The Impact of AI-Based Learning Feedback on Academic Writing Competence and Learner Autonomy Among English Learners: A Self-Regulated Learning Perspective

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ABSTRACT

AI-based Learning Feedback (AIF) is increasingly used to improve academic writing in higher education; nonetheless, the relationships among AIF, writing competency, and learner autonomy are not yet sufficiently clarified. This study aims to examine the relationship between AI-based Learning Feedback (AIF) and Academic Writing Competence (AWC) and Learner Autonomy (LA) via two mediating processes of self-regulated learning: metacognitive self-regulation (MSR) and strategic motivational regulation (SMR). This study used a cross-sectional, quantitative survey method, involving 350 university students who were enrolled in academic writing courses. Data were collected using a 5-point Likert scale questionnaire, which assessed 27 observable characteristics; the data were then analyzed using the PLS-SEM method. The results showed that AI feedback (AIF) didn't directly affect academic writing competence (AWC) and learning autonomy (LA). In contrast, its effect was indirect, working through metacognitive self-regulation (MSR) and self-motivation regulation (SMR). These findings clarify the role of self-regulated learning as a mediator in the context of AI feedback, which has important implications for the design of AI feedback systems. Furthermore, the key purpose of these systems is to support learners advance as more effective writers and more independent in higher education.

Keywords: AI-based feedback; self-regulated learning; academic writing; learner autonomy; PLS-SEM.

INTRODUCTION

Research Context

In the current digital transformation of higher education, Artificial Intelligence (AI) is becoming a more common part of teaching methods. A key use of this technology is in using AI-based feedback (AIF) for academic writing. This provides students with immediate, consistent, and highly personalized feedback (Zhai et al., 2021).

Unlike conventional instructor feedback, AI feedback can be provided continuously throughout the writing process, encompassing stages from ideation and outlining to language refinement and formatting (Shute, 2008). Students are increasingly turning to tools such as ChatGPT, Grammarly, and Write & Improve to refine their academic writing, whether they're working in English or their mother tongue. These tools not only identify linguistic inaccuracies but also suggest lexical selections and syntactic constructions, thus improving textual coherence (Ranalli et al., 2022).

As a result, students gain more chances to practice writing independently, which reduces their complete dependence on teacher feedback, especially in large classes with limited time (Feng et al., 2023). However, the effectiveness of AI feedback isn't just about how advanced the algorithms are; it also depends on how students understand, think about, and use the feedback while writing. Researchers suggest that AI feedback is most useful when it encourages students' thinking and self-management skills (Panadero, 2017). Besides, it is als highlights the vital of seeing AI feedback as a teaching tool connected to learning behaviors, rather than just a piece of technology.

Research Gap

Although there has existed a lot of studies on AI feedback in academic writing, almost all of them have been on how AI feedback directly affects the quality of writing or academic achievement (Liu & Kunnan, 2016; Zhang & Hyland, 2023). On the one hand, this approach helps determine how well AI feedback works, on the other hand it doesn't fully explain the basic processes through which AI affects the writing process.

The role of self-regulated learning (SRL) processes, in particular, is not sufficiently explored within the framework of AI-mediated feedback. Self-regulated learning (SRL) involves crucial elements like metacognitive self-regulation (MSR) and self-motivational regulation (SMR); however, these are often viewed as distinct characteristics rather than as mediating factors that can be influenced by feedback interventions (Zimmerman, 2002; Panadero & Alonso-Tapia, 2014).

Furthermore, a significant proportion of existing research has focused on isolated outcomes, thereby precluding the integration of long-term developmental constructs like academic writing competence (AWC) and learner autonomy (LA) within a unified theoretical framework. As a result, comprehensive theoretical models that elucidate the principles of AI feedback in relation to learners' self-regulatory processes are currently lacking.

Objectives and Contributions

This research intends to contribute in the gap by offering and evaluating a theoretical model that describes how AI-based academic writing feedback (AIF) works via learners' self- regulated learning processes. This study investigates the mediating functions of metacognitive self-regulation (MSR) and self-motivational regulation (SMR) in the association between academic feedback (AIF) and two essential learning outcomes: academic writing competence (AWC) and learner autonomy (LA). The suggested model is framed within the causal pathway: AIF → MSR/SMR → AWC/LA.

