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From AI Literacy to Situated Academic Writing Self-Efficacy: The Mediating Role of GenAI Use

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Abstract: Generative artificial intelligence (GenAI) is reshaping university students' literature retrieval, information integration, and thesis writing processes. Taking university students with thesis writing experience as the research participants, this study constructs a mediation model linking AI Literacy, GenAI Use, and learning outcomes. In this model, learning outcomes are operationalized as Situated Academic Writing Self-Efficacy (SAWSES) in the context of thesis writing. Based on structural equation modeling and Bootstrap tests using 401 valid responses, the results show that AI Literacy has significant positive effects on both GenAI Use and learning outcomes. GenAI Use also has a significant positive effect on learning outcomes and plays a partial mediating role between AI Literacy and learning outcomes. The dimension-level analysis further shows that AI Technical Cognition has stronger independent explanatory power for learning outcomes. GenAI Use has positive effects on Writing Essentials, Relational-Reflective, and Creative Identity, with a relatively stronger effect on Relational-Reflective. The findings suggest that universities should integrate AI Literacy cultivation with thesis writing training, guide students to use GenAI for literature comprehension, idea organization, structural optimization, and feedback-based revision, and promote the transformation of AI tool use into academic writing competence.

Keywords: AI Literacy; GenAI Use; Situated Academic Writing Self-Efficacy; Thesis Writing; Mediation Effect

1. Introduction

Generative artificial intelligence (GenAI) is reshaping the ways in which university students acquire information, process knowledge, and engage in academic writing. In the context of thesis writing, students are required to do more than generate text; they must also engage in a series of complex processes, including topic conceptualization, literature evaluation, information integration, argument organization, academic norms, and reflective revision. Thesis writing therefore serves as both a comprehensive development of students' digital literacy and an assessment of their learning outcomes. The involvement of GenAI raises new questions for thesis writing instruction: whether students can understand the functional boundaries of AI tools, whether they can use AI appropriately to support academic writing, and whether they can transform AI tools into genuine learning support. The use of AI in education is no longer merely a technological issue; it has increasingly become central to student development and educational transformation. The UNESCO AI Competency Framework for Students also extends the goals of AI education to the integrated development of values, knowledge, skills, and responsible use, emphasizing that students should become responsible users and co-creators of AI [1]. Existing research has also emphasized that students' information retrieval, critical thinking, and academic writing abilities can be enhanced through competence training in systematic inquiry, critical verification, data-driven decision-making, and ethical anticipation [2]. Taken together, these policies and international frameworks indicate that universities need to move from the question of whether students should be allowed to use AI toward the question of how to cultivate students' responsible, effective, and judicious use of AI. For courses on literature retrieval and thesis writing, students' AI Literacy is reflected not only in tool operation ability, but also in comprehensive abilities such as problem identification, information verification, data judgment, and ethical anticipation.

Existing studies have discussed the impact of GenAI in educational contexts. Yang et al. [3] argued that ChatGPT and GenAI have exerted important influences on educational concepts, teaching models, and assessment methods, and that education systems need to move from technological adaptation toward competence reconstruction. From the perspective of both opportunities and risks, Wang et al. [4] noted that ChatGPT may provide new opportunities for learning support, personalized feedback, and knowledge generation, while also bringing risks related to academic integrity, cognitive dependence, and assessment distortion. Based on a survey of students at Zhejiang University, Li et al. [5] found that university students have widely encountered GenAI in learning and research processes, but differences remain in application scenarios, depth of use, and awareness of academic norms. Wang and Huang [6] further discussed the dual effects of GenAI in promoting and inhibiting university students' creativity, suggesting that AI tools do not necessarily improve learning outcomes; rather, their effects depend on students' ways of using AI and their cognitive regulation ability.

Based on the above, this study takes university students with thesis writing experience as the research participants and examines the direct effect of AI Literacy on learning outcomes, as well as the mediating role of GenAI Use between the two. The study aims to provide empirical evidence for the reform of literature retrieval and thesis writing courses, AI Literacy education, and process-based guidance for thesis writing in higher education.

2. Literature Review

2.1 Conceptualization and Dimensions of AI Literacy

AI Literacy is an important antecedent for understanding whether students can effectively use GenAI. Long and Magerko [7] developed an early AI Literacy framework from the perspective of competency composition, arguing that individuals need to understand AI concepts, identify AI applications, judge the functional boundaries of AI, and interact with AI systems. Carolus et al. [8] further operationalized the measurement of AI Literacy through the Meta AI Literacy Scale, emphasizing dimensions such as AI use and application, AI understanding, AI recognition, and AI ethics. In a systematic review of AI Literacy scales, Lintner [9] found that existing scales generally focus on technical understanding, application ability, critical evaluation, and ethical awareness, indicating that AI Literacy has developed from a single form of technical knowledge into a comprehensive competence that integrates cognition, practice, and norms. As the cognitive foundation for students to understand, judge, and appropriately use AI tools, AI Literacy may influence their AI use in thesis writing. AI use, as an applied transformation process, may further affect students' learning outcomes in information integration, academic expression, feedback-based revision, and creative writing.

Recent studies have also expanded the conceptualization, structure, and evaluation system of AI Literacy. Zhang et al. [10] proposed that AI Literacy includes not only AI knowledge and skills, but also problem-solving, innovative application, and ethical responsibility. From the perspective of library and information science and education in the digital-intelligence era, Cai et al. [11] emphasized that AI Literacy should include understanding AI, applying AI, evaluating AI, and using AI responsibly. Zhou et al. [12] constructed an AI Literacy assessment framework for university students, identifying technical cognition, tool application, innovative practice, and ethical responsibility as important components. From the paradigm shift from information literacy and digital literacy to intelligent literacy, Wang and Wang [13] pointed out that AI Literacy reflects individuals' understanding, interaction, collaboration, critical thinking, and reflection in the process of working with AI systems. These studies suggest that AI Literacy has multiple attributes, including technical understanding, tool application, critical evaluation, and ethical responsibility. Considering the thesis writing context and the formal questionnaire items used in this study, AI Literacy is further operationalized into two dimensions: AI Technical Cognition and AI Ethics.

