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Analysis of the Impact of Artificial Intelligence Technology on the Development of Students' Academic Writing Skills in the Digital Learning Era

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ABSTRACT

The rapid advancement of Artificial Intelligence (AI) has transformed academic practices, particularly in supporting the development of students' academic writing. However, empirical evidence explaining how AI utilization, automatic feedback, and personalized learning contribute to writing performance in higher education remains limited. This study examines the effects of AI utilization, AI-based automatic feedback, and AI-driven personalized learning on Students' Academic Writing Skills (SAWS). Using an explanatory quantitative approach with a cross-sectional design, data were collected from 88 Indonesian university students through purposive sampling. Partial Least Squares–Structural Equation Modeling (PLS-SEM) was employed to evaluate the measurement and structural models. The findings show that Automatic Feedback Based on AI (AFBAI) is the strongest predictor of SAWS ($\beta = 0.531$; $p = 0.000$). The Utilization of AI Technology (UAIT) also has a significant positive effect ($\beta = 0.290$; $p = 0.007$), indicating that frequent use of AI tools contributes to improved writing skills. Conversely, Personalized Learning Based on AI (PLBAI) has no significant direct effect ($\beta = 0.053$; $p = 0.350$). The structural model demonstrates substantial predictive power with an R^2 value of 0.660. AI technologies play an essential role in enhancing academic writing performance, especially through automated feedback and consistent utilization. However, AI-driven personalized learning systems still require further optimization and deeper user engagement to meaningfully support the development of complex writing competencies.

1. INTRODUCTION

Recent developments in *artificial intelligence* (AI) have reshaped various sectors, including education, by influencing how learning processes are designed and implemented. UNESCO (2023) reports that more than 60% of higher education institutions worldwide have begun integrating AI to support instruction, assessment, and academic administration. The World Economic Forum highlights digital literacy and AI proficiency as essential skills for the 21st century [1]. Ling Luo and Yang further note that AI assists educators through automated feedback, analytical tools, and streamlined assessment processes [2]. These trends demonstrate that AI in education is no longer optional but a strategic necessity requiring systematic examination.

In Indonesia, the adoption of AI in higher education is supported by initiatives from the Ministry of Education, Culture, Research, and Technology [3], which aim to enhance digital literacy and modern learning competencies. However, the increased use of platforms such as ChatGPT, Grammarly, and QuillBot introduces challenges related to academic ethics and reduced student independence [4]. Studies show that AI can improve interactivity and personalization, yet may inhibit critical thinking without proper guidance [5]. These issues highlight the need to understand the dual impact of AI on students' academic writing development. Similar concerns were also raised by Rahis Pasaribu et al. [6], who emphasized the importance of evaluating writing competence in AI-supported environments.

The integration of AI in writing instruction is supported by constructivist theory, as proposed by Piaget (1970) [7] and Vygotsky [8], which suggests that learning occurs through active knowledge construction and social interaction. AI tools can help students generate ideas, revise drafts, and receive immediate feedback, aligning with constructivist principles. Adaptive AI systems further personalize learning by adjusting pacing and content to individual needs [9], [10]. These pedagogical alignments show that AI serves not only as a technological innovation but also as an instructional tool. Therefore, understanding AI's role in writing improvement is essential within today's higher education context.

Existing studies show that AI can improve writing performance, but its overall impact remains mixed and requires deeper investigation. Farhood et al. [11] report increased writing speed and quality among students using AI for academic essays, while López-de-Arana Prado et al. [12] observe faster editing processes when AI feedback is used. However, Farhood et al. [11] note that AI contributes little to critical thinking development. Research by Sulaeman et al. [4], Rahim et al. [13], and Ling Luo and Yang [2] mainly focuses on conceptual or technological aspects rather than measurable improvements in academic writing. These findings indicate that more empirical evidence is needed, particularly concerning writing skills in Indonesian higher education.

A clear research gap exists regarding how AI utilization, AI-based automatic feedback, and AI-driven personalized learning influence students' academic writing skills in a direct and measurable way. Previous studies rarely examine these three dimensions simultaneously, and limited evidence is available from Indonesian university contexts. The specific effectiveness of AI in improving structural clarity, linguistic accuracy, and paragraph cohesion is also understudied. As a result, empirical research is needed to determine whether current AI applications genuinely support writing development. The present study addresses these gaps through focused investigation.

