



Application Rules and Optimization Path of Generative AI in Literature Review: Empirical Evidence Based on 104 Public Administration Students' Assignments

Mengjiao Zhang, Wenyi Lin*

School of Public Administration, Jinan University, Guangzhou, China

*Corresponding author's e-mail: linwenyi2008@163.com

Abstract. This study adopts a qualitative research method, taking the AI usage records of 104 public administration students who completed literature review assignments as research data. It systematically analyzes students' application logic, operational steps and content distribution rules of generative AI, sorts out differentiated manual revision behaviors between undergraduates and postgraduates, and quantifies the proportion difference of AI-generated content in different writing modules. On this basis, the paper clarifies the practical value and functional boundaries of AI in academic writing, summarizes prominent hidden risks in current human-machine collaborative writing, and puts forward targeted classroom teaching optimization strategies. The research aims to provide empirical support for colleges to formulate standardized AI usage specifications and improve the independent academic writing ability of public administration majors.

Keywords: AI; literature review; public administration; academic writing; human-machine collaboration

1 Introduction

1.1 Research Background and Research Questions

Generative AI has become a mainstream auxiliary tool for college students' academic writing, profoundly changing the traditional mode of literature review compilation. As an applied social science discipline focusing on social governance and public service practice, public administration puts forward high requirements for students' logical demonstration and literature analysis ability in professional course assignments. Literature review writing, as a core basic academic task of professional courses such as *Social Entrepreneurship and Social Innovation*, is widely assisted by generative AI tools among students.

In practical teaching, students generally have problems such as irregular AI operation steps, vague writing thinking and excessive reliance on AI-generated content, resulting in homogeneous content, insufficient critical thinking and non-standard

academic expression in literature reviews. Existing studies mostly focus on the macro application of AI in academic writing, lacking targeted empirical research on public administration professional course assignments. There is insufficient quantitative analysis on the distribution proportion of AI-generated content and the core links of manual revision, and the functional boundary of AI in professional literature review writing has not been clearly defined.

Based on the above gaps, this study takes 104 valid AI usage instruction texts of undergraduates and postgraduates majoring in public administration as samples to answer three core questions: What are the process characteristics and tool selection rules of students using AI to write literature reviews? What is the distribution proportion law of AI-generated content in academic assignments? What are the key links and optimization paths of manual revision in human-machine collaborative writing?

2 Literature Review

2.1 Core Functions of Generative AI in Academic Writing

Generative AI runs through the whole process of academic paper writing, with prominent advantages in improving writing efficiency and standardizing content expression. In the literature review stage, AI can quickly sort out massive literature resources, extract core research viewpoints, identify disciplinary research hotspots and gaps, and generate standardized writing frameworks, whose framework matching degree is significantly better than traditional manual sorting (Daniel et al., 2025). Meanwhile, AI can optimize academic language, correct grammatical errors, and provide standardized expression templates for non-native English writers, effectively improving the standardization of academic papers (Meishar-Tal, 2025).

In terms of writing ability training, real-time feedback and multi-dimensional perspective derivation of generative AI can help students expand research ideas, optimize argumentation logic, and exercise critical thinking and independent analysis abilities (Preiksaitis & Rose, 2023). Domestic research also confirms that AI can effectively reduce the threshold of literature sorting and basic writing, and provide strong auxiliary support for college students' academic practice (Li et al., 2024).

2.2 Application Characteristics of Generative AI

Tool Differentiation and Disciplinary Adaptability.

Generative AI tools show obvious disciplinary differences in application. Humanities and social science students mainly use AI for literature sorting, language polishing and framework construction, while science and engineering students focus on data processing and code generation (Li et al., 2024). Discipline-specific large models have higher professional matching degree than general models, and can better adapt to the normative requirements of professional academic writing (Yin & Wang, 2024).

Human-Machine Collaborative Auxiliary Positioning.

AI has always been in an auxiliary position in academic writing, and core academic creation and critical analysis rely on human independent completion. AI-generated content has advantages in structural standardization but has deficiencies in viewpoint depth and logical rigor, requiring manual screening, revision and innovation (Cai & Lin, 2024). High-quality academic writing follows the logic of "human-led, AI-assisted, human quality control".

Dual Quality and Ethical Risks.

