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Enhancing scientific writing skills: the roles of artificial intelligence use, intrinsic motivation, and critical literacy

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ABSTRACT

This study examines how artificial intelligence or AI use influences scientific writing skills through motivational and cognitive mechanisms among university students. Employing a cross-sectional survey methodology, data were collected from students across multiple Indonesian universities and analyzed using partial least squares structural equation modeling (PLS-SEM). Findings demonstrate that AI use does not function as a primary direct predictor of scientific writing performance; rather, intrinsic motivation and critical literacy serve as the pivotal conduits through which its effects operate. AI-integrated academic settings were found to strengthen learners' motivational engagement and evaluative capabilities, which in turn facilitated the production of well-structured and analytically coherent scientific texts. Intrinsic motivation constitutes a foundational engine for sustained participation in writing tasks, while critical literacy operates as an indispensable cognitive instrument enabling learners to assess, synthesize, and refine information within AI-assisted writing environments. These outcomes underscore the necessity of conceptualizing AI as a pedagogical affordance that nurtures psychological engagement and analytical judgment, rather than as a substitute for independent academic writing. The study provides theoretical and practical insights for integrating AI tools into higher education writing instruction in ways that enhance motivation, critical literacy, and responsible academic writing practices.

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1. INTRODUCTION

Artificial intelligence (AI) has increasingly reshaped learning practices in higher education, especially in the areas of academic writing and scholarly communication. Advances in natural language processing and the proliferation of generative AI platforms such as ChatGPT, Gemini, and Claude have equipped students with the capacity to receive instantaneous feedback, restructure their prose, reframe textual content, consolidate scholarly literature, and generate writing concepts with unprecedented ease [1]–[5]. Although these technologies hold considerable promise for improving instructional efficacy, academic writing quality, and overall student achievement, a comprehensive understanding of their educational ramifications remains incomplete. Available empirical evidence suggests that the adoption of AI tools may concurrently strengthen learner motivation and pose challenges to deeper cognitive processing, underscoring the urgent need for more fine-grained inquiry into the specific pathways through which AI shapes educational outcomes [6]–[11]. Such inconsistent findings suggest that the educational consequences of AI adoption cannot be adequately captured by examining performance indicators alone; a more nuanced investigation of the motivational and cognitive processes mediating AI engagement with learning is therefore imperative.

The ability to scrutinize, interpret, and critically examine information, commonly referred to as critical literacy, occupies a central position in scientific writing, especially within academic environments where AI-generated material is becoming increasingly prevalent. Scholarly evidence indicates that learners need well-developed critical literacy competencies to adequately evaluate the factual accuracy, potential biases, logical coherence, and overall reliability of content produced by AI systems [12]–[16]. Without adequate critical literacy, AI-assisted writing practices risk fostering surface-level textual production rather than facilitating substantive intellectual engagement with academic literature. Likewise, despite the central importance of scientific writing for academic achievement, limited research has systematically explored the psychological and cognitive mechanisms through which AI engagement affects students' writing performance. Existing literature tends to focus on the technical use of AI tools rather than exploring the integrated interactions between AI use, intrinsic motivation, critical literacy, and scientific writing skills. This disproportion in the literature has led to a fragmented conceptualization of AI-assisted writing, with greater attention given to technological features than to the learner-centered processes they stimulate. This creates an important gap, as scientific writing is not solely a mechanical activity but a complex interplay of cognitive, motivational, and evaluative processes [17], [18]. Furthermore, past research rarely incorporates a comprehensive structural model that examines these variables simultaneously using robust statistical approaches such as partial least squares structural equation modeling (PLS-SEM). As a result, the pathways through which AI facilitates writing development remain insufficiently theorized and lack integrated empirical investigation.

In response to these gaps, the current study develops and empirically tests a structural model aimed at examining the extent to which AI use predicts learners' intrinsic motivation, critical literacy capacities, and scientific writing proficiency. Drawing on self-determination theory [19], [20], this study proposes that intrinsic motivation serves as a key mediating mechanism influencing students' learning outcomes in digitally mediated environments. Furthermore, perspectives from critical literacy theory indicate that AI-supported writing contexts can either enhance or constrain learners' evaluative and analytical capacities. The integration of these two theoretical frameworks provides a more holistic account of how AI engagement interacts with learners' internal processes and offers deeper insight into the psychological and cognitive mechanisms underlying AI-supported academic writing. Aligning with the aspirations of Sustainable Development Goal 4 (SDG 4), which advocates for inclusive and high-quality education, the present study situates AI-supported writing within broader agendas focused on democratizing access to structured academic guidance, individualized learning experiences, and writing skill development across varied higher education contexts [21]. At the same time, the study highlights that unregulated pedagogical use of AI may threaten academic integrity and critical thinking, reinforcing the importance of theory-informed integration approaches.

