Journal of Education, Religious, and Instructions (JoERI)
E-ISSN: 3025-3012
Volume 4 Number 1, June 2026, page 52-64
Doi: 10.60046/joeri.v4i1.316
https://ejournal.stiab-jinarakkhita.ac.id/index.php/joeri

Metacognition as a Mediator Between Human–AI Collaborative Learning and the Ability to Adapt Learning Strategies

Lukman Abdul Majid[1]* https://orcid.org/0009-0001-5287-4039
Adhi Kumara Saddhadhika[2] https://orcid.org/0009-0007-2789-9182
Sutiyono[3] https://orcid.org/0009-0007-4978-751X
Moses Adeleke Adoye[4] https://orcid.org/0000-0003-0755-3532

[1]*Islamic Education Management Department, Al Mubarok College of Tarbiyah Bandar Mataram, Lampung, Indonesia*
[2,3]*Buddhist Education Department, Jinarakkhita Buddhist College, Lampung, Indonesia*
[4]*Al-Hikmah University, Ilorin, Nigeria*
**Corresponding author: Manluk680@gmail.com*

ABSTRACT

This study investigates the influence of Human–AI Collaborative Learning on students' Adaptive Learning Strategies, with Metacognition serving as a mediating mechanism. A quantitative research design was employed using a survey of university students, with data collected through a structured questionnaire measuring Human–AI Collaborative Learning, Metacognition, and Adaptive Learning Strategies. The data were analyzed using Partial Least Squares Structural Equation Modeling to examine both the direct and indirect relationships among the proposed constructs. The findings reveal that Human–AI Collaborative Learning positively enhances students' metacognitive abilities and adaptive learning strategies. Furthermore, metacognition exerts a significant positive influence on adaptive learning strategies and functions as a partial mediator in the relationship between Human–AI Collaborative Learning and students' adaptive learning strategies. The proposed model demonstrates substantial explanatory capability, indicating that collaborative interactions with artificial intelligence contribute meaningfully to students' capacity for self-monitoring, learning regulation, and strategic adaptation. These findings underscore the importance of integrating artificial intelligence as a collaborative learning partner to strengthen students' metacognitive development and foster adaptive learning strategies in higher education. The study contributes to the growing literature on human–AI collaboration by providing empirical evidence that metacognition constitutes a key psychological mechanism through which AI-supported learning environments promote adaptive learning.

ARTICLE INFO

Keywords:
Human–AI Collaborative Learning; Metacognition; Adaptive Learning Strategies; Self-Regulated Learning; PLS-SEM.

Article History:
Received: June 18, 2026
Revised: June 29, 2026
Accepted: June 29, 2026
Published: June 30, 2026

How to Cite in APA Style:
Majid, L. A., Saddhadhika, A. K., Sutiyono, & Adoye, M. A. (2026). How Human–AI Collaborative Learning Enhances Adaptive Learning Strategies: The Mediating Role of Metacognition. *Journal of Education, Religious, and Instructions,* vol 4 (1), 52-64

Introduction

The rapid advancement of artificial intelligence (AI) technology has driven a transformation in educational practices, particularly in higher education and technology-based learning. The use of AI is no longer limited to serving as a tool for delivering content; it has evolved into a technology capable of providing adaptive feedback, analyzing learning activities, monitoring student progress, and offering recommendations for next steps in the learning process. In the context of online learning, AI applications also have the potential to help students manage their learning process more independently. Students view AI applications as useful in supporting metacognitive, cognitive, and behavioral regulation during the planning, implementation, and reflection stages of learning, although their support for motivational regulation remains limited (Jin et al., 2023).

Collaborative learning emphasizes interaction, shared responsibility, knowledge building, and group problem-solving. The success of collaborative learning depends on the group members' ability to set goals, develop plans, choose strategies, monitor the learning process, and make adjustments together (Järvelä et al., 2023; Zheng et al., 2023). The integration of AI into collaborative learning environments enhances the process through real-time feedback, automated assessment, analysis of group interactions, and recommendations for next learning steps. AI-based automated assessment and feedback systems have been shown to support knowledge elaboration, group performance, monitoring of the collaboration process, and the adjustment of group learning goals and strategies (Zheng et al., 2023). In addition, feedback- and feedforward-based AI approaches can enhance collaborative knowledge building, co-regulatory behavior, and group performance (Zheng et al., 2024).

Although various studies have demonstrated the potential of AI to support collaborative learning and learning regulation, our understanding of the mechanisms underlying human–AI interactions remains incomplete. In particular, there is a need for empirical research that explains how AI support influences learners' regulatory processes, how learners interpret AI feedback, and how these processes help them adjust their learning strategies (Järvelä et al., 2023; Jin et al., 2023). Therefore, metacognition is a key concept for explaining the relationship between human–AI collaborative learning and learners' ability to adapt their learning strategies.