In the context of thesis writing, AI Literacy has a clearer task orientation. Students need to understand the basic principles and applicable scope of AI tools, evaluate the reliability of AI-generated content, identify false information and unreliable sources, and comply with academic norms in literature use, content generation, and text revision. Guo et al. [14] linked AI Literacy with the construction of evaluation standards, emphasizing that AI Literacy needs to be assessed through specific competency indicators. Zhao et al. [15] also noted that the evaluation of AI Literacy should focus on knowledge understanding, tool use, ethical norms, and comprehensive application ability. Thus, AI Literacy is not an abstract technological attitude, but a foundational ability that enables students to understand, judge, and appropriately use AI in specific learning tasks.

2.2 GenAI Use and the Academic Learning Process

GenAI Use is a key process variable linking AI Literacy and learning outcomes. Unlike traditional information technology tools, GenAI can participate in learning activities such as problem explanation, information summarization, text generation, language revision, and structural suggestions. However, the quality of its outputs depends on how users define tasks, design prompts, verify information, and reprocess generated content. Köhler and Hartig [16] designed measurement instruments for university students' ChatGPT knowledge, use, perceived value, and attitudes, suggesting that the educational application of GenAI needs to distinguish among cognitive understanding, actual use, and attitudinal acceptance. Nemt-Allah et al. [17] developed and validated the ChatGPT Usage Scale, distinguishing ChatGPT use into academic writing assistance, academic task support, and trust and dependence. This indicates that GenAI Use is not a single behavior, but a multidimensional learning practice.

Chinese studies have also focused on the current use of GenAI among university students and its educational implications. Based on a survey of university students, Li et al. [5] found that GenAI has entered students' learning, writing, and research practices, but students still need to improve their understanding of the accuracy, norm compliance, and applicable boundaries of AI-generated content. From the perspective of digital literacy cultivation, Tang et al. [18] argued that university students need to develop comprehensive abilities in technical understanding, information judgment, collaborative innovation, and ethical norms in the context of GenAI. In constructing an AI Literacy evaluation indicator system for researchers, Chen et al. [19] included the use of AI for academic translation, information extraction, information search, literature analysis, and paper writing as important aspects of AI application and practice. These studies provide a basis for designing AI use items in the thesis writing context of the present study.

The influence of GenAI Use on learning outcomes is conditional. When students merely treat AI as a substitute for their own writing, their independent thinking and academic judgment may be weakened. When students use AI as a tool for retrieval, explanation, feedback, and revision, their self-regulation and knowledge integration in the writing process may be improved. Wang et al. [4], in their discussion of the potential and risks of ChatGPT in education, indicated that GenAI may enhance learning support, but may also lead to dependence and normative risks. Wang and Huang's study [6] on creativity further suggests that whether GenAI promotes learning outcomes depends on whether students can make independent judgments, selections, and creative elaborations based on AI-generated content. Therefore, this study defines GenAI Use as students' learning-oriented use of AI tools in thesis writing, rather than as simple frequency of use or degree of tool exposure.

2.3 Learning Outcomes and Situated Academic Writing Self-Efficacy

Learning outcomes are an important outcome variable for evaluating the effects of AI educational applications. This study operationalizes learning outcomes as situated academic writing self-efficacy in the context of thesis writing. Writing self-efficacy refers to students' judgments of their own ability to complete writing tasks, and it reflects their confidence in dealing with writing difficulties, academic expression, information integration, and feedback-based revision. Mitchell et al. [20] developed and validated the Situated Academic Writing Self-Efficacy Scale (SAWSES), noting that traditional writing self-efficacy scales have paid insufficient attention to specific academic writing contexts. Therefore, students' judgments of their ability to complete academic writing tasks need to be measured from a situated perspective. The scale includes three dimensions: Writing Essentials, Relational-Reflective, and Creative Identity, which respectively reflect fundamental writing ability, relational-reflective ability, and creative writing identity.

In multiple-source academic writing, students need to understand, compare, integrate, and transform ideas from different sources, which is highly consistent with the requirements of thesis writing. Bråten et al. [21] conducted a measurement study on multiple-source-based academic writing self-efficacy, pointing out that students' confidence in source integration, evidence use, and academic expression is an important psychological variable for understanding their academic writing performance. For thesis writing, students' learning outcomes should not be evaluated only by the completion of the final text. Attention should also be paid to whether students can effectively integrate literature, respond to feedback, adjust structure, and develop professional academic expression.

GenAI may affect several aspects of SAWSES. On the one hand, AI tools can help students conduct preliminary literature screening, explain concepts, polish language, and optimize structure, thereby reducing some writing difficulties. On the other hand, the uncertainty of AI-generated content also requires students to have stronger abilities in information verification and independent judgment. When students can appropriately use AI for literature comprehension, idea organization, and feedback-based revision, their Writing Essentials, Relational-Reflective, and Creative Identity may be improved. Therefore, using SAWSES as the learning outcome variable helps explain more specifically the learning support role of GenAI in thesis writing.

Taken together, previous studies have established certain research foundations for AI Literacy, GenAI Use, and academic writing ability, but the relationships among the three still require further examination. First, AI Literacy studies have mainly focused on conceptual clarification, framework construction, and scale development, with relatively limited attention to its mechanism in the specific learning task of thesis writing [7-9,12]. Second, studies on the educational application of GenAI have discussed tool use, application potential, and risks, but further explanation is needed regarding what kinds of students are more capable of using AI effectively and how AI use is transformed into learning outcomes [3-5,17]. Third, academic writing self-efficacy research provides a mature tool for explaining students' writing-related learning outcomes. However, in the context of GenAI, how AI Literacy and GenAI Use influence writing self-efficacy still needs to be empirically tested in real university thesis writing contexts [20,21].