Accordingly, this study addresses the central research question: how does AI usage affect intrinsic motivation, critical literacy, and scientific writing skills among university students? Specifically, the study investigates both direct and indirect relationships among AI utilization, intrinsic motivation, critical literacy, and scientific writing performance using an integrated structural framework. Through simultaneous examination of these relational dynamics, the study aims to establish whether AI's contribution to writing development is predominantly realized via indirect motivational and cognitive channels rather than through direct performance enhancement. The mediating functions of intrinsic motivation and critical literacy are further explored to clarify the psychological and cognitive processes connecting AI engagement with scientific writing outcomes.

Based on these objectives, a set of hypotheses was developed to reflect the structural relationships tested through SEM. AI use is hypothesized to positively influence intrinsic motivation (H1) and critical literacy (H2). Intrinsic motivation is expected to have a positive impact on critical literacy (H3) and scientific writing skills (H4). Critical literacy is also predicted to significantly contribute to scientific writing skills (H5). Additionally, AI use is assumed to have a direct effect on scientific writing skills (H6). The mediating effects of intrinsic motivation and critical literacy are assessed through hypotheses (H7-H10). Finally, the study examines whether these structural relationships differ across gender and educational levels (H11), providing insights into the consistency of these effects across diverse student groups. This hypothesized structure reflects the study's emphasis on mechanism-based explanation rather than isolated variable effects.

Figure 1 presents the conceptual framework of this study, depicting the proposed relationships among artificial intelligence use (AIU), intrinsic motivation (IM), critical literacy (CL), and scientific writing skills (SWS). Drawing on self-determination theory and critical literacy theory, the model conceptualizes AI use as a learning resource that affects scientific writing outcomes both directly and indirectly through motivational and cognitive processes. Specifically, AI use is hypothesized to influence intrinsic motivation and critical literacy, which subsequently contribute to scientific writing development, while a direct pathway from AI use to writing performance is also examined. By integrating these relationships within a unified structural framework, the model emphasizes process-oriented mechanisms rather than isolated variable effects and provides a theoretical basis for the subsequent PLS-SEM analysis.

Beyond assessing the independent effects of AI use, intrinsic motivation, and critical literacy, this study seeks to explain how AI-supported learning environments shape scientific writing performance through identifiable psychological and cognitive mechanisms. The proposed PLS-SEM framework does not conceptualize AI as an autonomous determinant of writing achievement; instead, AI use is viewed as a behavioral learning affordance whose impact operates primarily through intrinsic motivation and critical literacy. Empirical mediation findings indicate that AI contributes to scientific writing largely via indirect pathways, particularly by strengthening students' motivational engagement and their ability to critically evaluate and synthesize information. By integrating self-determination theory and critical literacy theory into a single analytical model, this study offers both theoretical and empirical clarification of the pathways linking AI engagement with scientific writing outcomes among university students. This mechanism-oriented perspective responds directly to calls for theory-driven models in AI-in-education research and provides an evidence-based explanation that extends beyond simplified cause–effect interpretations of AI-supported writing.