Metacognition refers to an individual's awareness and ability to plan, monitor, evaluate, and control their own learning process. Metacognition is a key component of self-regulated learning because it enables learners to set goals, choose appropriate strategies, assess their progress, and adjust their strategies when the results do not align with their learning objectives (Winne & Hadwin, 1998). In an AI-based learning environment, metacognitive processes are not only related to learners' internal strategy management but also involve the ability to critically understand, evaluate, and utilize the feedback and recommendations generated by AI systems (Järvelä et al., 2023; Zheng et al., 2023).

Although various studies have demonstrated the potential of AI to support collaborative learning and learning regulation, our understanding of the mechanisms underlying Human–AI Collaborative Learning remains incomplete. In particular, there is a need for empirical research that explains how AI support influences learners' regulatory processes, how learners interpret AI-generated feedback, and how these processes enable them to adapt their learning strategies (Järvelä et al., 2023; Jin et al., 2023). Metacognition is therefore considered a key mechanism for explaining the relationship between Human–AI Collaborative Learning and students' Adaptive Learning Strategies. Within the Self-Regulated Learning (SRL) framework, metacognition refers to learners' ability to plan, monitor, evaluate, and regulate their cognitive processes throughout learning (Panadero, 2017a; Winne & Hadwin, 1998). In AI-supported learning environments, these metacognitive processes extend beyond internal self-regulation to include learners' ability to critically interpret, evaluate, and utilize AI-generated feedback and recommendations for improving their learning strategies (Järvelä et al., 2023; Zheng et al., 2023).

Drawing on the Self-Regulated Learning framework Panadero (2017a); Winne & Hadwin (1998), this study proposes that metacognition functions as the psychological mechanism through which Human–AI Collaborative Learning enhances students' Adaptive Learning Strategies. AI-supported collaborative learning provides learners with personalized feedback, adaptive recommendations, and opportunities for reflection, while metacognition enables learners to use these supports to plan, monitor, evaluate, and adjust their learning strategies effectively (Dhaifullah et al., 2025; Järvelä et al., 2023). Accordingly, this study aims to examine the direct effect of Human–AI Collaborative Learning on students' Adaptive Learning Strategies and the mediating role of Metacognition. Specifically, this study addresses the following research question: Does Metacognition mediate the relationship between Human–AI Collaborative Learning and students' Adaptive Learning Strategies? By answering this question, the study contributes to the literature by extending the Self-Regulated Learning framework and providing empirical evidence on the psychological mechanism underlying AI-supported collaborative learning.

Human–AI Collaborative Learning and Self-Regulated Learning

Self-regulated learning (SRL) is a process in which learners manage their own learning goals, strategies, and reflections in order to achieve optimal results. SRL involves cognitive, metacognitive, and behavioral regulation components (Winne & Hadwin, 1998). AI has been adopted in various forms, such as intelligent tutoring systems, adaptive platforms, and automated feedback, which support aspects of self-regulated learning by providing information on learning progress, strategy recommendations, and monitoring support (Dhaifullah et al., 2025).

Research by Jin et al. (2023) indicates that students view AI applications as useful tools for supporting metacognitive, cognitive, and behavioral regulation in online learning environments. These findings underscore the potential of AI to support metacognitive skills, which are a core component of SRL.

The Role of AI in Collaborative Learning and Strategic Regulation

Technology-based collaborative learning requires strategic coordination skills and shared responsibility among learners (Dignath & Veenman, 2021). The integration of AI into collaborative learning provides opportunities for more personalized and adaptive support, such as automated feedback and interaction analytics to identify group and individual needs (Zheng et al., 2023).

AI components that facilitate real-time feedback and strategy recommendations strengthen the process of monitoring and adjusting students' learning strategies, which in SRL is known as a key metacognitive function (Dhaifullah et al., 2025). In addition, intelligent systems can help learners monitor their status, identify areas of weakness, and reflect on their learning approaches more effectively, which impacts their ability to adapt their learning strategies (Zheng et al., 2023).

Metacognition as a Mediator

Metacognition serves as a cognitive bridge between learning experiences and desired

Journal of Education, Religious, and Instructions (JoERI)
E-ISSN: 3025-3012
Volume 4 Number 1, June 2026, page 52-64
Doi: 10.60046/joeri.v4i1.316
https://ejournal.stiab-jinarakkhita.ac.id/index.php/joeri

learning outcomes. Metacognitive skills help students evaluate the effectiveness of their learning strategies and adjust them based on the context of the task and the feedback they receive (Winne & Hadwin, 1998). In the context of AI, metacognition also involves reflecting on feedback provided by AI systems to develop internal structures for strategic decision-making (Järvelä et al., 2023).