This research presents three key contributions:

- First, it puts the idea of AI feedback into practice in the setting of university-level academic writing, which is in accordance with the subjects that is being spoken regarding in the educational technology literature currently.
- Second, it develops and expands the theoretical model of self-regulated learning by examining the interaction between MSR and SMR in the context of the AI-based feedback system.
- Third, the research findings are expected to carry implications for the design of an AI feedback system to promote self-regulated learning and the development of writing ability.

THEORETICAL FRAMEWORK AND HYPOTHESES DEVELOPMENT

AI-based Learning Feedback (AIF)

The term "AI-based learning feedback (AIF)" refers to the guidance provided by an AI system or an AI-based learning tool to help learners improve their approaches to learning and attain better results.. In academic settings, automated intelligence feedback (AIF) often uses machine learning techniques in natural language processing to provide initial assessments of linguistic accuracy, structure, coherence, and academic appropriateness (Zhai et al., 2021). Artificial Intelligence Feedback (AIF) offers specific advantages compared to traditional instructor feedback, particularly in terms of speed, adaptability, and consistency.

In this research, AIF can be implemented as an unconscious concept which reflects learners' perceptions regarding the quality and educational impact of AI feedback, regardless of its technological features. This perspective of feedback complies with the concept that feedback is an important part of formative assessment (Shute, 2008). The AIF construct is evaluated using six observed items (AIF1–AIF6), which come from previous research on automated and digital feedback in higher education (Ranalli et al., 2022).

More importantly, recent studies highlight that AIF not only serves as a corrector but also as a learning agent capable of activating learners' cognitive and self-regulating processes (Feng et al., 2023). When learners actively interact with AI feedback, they can use the feedback as a basis for planning, tracking progress, and adjusting their writing strategies. Therefore, viewing AIF as a pedagogical variable is a crucial prerequisite for building research models based on self-regulated learning.

Self-Regulated Learning (SRL)

Self-regulated learning (SRL) is defined as an active and constructive process in which learners establish objectives, assess their progress, adjust their strategies, and evaluate their learning results (Zimmerman, 2002). SRL indicates the learner's ability to make choices, especially in technology-enhanced learning contexts when automatic feedback is constantly available (Panadero, 2017).

In academic writing, self-regulated learning (SRL) prepares students to manage challenging tasks that include making arguments, organizing their thoughts, and rewriting texts. This research focuses on two primary components of self-regulated learning (SRL) as indicated in the literature:

Metacognitive Self-Regulation (MSR): This is the ability to plan, keep an eye on, and judge the writing process. MSR allows students identify mistakes in writing and change their strategies depending on what they learn (Schraw & Dennison, 1994). There are five things that are looked at to see how well MSR is doing (MSR1–MSR5).

Self-Motivational Regulation (SMR): Refers to the capacity to remain in effort, manage emotions, and maintain goal orientation when faced with difficult academic writing assignments (Wolters, 2003). SMR makes it easier to get feedback and then keep using that input to do better all the time. Five items (SMR1–SMR5) are used to measure this dimension. Separating MSR and SMR makes it possible to accurately describe different mental and emotional processes in an AI feedback context.

Academic Writing Competence and Learner Autonomy

Academic Writing Competence (AWC) is the ability to write academic papers that meet higher education requirements for content, argumentation, organization, and language use (Hyland, 2019). AWC assesses both the quality of the final text and the learner's skill in writing. This is measured using six items (AWC1–AWC6), which evaluate self-reported abilities in creative thinking, academic writing, and revision.

At the same time, Learner Autonomy (LA) is a key learning outcome in digital environments. LA reflects how much learners take responsibility for their learning by making choices, being accountable, and controlling their learning (Little, 1991). The study suggests that formative feedback can help develop LA by encouraging students to assess and improve their own work (Nicol & Macfarlane-Dick, 2006).

LA is assessed using five questions (LA1–LA5), which measure how organized, confident, and independent students are when they write. Combining assessments of AWC and LA provides a complete evaluation of both skill development and lasting student progress supported by AI.

Hypotheses Development

This study, grounded in the Self-Regulated Learning (SRL) framework, suggests that artificial intelligence (AI) feedback activates learners' self-regulatory mechanisms. The immediacy of AI feedback furnishes essential data, enabling learners to manage and assess their writing processes, thereby fostering improved metacognitive control (Shute, 2008). Consequently, the subsequent hypothesis is proposed:

H1: AIF is positively associated with MSR.