3. Research Methods

3.1 Participants and Data Collection

This study adopted a questionnaire survey method and selected university students who had experienced or were currently experiencing thesis writing as the research participants. The study examined the relationships among students' AI Literacy, GenAI Use, and learning outcomes in thesis writing in the context of generative artificial intelligence. Screening questions were included in the questionnaire to ensure a direct connection between the sample and the research topic. Convenience sampling and snowball sampling were used. A total of 450 questionnaires were distributed, and 401 valid responses were collected.

3.2 Measurements

This study constructed a variable system around the relationships among AI Literacy, GenAI Use, and learning outcomes. All variables were generated based on the formal questionnaire items and were adapted from established scales and relevant studies. A five-point Likert scale was used for measurement.

The independent variable is AI Literacy. This variable mainly reflects students' foundational ability to understand, judge, and appropriately use AI tools in the thesis writing process. The questionnaire items were designed with reference to previous AI Literacy studies on technical understanding, tool cognition, critical evaluation, and ethical responsibility [7,8]. In combination with the context of this study, AI Literacy was divided into two dimensions: AI Technical Cognition and AI Ethics, with a total of seven items. AI Technical Cognition focuses on students' understanding of basic AI concepts, working principles, mainstream tools, application scenarios, and the risks of AI-generated content. AI Ethics focuses on students' awareness of the boundary between AI assistance and academic misconduct, the identification of false information, privacy protection, and data security.

The mediating variable is GenAI Use. This variable mainly reflects students' actual use of

GenAI tools in thesis writing tasks. The questionnaire items were designed with reference to the ChatGPT Usage Scale and studies on university students' GenAI use [16,17]. They were also informed by research on the use of AI tools in research and academic writing contexts, including literature retrieval, information extraction, academic translation, and paper writing assistance [19]. The formal questionnaire included seven items, covering effective interaction, information screening and verification, tool selection, literature retrieval, writing structure optimization, improvement of thesis writing efficiency, literature translation, and key information extraction.

The dependent variable is learning outcomes. In this study, learning outcomes were operationalized as Situated Academic Writing Self-Efficacy (SAWSES) in the context of thesis writing, which was used to measure students' confidence in completing thesis writing tasks. The items were mainly adapted from the Situated Academic Writing Self-Efficacy Scale, namely the SAWSES scale developed by Mitchell et al. [20], and were contextualized according to thesis writing tasks. The formal questionnaire included 15 items covering three dimensions: Writing Essentials, Relational-Reflective, and Creative Identity, which respectively correspond to fundamental writing ability, feedback-based reflective ability, and creative academic expression ability. Bråten et al.'s study [21] on multiple-source-based academic writing self-efficacy also provided a reference for incorporating source integration, source use, and confidence in academic expression into the measurement of learning outcomes.

3.3 Research Model and Hypotheses

AI Literacy serves as the cognitive and normative foundation for students' learning-oriented application of GenAI. GenAI Use functions as a process variable through which students transform AI Literacy into specific learning behaviors, while learning outcomes are reflected in Situated Academic Writing Self-Efficacy (SAWSES) in the context of thesis writing. AI Literacy includes not only students' understanding of AI concepts, technical mechanisms, and applicable boundaries, but also their ability to identify, evaluate, and make ethical judgments about AI outputs. AI Literacy reflects individuals' understanding, interaction, collaboration, critical thinking, and reflection in the process of working with AI systems [13]. Existing scales also generally emphasize technical understanding, AI use, evaluation ability, and ethical dimensions [9]. Therefore, students with higher levels of AI Literacy are more likely to understand the functional boundaries and risks of AI tools, and to use AI tools in thesis writing in a task-oriented, process-controllable, and outcome-verifiable manner. Accordingly, this study proposes the following hypothesis:

H1: AI Literacy has a significant positive effect on GenAI Use.

AI Literacy may also directly affect learning outcomes. Thesis writing is not merely a process of text generation; it also involves complex tasks such as topic conceptualization, literature evaluation, information integration, idea organization, academic norms, and reflective revision. Students with higher levels of AI Literacy are generally better able to understand the applicable boundaries of AI-generated content, identify false information and unreliable sources, and develop stronger information judgment, normative awareness, and self-regulation ability during the writing process. Writing self-efficacy emphasizes students' judgments of their own ability to complete specific writing tasks. AI Technical Cognition, critical evaluation, and ethical responsibility within AI Literacy can provide cognitive support and normative safeguards for students' thesis writing. Therefore, this study proposes the following hypothesis:

H2: AI Literacy has a significant positive effect on learning outcomes.

The effect of GenAI Use on learning outcomes is mainly reflected in retrieval support, information integration, expression optimization, and feedback-based revision during thesis writing. Nemt-Allah et al. [17] showed that ChatGPT can be used in academic writing for idea generation, draft revision, paraphrasing complex concepts, constructing counterarguments, organizing ideas, and searching for materials. Chen et al. [19] also identified the use of AI tools for academic translation, information extraction, information search, literature analysis, and paper writing as important components of AI application and practice in the evaluation of researchers' AI Literacy. The more appropriately students use AI tools to assist retrieval, integration, revision, and expression, the higher their thesis writing self-efficacy is likely to be. Accordingly, this study proposes the following hypothesis:

H3: GenAI Use has a significant positive effect on learning outcomes.

Students with higher levels of AI Literacy are generally more capable of identifying the limitations of AI outputs, understanding how prompts, training data, and tool contexts influence generated results, and engaging in information verification, structural adjustment, and appropriate use during the writing process. Only when such cognitive and normative abilities are transformed into specific AI use behaviors are they more likely to influence self-efficacy in thesis writing. That is, AI Literacy further improves students' thesis writing self-efficacy by promoting their appropriate use of AI tools. Therefore, this study proposes the following hypothesis:

H4: GenAI Use mediates the relationship between AI Literacy and learning outcomes.

The research model is shown in Figure 1.