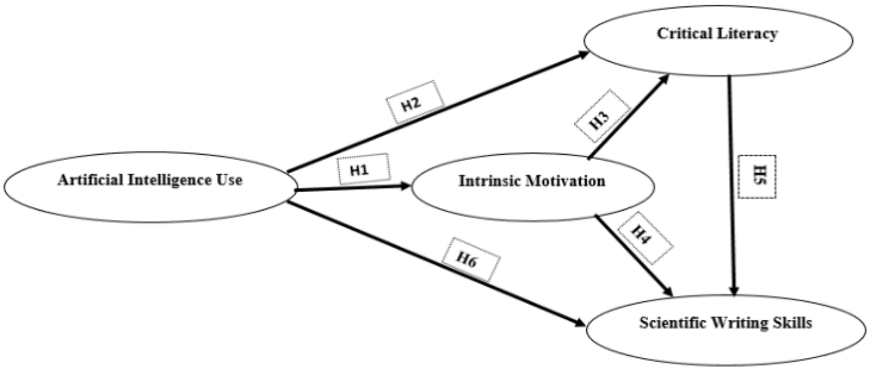

Figure 1. Conceptual model of the study

2. METHOD

The present investigation employed a cross-sectional design to explore the structural linkages connecting AI use, intrinsic motivation, critical literacy, and scientific writing proficiency within a theoretically informed analytical framework. Such a design is suitable for evaluating hypothesized mechanisms and mediation structures derived from established theoretical perspectives, especially self-determination theory and critical literacy theory, where the focus is on examining relational dynamics rather than changes over time [22], [23]. Although longitudinal or experimental approaches may offer stronger evidence for causal inference, a cross-sectional strategy allows efficient empirical testing of complex structural models that incorporate multiple latent variables [24]. Therefore, the results are interpreted as theoretically informed associations rather than definitive causal relationships, consistent with the study's explanatory and model-validation orientation.

2.1. Participants

The study involved 615 students recruited from six universities in Indonesia who voluntarily agreed to participate. Participants were enrolled in undergraduate, master's, and doctoral programs, thereby representing diverse academic experiences across multiple educational levels. Eligibility criteria required participants to be actively registered university students, to have experience using artificial intelligence tools (e.g., ChatGPT, Gemini, Grammarly, or Quillbot) for academic activities, and to have previously completed at least one scientific writing task. within the past two years. A cluster random sampling technique was implemented by grouping students based on their educational level and university, followed by random selection within each cluster [25], [26]. This sampling approach enhanced representativeness while reducing the risk of sampling bias.

2.2. Instruments

Four standardized measurement instruments were adapted from well-established international theoretical frameworks and previously validated scales. Participants responded to each survey item on a five-point Likert-type scale anchored at 1 (strongly disagree) and 5 (strongly agree) [27]. All instruments underwent expert review by three professors specializing in educational psychology and assessment. A pilot test (n=60) confirmed reliability (α and CR >0.70) and validity (average variance extracted (AVE)>0.50). Only refined items were used in the final survey. Table 1 shows the summary of research instruments.

Table 1. Summary of research instruments

Variable	Source/theory	Total items	Indicators measured	Scale
AI use	[1]	25	Literature search and summarization; grammar and style improvement; assistance in writing sections; paraphrasing and text restructuring; reference and citation generation	5-point Likert
Critical literacy	[18]	20	Access and retrieve information; compare and evaluate texts; identify authors' arguments; reflect and contextualize information	5-point Likert
Intrinsic motivation	[28]	40	Enjoyment; mastery orientation; autonomy; competence; curiosity; focused attention; satisfaction; internal achievement	5-point Likert
Scientific writing skills	[29]	26	Clarity; accuracy; logical transparency; completeness; quality of conclusions	5-point Likert

2.3. Data collection procedure

Primary data were obtained through an online questionnaire distributed via a password-protected digital survey platform. Before completing the survey, participants received concise information regarding the study objectives, their voluntary participation, and the protection of response confidentiality [30]. Informed consent was obtained electronically before participants could proceed to the survey. The data collection process began with the distribution of the survey link through university coordinators across six universities. Respondents were initially screened for eligibility based on the predefined inclusion criteria. Eligible participants then completed the research instruments within an estimated duration of 15-20 minutes. Following data submission, responses were carefully reviewed through a systematic screening and cleaning process to identify missing values, detect straight-lining behavior, and ensure overall data integrity [31]. The final cleaned dataset was subsequently prepared for analysis using the PLS-SEM approach [32].

2.4. Data analysis

The dataset was processed using SmartPLS 4.0 following a two-stage analytical procedure. In the initial phase, the measurement model was assessed against multiple psychometric benchmarks: indicator loadings exceeding 0.70, AVE surpassing 0.50, composite reliability (CR) above 0.70, and Cronbach's alpha values meeting the 0.70 threshold to confirm internal consistency [33]. The discriminant validity of the constructs was evaluated through dual assessment employing the Fornell-Larcker criterion alongside the heterotrait–monotrait (HTMT) ratio, with values below 0.90 considered satisfactory [34]. Additionally, collinearity was checked using variance inflation factor (VIF) values, ensuring all indicators were below the threshold of 5.0 [35]–[37]. The second phase focused on the structural model, wherein path coefficients were computed through bootstrapping with 5,000 resampling iterations; explanatory power was gauged via R^2 and Q^2 values, and global model fit was assessed using the standardized root mean square residual (SRMR) index [38]. Effect size values (f^2) were computed to estimate the strength of inter-construct relationships, while predictive performance was additionally assessed using the PLSpredict technique to examine out-of-sample accuracy [39], [40]. Mediation testing was performed by evaluating indirect pathways with bootstrapped confidence intervals to establish whether intrinsic motivation and critical literacy functioned as mediators between AI use and scientific writing outcomes [41]–[43]. In addition, multi-group analysis (MGA) was applied to investigate potential differences in structural paths across gender categories (male and female) and academic levels (S1, S2, S3). A non-parametric approach was applied due to the non-normal distribution characteristics of the data.