Writing skills remain essential for academic success, and AI-powered automatic feedback provides immediate recommendations that help students refine content and structure Chen [9]. This aligns with efforts by the Ministry of Education, Culture, Research, and Technology [3] to encourage technology-enhanced learning in higher education. Research also indicates that AI-based chatbots can enhance motivation through adaptive interaction [5], [14], [15]. These findings suggest that AI has strong potential to support writing instruction when used appropriately. Therefore, understanding its effectiveness in real learning environments is crucial for guiding practice and policy.

Ultimately, this study examines how AI supports students in developing focused, independent, and reflective academic writing skills. It analyzes general AI utilization, evaluates AI-based automatic feedback, and investigates personalized learning features adapted to individual needs. Through these objectives, the study seeks to provide evidence-based insights that contribute to both theoretical understanding and practical implementation. The findings are expected to inform institutional strategies and support ongoing policy development regarding AI integration in higher education.

2. METHOD

Research Design

This study employs an explanatory quantitative approach with a cross-sectional survey design to examine the influence of AI technology, automatic feedback, and personalized learning on students' academic writing skills. Relationships between variables were analyzed using Partial Least Squares–Structural Equation Modeling (PLS-SEM), which is suitable for validating latent constructs with relatively small but heterogeneous samples [16], [17], [18]. The conceptual model includes three independent variables, AI technology use (X_1), AI-based automatic feedback (X_2), and personalized learning (X_3), with students' academic writing skills (Y) as the dependent variable.

Participants were 88 active students from various departments at public and private universities in Indonesia. Inclusion criteria required students to have used AI-based applications such as ChatGPT, Grammarly, or QuillBot for academic writing and to be enrolled in courses involving research reports or scientific articles. Recruitment was conducted online via a Google Forms questionnaire shared through lecturer networks and student organizations. This sampling strategy ensured that respondents had direct experience applying AI tools in real academic tasks. The selected participants represent a diverse range of disciplines and academic levels, allowing for a more comprehensive understanding of AI's role in enhancing academic writing skills.

Population and the methods of sampling Instrumentation

The research population involved active students from various universities in Indonesia who had access to and experience in using Artificial Intelligence (AI)-based technology in academic activities. The sampling method used was purposive sampling, as this method is recommended for research that requires respondents with specific characteristics to suit the research objectives [19], [20]. The criteria for selecting respondents included students who actively used AI tools such as ChatGPT, Grammarly, or QuillBot in the process of writing academic assignments, as these technologies are the most commonly used forms of AI in the context of higher education today, particularly in improving academic writing skills [2], [16]. This study focuses on generative text-based AI and automatic feedback tools in writing, as these technologies have been proven to contribute directly to improving the quality of students' writing compared to other forms of AI such as adaptive training systems or AI analysis [5]. This approach ensures that the data collected is relevant to the analysis needs and supports a consistent relationship between the problem formulation, research variables, and discussion results.

Instrument

The study used a closed questionnaire with a five-point Likert scale (1 = strongly disagree to 5 = strongly agree) to measure students' perceptions and use of AI in academic activities, as this scale effectively captures attitudes and agreement levels [21], [22]. The instrument included indicators adapted from relevant sources to measure four constructs: AI Technology Utilization, AI-Based Automatic Feedback, AI-Based Personalized Learning, and Students' Academic Writing Skills, with details presented in Table 1.