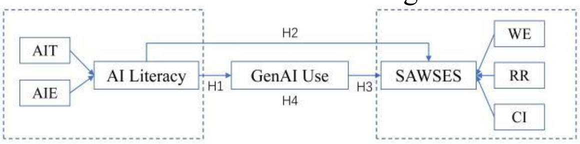

Figure 1. Research Model

4. Data Analysis and Results

4.1 Sample Characteristics and Distributional Characteristics

A total of 450 questionnaires were distributed in this study, and 401 valid responses were collected (Table 1). The gender distribution of the sample was relatively balanced, with 208 male students, accounting for 51.9%, and 193 female students, accounting for 48.1%. In terms of educational stage, junior college students, undergraduate students, and postgraduate students and above accounted for 24.9%, 55.4%, and 19.7%, respectively. Regarding commonly used AI software, Doubao had the highest usage rate, accounting for 60.8%, followed by DeepSeek at 55.4%, ChatGPT at 40.9%, and Kimi at 32.2%. In terms of school location, the sample was mainly distributed in Shandong Province, Guangdong Province, and Jiangsu Province.

The descriptive statistics of the key variables show that the mean values of AI Literacy, GenAI Use, and learning outcomes were 2.247, 2.282, and 2.281, respectively, all of which were lower than the theoretical midpoint of the five-point scale (Table 2). This may indicate that students in the sample still have room for improvement in AI Literacy, AI tool application ability, and academic writing self-efficacy in the context of thesis writing. At the same time, given that norms for GenAI use in universities have not yet been fully unified, some students may have responded cautiously because of concerns that AI use could be associated with thesis evaluation or risks related to academic norms. Therefore, this result should also be interpreted in light of students' possible response concerns. The skewness values of the three key variables ranged from 1.306 to 1.390, indicating a certain degree of positive skewness. The kurtosis values ranged from 0.236 to 0.524, suggesting no serious kurtosis abnormality (Table 2).

Table 1. Basic Characteristics of the Sample

Variable	Category	Percentage
Gender	Male	51.90%
	Female	48.10%
Educational stage	Junior college students	24.90%
	Undergraduate students	55.40%
	Postgraduate students and above	19.70%
Commonly used AI software (multiple choices)	Doubao	60.80%
	Kimi	32.20%
	DeepSeek	55.40%
	ChatGPT	40.90%
School location	Guangdong Province	21.20%
	Shandong Province	22.20%
	Henan Province	18.50%
	Jiangsu Province	20.90%
	Hubei Province	17.20%

Table 2. Descriptive Statistics and Distributional Characteristics of Key Variables

Variable	Mean	Standard deviation	Skewness	Kurtosis
AI Literacy	2.247	0.901	1.306	0.360
GenAI Use	2.282	0.890	1.390	0.524
Learning Outcomes/SAWSES	2.281	0.858	1.383	0.236
AI Technical Cognition	2.255	0.965	1.186	0.249
AI Ethics	2.235	0.920	1.141	0.410
Writing Essentials	2.293	0.967	1.130	0.339
Relational-Reflective	2.292	0.857	1.352	0.515
Creative Identity	2.259	0.926	1.225	0.302

4.2 Measurement Model Assessment and Factor Structure

Table 3. Exploratory Factor Analysis Results

Dimensions and Items	Factor Loadings	Communality	Eigenvalue	Variance Explained
AI Literacy (KMO = 0.918; Bartlett's $\chi^2(21) = 1491.087$***)			4.443	63.476
Understanding AI concepts, principles, and mainstream models	0.788	0.621		
Evaluating AI's impact and technological limitations	0.793	0.629		
Knowing mainstream AI tools and application scenarios	0.807	0.651		
Identifying and verifying inaccurate AI-generated content	0.814	0.663		
Distinguishing AI assistance from academic misconduct	0.765	0.585		
Identifying harmful AI-generated information and avoiding its spread	0.804	0.647		
Protecting privacy and data security when using AI	0.805	0.648		
GenAI Use (KMO = 0.925; Bartlett's $\chi^2(21) = 1385.109$***)			4.340	61.993
Interacting with AI tools for content generation	0.750	0.562		
Screening and verifying AI-provided information	0.786	0.618		
Selecting suitable AI tools according to learning needs	0.763	0.582		
Using AI for literature retrieval and writing structure without copying	0.802	0.644		
Locating academic resources and identifying research trends	0.805	0.649		
Improving thesis writing efficiency and quality	0.807	0.652		
Translating literature and extracting key information	0.796	0.633		
Learning Outcomes / SAWSES(KMO = 0.967; Bartlett's $\chi^2(105) = 3826.866$***)			8.763	58.423
Overcoming difficulties in thesis writing	0.773	0.597		
Using academic vocabulary and expression	0.792	0.627		
Integrating multiple sources into original thesis writing	0.770	0.593		
Expressing ideas clearly for readers	0.748	0.560		
Using feedback to improve future writing	0.705	0.497		
Improving writing through reflection	0.738	0.544		
Connecting literature with one's own ideas	0.793	0.628		
Judging whether the thesis argument is complete	0.699	0.488		
Identifying irrelevant ideas in thesis writing	0.770	0.593		
Judging which feedback should be adopted	0.797	0.636		
Applying creativity in academic writing	0.774	0.600		
Maintaining creativity while sounding professional	0.770	0.593		
Developing a personal academic writing style	0.765	0.586		
Making thesis writing original under specific requirements	0.791	0.626		
Expressing disciplinary concepts, language, and values	0.772	0.596		

Note: *** indicates $p < 0.001$.

