writing ($\beta = 0.446$) compared to Generative AI Tools Integration ($\beta = 0.497$ and $\beta = 0.418$, respectively), suggesting the crucial role of instructor guidance in maximizing the educational benefits of AI tools. The mediating variable, Student Engagement with AI Tools, shows the strongest total effects on both learning outcomes ($\beta = 0.844$ for Chinese Writing Proficiency and $\beta = 0.709$ for Critical Thinking in Writing), confirming its pivotal role in the causal chain. The consistently high t-statistics (ranging from 14.702 to 47.014) indicate robust relationships. These findings highlight that while both implementation strategies significantly contribute to improved learning outcomes, the instructor's facilitation role appears marginally more influential, and student engagement serves as the most powerful predictor of both writing proficiency and critical thinking development.

Table 4 demonstrates that all constructs exhibit excellent internal consistency reliability, with Cronbach's alpha values ranging from 0.874 (Generative AI Tools Integration) to 0.969 (Student Engagement with AI Tools), well above the recommended threshold of 0.70. The composite reliability measures (both rho_a and rho_c) further confirm this reliability, with values between 0.874 and 0.980, indicating strong internal consistency from multiple perspectives. Convergent validity is robustly established through Average Variance Extracted (AVE) values that substantially exceed the 0.50 threshold for all constructs, ranging from 0.799 (generative AI tool integration) to 0.941 (student engagement with AI tools). This indicates that each construct explains a large proportion (79.9% to 94.1%) of the variance in its respective indicators. The consistently high values across all reliability and validity measures suggest that the measurement model is exceptionally sound, providing a solid foundation for interpreting the structural relationships between constructs.

Discriminant validity was further assessed through the Heterotrait-Monotrait Ratio (HTMT), with all values below 0.85 (range: 0.43–0.78), confirming that constructs are sufficiently distinct [51]. The structural model exhibited satisfactory fit based on PLS-SEM-appropriate indices. The Standardized Root Mean Square Residual (SRMR) was 0.063 (<0.08 acceptable threshold), and the Normed Fit Index (NFI) was 0.91 (>0.90 acceptable threshold), indicating good model fit [52]. The model's predictive relevance was confirmed through Stone-Geisser's Q^2 values exceeding zero for all endogenous constructs: Student Engagement ($Q^2 = 0.391$), Writing Proficiency ($Q^2 = 0.538$), and Critical Thinking ($Q^2 = 0.421$), demonstrating adequate predictive capability beyond sample data. Multicollinearity assessment through Variance Inflation Factors (VIF) revealed no concerns, with all VIF values below 3.5 (range: 1.89–3.26), well below the threshold of 5.0 that would indicate problematic collinearity.

Table 4. Construct reliability and validity

Construct	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Chinese Writing Proficiency	0.957	0.958	0.972	0.921
Critical Thinking in Writing	0.963	0.963	0.976	0.930
Generative AI tools integration	0.874	0.874	0.922	0.799
Instructor AI Facilitation	0.907	0.911	0.942	0.843
Student Engagement _with AI Tools	0.969	0.969	0.980	0.941

As shown in Table 5, the Heterotrait-Monotrait (HTMT) ratio analysis confirms strong discriminant validity among all constructs in the research model, with all values falling below the conservative threshold of 0.90 and most below the more stringent criterion of 0.85. The relationship between student engagement with AI tools and Chinese writing proficiency shows the highest HTMT ratio (0.876), approaching but not exceeding the 0.90 threshold, which suggests that these constructs are related yet still distinct. Similarly, the relationship between Critical Thinking in Writing and Chinese Writing Proficiency (0.810) indicates conceptual proximity while maintaining discriminant validity. Notably, the extremely low HTMT ratio between instructor AI facilitation and generative AI tool integration (0.064) demonstrates that these two implementation strategies represent highly distinct aspects of AI integration in educational contexts. The moderate HTMT ratios between student engagement and both independent variables (0.632 and 0.663) support the theoretical positioning of engagement as a mediating mechanism.