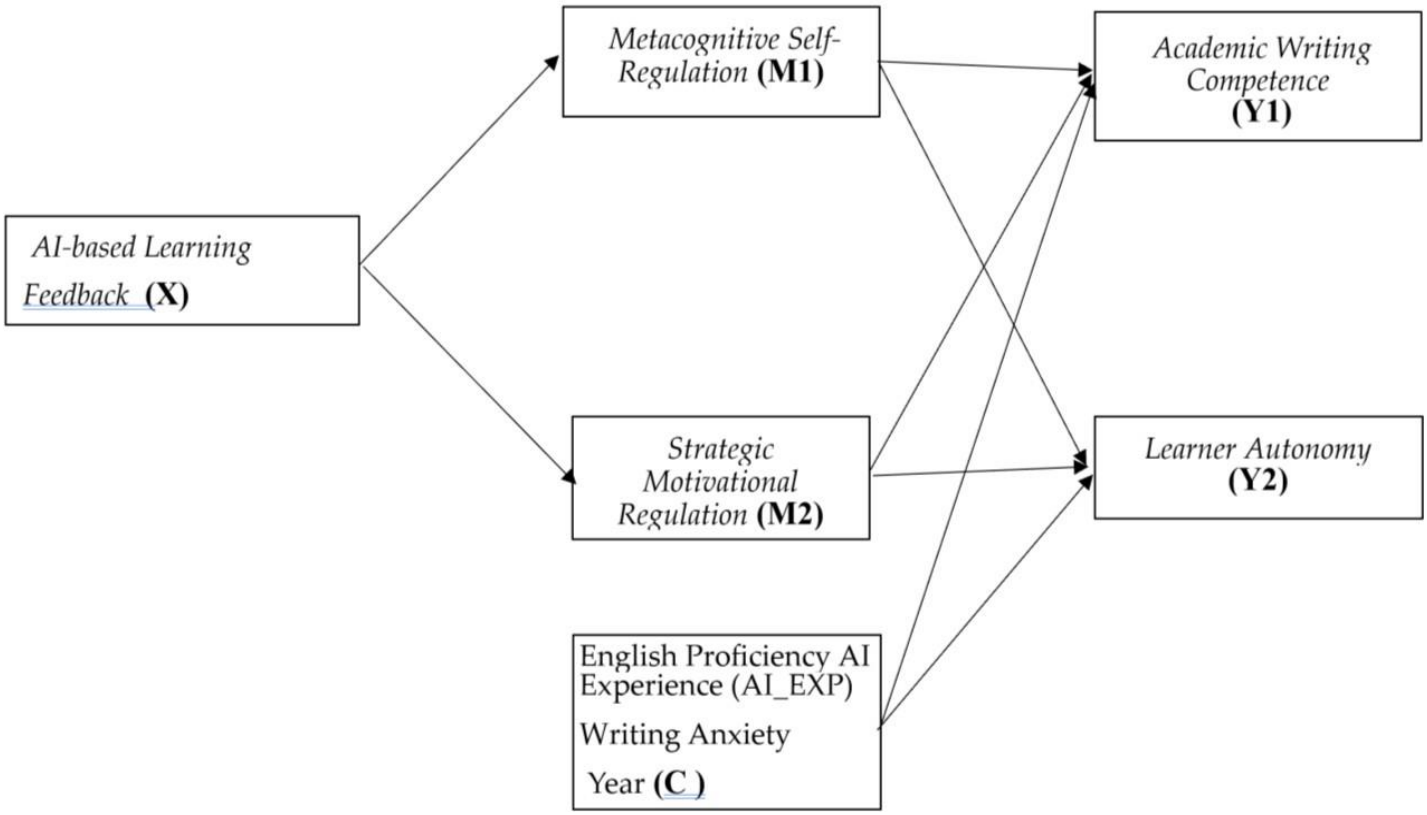
Moreover, supportive and constructive AI feedback aids learners in maintaining motivation and persistence when engaged in challenging writing assignments (Wolters, 2003). Therefore, the following hypothesis is proposed:

H2: AIF shows a positive relationship with SMR.

Regarding the relationship between SRL and academic outcomes, MSR is expected to help learners improve their academic writing skills and increase autonomy through control over their learning strategies, related to hypotheses H3a and H3b. Additionally, self-regulated learning (SRL) is expected to enhance academic writing skills and learning results by promoting sustained effort. (Zimmerman, 2002; Panadero, 2017). Therefore, the following hypotheses are proposed:

H3a: MSR shows a positive relationship with AWC. H3b: MSR shows a positive relationship with LA. H4a: SMR shows a positive relationship with AWC. H4b: SMR shows a positive relationship with LA.