To examine the structural suitability of the formal questionnaire items in the sample, this study first conducted exploratory factor analysis (EFA) separately for the three scales: AI Literacy, GenAI Use, and learning outcomes (Table 3). The results show that the KMO value of the AI Literacy scale was 0.918, and Bartlett's test of sphericity was significant. One factor with an eigenvalue greater than 1 was extracted, explaining 63.476% of the cumulative variance, and the factor loadings ranged from 0.765 to 0.814. The KMO value of the GenAI Use scale was 0.925, and Bartlett's test of sphericity was significant. One factor was extracted, explaining 61.993% of the cumulative variance, and the factor loadings ranged from 0.750 to 0.807. The KMO value of the learning outcomes scale was 0.967, and Bartlett's test of sphericity was significant. One factor was extracted, explaining 58.423% of the cumulative variance, and the factor loadings ranged from 0.699 to 0.797. These results indicate that the scales used in this study have good internal structures in the present sample and are suitable for entering subsequent model analysis as overall variables. Since the learning outcome items were derived from the three-dimensional structure of SAWSES, this study treated them as an overall measure of academic writing self-efficacy in the main model and further examined the three dimensions of Writing

Essentials, Relational-Reflective, and Creative Identity in the subsequent extension analysis.

Considering that both AI Technical Cognition and AI Ethics serve the measurement of the overall competence of AI Literacy, this study treated AI Literacy as an overall latent variable in the main model and further examined the differentiated effects of the two subdimensions in the dimension-level extension analysis.

Based on the exploratory factor analysis, this study further used confirmatory factor analysis (CFA) to test the three-factor measurement model (Table 4). The results show that the standardized factor loadings of AI Literacy, GenAI Use, and learning outcomes ranged from 0.716 to 0.777, 0.699 to 0.773, and 0.671 to 0.781, respectively, all reaching acceptable levels. The AVE values of the three latent variables were 0.574, 0.557, and 0.555, respectively, all above 0.5. The CR values were 0.904, 0.898, and 0.949, respectively, all above 0.7, indicating that the scales had good convergent validity and composite reliability.

Table 4. Confirmatory Factor Analysis Results

Latent variable	Standardized loading range	AVE	CR	Square root of AVE
AI Literacy	0.716–0.777	0.574	0.904	0.758
GenAI Use	0.698–0.773	0.557	0.898	0.746
Learning Outcomes/SAWSES	0.671–0.781	0.555	0.949	0.745

In terms of discriminant validity, the square roots of AVE for AI Literacy, GenAI Use, and learning outcomes were 0.758, 0.746, and 0.745, respectively, all of which were greater than their correlations with the other latent variables. The HTMT values ranged from 0.297 to 0.349, all below 0.85. In addition, both MSV and ASV were lower than the corresponding AVE values. These results indicate that the three latent variables had good discriminant validity.

4.3 Structural Equation Modeling

After the measurement model passed the relevant tests, this study further used structural equation modeling to examine the structural relationships among AI Literacy, GenAI Use, and learning outcomes (Table 5). The model fit results showed that $\chi^2/df = 1.551$, GFI = 0.913, RMSEA = 0.037, RMR = 0.043, CFI = 0.970, NFI = 0.920, TLI = 0.967, and SRMR = 0.033. The main fit indices all met or approached commonly used criteria, indicating that the overall model fit was good.

The path test results are shown in Table 6. AI Literacy had a significant positive effect on GenAI Use, with a standardized path coefficient of 0.327 and $p < 0.001$, supporting H1. AI Literacy had a significant positive effect on learning outcomes, with a standardized path coefficient of 0.281 and $p < 0.001$, supporting H2. GenAI Use also had a significant positive effect on learning outcomes, with a standardized path coefficient of 0.207 and $p < 0.001$, supporting H3. These results indicate that AI Literacy can not only promote students' use of GenAI tools in thesis writing, but also directly enhance their academic writing self-efficacy. Meanwhile, GenAI Use itself is also an important process variable influencing learning outcomes.

Table 5. Model Fit Indices of the Structural Equation Model

Index	χ^2/df	GFI	RMSEA	RMR	CFI	NFI	TLI	SRMR
Result	1.551	0.913	0.037	0.043	0.970	0.920	0.967	0.033
Criterion	<3	>0.90	<0.08	<0.05	>0.90	>0.90	>0.90	<0.08

Table 6. Structural path estimates

Hypothesis	Path	Unstandardized coefficient	SE	z	p	Standardized coefficient
H1	AI Literacy → GenAI Use	0.277	0.049	5.685	<0.001	0.327
H2	AI Literacy → Learning Outcomes/SAWSES	0.260	0.052	5.002	<0.001	0.281
H3	GenAI Use → Learning Outcomes/SAWSES	0.225	0.060	3.730	<0.001	0.207

Based on the model fit results and path test results, a standardized path coefficient diagram of the structural equation model was further drawn to visually present the structural relationships among the latent variables and the factor loadings of the observed variables. Figure 2 showed that AI Literacy had significant positive effects on both GenAI Use and learning outcomes, and GenAI Use also had a significant positive effect on learning outcomes. In addition, the standardized loadings of the observed variables on their corresponding latent variables were generally within an acceptable range, further supporting the model specification of this study.