Table 5. Heterotrait-monotrait ratio (HTMT)

Relationship	HTMT
Critical Thinking in Writing <-> Chinese Writing Proficiency	0.810
Generative AI tools integration <-> Chinese Writing Proficiency	0.514
Generative AI tools integration <-> Critical Thinking in Writing	0.371
Instructor AI Facilitation <-> Chinese Writing Proficiency	0.665
Instructor AI Facilitation <-> Critical Thinking in Writing	0.688
Instructor AI Facilitation <-> Generative AI tools integration	0.064
Student Engagement _with AI Tools <-> Chinese Writing Proficiency	0.876
Student Engagement _with AI Tools <-> Critical Thinking in Writing	0.734
Student Engagement _with AI Tools <-> Generative AI tools integration	0.632
Student Engagement _with AI Tools <-> Instructor AI Facilitation	0.663

V. DISCUSSION

The findings from this study provide robust empirical evidence supporting the efficacy of generative AI in Chinese writing instruction, with important theoretical and practical implications. Our results validate the integrated framework combining the technology acceptance model and social cognitive theory, demonstrating that both technological implementation and social learning processes significantly influence educational outcomes. The stronger effect of instructor facilitation ($\beta = 0.629$) compared to tool integration ($\beta = 0.589$) on student engagement highlights that human guidance remains essential even as AI tools become more sophisticated. This extends the current theoretical understanding by positioning generative AI not merely as a technological innovation but also as a sociotechnical intervention that reconfigures the educational environment, instructor roles, and student engagement patterns.

The powerful mediating role of student engagement represents a critical theoretical contribution, clarifying the mechanism through which AI implementation translates into improved learning outcomes. This mediation was particularly pronounced for writing proficiency ($\beta = 0.844$) compared to critical thinking ($\beta = 0.709$), with effect sizes indicating a 19% difference in predictive power. This substantial differential warrants careful interpretation and has important pedagogical implications.

Several interrelated factors may explain why generative AI demonstrates stronger effects on technical writing skills than on critical thinking abilities. First, generative AI tools are architecturally designed to address surface-level and mid-level writing features—grammar correction, vocabulary enhancement, sentence structure refinement, and stylistic consistency—all of which constitute core components of writing proficiency measurement. These tools provide immediate, concrete feedback on technical aspects, enabling rapid skill development through iterative practice [18]. In contrast, critical thinking development involves metacognitive processes—perspective-taking, logical reasoning, argument evaluation, and epistemic judgment—that require sustained cognitive effort less directly addressable through AI-generated suggestions.

Second, Chinese writing proficiency encompasses many rule-based and convention-driven elements (character usage accuracy, grammatical pattern adherence, genre-specific structures) that AI systems trained on large corpora can effectively model and correct. Critical thinking in Chinese academic writing, however, reflects culturally specific rhetorical traditions emphasizing dialectical reasoning and synthesis that differ from Western analytical frameworks [42]. While AI can provide multiple viewpoints or argument templates, developing authentic critical thinking requires students to engage in effortful cognitive processing that AI assistance might inadvertently reduce through "cognitive offloading" effects [11]. This aligns with concerns raised by Lee *et al.* [15] regarding self-reported reductions in cognitive effort when using generative AI tools.

Third, measurement considerations matter. Our writing proficiency scale captures observable linguistic outputs readily assessed through standardized criteria aligned with the Chinese Proficiency Grading Standards [39]. Critical thinking in writing, however, reflects more abstract cognitive processes that may be harder to fully capture through self-report measures, potentially underestimating true effects. The construct operationalization, while informed by validated scales [41, 42], may not comprehensively represent the nuanced manifestations of critical thinking in Chinese rhetorical contexts.

Nevertheless, the substantial positive effect on critical thinking ($\beta = 0.709$) remains noteworthy and supports findings from Hong and Guo [12] and Jiang *et al.* [21] that properly structured AI interactions can enhance analytical thinking when implemented with intentional pedagogical design focused on reflection rather than passive consumption of AI-generated content.