Dhaifullah et al. (2025) found that AI-based analytical and adaptive tools, such as predictive models and intelligent tutoring systems, can enhance learners' abilities in goal setting, monitoring, strategy adjustment, and reflective evaluation key aspects of metacognition. Therefore, metacognition is viewed as a crucial mediator linking human–AI collaborative experiences with learners' ability to adapt their learning strategies efficiently and effectively.

Research Hypothesis

Based on the literature review and theoretical framework developed above, this study proposes the following hypotheses:

H1: Human–AI collaborative learning has a positive effect on students' ability to adapt learning strategies.
H2: Human–AI collaborative learning has a positive effect on students' metacognition.
H3: Metacognition has a positive effect on students' ability to adjust learning strategies.
H4: Metacognition mediates the relationship between human–AI collaborative learning and students' ability to adjust learning strategies.

Method

This study employed a quantitative survey design to examine the relationships among Human–AI Collaborative Learning, Metacognition, and students' Adaptive Learning Strategies (Creswell & Creswell, 2018). The study was conducted in the Bangka Belitung Islands Province, Indonesia. Human–AI Collaborative Learning in this study refers to learning activities in which students interact with artificial intelligence as a learning partner to search for information, generate ideas, obtain feedback, solve academic problems, and reflect on their learning process. Through these interactions, students were encouraged to critically evaluate AI-generated responses, discuss alternative solutions with peers, and adjust their learning strategies accordingly.

The study used both primary and secondary data. Primary data were collected through classroom observations, questionnaire administration, and documentation of students' interactions with AI-assisted learning activities, whereas secondary data were obtained from scientific journals, books, and relevant literature. Participants were selected using purposive sampling based on predetermined inclusion criteria. The respondents were students who had experience using AI to support collaborative learning activities and completed all questionnaire items. A total of 216 valid responses were obtained from several schools in the Bangka Belitung Islands Province. According to Hair et al. (2022), the sample size in PLS-SEM should consider the complexity of the structural model, the number of relationships among constructs, the expected effect size, and the required statistical power.

The research instrument consisted of a structured questionnaire using a five-point Likert scale to measure three constructs: Human–AI Collaborative Learning, Metacognition, and

Journal of Education, Religious, and Instructions (JoERI)
E-ISSN: 3025-3012
Volume 4 Number 1, June 2026, page 52-64
Doi: 10.60046/joeri.v4i1.316
https://ejournal.stiab-jinarakkhita.ac.id/index.php/joeri

Adaptive Learning Strategies. The questionnaire items were adapted from previous studies on AI-supported collaborative learning, self-regulated learning, and metacognition. Data were analyzed using Structural Equation Modeling (SEM) with the Partial Least Squares (PLS) approach through SmartPLS 3.0 (Hair. et al., 2022; Ringle et al., 2015). The analysis involved evaluating the measurement model (outer model) to assess indicator validity and reliability, followed by evaluation of the structural model (inner model) to examine the hypothesized relationships among constructs. The mediating role of Metacognition was tested using the bootstrapping procedure by examining the significance of both direct and indirect effects in accordance with the mediation procedure recommended by (Nitzl et al., 2016).

The PLS-SEM approach enabled simultaneous assessment of measurement quality and structural relationships among latent variables. This method provides a robust analytical framework for explaining how Human–AI Collaborative Learning contributes to students' Adaptive Learning Strategies directly and indirectly through Metacognition.

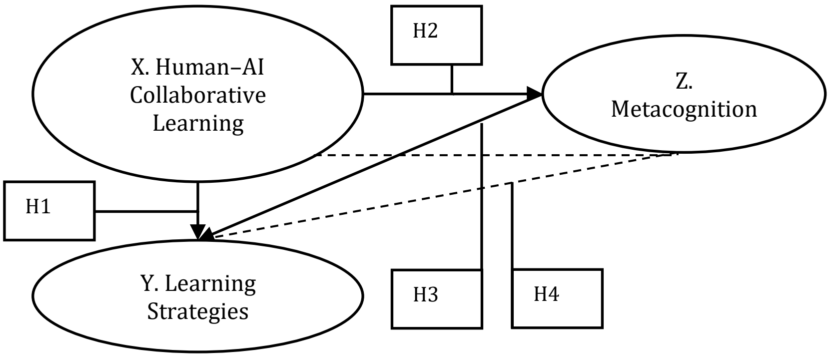

Figure 1. Conceptual Framework

Findings

Table 1. Outer Loadings

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Y1 <- Learning Strategies	0,799	0,798	0,035	22,608	0,000
Y2 <- Learning Strategies	0,827	0,826	0,030	27,706	0,000
Y3 <- Learning Strategies	0,814	0,813	0,036	22,657	0,000
Y4 <- Learning Strategies	0,832	0,831	0,025	33,134	0,000
x1 <- Human–AI Collaborative Learning	0,880	0,878	0,021	42,483	0,000
x2 <- Human–AI Collaborative Learning	0,885	0,883	0,018	48,449	0,000
x3 <- Human–AI Collaborative Learning	0,877	0,875	0,022	40,208	0,000
z1 <- Metacognition	0,853	0,852	0,024	35,242	0,000
z2 <- Metacognition	0,815	0,813	0,030	27,265	0,000
z3 <- Metacognition	0,837	0,834	0,029	28,439	0,000
z4 <- Metacognition	0,857	0,855	0,025	34,135	0,000