Tabel 1. Research Instrument

Construct/Aspect	Item Code	Item Description	Adaptation of
Utilization of Artificial Intelligence (AI) Technology	UAIT1	I frequently use AI-based technologies for academic activities.	Rahim et al. [13]; Uludağ et al. [17]; Wang et al. [18]

	UAIT2	I use various AI tools such as ChatGPT, Grammarly, or learning chatbots to support my studies.	
	UAIT3	I have sufficient competence to use AI technologies in my learning process.	
	UAIT4	The use of AI helps me understand materials relevant to my field of study.	
Automatic Feedback Based on Artificial Intelligence (AI)	AFBAI1	Feedback or corrections provided by AI help me improve my writing accuracy.	Ozfidan et al. [16]; Prihandoko et al. [23]; Rahim et al. [13]
	AFBAI2	AI-generated feedback is clear and relevant to the content of my writing.	
	AFBAI3	I revise my writing based on the feedback provided by AI.	
	AFBAI4	Feedback from AI increases my confidence in writing academically.	
Personalized Learning Based on Artificial Intelligence (AI)	PLBAI1	AI technology adjusts learning materials according to my abilities.	Uludağ et al. [17]; Wang et al. [18]
	PLBAI2	AI provides learning recommendations that match my learning needs.	
	PLBAI3	AI helps me understand difficult concepts.	
	PLBAI4	AI features make me more active and engaged in the learning process.	
	PLBAI5	Personalized learning supported by AI helps me learn more efficiently.	
Students' Academic Writing Skills	SAWS1	My academic writing has a systematic structure and organization.	Ozfidan et al. [16]; Prihandoko et al. [23]
	SAWS2	I use correct grammar and spelling in academic writing.	
	SAWS3	I am able to develop ideas and arguments clearly in my writing.	
	SAWS4	The paragraphs in my writing are cohesive and logically connected.	
	SAWS5	I revise my writing based on feedback I receive from AI tools.	

Procedures

The study began with the development and validation of a questionnaire by experts in educational technology and academic English to ensure clarity, relevance, and alignment with the research objectives and variables [18], [23]. The validated questionnaire was then distributed online to students with experience using AI in academic writing through purposive sampling [16], [17]. Collected data were analyzed descriptively to profile respondents and inferentially to examine the relationships between variables, ensuring valid, reliable, and relevant insights into the role of AI in higher education writing skills.

Figure 1. Research Procedure Flowchart

Analysis plan (descriptive and inferential statistical tests)
Data analysis was conducted in two stages: descriptive and inferential. Descriptive analysis was used to examine respondent characteristics, frequency of AI use, types of AI technologies used, and students' perceptions of AI effectiveness in academic writing. Inferential analysis employed PLS-SEM to test the effects of AI technology use, AI-based automatic feedback, and AI-driven personalized learning on students' academic writing skills. The analysis assessed measurement quality and structural relationships among variables to generate conclusions relevant to the research objectives

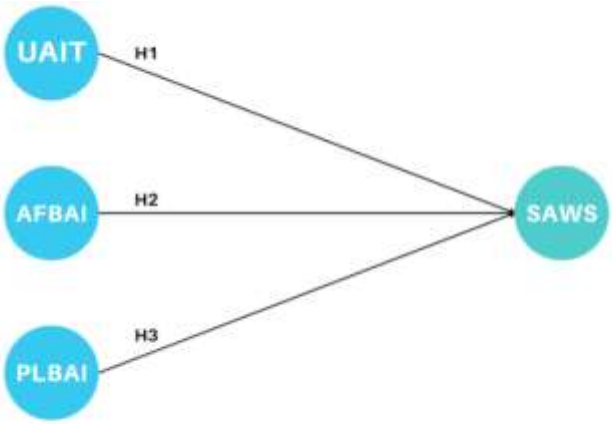

Figure 2. Proposed Research Conceptual Model

Hypothesis:
H1: The use of Artificial Intelligence Technology (UAIT) has a positive and significant effect on students' academic writing skills.
H2: Artificial Intelligence-Based Automatic Feedback (AFBAI) has a positive and significant effect on students' academic writing skills.
H3: Artificial Intelligence-Based Personalized Learning (PLBAI) has not positive and significant effect on students' academic writing skills.

3. RESULTS AND DISCUSSION

Results

Respondents Characteristics and Usage
The characteristics of the respondents are crucial to understand because they can influence how students use Artificial Intelligence (AI) technology in their learning activities. Information about

gender, age, semester, study program, and how they use AI provides initial insights into the diversity of respondents. This data supports an understanding of the research context so that the results obtained can be interpreted more accurately.