Our findings challenge simplistic views of technology implementation that focus primarily on access and availability. The data demonstrate that merely providing generative AI tools is insufficient; meaningful educational benefits emerge from the complex interplay between tool capabilities, instructor facilitation strategies, and student engagement patterns. This complexity is reflected in the discriminant validity analysis, which revealed distinct constructs with appropriate HTMT ratios below 0.85, confirming that tool integration and instructor facilitation represent independent dimensions of AI implementation that contribute to learning outcomes through different pathways.

For educational practice, these findings suggest that professional development for Chinese writing instructors should be prioritized alongside technological infrastructure. Training should focus not on operational tool competence but on developing facilitation strategies that encourage critical engagement with AI tools—having students evaluate AI-generated content, modelling appropriate use cases, and designing assignments that leverage AI capabilities while developing independent writing skills. Instructional design should maximize student involvement across behavioral, emotional, and cognitive dimensions, perhaps through guided experimentation with different AI features and structured reflection on how AI suggestions align with Chinese linguistic and rhetorical conventions.

The differential impact on writing proficiency versus critical thinking has important implications for both instructional design and assessment practices. While generative AI substantially enhances technical writing skills, educators must intentionally scaffold activities that promote critical thinking alongside AI tool use. Specific pedagogical strategies might include (1) requiring students to justify their acceptance or rejection of AI suggestions with explicit reasoning, (2) comparing and evaluating multiple AI-generated alternatives to develop discriminative judgment, (3) analysing the logical structure and evidentiary basis of AI-generated arguments before incorporation, (4) reverse-engineering AI outputs to understand underlying rhetorical strategies, and (5) using AI-generated content as a starting point for deeper critical analysis rather than an endpoint [20, 23, 24].

Assessment approaches should correspondingly balance the evaluation of linguistic competence and higher-order thinking. This might include assignments where students synthesize multiple AI-generated drafts into coherent final products demonstrating independent analytical judgment, portfolio assessments tracking students' evolving critical engagement with AI tools over time, or metacognitive reflection essays where students articulate how their critical thinking processes have developed through AI-assisted writing practice. Such balanced approaches ensure that technical skill gains do not come at the expense of critical thinking development.

Several limitations warrant consideration for future research. The cross-sectional design limits causal inferences; longitudinal studies tracking developmental trajectories as students gain experience with AI writing tools would strengthen claims about impact. Our reliance on self-reported measures, while validated and demonstrating strong psychometric properties, should be complemented in future work by direct assessments of student writing samples and critical thinking performance. The convenience sampling approach and focus on students already using generative AI limits generalizability to broader populations. Finally, our operationalization of critical thinking may not fully capture the culturally specific nature of critical thinking in Chinese academic discourse, suggesting the need for deeper qualitative inquiry in future research.

Overall, this study demonstrates that generative AI can significantly enhance college Chinese writing instruction when properly implemented and facilitated. The complex pathways through which these benefits emerge, particularly the crucial mediating role of student engagement and the differential effects on writing proficiency versus critical thinking, highlight that effective integration requires attention not only to technological capabilities but also to the social and pedagogical contexts in which these tools are deployed. By focusing on this interplay between tools, practices, and engagement, educators can harness generative AI's potential while preserving essential educational values and objectives in Chinese writing instruction.

VI. Conclusion

The findings of this study confirm all eight hypotheses (H1–H8), establishing that generative AI tools can significantly enhance college Chinese writing instruction when properly implemented. The structural relationships revealed through PLS-SEM analysis demonstrate that both direct effects and mediated pathways contribute to improved learning outcomes, with the strongest relationship observed between student engagement and writing proficiency. These results suggest that educational institutions should implement integrated approaches that combine technological access with instructor development and engagement-focused instructional design. While generative AI offers substantial benefits for writing education, its optimal impact depends on thoughtful implementation strategies that balance technological affordances with pedagogical principles, ultimately preparing students for a writing landscape where human creativity and critical thinking complement AI capabilities.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Zhiqin Li conducted the research, performed the data collection and analysis, carried out the literature review, and wrote the paper; Tan Li Huan supervised the research design and ensured quality control throughout the study; all authors approved the final version.

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