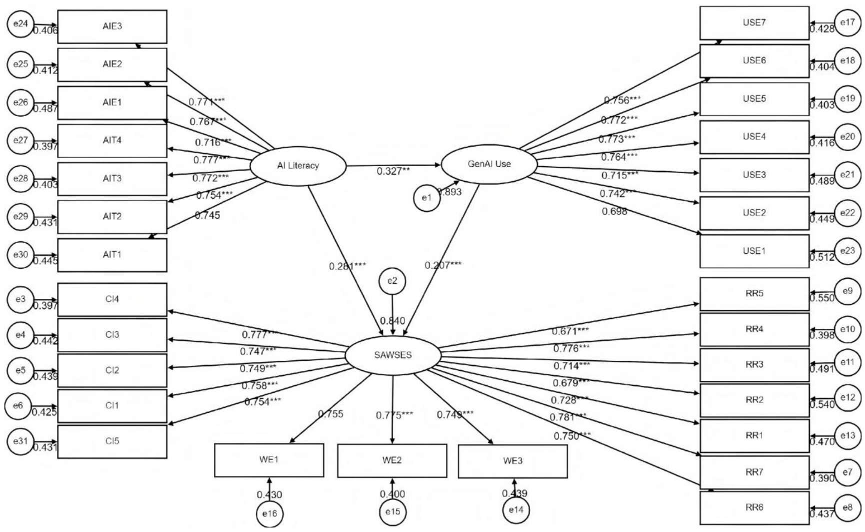

Figure 2. Standardized Path Coefficient Diagram of the Structural Equation Model

4.4 Mediation Analysis

To further examine the mediating role of GenAI Use between AI Literacy and learning outcomes, this study conducted a Bootstrap mediation analysis based on the composite scores of each variable after the structural equation model path test (Table 7). The results showed that the total effect of AI Literacy on learning outcomes was 0.307, $p < 0.01$. The effect of AI Literacy on GenAI Use was 0.292, $p < 0.01$, and the effect of GenAI Use on learning outcomes was 0.188, $p < 0.01$. After GenAI Use was included in the model, the direct effect of AI Literacy on learning outcomes remained significant, with a direct effect of 0.252, $p < 0.01$. The Bootstrap results showed that the indirect effect was 0.055, and the 95% confidence interval was [0.022, 0.101], which did not include zero. This indicates that GenAI Use played a significant partial mediating role between AI Literacy and learning outcomes. The mediating effect accounted for 17.862% of the total effect, supporting H4.

This result indicates that the effect of AI Literacy on learning outcomes is not achieved only through a direct path, but is also partially transformed into learning outcomes through GenAI Use. For thesis writing instruction, improving students' understanding of AI tools alone is not sufficient. It is also necessary to guide students to transform AI Literacy into specific writing behaviors, such as retrieval, integration, structural optimization, feedback-based revision, and information verification.

Table 7. Bootstrap Mediation Analysis Results

Path	Total effect c	Path a	Path b	Direct effect c′	Indirect effect a×b	Boot SE	95% CI	Proportion of effect
AI Literacy → GenAI Use → Learning Outcomes/SAWSES	0.307	0.292	0.188	0.252	0.055	0.020	[0.022, 0.101]	17.86%

4.5 Additional Dimension-Level Analysis

To further identify differences in the effects of different dimensions, this study divided AI Literacy into two dimensions, AI Technical Cognition and AI Ethics, for extension analysis (Table 8). The results showed that AI Technical Cognition had a significant positive effect on learning outcomes, with a standardized path coefficient of 0.269 and $p = 0.001$. The effect of AI Ethics on learning outcomes was not significant, with a standardized path coefficient of 0.068 and $p = 0.399$. Further mediation analysis showed that AI Technical Cognition could influence learning outcomes through GenAI Use, with an indirect effect of 0.033 and a 95% confidence interval of [0.006, 0.069], indicating partial mediation. The indirect effect of AI Ethics on learning outcomes through GenAI Use was 0.021, with a 95% confidence interval of [-0.005, 0.056], which was not significant.

Since the correlation coefficient between AI Technical Cognition and AI Ethics was 0.808, indicating a relatively strong correlation, this study further conducted collinearity diagnostics. The results showed that the VIF values of the two dimensions were both 2.882, and the tolerance values were both 0.347, which did not exceed commonly used warning thresholds. This indicates that there was no serious multicollinearity. Based on this, both dimensions were retained in the extension analysis, while the non-significant result of the AI Ethics dimension was interpreted cautiously. The results suggest that when AI Technical Cognition and AI Ethics entered the model simultaneously, AI Technical Cognition showed stronger independent explanatory power. AI Ethics may function more as a normative foundation and risk constraint, while its direct effect on improving writing self-efficacy was not reflected in the present model.

Table 8. Additional Dimension-Level Analysis Results

Analysis type	Path	Unstandardized coefficient	Standardized coefficient	*p* value	Result
AI Literacy dimension	AI Technical Cognition → Learning Outcomes/SAWSES	0.239	0.269	0.001	Significant
AI Literacy dimension	AI Ethics → Learning Outcomes/SAWSES	0.063	0.068	0.399	Not significant
Learning outcome dimension	GenAI Use → Writing Essentials	0.245	0.226	<0.001	Significant
Learning outcome dimension	GenAI Use → Relational-Reflective	0.267	0.277	<0.001	Significant
Learning outcome dimension	GenAI Use → Creative Identity	0.269	0.259	<0.001	Significant
Dimensional mediation	AI Technical Cognition → GenAI Use → Learning Outcomes/SAWSES	0.033	—	0.045	Partial mediation
Dimensional mediation	AI Ethics → GenAI Use → Learning Outcomes/SAWSES	0.021	—	0.166	Not significant

This study also further examined the effects of GenAI Use on the three dimensions of learning outcomes. The results showed that GenAI Use had significant positive effects on Writing Essentials, Relational-Reflective, and Creative Identity, with standardized path coefficients of 0.226, 0.277, and 0.259, respectively. Among them, the effect on Relational-Reflective was relatively stronger, indicating that GenAI tools provide relatively clear support for process-oriented writing abilities, such as feedback comprehension, idea connection, reflective revision, and topic judgment.

Overall, the main model of this study was supported by the data. AI Literacy significantly promoted GenAI Use and directly enhanced learning outcomes in the thesis writing context. GenAI Use also significantly improved learning outcomes and played a partial mediating role between AI Literacy and learning outcomes. The dimension-level analysis further showed that AI Technical Cognition had a more direct effect on learning outcomes than AI Ethics, while GenAI Use had positive effects on all three dimensions of learning outcomes, with a relatively stronger effect on Relational-Reflective. These findings suggest that AI empowerment in thesis writing is not merely a matter of tool use, but involves a continuous transformation process. When integrating GenAI into thesis writing instruction, universities should improve students' technical understanding of AI and their ability to apply AI tools, while also strengthening AI Ethics and academic norms education. Students should be guided to use AI for literature comprehension, idea organization, structural optimization, and feedback-based revision, rather than simply relying on AI-generated text.