Tabel 2. Respondents Characteristics and Usage

No	Category	Subcategory	n	%
1.	Gender	Male	29	33.0%
		Female	59	67.0%
2.	Age	18	10	11.4%
		19	43	48.9%
		20	11	12.5%
		21	14	15.9%
		22	8	9.1%
		23	2	2.3%
3.	Semester	I	7	8.0%
		III	52	59.1%
		IV	1	1.1%
		V	8	9.1%
		VII	19	21.6%
		VIII	1	1.1%
4.	Major	Non-STEM	42	47.7%
		STEM	46	52.3%
5.	Frequency of AI Use	1–2 times per week	5	5.7%
		3–5 times per week	32	36.4%
		Rarely	2	2.3%
		Every day	49	55.7%
6.	AI-Based Revision	Sometimes	20	22.7%
		Always	30	34.1%
		Often	35	39.8%
		Never	3	3.4%
7.	AI Writing Assistance	Quite helpful	37	42.0%
		Very helpful	51	58.0%

Overall, Table 2 shows that most participants were female, in the late stages of adolescence, and mostly third-semester university students. There was a fairly good balance between STEM and non-STEM groups, indicating that the sample included perspectives from various disciplines. In addition, the high frequency of AI use and the tendency to make adjustments and accept support from AI in academic writing indicate that this technology has become a crucial element in the learning process for students. These results provide a solid foundation for further analysis of how AI affects the effectiveness and academic work patterns of participants.

Outer Model

Measurement Model Evaluation

Reliability analysis shows that all constructs have met the required standards with Cronbach's Alpha and Composite Reliability values higher than 0.70. Convergent validity has also been achieved because all AVEs exceed 0.50, and each indicator has an outer loading of more than 0.70. These results confirm that the indicators consistently represent the constructs under study, so that the measurement model is declared to have reliability and validity for further structural analysis.

Tabel 3. Construct Reliability & Validity

Constructs	Cronbach's Alpha	rho_A	Composite Reliability (CR)	AVE
AFBAI	0.848	0.857	0.898	0.687
PLBAI	0.807	0.814	0.865	0.562
SAWS	0.860	0.865	0.899	0.641
UAIT	0.798	0.805	0.869	0.624

Based on the data in Table 3, all AFBAI, PLBAI, SAWS, and UAIT constructs showed Cronbach's Alpha values between 0.798 and 0.860, indicating excellent internal reliability. The Composite Reliability values all exceed 0.86, confirming a high level of measurement consistency. The AVE of each construct is above 0.56, implying that more than half of the indicator variance can be explained by the latent construct. Therefore, all constructs meet the criteria for reliability and convergent validity, so they can be used without hesitation in further structural model analysis.

External load testing indicates that most indicators obtained values greater than 0.70, which shows effective performance in describing the construct. The indicators in AFBAI, SAWS, and UAIT show good strength and stability, while some PLBAI indicators are slightly below but still within acceptable limits. Overall, these findings confirm that convergent validity in the measurement model has been fulfilled.

Tabel 4. Outer Loadings

No	Constructs	Indicator	Loading
1.	Automatic Feedback Based on Artificial Intelligence (AI)	AFBAI1	0.808
		AFBAI2	0.818
		AFBAI3	0.898
		AFBAI4	0.788
2.	Personalized Learning Based on Artificial Intelligence (AI)	PLBAI1	0.711
		PLBAI2	0.734
		PLBAI3	0.767
		PLBAI4	0.767
		PLBAI5	0.767
3.	Students' Academic Writing Skills	SAWS1	0.743
		SAWS2	0.823
		SAWS3	0.793
		SAWS4	0.855
		SAWS5	0.785
4.	Utilization of Artificial Intelligence (AI) Technology	UAIT1	0.811
		UAIT2	0.852
		UAIT3	0.741
		UAIT4	0.751

The AFBAI construct has high loading indicators, especially AFBAI3 with 0.898, which shows a significant contribution to the construct. The PLBAI construct loading values range from 0.711 to 0.767, which is still sufficient to meet the minimum validity standards for indicators. The SAWS2 and SAWS4 indicators show the highest loading strength in the SAWS construct, indicating that academic writing skills remain stable. The UAIT construct, on the other hand, shows a high level of consistency, especially UAIT2 with 0.852. Overall, all indicators in the table meet the measurement quality criteria and reinforce the construct structure of the research model.