PROPOSED MODEL



METHODOLOGY

Research Design and Sampling

This study uses a quantitative, cross-sectional approach to examine the relationships between AI-based feedback, self-regulated learning, and writing performance. The cross-sectional design is useful for studying how different variables interact at a specific point in time. This method is commonly used in educational research that employs variance-based structural equation modeling (Hair et al., 2022).

The participants in this study were university students enrolled in English-language academic writing courses. A convenience sampling method was used, resulting in a sample of 350 students. In higher education, non-probability sampling is often suitable for exploratory modeling, as Creswell and Creswell (2018) have shown. The sample size is much larger than the minimum needed for PLS-SEM analysis, especially for models with many hidden components and structural patterns (Hair et al., 2022).

The study was conducted in academic writing courses where students regularly used AI technologies to get feedback. This setting allows for an environmentally sustainable evaluation of AI feedback by observing learners as they use technology to complete complex writing tasks.

Measurement Instruments

Data were collected by a questionnaire that was administered by the participant employing a 5-point Likert scale, from 1 (strongly disagree) to 5 (strongly agree). The 5-point scale was chosen for its cognitive simplicity and strong use in behavioral and educational studies (DeVellis, 2017).

There were 27 items on the test that measured five components in the research model. Specifically, the AIF construct was assessed using six items, while the MSR and SMR constructs were each measured with five items. Furthermore, the AWC construct was evaluated through six items, and the LA construct was assessed using five items. These multi- item scales were developed based on existing literature concerning formative feedback, self-regulated learning, and academic writing, thereby ensuring both contextual and content validity (Shute, 2008; Panadero, 2017).

Before its administration, the questionnaire went through expert review to ensure its clarity and appropriateness for the target group.

Control Variables

To reduce the effects of external factors and ensure the reliability of the research model, several control variables related to academic writing and self-regulated learning were included.

- **English Proficiency:** This variable was controlled for, acknowledging its substantial impact on individuals' comprehension of feedback and their writing proficiency (Hyland, 2019).
- **AI Experience:** The study considered the students' previous experience with AI technologies, which could affect how they understand and use automated feedback.
- **Writing Anxiety:** recognized as a significant emotional factor that can affect self- control and how we think (Cheng, 2004).
- **Academic Year:** controlled for to account for differences in academic age and previous educational experiences. By including these factors, the structural estimations accurately separated the effects of the main theoretical concepts.

Data Analysis Strategy

The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS- SEM), a variance-based method that is best for predictive modeling and complicated structural frameworks in educational research (Hair et al., 2022). The analysis occurred in two phases:

First, the measuring model was assessed for internal consistency reliability (utilizing Cronbach’s alpha and Composite Reliability [CR]) and convergent validity (via Average Variance Extracted [AVE]) (Henseler et al., 2015).

Second, bootstrapping methods are used to evaluate the structural model and find the path coefficients and the statistical significance of the study hypotheses. This method lets you look at both the model's fit and the strength of the suggested theoretical connections at the same time.