Journal of Education, Religious, and Instructions (JoERI)
E-ISSN: 3025-3012
Volume 4 Number 1, June 2026, page 52-64
Doi: 10.60046/joeri.v4i1.316
https://ejournal.stiab-jinarakkhita.ac.id/index.php/joeri

Based on the results of outer loading tests conducted using the bootstrapping procedure, all indicators within the constructs of Learning Strategies, Human–AI Collaborative Learning, and Metacognition were found to be valid and significant in reflecting their respective constructs. The Learning Strategies indicators had outer loading values ranging from 0.799 to 0.832, the Human–AI Collaborative Learning indicators from 0.877 to 0.885, and the Metacognition indicators from 0.815 to 0.857. All these values exceeded the minimum threshold of 0.70, thus meeting the criteria for convergent validity. The sample means, which are very close to the original sample values, along with relatively small standard deviations ranging from 0.018 to 0.036, indicate that the parameter estimates exhibit good stability and consistency. Furthermore, all indicators obtained T-statistic values ranging from 22.608 to 48.449, far exceeding the critical value of 1.96, with P-values of 0.000 or less than 0.05. Thus, all indicators have a significant effect on the constructs they measure and can be retained in the measurement model for use in subsequent analysis stages.

Table 2. Discriminant validity

	Metacognition	Human–AI Collaborative Learning	Learning Strategies
Metacognition	0,841		
Human–AI Collaborative Learning	0,893	0,880	
Learning Strategies	0,863	0,870	0,818

Based on the results of the discriminant validity test using the Fornell–Larcker criteria, the measurement model does not yet adequately meet discriminant validity. The root-mean-square error of approximation (RMSEA) value for the Metacognition construct, at 0.841, is lower than its correlation with Human–AI Collaborative Learning (0.893) and Learning Strategies (0.863). The AVE for Human–AI Collaborative Learning, at 0.880, is also lower than its correlation with Metacognition (0.893), although it remains higher than its correlation with Learning Strategies (0.870). Meanwhile, the root-mean-square error (RMSE) for Learning Strategies is 0.818, which is lower than its correlation with Metacognition (0.863) and Human–AI Collaborative Learning (0.870). These findings indicate that the three constructs, particularly Metacognition and Human–AI Collaborative Learning, have such a strong relationship that they cannot yet be empirically distinguished well.

Table 3. Construct reliability and validity

	Cronbach's Alpha	rho_A	Composite Reliability	Average Variance Extracted (AVE)
Metacognition	0,862	0,862	0,906	0,707
Human–AI Collaborative Learning	0,855	0,855	0,912	0,775
Learning Strategies	0,835	0,838	0,890	0,669

Based on the results of the construct reliability and validity tests, all constructs in the model met the criteria for reliability and convergent validity. The Metacognition construct had a Cronbach's Alpha of 0.862, a rho_A of 0.862, a composite reliability of 0.906, and an AVE of 0.707. The Human–AI Collaborative Learning construct obtained a Cronbach's Alpha of 0.855, a rho_A of 0.855, a composite reliability of 0.912, and an AVE of 0.775.

Journal of Education, Religious, and Instructions (JoERI)
E-ISSN: 3025-3012
Volume 4 Number 1, June 2026, page 52-64
Doi: 10.60046/joeri.v4i1.316
https://ejournal.stiab-jinarakkhita.ac.id/index.php/joeri

Meanwhile, the Learning Strategies construct had a Cronbach's Alpha of 0.835, a rho_A of 0.838, a composite reliability of 0.890, and an AVE of 0.669. All Cronbach's Alpha, rho_A, and composite reliability values were above the minimum threshold of 0.70, indicating that the indicators within each construct possess good internal consistency. Additionally, all AVE values exceeded 0.50, meaning each construct explains more than 50% of the variance in its indicators.