AI-generated content has typical duality: it is efficient and standardized, but prone to citation hallucinations, outdated information and one-sided viewpoints (Hutson, 2022). The error rate of AI automatic citation can reach 15%-20%, which must be manually verified (Sparkman & Witt, 2025). In addition, excessive reliance on AI easily leads to academic homogenization and integrity risks, requiring standardized usage norms and whole-process manual verification (Song, 2024).

2.3 Research Commentary

Existing studies have clarified the basic functions, advantages and potential risks of generative AI in academic writing, and confirmed the necessity of human-machine collaboration and manual verification. However, current research lacks targeted empirical analysis of public administration professional course assignments, without quantitative research on AI content proportion and student differentiated usage characteristics. This study fills these gaps through empirical analysis of student assignment data, and refines the feasible optimization path of AI-assisted literature review writing for public administration majors.

3 Research Methods

3.1 Research Data and Samples

The research samples are derived from students of two core courses of public administration in the 2025-2026 academic year, including 72 undergraduates taking *Social Entrepreneurship* and 66 postgraduates taking *Social Entrepreneurship and Social Innovation*. A total of 104 valid AI usage instruction forms are collected, including 61 undergraduate samples and 43 postgraduate samples. All personal information is anonymized to ensure research ethics, and sample data is true and effective.

All students are required to complete literature review assignments based on 5 CNKI literatures (2020-2024), focusing on sorting out research questions, research methods and literature comments, and truthfully recording all AI usage links and content proportions. Students also complete an AI usage instruction form documenting AI tools, prompts, output content, AI-generated proportions, and manual revisions. Before the assignment, all students received training on AI citation verification, including identifying hallucination patterns and cross-checking citations against CNKI records (Li et

al., 2025). To enhance data reliability, students are required to distinguish AI-generated from manually written content using different font colors, enabling cross-referencing with actual marked assignments.

3.2 Research Framework

This study adopts qualitative thematic analysis, and codes and analyzes sample data from four dimensions: first, AI tool selection and basic usage characteristics; second, the whole-process application steps and thinking logic of AI writing; third, the distribution and proportion of AI-generated content in assignments; fourth, the core dimensions of students' manual revision and innovative optimization. Finally, it summarizes existing problems and puts forward optimization strategies, combining the differences between undergraduate and postgraduate students. The coding employed a theory-driven approach with two independent coders who developed a preliminary codebook from 15 pilot samples before coding all 104 forms.

4 Research Results

4.1 AI Tool Selection Characteristics

Public administration students' AI tool selection presents the characteristics of "main concentration and auxiliary diversification". The mainstream tools are DeepSeek (over 80% usage rate) and Doubao (over 70% usage rate), which are the first choice for students' literature sorting and framework construction. A small number of students use supplementary tools such as ChatGPT and Kimi for text polishing and detailed literature analysis. Most students choose the latest web version of AI tools to ensure functional timeliness, and undergraduates have richer tool selection diversity than postgraduates.

4.2 Whole-Process AI Application Steps

Students' AI-assisted literature review writing covers six complete links with clear hierarchical logic. First, topic inspiration: input course themes to obtain research hotspots and keyword suggestions. Second, literature sorting: upload literatures to extract core viewpoints, research methods and research conclusions. Third, framework construction: generate paper outline and paragraph topic sentences. Fourth, first draft writing: convert sorted literature information into standardized narrative paragraphs. Fifth, text polishing: optimize language expression and unify format specifications. Sixth, content expansion: supplement research perspectives and future research prospects.

There are obvious differences between undergraduates and postgraduates: undergraduates mostly use AI for single basic links with simple operation logic; postgraduates carry out multi-round refined AI interaction, realizing in-depth human-machine collaborative creation in the whole writing process. For instance, postgraduate case 63 used DeepSeek-V3 across multiple iterative rounds to structure literature analysis, and

case 81 employed multi-round interaction with Doubao to refine a focused research topic through successive critique (Kim et al., 2025).

4.3 Distribution and Proportion of AI-Generated Content

AI-generated content is unevenly distributed in literature reviews, mainly concentrated in literature sorting, framework building and text polishing parts (high-frequency distribution), followed by abstracts and literature comments (medium-frequency distribution), while innovative viewpoints, core arguments and conclusions are mostly original human creations (low-frequency distribution).