RESULTS

Reliability and Validity of Scales

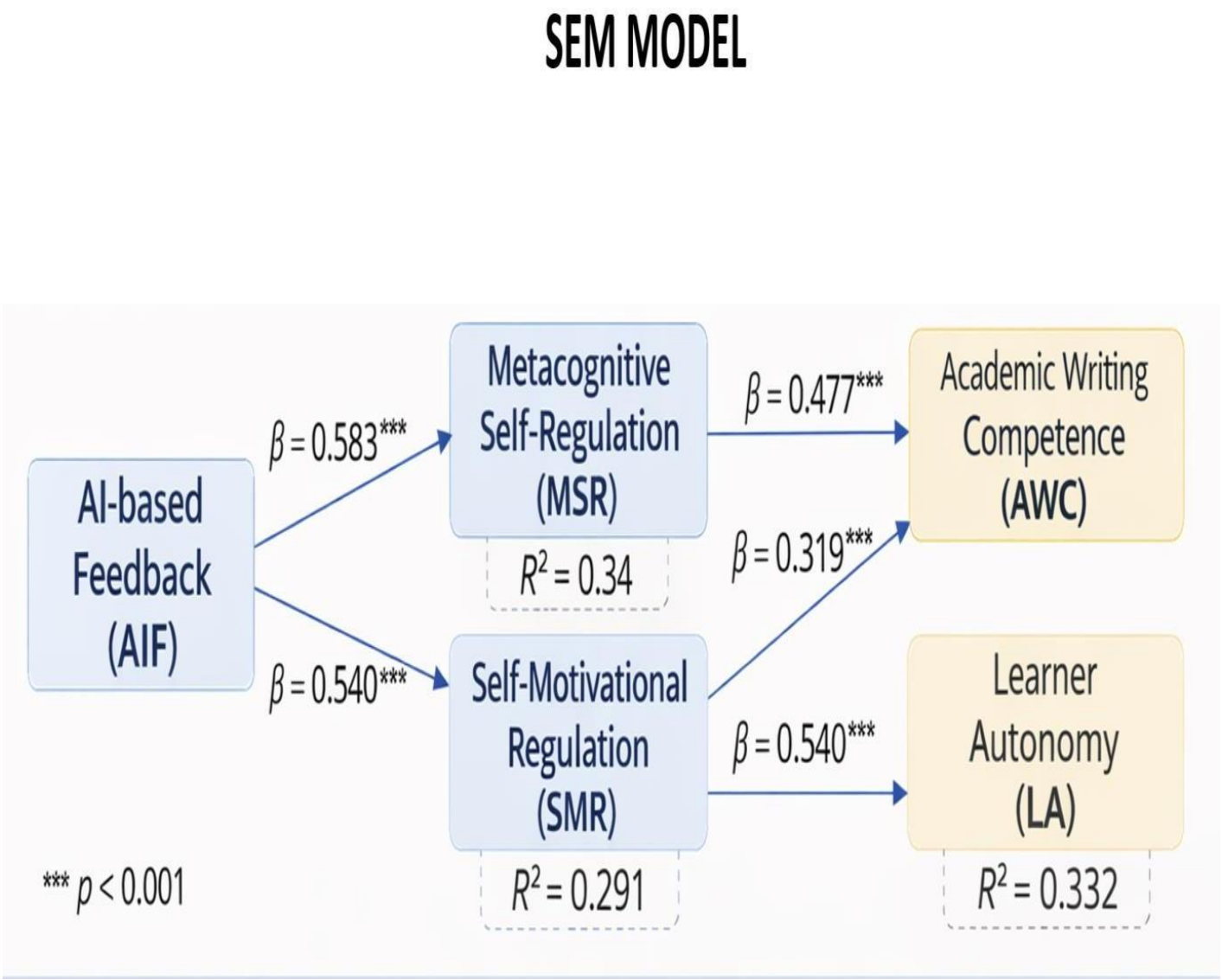


Table 1. Cronbach's Alpha

Construct	Items	Cronbach's Alpha
AIF	6	0.919
MSR	5	0.937
SMR	5	0.919
AWC	6	0.946
LA	5	0.933

Note: Alpha >= 0.70 indicates acceptable reliability.

Table 2. EFA: KMO, Bartlett's Test and Factor Loadings (Varimax, 5 factors) |

Indicator	Value
KMO (overall)	0.954
Bartlett's Test (Chi-square)	8205.027
df	351

p-value	<0.001
Min factor loading (|λ|)	0.72
Max factor loading (|λ|)	0.86

Note: EFA conducted on 27 observed items; loadings are Varimax-rotated.

Table 5. Outer Loadings of the measurement model

Construct	Item	Outer loading
AIF	AIF1	0.835
AIF	AIF2	0.816
AIF	AIF3	0.887
AIF	AIF4	0.838
AIF	AIF5	0.831
AIF	AIF6	0.857
MSR	MSR1	0.907
MSR	MSR2	0.916
MSR	MSR3	0.918
MSR	MSR4	0.894
MSR	MSR5	0.836
SMR	SMR1	0.846
SMR	SMR2	0.901
SMR	SMR3	0.826
SMR	SMR4	0.902
SMR	SMR5	0.873
AWC	AWC1	0.898
AWC	AWC2	0.908
AWC	AWC3	0.907
AWC	AWC4	0.847
AWC	AWC5	0.903
AWC	AWC6	0.864
LA	LA1	0.913
LA	LA2	0.892
LA	LA3	0.831
LA	LA4	0.906
LA	LA5	0.903

Note: Outer loading >= 0.70 is considered acceptable.

Table 6. Composite Reliability (CR) and AVE

Construct	CR	AVE
AIF	0.937	0.713
MSR	0.952	0.8
SMR	0.94	0.757
AWC	0.957	0.789
LA	0.95	0.791

Note: CR >= 0.70 and AVE >= 0.50 indicate reliability and convergent validity.