The results of the discriminant validity test using the Fornell-Larcker criteria show that, when compared to correlations with other structures, each structure has a higher AVE square root value. This indicates that there is no overlap between latent variables and that each construct can be clearly distinguished. Therefore, the entire model structure has good discriminant validity.

Table 5. Discriminant Validity – Fornell Larcker Criterion

Constructs	AFBAI	PLBAI	SAWS	UAIT
AFBAI	0.829			
PLBAI	0.794	0.750		
SAWS	0.785	0.678	0.801	
UAIT	0.728	0.701	0.714	0.790

The diagonal values (square root of AVE) for each construct, AFBAI at 0.829, PLBAI at 0.750, SAWS at 0.801, and UAIT at 0.790, were higher than their correlations with other constructs, as shown in Table 5. This indicates that AFBAI has the highest correlation with SAWS at 0.785, although its value remains lower than 0.829, which meets the Fornell–Larcker criteria. In addition, PLBAI, SAWS, and UAIT have similar patterns. All of this indicates that the diagonal values are better than the correlations between constructs. This proves the discriminant validity of the model because each construct stands alone and does not experience overlap issues.

Inner Model

Structural Model Evaluation

The structural model in the figure shows the relationship patterns tested in the study, specifically how three exogenous constructs, UAIT, AFBAI, and PLBAI, affect the endogenous construct SAWS. Each exogenous construct is supported by indicators with outer loading values above 0.70, which ensures that each indicator is valid in representing its construct. This model visualization also confirms the use of the Partial Least Squares – Structural Equation Modeling (PLS-SEM) approach as the basis for analyzing the relationships between latent variables, with the loading values displayed reinforcing the quality of the measurement model before structural analysis is performed. In addition, the lines connecting the constructs provide an initial overview of the direction and strength of the influence paths that are the focus of hypothesis testing. Based on this model, the next step is to evaluate the significance of each path through hypothesis testing, the results of which are presented in the following hypothesis testing table.

Only two exogenous constructs, AFBAI and UAIT, had a significant effect on SAWS, as shown by the path analysis. AFBAI had the strongest effect, with the highest significant coefficient, while UAIT had a weaker effect. Because the p-value exceeded the specified limit, PLBAI did not show a significant effect. The results show that only two predictors directly contribute to SAWS.

Table 6. Hypothesis testing

Hypothesis	Route	Path Coefficients (β)	t-value	p-value	Description
H1	UAIT → SAWS	0.290	2.449	0.007	Positive & Significant
H2	AFBAI → SAWS	0.531	4.021	0.000	Positive & Significant
H3	PLBAI → SAWS	0.053	0.386	0.350	Not Positive & Significant

Table 6 shows that the AFBAI → SAWS pathway has the highest coefficient (β = 0.531; p = 0.000), making it the main predictor influencing academic writing ability. UAIT → SAWS is also significant (β = 0.290; p = 0.007), indicating that, although with less strength, the use of AI technology also supports the improvement of SAWS. Conversely, the PLBAI → SAWS path does not contribute directly to the model because it has a low coefficient (β = 0.053) and low significance (p = 0.350).

Table 7. R-Square

Constructs	R-square	P-values	Interpretation
Students' Academic Writing Skills	0.660	0.000	Strong / Substantive

The structural model evaluation guidelines recommended by are used to calculate the R-squared value to measure how well the endogenous construct is explained by its predictor variables [24]. In addition, to ensure the statistical significance of the model's predictive ability, the p-value is also included. Table 7 shows that SAWS has an R-square value of 0.660, indicating that the exogenous construct in the model accounts for 66% of its variance. This value falls into the substantial category, indicating a strong contribution of predictors to SAWS. Furthermore, the p-value of 0.000 indicates that the predictive ability of the model is statistically significant. Therefore, the structural model is suitable for further analysis because it has good predictive quality.