2.5. Ethical considerations

The research protocol received ethical approval from the institutional review board at Universitas Negeri Malang. Participation in the study was fully voluntary; all participants provided informed consent with assurances of complete confidentiality and the unrestricted right to withdraw at any point during the investigation. All collected data were anonymized and stored securely, and the entire research procedure was conducted in accordance with the ethical principles of the Declaration of Helsinki.

3. RESULTS AND DISCUSSION

This section reports the outcomes of the PLS-SEM analysis and offers an in-depth interpretation of the findings. The discussion is structured by first addressing the evaluation of the measurement model, followed by the examination of the structural model, mediation analysis, and multi-group comparisons. This analytical sequence enables a systematic interpretation of the interrelationships among artificial intelligence use, intrinsic motivation, critical literacy, and scientific writing performance.

3.1. Measurement model evaluation

As a preliminary step, the measurement model underwent rigorous assessment to verify indicator reliability, internal consistency, convergent validity, and discriminant validity across all constructs. Model evaluation adhered to widely accepted PLS-SEM criteria, systematically addressing indicator-level reliability, overall construct consistency, convergent validity, and discriminant validity [34], [35]. Construct reliability was verified through CR coefficients, while convergent validity was established by examining the AVE for each latent variable [44]. The extent to which constructs were empirically distinct from one another was verified using the HTMT ratio as the primary discriminant validity criterion [45]. Every measurement indicator met or exceeded the established minimum thresholds, confirming that all constructs demonstrated satisfactory psychometric quality in terms of both reliability and validity. Detailed statistical results for the measurement model are presented in Table 2.

As displayed in Table 2, all constructs satisfactorily fulfilled the established benchmarks for convergent validity and internal consistency. Individual indicator loadings surpassed the minimum acceptable threshold, and the values for Cronbach's alpha, CR, and average variance extracted were all within the recommended ranges. These outcomes indicate that the measurement model demonstrates satisfactory statistical quality and is suitable for further structural model evaluation.

To verify discriminant validity, the study employed a dual approach involving both the Fornell-Larcker criterion and the HTMT ratio. As presented in Table 3 (Fornell-Larcker matrix), the square roots of AVE for all constructs exceeded their corresponding inter-construct correlations, confirming acceptable discriminant validity. HTMT values reported in Table 4 (HTMT ratio matrix) remained below the 0.90 threshold for all construct pairs, providing additional evidence of discriminant validity. To further confirm discriminant validity, the Fornell–Larcker criterion was initially evaluated. This approach requires the square root of each construct's AVE to exceed its correlations with other constructs. As illustrated in Table 3, all constructs exhibited satisfactory discriminant validity, as the square roots of AVE values consistently surpassed the corresponding inter-construct correlations. These findings suggest that each latent variable is empirically distinct and represents a unique dimension within the proposed structural model.

Beyond the Fornell–Larcker evaluation, discriminant validity was additionally examined using the HTMT. This index is regarded as a rigorous indicator, especially when assessing constructs with conceptual proximity. HTMT coefficients remaining below the 0.90 threshold are interpreted as evidence of adequate construct distinctiveness and minimal conceptual redundancy. As reported in Table 4, all HTMT coefficients remained under the recommended threshold, indicating that the constructs are sufficiently distinct within the proposed model.