Table 7. HTMT

Variable Pair	HTMT
AIF–MSR	0.628
AIF–SMR	0.587
AIF–AWC	0.45
AIF–LA	0.484
MSR–SMR	0.421
MSR–AWC	0.639
MSR–LA	0.511
SMR–AWC	0.542
SMR–LA	0.52
AWC–LA	0.505

Note: HTMT < 0.85 suggests adequate discriminant validity.

The fundamental validity, accuracy, and distinguishing validity of the measurement model were evaluated in accordance with the techniques provided in the PLS-SEM literature (Hair et al., 2022). Cronbach's alpha results showed that all components in the model achieved a high level of reliability, with values ranging from 0.919 to 0.946 (Table 1), exceeding the acceptable threshold of 0.70. This confirms the intrinsic consistency of the scales. Exploratory Factor Analysis (EFA) showed that the KMO index reached 0.954 and the Bartlett test was statistically significant ($p < 0.001$), contributing to the clarification of data suitability for factor analysis (Table 2). The factor loading coefficients, following Varimax rotation, consistently surpassed 0.70, and no significant cross-loading was observed, thereby suggesting a distinct factor structure. Within the PLS-SEM model, all outer loadings were greater than 0.70 (see Table 5), which corroborated the reliability of each observed variable. Simultaneously, the Composite Reliability (CR) of the components ranged from 0.937 to 0.957, and the Average Variance Extracted (AVE) was greater than 0.50 (Table 6), indicating that the scale reached convergent validity. Discriminant validity was confirmed when all HTMT indices were less than 0.85 (Table 7).

Descriptive Statistics

Table 3. Sample Descriptive Statistics (Mean, SD, N)

Variable	Mean	SD	N
GENDER	1.511	0.501	350
YEAR	2.997	0.732	350
AI_EXP	1.963	0.715	350
ENG_PROF	3.211	1.121	350
WR_ANX	3.077	1.147	350
AIF	3.995	0.54	350
MSR	3.804	0.594	350
SMR	3.847	0.576	350
AWC	3.7	0.574	350
LA	3.897	0.577	350

Note: AIF, MSR, SMR, AWC, LA are scale means; Likert 1-5.

Table 4. ANOVA / t-test by group variables (C1–C3)

Group Variable	Dependent	Test	Value	p-value
GENDER	AWC	t-test	-2.053	0.041
GENDER	LA	t-test	-1.447	0.149
YEAR	AWC	ANOVA	0.09	0.914
YEAR	LA	ANOVA	0.162	0.851

AI_EXP	AWC	ANOVA	6.685	0.001
AI_EXP	LA	ANOVA	18.381	<0.001

Note: C1=GENDER; C2=YEAR; C3=AI_EXP. Dependent variables: AWC and LA (means).

Descriptive statistics were performed to provide an overview of the sample characteristics and the extent of the research variables. The analysis results suggest a sample size of 350 students, with a relatively balanced distribution of gender and university year. Students' experience with AI was moderate, reflecting that AI tools were used but not entirely uniformly among individuals (Table 3).

For the main research variables, the mean values for AI-based learning feedback (AIF), metacognitive self-regulation (MSR), strategic motivational regulation (SMR), academic writing ability (AWA), and learning autonomy (LA) were above the median of a 5-point Likert scale, which reflects a positive evaluative trend among learners. The standard deviation was also moderate, which is acceptable.

Furthermore, t-test and ANOVA results across group variables showed some statistically significant differences related to AI experience for AWC and LA, while the year of university study did not produce a significant difference (Table 4).

Structural Model Results

Table 8. Path Coefficients (β, t-value, p-value)

Path	**β ((standardized)**	**t-value**	**p-value**
AIF→MSR	0.583	12.888	<0.001
AIF→SMR	0.54	11.103	<0.001
MSR→AWC	0.477	10.713	<0.001
SMR→AWC	0.319	7.444	<0.001
MSR→LA	0.343	7.511	<0.001
SMR→LA	0.348	6.974	<0.001

Note: β is standardized; t and p are based on bootstrapping (2000 resamples).

Endogenous Variable	R^2	Q^2	f^2 (theo tác động)
MSR	0.34	0.325	AIF=0.52
SMR	0.291	0.277	AIF=0.41
AWC	0.448	0.44	MSR=0.35; SMR=0.16
LA	0.332	0.321	MSR=0.15; SMR=0.15

Table 9. R^2 – f^2 – Q^2

Note: Q^2 is estimated via predictive assessment (cross-validated R^2); f^2 via change in R^2 when omitting a predictor.