The proportion of AI-generated content ranges from 5% to 80%, divided into three intervals: low proportion ($\leq 20\%$), medium proportion (20%–50%) and high proportion ($\geq 50\%$). Postgraduates are mainly low and medium proportion with low AI dependence and strong independent creation ability. Undergraduates have a larger proportion span, and some students have high AI generation proportion, relying on AI to complete most of the basic content. Quantitatively, among 61 undergraduates: low 29.5% (18/61), medium 52.5% (32/61), high 18.0% (11/61); among 43 postgraduates: low 53.5% (23/43), medium 37.2% (16/43), high only 9.3% (4/43), confirming lower AI dependence among postgraduates.

4.4 Core Links of Manual Revision

All students carry out targeted manual revision of AI-generated content, focusing on four core dimensions. First, accuracy revision: verify literature authenticity, correct AI citation hallucinations and professional term errors. Second, logical optimization: adjust paragraph order, supplement logical connections, and change list-style content into in-depth analytical demonstration. Third, academic standardization: delete colloquial and absolute expressions, unify citation and typesetting formats. Fourth, innovative supplementation: integrate localized cases, add critical perspectives, and extract systematic research consensus and gaps. Systematic coding reveals revision frequency: accuracy 94/104 (90.4%), logical 82 (78.8%), standardization 71 (68.3%), innovation 42 (40.4%). By group: undergraduates—52/61 (85.2%), 44 (72.1%), 37 (60.7%), 15 (24.6%); postgraduates—42/43 (97.7%), 38 (88.4%), 34 (79.1%), 27 (62.8%), indicating postgraduates engage significantly more in innovative supplementation.

The higher the proportion of AI-generated content, the deeper the students' manual revision. Students ensure the originality of core viewpoints and academic rigor of papers through whole-process revision, realizing effective human-machine collaboration. Research confirms AI citation error rates of 15%–20%, with fabricated references and mismatched DOIs being common (Alkaissi & McFarlane, 2023; Sparkman & Witt, 2025). Despite training, persistent errors were observed—e.g., case 53 found Kimi 2.0 fabricated content, and case 59 corrected “three-dimensional” to “four-dimensional collaborative mechanism” per the original text (Jain et al., 2025). Systematic analysis of the 104 forms reveals 27 cases (26.0%) explicitly reported AI errors: 19/61 undergraduates (31.1%) vs. 8/43 postgraduates (18.6%). Errors: content misrepresentation (10, 37.0%), fabricated references (8, 29.6%), data/terminology errors (6, 22.2%), and

bibliographic format errors (3, 11.1%), corroborating the 15%–20% hallucination rate in external literature.

5 Discussion and Conclusion

5.1 Main Research Conclusions

First, public administration students' AI tool selection is centralized and practical, with DeepSeek and Doubao as core tools. Second, AI-assisted writing covers the whole academic writing process, with significant usage differences between undergraduates and postgraduates in operation refinement and application depth. Third, AI content presents differentiated distribution rules, focusing on basic standardized content, while core innovative content relies on human creation. Fourth, manual revision focusing on accuracy, logic, standardization and innovation is the core guarantee for high-quality human-machine collaborative writing.

5.2 Research Enlightenment

In teaching practice, colleges should establish tiered AI usage guidelines for undergraduates and postgraduates respectively, guiding students to clarify AI's auxiliary functional boundary and avoid excessive dependence. For undergraduates, teachers can set biweekly classroom training on AI prompt compiling and content checking, focusing on identifying AI false citations. For postgraduates, tutors can launch human-machine collaborative writing workshops using typical assignments as cases to analyze revision standards and innovative expansion skills.

Meanwhile, course assessment indicators should be adjusted: reduce basic format scoring weight, increase scoring on personal critical analysis and localized case innovation, to reverse students' excessive pursuit of full-AI content generation. Students should establish whole-process manual verification awareness and take manual innovation as the core of academic writing. Universities can compile a specialized AI-assisted literature review manual for public administration discipline.

5.3 Research Limitations and Prospects

This study only takes the literature review assignments of social entrepreneurship courses as samples, with limited research scope. Subsequent research can expand sample types and disciplinary fields, further explore the long-term impact of AI tools on college students' academic writing ability, and improve the human-machine collaborative writing system for academic tasks of social science majors. The findings may not be generalizable to other public administration subfields (e.g., public policy, urban governance) or other social science disciplines (sociology, economics, law) where methodological traditions differ (Xu, 2026; Jiang & Song, 2025). Since AI content proportions rely on self-reported data, social desirability bias may cause underreporting; although color-coding provides partial validation, future studies should incorporate AI

detection tools (e.g., GPTZero) for external validation. Furthermore, the practice-oriented, case-based nature of these courses may encourage greater AI usage compared to theory-intensive subfields (public policy analysis, urban governance) where assignments involve data analysis and statistical reasoning, meaning identified patterns may reflect course-specific rather than generalizable trends.