Table 4. Collinearity Statistics (VIF)

	VIF
Y1	1,745
Y2	1,913
Y3	1,802
Y4	1,841
X1	2,128
X2	2,147
X3	2,091
Z1	2,374
Z2	1,859
Z3	2,050
Z4	2,295

Based on the results of the Variance Inflation Factor (VIF) test, all indicators have VIF values ranging from 1.745 to 2.374. The indicators in the Learning Strategy construct have VIF values of 1.745–1.913, the Human–AI Collaborative Learning indicators have values of 2.091–2.147, while the Metacognition indicators have values of 1.859–2.374. All of these values are below the maximum limit of 5.00 and even fall below the stricter criterion of 3.30. Thus, it can be concluded that there are no issues of multicollinearity or high collinearity among the indicators in the measurement model. This indicates that each indicator provides relatively distinct information in explaining its respective construct, making all indicators worthy of retention.

Table 5. Path Coefficients

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Metacognition -> Learning Strategies	0,426	0,423	0,079	5,388	0,000
Human–AI Collaborative Learning -> Metacognition	0,893	0,891	0,021	43,256	0,000
Human–AI Collaborative Learning -> Learning Strategies	0,490	0,492	0,080	6,106	0,000

ased on the path coefficient analysis, all relationships between the variables are positive and significant. Human–AI Collaborative Learning has a significant positive effect on Metacognition (β = 0.893, t = 43.256, p < .001), indicating that greater engagement in collaborative learning with AI enhances students' metacognitive abilities. Metacognition also positively influences Learning Strategies (β = 0.426, t = 5.388, p < .001), while Human–

Journal of Education, Religious, and Instructions (JoERI)
E-ISSN: 3025-3012
Volume 4 Number 1, June 2026, page 52-64
Doi: 10.60046/joeri.v4i1.316
https://ejournal.stiab-jinarakkhita.ac.id/index.php/joeri

AI Collaborative Learning directly and significantly affects Learning Strategies (β = 0.490, *t* = 6.106, *p* < .001). The close similarity between the original sample and sample mean, together with the low standard deviations, indicates stable path coefficient estimates. Overall, these findings demonstrate that Human–AI Collaborative Learning exerts the strongest influence on Metacognition, whereas Learning Strategies are influenced by both Human–AI Collaborative Learning and Metacognition.

Table 6. Specific Indirect Effects

	Original Sample (O)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
Human–AI Collaborative Learning -> Metacognition -> Learning Strategies	0,380	0,377	0,072	5,280	0,000

Based on the specific indirect effects analysis, Human–AI Collaborative Learning has a positive and significant indirect effect on Learning Strategies through Metacognition (β = 0.380, *t* = 5.280, *p* < .001). These results indicate that Metacognition significantly mediates the relationship between Human–AI Collaborative Learning and Learning Strategies. The close similarity between the original sample (0.380) and the sample mean (0.377), together with the low standard deviation (0.072), suggests that the indirect effect estimate is stable. Since the direct effect of Human–AI Collaborative Learning on Learning Strategies remains positive and significant (β = 0.490), the mediation is classified as complementary partial mediation. Therefore, Human–AI Collaborative Learning enhances Learning Strategies both directly and indirectly through Metacognition, supporting the proposed hypothesis.

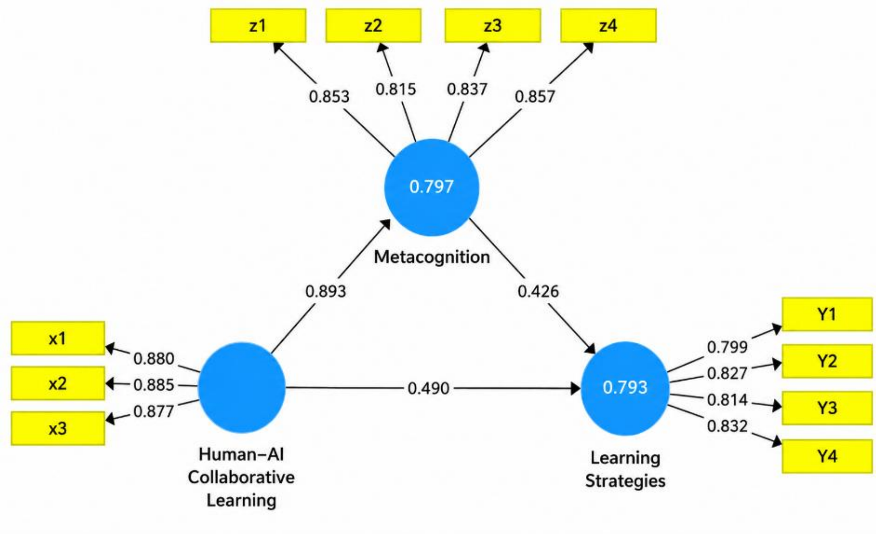

Figure 2. PLS-SEM Structural Model of the Effect of Human–AI Collaborative Learning on Learning Strategies Mediated by Metacognition

Based on the PLS-SEM model diagram, all indicators have outer loadings above 0.70, specifically the Human–AI Collaborative Learning indicators ranging from 0.877 to 0.885,