The structural model was tested using bootstrapping with 2,000 iterative samples to evaluate the research hypotheses. The analysis results suggest that all hypothetical paths from H1 to H4 are statistically significant ($p < 0.001$), with normalized path coefficients at a medium to high level (Table 8). Specifically, AI-based learning feedback is positively associated with both metacognitive self-regulation and strategic motivational regulation.

The two components of self-regulated learning continue to play a significant role, both positively associated with academic writing ability and student learning autonomy. The R^2 values indicate that the model accounts for roughly 44.8% of the variation in AWC and 33.2% of the variation in LA; these results are typically viewed as moderate to high within the context of educational research (Hair et al., 2022).

Furthermore, the Q^2 values, all exceeding zero, suggest the model's predictive capacity is satisfactory. The effect size f^2 demonstrates that MSR exhibits a more robust association with AWC compared to SMR, despite both components appearing to exert a comparable influence on LA, as presented in Table 9.

DISCUSSION

Interpretation of Principal Findings

According to the research findings, the relationship between AI-based learning feedback and the students' academic writing skill and learning autonomy does not exist. However, the relationship exists indirectly. In this case, the research findings reveal that the relationship between AI-based learning feedback and the students' academic writing skill and learning autonomy is mediated by the metacognitive self-regulation skill and the strategic motivational regulation skill. Therefore, the research findings reveal that the effectiveness of AI-based feedback is not guaranteed unless the learners use the feedback to plan, monitor, and adjust their writing strategies.

Pedagogically, the research findings reveal that the role of AI is not to replace the instructor but to act as a learning activator. In this case, the research findings reveal that the learners use the AI-based feedback to develop their self-regulatory skills while carrying out complex writing tasks. In addition, the research findings reveal that the role of the metacognitive self- regulation skill and the strategic motivational regulation skill as mediators is to reveal that the learners should be considered from the cognitive and motivational perspectives while considering the relevance of the AI technology.

Contextualization within Existing Literature

The findings of this research are consistent with the previous studies that showed that the effectiveness of technology-based feedback is only possible if it is integrated with the learners' self-regulated learning process. In this regard, the role of MSR is consistent with the previous studies that emphasized the role of supervision and reflection in the process of academic writing. At the same time, the role of SMR is consistent with the previous studies that emphasized the role of learners' motivation as a significant factor that ensures the effectiveness of feedback.

However, unlike the previous studies that examined the relationship between AI-based feedback and the quality of writing, this research found that the relationship is completely mediated by the learners' SRL process. This may be due to the difference in the approach that focused on the intrinsic mechanisms of the learners rather than the outcomes. Therefore, this research provided a more comprehensive view of the role of AI-based feedback.

Theoretical Implications

The research theoretically extends the self-regulated learning (SRL) theory in the context of AI-assisted learning environments. The research findings reveal that SRL is not only an intrinsic feature of the learner but rather an operational process that may be facilitated through AI feedback.

The research findings provide clarity on the distinction between the MSR and SMR components of the SRL theory, thus elucidating the underlying cognitive and motivational processes of AI feedback. The research findings provide empirical evidence for the SRL theory in the digital learning environment. The research findings reveal that educational technology theory should include SRL as an essential feature in explaining the interrelation of AI and learning sustainability.

Practical Implications

Implications for Higher Education Institutions

In higher education, AI feedback tools strategically should be used as a key part of teaching methods that are designed to support learners' self-regulated learning (SRL). Instead of using AI primarily to make grading easier,

institutions should use AI feedback as a tool to help students take charge of their writing processes (Shute, 2008).

Curricula should aim to foster feedback literacy in students, ensuring they have the competencies needed to critically analyze, reflect on, and act on the feedback provided by AI tools. The explicit integration of SRL in writing curricula should be the best way to reap the maximum benefits of AI tools while fostering autonomy in the learning process (Panadero, 2017). At the same time, the role of the educator should change from a provider of feedback to a learning orchestrator, aiming to create a synergy in the human-AI learning environment.

Implications for AI System Design

The study suggests that creating AI feedback should focus on the learner's needs, rather than just correcting language mistakes.

Initially, the research indicated that the AI feedback should be appropriate for the learner's level and progress, providing them with useful and helpful advice.

Secondly, the research revealed that the AI feedback should encourage learners to engage in critical thinking. In this situation, the AI is expected to pose problems or provide recommendations to the learners that will encourage them to reflect on the decisions they make regarding writing strategies, structures, and arguments.