Table 2. Outer loadings, Cronbach's alpha, CR, and AVE

Construct	Indicator	Loading	Cronbach's alpha	CR	AVE
AI use	AIU1	0.812	0.944	0.953	0.671
	AIU2	0.845			
	AIU3	0.867			
	AIU4	0.801			
	AIU5	0.832			
Intrinsic motivation	IM1	0.884	0.964	0.971	0.735
	IM2	0.861			
	IM3	0.903			
	IM4	0.876			
	IM5	0.842			
Critical literacy	CL1	0.828	0.927	0.941	0.727
	CL2	0.864			
	CL3	0.892			
	CL4	0.841			
Scientific writing skills	SWS1	0.853	0.951	0.960	0.742
	SWS2	0.884			
	SWS3	0.873			
	SWS4	0.852			
	SWS5	0.886			

Table 3. Fornell-Larcker criterion

Construct	AI use	Intrinsic motivation	Critical literacy	Scientific writing skills
AI use	0.819	—	—	—
Intrinsic motivation	0.612	0.857	—	—
Critical literacy	0.511	0.654	0.852	—
Scientific writing skills	0.533	0.698	0.744	0.861

Table 4. HTMT ratio matrix

Construct	AI use	Intrinsic motivation	Critical literacy	Scientific writing skills
AI use	—	0.681	0.597	0.611
Intrinsic motivation	0.681	—	0.734	0.781
Critical literacy	0.597	0.734	—	0.802
Scientific writing skills	0.611	0.781	0.802	—

3.2. Structural model evaluation

Following confirmation of measurement model adequacy, the structural model was examined to assess both the strength and statistical significance of the proposed relationships. Figure 2 illustrates the complete structural framework along with standardized path coefficients. Figure 2 presents the structural framework together with standardized path coefficients across the latent constructs. The results reveal significant directional associations among artificial intelligence use, intrinsic motivation, critical literacy, and scientific writing skills, confirming empirical support for the proposed model. These findings indicate that AI-supported learning contexts foster not only motivational engagement but also advanced literacy development, which in turn strengthens postgraduate students' scientific writing outcomes.

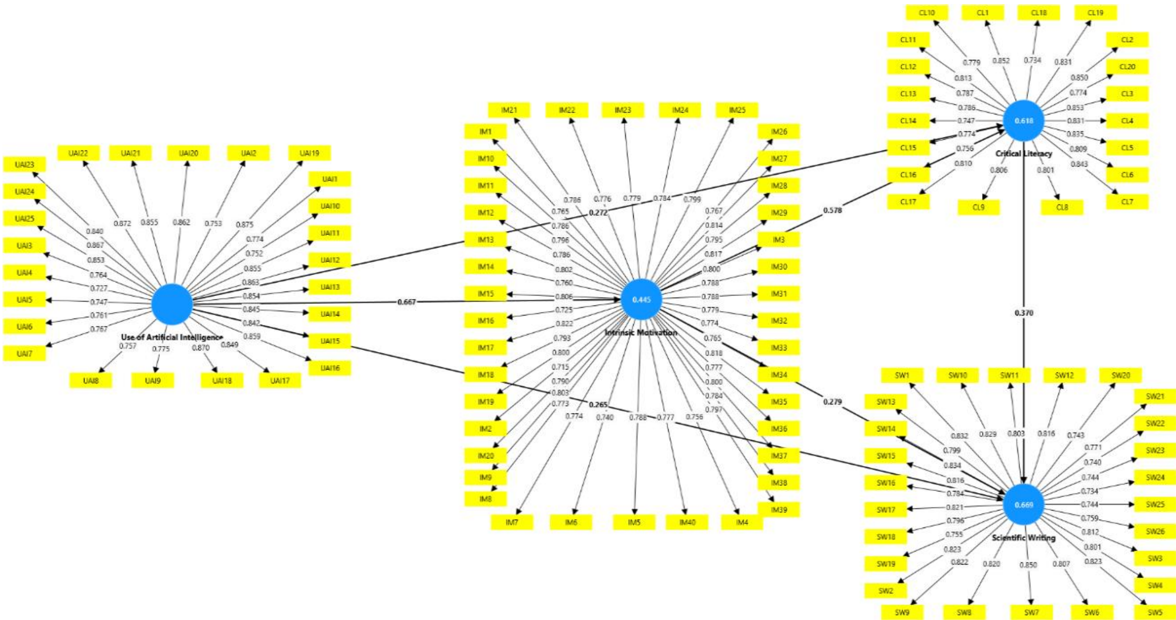

Figure 2. Structural model and path coefficients (PLS-SEM)

All proposed paths reached statistical significance ($p<0.05$). The largest effect emerged for the relationship between AI use and intrinsic motivation ($\beta=0.667$), suggesting that consistent and goal-oriented engagement with AI-supported writing activities significantly enhanced learners' intrinsic motivation. In addition, AI use demonstrated a moderate direct influence on critical literacy ($\beta=0.272$).