Journal of Education, Religious, and Instructions (JoERI)
E-ISSN: 3025-3012
Volume 4 Number 1, June 2026, page 52-64
Doi: 10.60046/joeri.v4i1.316
https://ejournal.stiab-jinarakkhita.ac.id/index.php/joeri

the Metacognition indicators ranging from 0.815 to 0.857, and the Learning Strategies indicator ranging from 0.799 to 0.832. Thus, all indicators are deemed capable of adequately reflecting their constructs and meeting the criteria for convergent validity. In the structural model, Human–AI Collaborative Learning has a very strong positive influence on Metacognition with a path coefficient of 0.893. Furthermore, Metacognition has a positive influence on Learning Strategies of 0.426, while Human–AI Collaborative Learning also has a direct positive influence on Learning Strategies of 0.490. The R-square value for Metacognition of 0.797 indicates that 79.7% of the variation in Metacognition can be explained by Human–AI Collaborative Learning, while the R-square value for Learning Strategies of 0.793 indicates that 79.3% of the variation in Learning Strategies can be explained jointly by Human–AI Collaborative Learning and Metacognition. In addition to direct effects, Human–AI Collaborative Learning also has an indirect effect on Learning Strategies through Metacognition of 0.380. Thus, the model suggests that collaborative learning between humans and AI can enhance learners' ability to adapt their learning strategies, both directly and through improved metacognitive skills, such that metacognition acts as a complementary partial mediator in this relationship.

Discussion

H1: Human–AI Collaborative Learning has a positive effect on students' Adaptive Learning Strategies

Human–AI Collaborative Learning can enhance students' Adaptive Learning Strategies because AI functions as a learning partner that provides timely feedback, alternative solutions, and personalized support tailored to learners' needs (Febrianti et al., 2025; Pahi et al., 2024; Zhang et al., 2025). Within the Self-Regulated Learning framework, AI facilitates adaptive learning through intelligent tutoring systems, personalized learning environments, and automated feedback that help students manage their learning processes more effectively (Jin et al., 2023). Consequently, students who actively collaborate with AI are better able to evaluate their learning approaches, identify ineffective strategies, and adopt more appropriate ones (Banihashem et al., 2025). Furthermore, generative AI supports learners in setting learning goals, locating and integrating information, monitoring their progress, and engaging in self-reflection, all of which contribute to the development of adaptive learning strategies (Lan & Zhou, 2025).

H2: Human–AI Collaborative Learning has a positive effect on students' Metacognition

The findings indicate that Human–AI Collaborative Learning positively influences students' Metacognition by encouraging them to plan, monitor, and evaluate their own thinking processes (Han et al., 2026; Lan & Zhou, 2025; Zhang et al., 2025). Students perceive AI applications as valuable tools for supporting cognitive, metacognitive, and behavioral regulation throughout the learning process. Previous studies have shown that AI-supported learning environments enhance metacognitive strategies, learning strategies, and student engagement by providing immediate feedback, personalized responses, and opportunities for reflection (Chen et al., 2024; Li et al., 2024; Yan et al., 2023; Zhu et al., 2023). These findings suggest that AI not only facilitates knowledge acquisition but also promotes learners' awareness of how they understand, evaluate, and regulate their own learning.

H3: Metacognition has a positive effect on students' Adaptive Learning Strategies

Journal of Education, Religious, and Instructions (JoERI)
E-ISSN: 3025-3012
Volume 4 Number 1, June 2026, page 52-64
Doi: 10.60046/joeri.v4i1.316
https://ejournal.stiab-jinarakkhita.ac.id/index.php/joeri

Metacognition positively influences students' Adaptive Learning Strategies because learners with strong metacognitive awareness are better able to evaluate the effectiveness of their learning strategies and modify them when necessary (Panadero, 2017b; Veenman et al., 2006). Students with higher levels of metacognitive regulation tend to employ more effective task strategies and manage their learning time more efficiently, both of which are essential components of self-regulated learning (Abdelshiheed et al., 2023; Martinie et al., 2023; Wolters et al., 2017; Wolters & Brady, 2021). Moreover, instructional approaches that explicitly foster metacognitive skills have been shown to improve students' self-regulated learning and strategic adaptation compared with learning environments that provide limited metacognitive support (Brasoveanu et al., 2020; Chen et al., 2025). These findings reinforce the importance of metacognition in enabling learners to monitor their progress, evaluate outcomes, and continuously refine their learning strategies.