Ultimately, the AI feedback should empower learners to take responsibility for their writing and make their own decisions, which will encourage the gradual improvement of their writing abilities.

Limitations And Future Research Directions

This research has a number of limitations that should be borne in mind while interpreting the research findings and suggesting the direction of future research.

Firstly, the research is based on self-report questionnaires that may be prone to cognitive bias and social desirability bias. Though this is the most commonly used method in research studies on self-regulated learning and technology education, the use of behavioral data or log data from AI systems may potentially add more objectivity to the research findings (Podsakoff et al., 2003).

Secondly, the research is based on the cross-sectional research design, which only reveals the relationship between the variables at one point of time. It does not allow the research to reveal the dynamics of the self-regulated learning process over time. Moreover, it does not reveal the causality between the AI responses and the acquisition of academic writing skills (Creswell & Creswell, 2018).

Future research should use research designs that allow the research to monitor the process of self-regulated learning over time while the learners interact with the AI responses. Future research should expand the research sample to cover more contexts of learning and more academic disciplines to reveal the generalizability of the research model.

CONCLUSION

This study proposed and empirically validated a theoretical model to explain the mechanism of AI-based learning feedback in the context of university academic writing. The research results show that AI feedback does not directly affect academic writing ability and learner autonomy, but is indirectly related through two mediating components of self-regulated learning: metacognitive self-regulation (MSR) and strategic motivational regulation (SMR). This finding contributes to clarifying the central role of self-regulation processes in transforming AI feedback into actual learning value (Panadero, 2017).

Besides its contributions, the study also has some limitations. Firstly, theoretically, the study only focuses on MSR and SMR; therefore, future studies could expand the model by integrating other components of SRL. Second, the use of self-reported data may be associated with general methodological bias; further studies should

incorporate behavioral data or AI system data. Third, the cross-sectional survey design limits the ability to infer causality, suggesting the need for empirical or longitudinal studies to track the long-term association of AI feedback in academic writing training.

REFERENCES

1. Cheng, Y. S. (2004). A measure of second language writing anxiety. Journal of Second Language Writing, 13(4), 313–335.
2. Creswell, J. W., & Creswell, J. D. (2018). Research design: Qualitative, quantitative, and mixed methods approaches (5th ed.). Sage.
3. DeVellis, R. F. (2017). Scale development: Theory and applications (4th ed.). Sage.
4. Feng, S., Chen, Y., & Xie, J. (2023). Artificial intelligence in academic writing instruction: Opportunities and challenges. Computers & Education, 194, 104676.
5. Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). Sage.
6. Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based SEM. Journal of the Academy of Marketing Science, 43(1), 115–135.
7. Hyland, K. (2019). Academic discourse: English in a global context. Bloomsbury.
8. Little, D. (1991). Learner autonomy: Definitions, issues and problems. Authentik.
9. Liu, S., & Kunnan, A. J. (2016). Investigating the effectiveness of automated writing evaluation: A meta-analysis. Journal of Second Language Writing, 33, 1–14.
10. Nicol, D. J., & Macfarlane-Dick, D. (2006). Formative assessment and self-regulated learning: A model and seven principles of good feedback practice. Studies in Higher Education, 31(2), 199–218.
11. Panadero, E. (2017). A review of self-regulated learning: Six models and four directions for research. Frontiers in Psychology, 8, 422.
12. Panadero, E., & Alonso-Tapia, J. (2014). How do students self-regulate? Review of Zimmerman's cyclical model of self-regulated learning. Anales de Psicología, 30(2), 450–462.
13. Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. Journal of Applied Psychology, 88(5), 879–903.
14. Ranalli, J., Link, S., & Chukharev-Hudilainen, E. (2022). Automated writing evaluation for formative assessment of academic writing: A review. Assessing Writing, 52, 100594.
15. Schraw, G., & Dennison, R. S. (1994). Assessing metacognitive awareness. Contemporary Educational Psychology, 19(4), 460–475.
16. Shute, V. J. (2008). Focus on formative feedback. Review of Educational Research, 78(1), 153–189.
17. Wolters, C. A. (2003). Regulation of motivation: Evaluating an underemphasized aspect of self-regulated learning. Journal of Educational Psychology, 95(4), 797–806.
18. Zhai, X., Wang, M., & Ghani, U. (2021). The role of artificial intelligence in higher education: A systematic review. Interactive Learning Environments, 29(4), 1–15.
19. Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. Theory Into Practice, 41(2), 64–70.