The structural model exhibited strong explanatory capacity. The R^2 value for intrinsic motivation reached 0.445, showing that AI use accounted for a considerable portion of motivational variance. Likewise, R^2 values of 0.512 for critical literacy and 0.669 for scientific writing skills reflected moderate to substantial explanatory strength. Furthermore, blindfolding results produced Q^2 values above zero across all endogenous constructs, confirming adequate predictive relevance, while effect size estimates indicated medium-to-large f^2 values for the primary relationships.

3.2.1. Mediation analysis
The mediating roles of intrinsic motivation and critical literacy were examined through bootstrapped indirect effects. Results in Table 5 (mediation effects) confirm that both constructs significantly mediated the relationship between AI use and scientific writing skills. The mediation results show that intrinsic motivation serves as a partial mediator between artificial intelligence use and scientific writing skills. Conversely, critical literacy exhibits a full mediating effect in certain pathways, underscoring its central contribution to the development of students' analytical writing abilities. Overall, these outcomes indicate that motivational and literacy-based mechanisms operate as key psychological channels through which AI use affects postgraduate students' writing achievement.

Table 5. Mediation effects and bootstrapped indirect paths

Mediation path	Indirect effect	t-value	p-value	Result
AIU→IM→SWS	0.267	5.841	0.000	Significant
AIU→CL→SWS	0.203	4.922	0.000	Significant
AIU→IM→CL	0.436	8.014	0.000	Significant
Parallel mediation (IM+CL)	0.471	9.102	0.000	Significant

Note: AIU=AI use; IM=intrinsic motivation; CL=critical literacy; and SWS=scientific writing skills

3.2.2. Multi-group analysis
To identify potential differences in model relationships across demographic groups, MGA was performed based on gender (male vs. female) and educational level (S1, S2, S3). Results in Table 6 (MGA Path Comparisons) show significant differences in the strength of several pathways. Table 6 presents the results of the MGA across gender and educational levels. The results reveal a statistically significant gender-based difference in the association between artificial intelligence use and intrinsic motivation, with male students demonstrating a stronger effect. However, no significant gender differences were identified in the relationships linking intrinsic motivation with critical literacy, critical literacy with scientific writing skills, or artificial intelligence use with scientific writing skills. With respect to educational levels, the analysis indicates that the relationship between critical literacy and scientific writing skills was stronger among doctoral students than among students at lower academic levels, while no other structural paths demonstrated statistically significant differences.

Table 6. MGA results for gender and educational levels

Path	Male β	Female β	Difference	p-value	Result
AIU→IM	0.711	0.642	0.069	0.041	Significant
IM → CL	0.653	0.611	0.042	0.118	Not significant
CL→SWS	0.781	0.724	0.057	0.049	Significant
AIU→SWS	0.211	0.184	0.027	0.201	Not significant

Note: AIU=AI use; IM=intrinsic motivation; CL=critical literacy; and SWS=scientific writing skills

3.2.3. Structural model summary
The structural model evaluation confirmed that all proposed direct relationships reached statistical significance ($p<0.05$). Artificial intelligence use demonstrated a strong positive relationship with intrinsic motivation and a moderate positive relationship with critical literacy. Both intrinsic motivation and critical literacy were positively associated with scientific writing skills, highlighting the central role of motivational and cognitive processes in academic writing development. Furthermore, artificial intelligence use exhibited a direct yet comparatively weaker relationship with scientific writing skills. Further analysis of indirect effects revealed that the influence of artificial intelligence use on scientific writing skills was predominantly mediated by intrinsic motivation and critical literacy.

3.1. Discussion
3.3.1. Interpretation of main findings
The empirical outcomes of this investigation reveal that artificial intelligence primarily fosters scientific writing growth through mediated, indirect routes rather than producing direct or instantaneous improvements in writing performance. Although AI use is associated with writing outcomes, its strongest influence operates through intrinsic motivation and critical literacy. This pattern supports the view that AI-supported writing environments function as contextual learning affordances that activate internal learner

processes, rather than as autonomous determinants of writing quality [46], [47]. Such a mechanism-based interpretation challenges simplified assumptions that AI tools automatically improve academic writing outcomes without mediating psychological and cognitive engagement.