H4:. Metacognition mediates the relationship between Human–AI Collaborative Learning and students' Adaptive Learning Strategies

The findings indicate that Metacognition serves as a significant mediator in the relationship between Human–AI Collaborative Learning and students' Adaptive Learning Strategies. This suggests that the positive influence of AI-supported collaborative learning on students' ability to adapt their learning strategies occurs through the enhancement of metacognitive processes. Within the Self-Regulated Learning framework, metacognition enables learners to plan, monitor, evaluate, and regulate their learning activities, allowing them to make effective use of AI-generated feedback and recommendations (Panadero, 2017a; Winne & Hadwin, 1998).

This finding is consistent with Jin et al. (2023), who reported that AI-supported metacognitive guidance enhances self-regulated learning, particularly in task strategy use and self-evaluation. Similarly, Zhang et al. (2025) found that effective use of generative AI strengthens self-regulation, which subsequently improves higher-order thinking and problem-solving skills. These findings suggest that AI is most effective when learners actively engage in metacognitive processes rather than relying solely on AI-generated responses.

The mediating role of Metacognition is further supported by Ouyang (2025), who demonstrated that the educational benefits of AI-based adaptive learning systems are largely achieved through self-regulated learning and learner engagement. Therefore, the present study extends previous research by providing empirical evidence that Metacognition functions as the psychological mechanism linking Human–AI Collaborative Learning with students' Adaptive Learning Strategies. This finding highlights the importance of designing AI-supported collaborative learning environments that encourage learners to critically interpret AI-generated feedback, monitor their understanding, and continuously adapt their learning strategies.

Conclusion

The results of the PLS-SEM analysis indicate that the constructs of Human–AI Collaborative Learning, Metacognition, and Learning Strategies met the criteria for reliability and convergent validity and did not exhibit multicollinearity issues. Human–AI Collaborative Learning was found to have a positive and significant effect on Metacognition and Learning Strategies, while Metacognition also had a positive and significant effect on Learning Strategies. Metacognition acts as a complementary partial mediator, indicating that human–AI collaborative learning enhances students' ability to adapt learning strategies, both directly and by strengthening their capacity to plan, monitor, and evaluate their learning processes. R^2 values of 0.797 for Metacognition and 0.793 for Learning Strategies indicate that the model possesses strong explanatory power.

These findings confirm that AI in education should not merely be used as an information provider or a tool for completing tasks, but rather be positioned as a learning partner that encourages reflection, evaluation of information, monitoring of understanding, and adjustment of learning strategies. Therefore, educators need to design AI-assisted activities that maintain students' independent thinking and metacognitive engagement. Scientifically, this study expands the body of research on AI-assisted learning by explaining metacognition as the mechanism linking human–AI collaboration with the ability to adapt learning strategies. Further research is recommended to employ longitudinal or experimental designs, involve participants from various educational levels and academic disciplines, and consider other variables such as AI literacy, learning motivation, cognitive engagement, educator support, and AI system characteristics. Such research is necessary to strengthen causal explanations and identify the most effective conditions for human–AI collaborative learning.

References

Abdelshiheed, M., Zhou, G., Maniktala, M., Barnes, T., & Chi, M. (2023). *Metacognition and Motivation: The Role of Time-Awareness in Preparation for Future Learning*. https://arxiv.org/abs/2303.13541

Banihashem, S. K., Bond, M., Bergdahl, N., Khosravi, H., & Noroozi, O. (2025). A systematic mapping review at the intersection of artificial intelligence and self-regulated learning. *International Journal of Educational Technology in Higher Education*, *22*(1), 50. https://doi.org/10.1186/s41239-025-00548-8

Brasoveanu, A., Moodie, M., & Agrawal, R. (2020). Textual evidence for the perfunctoriness of independent medical reviews. *CEUR Workshop Proceedings*, *2657*, 1–9.

Chen, A., Lian, J., Kuang, X., & Jia, J. (2025). *Can theory-driven learning analytics dashboard enhance human-AI collaboration in writing learning? Insights from an empirical experiment*. https://doi.org/10.48550/arXiv.2506.19364

Chen, A., Wei, Y., Le, H., & Zhang, Y. (2024). *Learning-by-teaching with ChatGPT: The effect of teachable ChatGPT agent on programming education*. https://arxiv.org/abs/2412.15226

Creswell, J. W., & Creswell, J. D. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches* (5th ed.). SAGE Publications.

Dhaifullah, R., Arrasyid, R., Widodo, S., & Elviani, U. (2025). *AI-Driven Learning Analytics for Self-Regulated and Metacognitive Learning: A Systematic Review*. 329–347. https://doi.org/10.57255/intellect.v4i2.1657

Dignath, C., & Veenman, M. V. J. (2021). The Role of Direct Strategy Instruction and Indirect Activation of Self-Regulated Learning Evidence from Classroom Observation Studies. *Educational Psychology Review*, *33*(2), 489–533. https://doi.org/10.1007/s10648-020-09534-0

Febrianti, K. R., Azizah, N., & Rusadi, F. (2025). Pemanfaatan Kecerdasan Buatan Artificial Intelligence (AI) dalam Membantu Kinerja Pembelajaran. *Jurnal Inovasi Pendidikan Dan Teknologi Informasi (JIPTI)*, *6*(1), 210–226. https://doi.org/10.52060/jipti.v6i1.2883

Hair Jr., 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 Publications.