5. Conclusions, Implications, and Limitations

5.1 Research Conclusions

This study took university students with thesis writing experience as the research participants, constructed a research model around the relationships among AI Literacy, GenAI Use, and learning outcomes, and conducted empirical analysis using structural equation modeling and Bootstrap mediation effect testing. The results showed that AI Literacy had a significant positive effect on GenAI Use, with a standardized path coefficient of 0.327. AI Literacy also had a significant positive effect on learning outcomes, with a standardized path coefficient of 0.281. GenAI Use had a significant positive effect on learning outcomes, with a standardized path coefficient of 0.207. These findings indicate that students' ability to understand, judge, and appropriately use AI tools can influence their academic writing self-efficacy in the thesis writing context through both direct and indirect paths. The model fit results showed that $\chi^2/df = 1.551$, RMSEA = 0.037, CFI = 0.970, TLI = 0.967, and SRMR = 0.033, indicating that the research model had good model fit.

The mediation effect test further showed that GenAI Use played a partial mediating role between AI Literacy and learning outcomes. The total effect of AI Literacy on learning outcomes was 0.307, the direct effect was 0.252, and the indirect effect was 0.055. The Bootstrap 95% confidence interval was [0.022, 0.101], and the mediating effect accounted for 17.862% of the total effect. This result indicates that AI Literacy can not only directly enhance students' thesis writing self-efficacy, but also further influence learning outcomes by promoting students' more effective use of GenAI tools.

The dimension-level extension analysis showed that different dimensions within AI Literacy had different effects. AI Technical Cognition had a significant positive effect on learning outcomes, with a standardized path coefficient of 0.269, whereas the direct effect of AI Ethics on learning outcomes was not significant. Further mediation analysis indicated that AI Technical Cognition could influence learning outcomes through GenAI Use, while the indirect effect of AI Ethics was not significant. Since the correlation between AI Technical Cognition and AI Ethics was relatively high, but the VIF value was 2.882 and did not reach the level of serious multicollinearity, this result is more appropriately interpreted as follows: when AI Technical Cognition and AI Ethics entered the model simultaneously, AI Technical Cognition showed stronger independent explanatory power, while AI Ethics functioned more as a normative foundation and risk constraint.

The dimension-level analysis of learning outcomes showed that GenAI Use had significant positive effects on Writing Essentials, Relational-Reflective, and Creative Identity, with standardized path coefficients of 0.226, 0.277, and 0.259, respectively. Among these dimensions, the effect of GenAI Use on Relational-Reflective was relatively stronger. This suggests that the instructional value of AI tools is not limited to language polishing and efficiency improvement but is also reflected in process-oriented aspects such as helping students understand feedback, connect ideas, reflect on structure, and judge writing content.

5.2 Theoretical Implications

This study introduces a framework of AI Literacy, GenAI Use, and learning outcomes into research on the educational application of GenAI and extends AI Literacy from a general discussion of technical competence to the specific learning context of thesis writing. Previous studies have mostly discussed AI Literacy in terms of concepts, competency frameworks, or risks of tool use. Based on student questionnaire data, this study verifies the direct effect of AI Literacy on learning outcomes and its indirect effect through GenAI Use, thereby providing empirical evidence for understanding how AI Literacy is transformed into learning outcomes.

This study operationalizes learning outcomes as academic writing self-efficacy in the thesis writing context and measures them based on the three-dimensional structure of SAWSES, thereby extending the understanding of learning outcomes in AI educational application research. The results show that GenAI Use has positive effects on Writing Essentials, Relational-Reflective, and Creative Identity. This indicates that AI tools are not only related to the efficiency of text generation, but also to students' writing confidence, feedback judgment, reflective revision, and creative expression. This finding helps extend research on GenAI learning effects from the level of tool use to the formation process of academic writing competence.

This study further distinguishes between AI Technical Cognition and AI Ethics within AI Literacy, finding that AI Technical Cognition has a more direct explanatory effect on learning outcomes, whereas the independent effect of AI Ethics is not significant. This result provides empirical clues for future research to further refine the internal structure of AI Literacy. AI Ethics may not directly manifest as an improvement in writing self-efficacy but may influence the quality of students' AI use through normative boundaries, risk awareness, and academic integrity constraints. Therefore, AI Literacy research needs to consider both competence-promoting mechanisms and norm-constraining mechanisms, rather than treating different dimensions as equivalent.

5.3 Practical Implications

The findings of this study provide implications for university thesis supervision and the reform of literature retrieval and thesis writing courses. First, the mean values of AI Literacy, GenAI Use, and learning outcomes among the sampled students were all lower than the theoretical midpoint of the scale. This indicates that students still have considerable room for improvement in their ability to use AI to support thesis writing. When integrating GenAI into teaching, universities should incorporate AI Literacy cultivation into the process of thesis writing training, rather than limiting it to tool introduction or general advocacy for tool use.

Second, AI Literacy had significant positive effects on both GenAI Use and learning outcomes. This suggests that improving students' AI Technical Cognition, tool judgment ability, and information screening ability is an important foundation for improving thesis writing quality. In course teaching, training tasks can be designed around AI tool application scenarios, prompt design, verification of AI-generated content, literature retrieval assistance, structural optimization, and academic expression revision, so that students can develop transferable AI use competence in specific writing processes.

Third, GenAI Use played a partial mediating role between AI Literacy and learning outcomes, indicating that AI Literacy is more likely to contribute to writing self-efficacy improvement when it is transformed into specific learning-oriented use behaviors. Therefore, thesis supervision should not simply prohibit or allow AI use without guidance. Instead, process-based guidelines should be established. For example, students may be required to explain the purpose of AI tool use, the writing stage in which AI was used, the verification method for AI-generated content, and the process of human revision. This can guide students to use AI as an auxiliary tool for information comprehension, idea organization, structural adjustment, and feedback-based revision, rather than as a direct substitute for thesis writing.