From a motivational perspective, AI-supported learning environments may foster intrinsic motivation by supporting learners' sense of autonomy and competence through flexible guidance, iterative feedback, and opportunities for independent exploration, as emphasized in self-determination theory [48]. These affordances can enhance students' willingness to invest sustained effort in complex academic writing tasks, which are inherently demanding and cognitively intensive. At the same time, the association between AI use and critical literacy underscores that effective engagement with AI-generated content requires evaluative judgment, verification, and synthesis [16], [49], rather than passive acceptance of automated outputs. Critical literacy thus functions as a necessary cognitive filter that determines whether AI use contributes to deeper learning or superficial text production.

Taken together, these findings indicate that the educational value of AI in academic writing lies not in the substitution of learners' cognitive labor, but in its capacity to invigorate motivational engagement and sharpen evaluative judgment, both of which are prerequisites for high-quality scientific writing. By activating these internal processes, AI-assisted writing environments can support more reflective, deliberate, and academically responsible writing practices, thereby aligning technological innovation with the core educational goals of higher education.

3.3.2. Mediation mechanisms

The mediation analysis specifies the mechanisms through which artificial intelligence contributes to scientific writing development by delineating the roles of intrinsic motivation and critical literacy as intervening processes. Intrinsic motivation and critical literacy operate as central mediators that link AI use to writing outcomes by structuring learners' motivational investment and cognitive evaluation processes. This pattern indicates that the educational effects of AI-supported writing environments are realized primarily through internal psychological and cognitive mechanisms, rather than through direct replacement of learners' intellectual work [50]–[52].

From a motivational perspective, intrinsic motivation supports sustained effort, persistence in cognitively demanding tasks, and deeper engagement in the writing process [53], [54], all of which are essential for the production of scientific texts. In parallel, critical literacy provides the cognitive framework required to evaluate the accuracy, relevance, and coherence of AI-generated content [55], enabling learners to verify information, integrate multiple sources, and make informed authorial decisions. In the absence of these mediating processes, AI use is unlikely to yield substantive improvements in writing quality and may instead encourage surface-level text generation without reflective engagement.

Taken together, these findings indicate that the effectiveness of AI-supported writing instruction is contingent upon the intentional integration of pedagogical practices that cultivate intrinsic motivation and critical literacy. When these mediators are adequately supported, AI functions as a facilitative learning tool that enhances cognitive engagement and responsible academic writing, rather than as a means of bypassing essential learning processes. This mechanism-focused interpretation provides a theoretically grounded basis for the design of AI-integrated writing curricula that prioritize educational value while preserving learners' intellectual agency.

3.3.3. Multi-group differences

The multi-group results suggest that the influence of artificial intelligence use on motivational and cognitive processes varies across learner groups [56], [57], highlighting the role of contextual and individual factors within AI-supported learning environments [58], [59]. The stronger association between AI use and intrinsic motivation observed among male students suggests that differences in technology-related confidence, engagement patterns, or prior exposure may shape how learners psychologically respond to AI-supported writing tools [60], [61]. Importantly, this finding should be interpreted as reflecting variation in engagement tendencies rather than inherent differences in cognitive ability.

Furthermore, the stronger relationship between critical literacy and scientific writing skills among doctoral students highlights the role of advanced academic training in strengthening evaluative, analytical, and epistemic judgment capacities [61], [62]. Doctoral-level learning typically entails sustained engagement with complex texts, methodological rigor, and critical examination of knowledge claims, which may amplify the contribution of critical literacy to writing performance. This pattern is consistent with prior research indicating that higher levels of academic socialization enhance learners' ability to critically assess and integrate AI-generated information into scholarly writing [62]–[64].

From an instructional perspective, these patterns suggest that AI-supported writing instruction should be designed with sensitivity to learners' characteristics and academic levels [65]. Tailoring AI integration strategies to diverse learner profiles may enhance motivational engagement, cognitive effectiveness, and equitable learning outcomes, rather than assuming uniform benefits across student populations. Such an adaptive approach supports inclusive pedagogy by aligning AI use with learners' developmental and contextual needs while maximizing its educational value.