Discussion

This study shows that the use of AI significantly improves students' academic writing skills, and these findings reinforce several major theoretical perspectives on AI-supported learning. Existing studies, such as those by Ling Luo & Yang [2], emphasize that AI-based feedback provides immediate corrective guidance that strengthens cognitive processing during revision, which aligns with the results of this research. Reports by Susiani et al. [25], Widodo et al. [5], and Yan et al. [26] also demonstrate that AI-enhanced learning environments increase personalization and engagement, illustrating how AI influences both affective and behavioral dimensions of learning. In comparing these studies, the present findings extend the theoretical understanding of AI's role by highlighting how high-frequency AI use shapes writing habits and metacognitive awareness among students, particularly within university contexts. Thus, the contribution of this research lies in strengthening the theoretical link between continuous AI use and the development of structured writing competence, positioning AI not merely as a tool but as a cognitive partner in academic work.

Research shows that AI-based automatic feedback (AFBAI) has a significant and powerful impact on students' academic writing skills (SAWS), with a coefficient of β = 0.531 and a p-value of 0.000. These results indicate that AI-based automatic feedback mechanisms are crucial in improving the quality of writing revisions, language accuracy, and the structure of arguments used by students. These findings align with the research by Escalante et al. [27], which states that AI feedback from ChatGPT is as effective as assistance from human tutors and is well-received by students. Additionally, a meta-analysis study by other researchers shows that AI feedback systems can increase metacognitive awareness in writing and support structured learning processes [28]. Thus, the results of this study prove that AFBAI is not only a tool but also an important part of significantly building academic writing skills.

The coefficient value of 0.290 and p 0.007 indicate a significant effect of the use of artificial intelligence technology (UAIT) on students' academic writing skills (SAWS). These findings show that the more often students use AI technology, the better they are at developing ideas, constructing arguments, and creating better writing structures. These results support research by Escalante et al. [27], which states that regular exposure to AI technology can improve academic productivity and task completion quality. Another study by Qushwa & Onia [29] also found that the intensity of AI use is proportional to the increase in analytical thinking in writing activities. As a result, the use of AI not only offers technical convenience, but also helps students improve their cognitive capacity to produce more systematic and higher-quality academic writing.

With a value of 0.053 and p 0.350, Personalized Learning Based on AI (PLBAI) does not contribute directly to students' academic writing skills (SAWS). This is despite the fact that two other AI-based constructs show a significant influence. These results are consistent with the claims of Alifah and Hidayat [30], who state that AI-based personalization is more effective in building procedural skills than complex skills such as academic writing. Other studies also show that the adaptive capabilities of AI systems often do not fully meet the specific needs of writers. As a result, their impact on writing outcomes is limited or requires additional support, such as instructional guidance [31], [32].

Previous studies have indicated that AI-based personalized learning does not always directly improve academic performance, especially if users are not accustomed to regularly using personalized recommendations or if the adaptation system is not yet running optimally [33]. The impact of personalization is usually indirect and highly dependent on the active participation of users in understanding and evaluating the recommendations provided by AI. Therefore, the insignificant results of PLBAI → SAWS in this study can be considered as the impact of introductory or regulatory variables that have not been included in the model, as well as the varying patterns of AI usage among students.

The findings indicate that AI has become an integral part of students' academic activities, where 92.1% of respondents regularly use AI tools and more than half use them daily, showing a strong reliance and growing digital literacy. Students reported that AI not only improves efficiency but also supports the revision process, with many selectively refining AI-generated suggestions. Structural model analysis confirms these behavioral patterns, showing that AI-based automatic feedback (AFBAI) has the strongest effect on students' academic writing skills (SAWS), with a path coefficient of $\beta = 0.531$ and a p-value of 0.000, while the model demonstrates strong reliability and predictive accuracy, reflected by an R-square value of 0.660. These results are consistent with previous studies reporting that AI feedback, such as ChatGPTmcan effectively support writing improvement through enhanced revision quality, linguistic accuracy, and metacognitive awareness. Therefore, the findings reinforce that AFBAI functions not only as a technological tool but as a critical learning mechanism that significantly shapes academic writing competence in higher education.