Finally, the dimension-level analysis showed that GenAI Use had a relatively stronger effect on Relational-Reflective. This suggests that the application of AI tools in thesis writing instruction should not be limited to helping students write faster but should also support them in thinking more clearly and revising more effectively. Teachers may incorporate AI-assisted feedback analysis, comparison of literature viewpoints, examination of argument structure, and generation of revision plans into course activities, thereby promoting students' academic writing ability through multiple rounds of feedback and reflection.

5.4 Research Limitations and Future Research

This study still has certain limitations. First, it used cross-sectional questionnaire data, which can reveal relationships among variables but cannot fully explain the dynamic causal process among AI Literacy, GenAI Use, and learning outcomes. Future studies may further verify these relationships through longitudinal tracking or teaching intervention experiments. Second, learning outcomes were mainly measured through academic writing self-efficacy, which reflects students' subjective judgments of their own abilities. Future research may combine thesis grades, text quality, teacher evaluation, and process-based writing data to develop a more comprehensive evaluation system. Third, the sample of this study was limited to university students with thesis writing experience. Future studies may expand the sample to include different types of institutions, disciplinary backgrounds, and learning stages to test the applicability of the model.

Finally, although this study emphasized during questionnaire distribution that the data would be used only for academic research and would be processed anonymously, some students may still have worried that AI use could be associated with academic misconduct, thesis evaluation, or graduation review, given that university norms for GenAI use have not yet been fully unified. This may have led to defensive responses or an underestimation of their own AI use. Therefore, the mean values of AI Literacy, GenAI Use, and learning outcomes being lower than the theoretical midpoint of the scale may reflect both the need to improve students' ability to use AI in thesis writing and the influence of response concerns and perceived risks of AI use. Future research may further verify these findings by combining interviews, process-based learning data, and anonymous situational measurement.

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References

[1] UNESCO.AI Competency Framework for Students. Paris: UNESCO, 2024. https://unesdoc.unesco.org/ark:/48223/pf0000391105.

[2] HUANG Y, CUI W. Exploration and practice of data-intelligent talent cultivation model based on CDIO-OBE framework: A case study of the literature retrieval and academic writing course .Journal of Higher Education Teaching, 2025, 2(2):265-276.

[3] YANG Zongkai, WANG Jun, WU Di, et al. Exploring the impact of ChatGPT/AIGC on education and strategies for response .Journal of East China Normal University (Educational Sciences), 2023, 41(7):26-35.

[4] WANG Youmei, WANG Dan, LIANG Weiyi, et al.” Aladdin’s Lamp” or “Pandora’s Box”: The potential and risks of ChatGPT’s educational application .Modern Distance Education Research, 2023, 35(2):48-56.

[5] LI Yan, XU Jie, JIA Chengyuan, et al. Investigation of college students’ generative artificial intelligence (GAI) usage status and its implication: Taking Zhejiang University as an example .Open Education Research,2024,30(1):89-98.

[6] WANG Siyao, HUANG Yating. Promote or inhibit: The impact of generative artificial intelligence on the creativity of college students. China Higher Education Research, 2024(11):29-36.

[7] LONG D, MAGERKO B. What is AI literacy? Competencies and design considerations//BERNHAUPT R, MUELLER F F, VERWEIJ D, et al. Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems. New York: Association for Computing Machinery, 2020:1-16.

[8] CAROLUS A, KOCH M J, STRAKA S, et al. MAILS—Meta AI literacy scale: Development and testing of an AI literacy questionnaire based on well-founded competency models and psychological change- and meta-competencies .Computers and Human Behavior: Artificial Humans, 2023, 1:100014.

[9] LINTNER T.A systematic review of AI literacy scales. npj Science of Learning, 2024, 9:50.

[10] ZHANG Yinrong, YANG Gang, XU Jiayan, et al. The cultivation of AI literacy model and its implementation path .Modern Educational Technology, 2022, 32(3):42-50.

[11] CAI Yingchun, ZHANG Jingbei, YU Chenlin, et al. Artificial intelligence literacy in the digital intelligence era: Connotation, framework and implementation pathways .Journal of Library Science in China, 2024, 50(4):71-84.

[12] ZHOU Xin, YANG Ming, LI Lexing, et al. Research on the assessment framework, current status, and educational optimization strategies of college students’ AI literacy. Research on Library Science, 2026(2):23-31, 62.

[13] WANG Rui, WANG Yong. Conceptual analysis of AI literacy: Paradigm evolution from information and digital to intelligence. Library Journal, 2026:1-11.

[14] GUO Yajun, KOU Xuying, FENG Siqian, et al. Artificial intelligence literacy: Connotation analysis and evaluation criteria .Library Tribune, 2025, 45(2):42-50.

[15] ZHAO Yimin, PENG Xueqin, CUN Guomei. Artificial intelligence literacy: Connotation, framework, and evaluation system .Library and Information Service, 2025, 69(13):83-93.

[16] KÖHLER C, HARTIG J. ChatGPT in higher education: Measurement instruments to assess student knowledge, usage, and attitude .Contemporary Educational Technology, 2024, 16(4):ep528.

[17] NEMT-ALLAH M, KHALIFA W, BADAWY M, et al. Validating the ChatGPT Usage Scale: Psychometric properties and factor structures among postgraduate students .BMC Psychology, 2024, 12(1):497.

[18] TANG Qianwen, YIN Zihan, ZHANG Hao. Cultivation goals and implementation strategies of digital literacy for college students in the context of generative artificial intelligence .Library Work and Study,2025(4):95-102.

[19] CHEN Rong, LI Jianxia, RAO Haixia, et al. Research on the construction and application of an artificial intelligence literacy evaluation index system for scientific researchers .Information Studies: Theory & Application, 2026:1-14.

[20]MITCHELL K M, MCMILLAN D E, LOBCHUK M M, et al. Development and validation of the Situated Academic Writing Self-Efficacy Scale (SAWSES) .Assessing Writing, 2021, 48:100524.

[21]BRÅTEN I, HAVERKAMP Y E, LATINI N, et al. Measuring multiple-source based academic writing self-efficacy. Frontiers in Psychology, 2023, 14:1212567.