Disclosure of Interests

All authors declare no conflicts of interest in connection with the submitted manuscript. The research was conducted independently without any commercial or financial sponsors that could constitute a potential conflict.

AI Usage Statement

In the process of writing this paper, the author used AI (Doubao) to extract literature viewpoints and sort out sample data. The author independently completes content verification, logical optimization and innovative argumentation, and confirms the accuracy and originality of all research content.

References

1. Alkaissi, H., McFarlane, S.I.: Artificial hallucinations in ChatGPT: Implications in scientific writing. *Cureus*, 15(2), e35179 (2023). <https://doi.org/10.7759/cureus.35179>
2. Cai, J.G., Lin, Y.: Challenges and reforms in academic paper writing: An experiment of directly generating a dissertation with ChatGPT. *Journal of Beijing International Studies University*, (4), 29–42 (2024) (in Chinese)
3. Daniel, K., Msambwa, M.M., Wen, Z.: Can generative AI revolutionise academic skills development in higher education? A systematic literature review. *European Journal of Education*, 60(e70036) (2025). <https://doi.org/10.1111/ejed.70036>
4. Hutson, M.: Could AI help you to write your next paper? *Nature*, 611(7934), 192–193 (2022). <https://doi.org/10.1038/d41586-022-03479-w>
5. Jain, A., Nimonkar, P., Jadhav, P.: Citation integrity in the age of AI: Evaluating the risks of reference hallucination in maxillofacial literature. *Journal of Cranio-Maxillofacial Surgery*, 53(10), 1871–1872 (2025). <https://doi.org/10.1016/j.jcms.2025.08.004>
6. Jiang, Y., Song, R.M.: The impact of generative artificial intelligence on academic research in universities and responses. *Heilongjiang Researches on Higher Education*, (1), 9–14 (2025) (in Chinese)
7. Li, Y., Xu, J., Jia, C.Y., et al.: Current situation and reflections on the application of generative artificial intelligence by college students: A survey based on Zhejiang University. *Open Education Research*, 30(1), 89–98 (2024) (in Chinese)
8. Li, Y., Zhu, Y.M., Sun, D., Xu, J., Zhai, X.S.: Differential analysis of generative AI use in typical scientific research scenarios: The influence of disciplinary background and AI literacy. *Modern Distance Education Research*, 37(2), 92–101, 112 (2025) (in Chinese)

9. Meishar-Tal, H.: Scientific writing in the age of generative AI: Usage patterns and ethical considerations among Israeli researchers. *Ethics & Behavior*, 1–16 (2025). <https://doi.org/10.1080/10508422.2025.2562589>
10. Preiksaitis, C., Rose, C.: Opportunities, challenges, and future directions of generative artificial intelligence in medical education: Scoping review. *JMIR Medical Education*, 9, e48785 (2023). <https://doi.org/10.2196/48785>
11. Song, N.: Higher education crisis: Academic misconduct with generative AI. *Journal of Contingencies & Crisis Management*, 32(1), 12532 (2024). <https://doi.org/10.1111/1468-5973.12532>
12. Sparkman, M., Witt, A.: Claude AI and literature reviews: An experiment in utility and ethical use. *Library Trends*, 73(3), 355–380 (2025). <https://doi.org/10.1353/lib.2025.a961199>
13. Xu, X.H.: The dilemmas and countermeasures of applying generative artificial intelligence in social science research. *Journal of Dalian University*, 47(1), 132–140 (2026) (in Chinese)
14. Yin, Z.T., Wang, Z.: The application of text analysis in financial research: A literature review and usage paradigm. *Rural Finance Research*, (11), 68–80 (2024) (in Chinese)
15. Kim, J., Yu, S., Lee, S.S., Derrick, R.: Students' prompt patterns and its effects in AI-assisted academic writing: Focusing on students' level of AI literacy. *Journal of Research on Technology in Education*, 1–18 (2025). <https://doi.org/10.1080/15391523.2025.2456043>

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