This study provides an important theoretical basis for the literature on artificial intelligence-based learning in higher education. The results showing that PLBAI has no significant impact open our eyes to the fact that when users have control over evaluation, the limitations of AI perception do not always hinder academic achievement. In addition, this study enhances our understanding of the cognitive and motivational processes involved in the use of artificial intelligence for complex tasks such as academic writing. Moreover, a strong predictive model ($R2 = 0.660$) indicates that artificial intelligence functions as an external factor associated with improved writing skills. Overall, this study advances the concept of AI-assisted learning in the context of contemporary learning.

In practical terms, the results of this study have many implications for higher education institutions. Since students often view AI as a partner in the writing process, universities must provide training in AI use that emphasizes evaluation skills. To ensure that AI use continues to encourage critical thinking, lecturers must responsibly incorporate it into their curricula. AI platform developers must also ensure that their features are transparent, accurate, and easy to explain so that users feel more comfortable and find them useful. To maintain academic integrity, educational institutions must also establish clear ethical policies on the use of AI. Overall, this study shows that AI has great potential as a pedagogical tool if used correctly.

This study advances our understanding of the role of Artificial Intelligence (AI) technology in enhancing students' academic writing skills (SAWS). The significant impact of AI Technology Utilization (UAIT) and AI-Based Automatic Feedback (AFBAI) on SAWS underscores the potential of adaptive technologies to strengthen cognitive processes and improve the quality of academic writing [11]. In contrast, AI-based Personalized Learning (PLBAI) did not demonstrate a significant effect, highlighting that automated personalized interventions do not always translate into immediate academic gains. These findings contribute to the literature on technology-enhanced pedagogy by clarifying the multifaceted role of AI as a learning tool, feedback provider, and adaptive agent.

Methodologically, this study demonstrates the utility of Partial Least Squares–Structural Equation Modeling (PLS-SEM) in evaluating the effects of multiple AI-related constructs on academic writing performance. The model's R-square value of 0.660 indicates strong predictive capability, while the reliability and validity are confirmed through outer loadings, composite reliability, discriminant validity, and AVE. This multi-construct approach provides a robust framework for future research on AI integration in higher education and offers a replicable structural model for studies exploring digital learning interventions.

Several limitations of this study should be considered. The cross-sectional method limits causal inferences, meaning that the results only show relationships between variables. In addition, the use of perception-based questionnaires may cause self-report bias. Furthermore, because respondents came from only one higher education setting, the results should be generalized with caution. The PLBAI construct also showed a small effect, suggesting that there are moderating or mediating variables that have not been studied. Finally, the study did not identify the type or platform of AI used by students, so differences in technology in academic writing skills could not be further explored.

The results of the study produced several recommendations that can be considered for the future development and implementation of higher education. Given the significant contribution of AFBAI and UAIT to improving academic writing skills, the integration of AI should be expanded, particularly in terms of automatic feedback features and the use of AI in learning. To improve the quality of user interaction, the development of AI-based writing assistants should be more contextual and adaptive. To make the model more comprehensive, future research should include elements such as digital literacy, academic motivation, and self-directed learning. To improve generalization, the scope of respondents should be expanded to various universities and study programs. In addition, to gain deeper qualitative insights from quantitative findings, mixed methods can be considered.

4. CONSLUSION

This study demonstrates that Artificial Intelligence (AI), particularly through automatic feedback (AFBAI) and regular use (UAIT), significantly enhances students' academic writing skills (SAWS) by supporting structured revisions, cognitive processes, and metacognitive awareness. The theoretical contribution lies in showing that AI can function as an effective learning mechanism, while the strong predictive capability of the model (R^2 = 0.660) confirms its relevance in higher education contexts. In contrast, AI-based Personalized Learning (PLBAI) did not show a significant effect, suggesting that automated personalization alone may be insufficient for complex skills like academic writing and may require additional guidance or scaffolding. Practically, the findings imply the need for integrating AI-assisted tools into curricula with emphasis on evaluation and critical thinking, providing AI literacy training for students and faculty, and developing adaptive, context-sensitive AI platforms. Limitations such as the cross-sectional design, self-reported data, and a single-institution sample affect generalizability, while the small effect of PLBAI points to unexamined moderating factors. Future research should investigate variables like motivation, self-regulation, and personalized AI interventions to optimize learning outcomes and maximize the educational potential of AI technologies.

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