3.3.4. Contributions, implications, and limitations

This study extends the literature on artificial intelligence in education by offering a mechanism-oriented explanation of AI-supported scientific writing, moving beyond isolated or direct effects of commonly examined variables. At the theoretical level, the integration of Self-Determination Theory and critical literacy theory within a single structural framework clarifies how motivational and cognitive processes jointly shape scientific writing skills in AI-assisted learning environments [66]. This integrative perspective addresses a gap in prior research that has frequently examined AI use, motivation, or literacy as independent predictors without specifying the mechanisms through which these constructs interact [67]. Empirically, the results indicate that AI influences scientific writing skills mainly through indirect pathways, mediated by intrinsic motivation and critical literacy [42], framing AI as a learning affordance that supports psychological engagement and evaluative competence rather than as a direct driver of writing performance [68].

The findings have important implications for academic writing instruction. Artificial intelligence tools should be intentionally and pedagogically integrated into curricula, accompanied by instructional guidance that fosters learner autonomy, evaluative judgment, and responsible use [69]. The observed motivational benefits indicate that AI-assisted writing activities can enhance student engagement when embedded within learning designs that promote active cognitive involvement. At the same time, the central role of critical literacy underscores the necessity of explicit instruction in evaluating, verifying, and contextualizing AI-generated content to prevent passive reliance on automated outputs [70], [71]. Ethical considerations, including transparency, authorship responsibility, and academic integrity, should therefore be integral to AI-supported writing pedagogy [72], ensuring that AI functions as a supportive learning resource rather than a substitute for students' intellectual effort.

Despite these contributions, several limitations should be acknowledged. The cross-sectional design, while appropriate for theory-driven model testing, does not permit causal inference regarding the temporal relationships among AI use, intrinsic motivation, critical literacy, and scientific writing skills. Future research employing longitudinal or experimental designs may further elucidate these dynamics [73]. In addition, the reliance on self-report measures reflects the psychological nature of the constructs examined; however, future studies may complement this approach with performance-based writing assessments, learning analytics, or external evaluations. Further refinement of measurement instruments may also enhance efficiency and scalability across diverse educational contexts.

4. CONCLUSION

The present study yields compelling empirical support for the proposition that artificial intelligence advances scientific writing development predominantly through indirect channels mediated by motivational and cognitive mechanisms, rather than exerting direct, immediate effects on writing performance. The PLS-SEM results consistently indicate that intrinsic motivation and critical literacy function as key mediating constructs linking AI use to scientific writing skills, thereby clarifying the internal processes through which AI-assisted learning environments exert their educational effects. Grounded in self-determination theory and critical literacy theory, these findings offer a theoretically coherent explanation for the observed relationships, demonstrating that AI-supported writing environments facilitate scientific writing not by substituting students' cognitive efforts, but by fostering psychological engagement and evaluative competence essential for academic text production. In this respect, AI use is best understood as a contextual learning affordance whose effectiveness depends on learners' motivational orientation and capacity for critical evaluation, rather than as an autonomous instructional agent.

The MGA further reinforces this interpretation by showing that the strength of these mechanisms varies across gender and academic levels, indicating that AI-supported writing processes are context-sensitive and contingent on learner characteristics. Collectively, these findings advance a mechanism- a theoretically grounded perspective on AI in higher education, redirecting prior research from descriptive or outcome-focused claims toward explanatory frameworks that clarify how and under what circumstances AI supports scientific writing development. Such an account provides a rigorous conceptual foundation for the responsible integration of AI in academic writing instruction and delineates clear directions for future inquiry into AI-supported learning processes.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that no conflicts of interest, financial or otherwise, influenced the conduct or reporting of this research.

INFORMED CONSENT

Prior to data collection, written informed consent was secured from every individual who participated in this study, in accordance with established ethical research protocols.

ETHICAL APPROVAL

The entire research process involving human subjects was carried out in strict conformity with prevailing national regulatory frameworks and institutional ethical standards. The study adhered to the foundational principles articulated in the Declaration of Helsinki and received formal approval from the ethics committee of the responsible institution prior to commencement.

DATA AVAILABILITY

All data collected and processed throughout this investigation are available from the corresponding author, [YAR], upon a reasonable and justified request. Given the privacy-sensitive nature of the participant information and the ethical constraints governing its disclosure, unrestricted public access to the dataset is not permitted. Nevertheless, a restricted-access version of the data may be made available to qualified researchers who submit a formal access request; the dataset is maintained in a secured repository accessible via the link provided: https://drive.google.com/file/d/1-nHvk64q81kqotAQ2LyKkrkXPuNWGOkL/view?usp=sharing

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