Han, I., Ji, H., Jin, S., & Choi, K. (2026). Mobile-based artificial intelligence chatbot for self-regulated learning in a hybrid flipped classroom. *Journal of Computing in Higher Education*, *38*(1), 285–309. https://doi.org/10.1007/s12528-025-09434-8

Järvelä, S., Nguyen, A., & Hadwin, A. F. (2023). Human and artificial intelligence collaboration for socially shared regulation in learning. *British Journal of Educational Technology*, *54*(5), 1057–1076. https://doi.org/10.1111/bjet.13325

Jin, S. H., Im, K., Yoo, M., Roll, I., & Seo, K. (2023). Supporting students' self-regulated learning in online learning using artificial intelligence applications. *International Journal of Educational Technology in Higher Education*, *20*, 37. https://doi.org/10.1186/s41239-023-00406-5

Lan, M., & Zhou, X. (2025). A qualitative systematic review on AI empowered self-regulated learning in higher education. *Npj Science of Learning*, *10*(1), 21. https://doi.org/10.1038/s41539-025-00319-0

Li, X., Fan, Y., Li, T., Rakovic, M., Singh, S., van der Graaf, J., Lim, L., Moore, J., Molenaar, I., Bannert, M., & Gasevic, D. (2024). *The FLoRA Engine: Using Analytics to Measure and Facilitate Learners' own Regulation Activities*. https://doi.org/10.18608/jla.2025.8349

Martinie, M.-A., Potocki, A., Broc, L., & Larigauderie, P. (2023). Predictors of procrastination in first-year university students: role of achievement goals and learning strategies. *Social Psychology of Education*, *26*(2), 309–331. https://doi.org/10.1007/s11218-022-09743-1

Nitzl, C., Roldán, J. L., & Cepeda, G. (2016). Mediation analysis in partial least squares path modeling: Helping researchers discuss more sophisticated models. *Industrial Management & Data Systems*, *116*(9), 1849–1864. https://doi.org/10.1108/IMDS-07-2015-0302

Ouyang, Z. (2025). Self-regulated learning and engagement as serial mediators between AI-driven adaptive learning platform characteristics and educational quality: A psychological mechanism analysis. *Frontiers in Psychology*, *16*, 1646469. https://doi.org/10.3389/fpsyg.2025.1646469

Pahi, K., Hawlader, S., Hicks, E., Zaman, A., & Phan, V. (2024). Enhancing active learning through collaboration between human teachers and generative AI. *Computers and Education Open*, *6*, 100183. https://doi.org/10.1016/j.caeo.2024.100183

Panadero, E. (2017a). A review of self-regulated learning: Six models and four directions for research. *Frontiers in Psychology*, *8*, 422. https://doi.org/10.3389/fpsyg.2017.00422

Panadero, E. (2017b). A review of self-regulated learning: Six models and four directions for research. In *Frontiers in Psychology* (Vol. 8, Number APR). Frontiers Media S.A. https://doi.org/10.3389/fpsyg.2017.00422

Ringle, C. M., Wende, S., & Becker, J.-M. (2015). *SmartPLS 3*. SmartPLS GmbH.

Veenman, M. V. J., Van Hout-Wolters, B. H. A. M., & Afflerbach, P. (2006). Metacognition and learning: conceptual and methodological considerations. *Metacognition and Learning*, *1*(1), 3–14. https://doi.org/10.1007/s11409-006-6893-0

Winne, P. H., & Hadwin, A. F. (1998). Studying as self-regulated learning. In D. J. Hacker, J. Dunlosky, & A. C. Graesser (Eds.), *Metacognition in educational theory and practice* (pp. 277–304). Lawrence Erlbaum Associates.

Wolters, C. A., & Brady, A. C. (2021). College Students' Time Management: a Self-Regulated Learning Perspective. *Educational Psychology Review*, *33*(4), 1319–1351.

Journal of Education, Religious, and Instructions (JoERI)
E-ISSN: 3025-3012
Volume 4 Number 1, June 2026, page 52-64
Doi: 10.60046/joeri.v4i1.316
https://ejournal.stiab-jinarakkhita.ac.id/index.php/joeri

https://doi.org/10.1007/s10648-020-09519-z

Wolters, C. A., Won, S., & Hussain, M. (2017). Examining the relations of time management and procrastination within a model of self-regulated learning. *Metacognition and Learning*, *12*(3), 381–399. https://doi.org/10.1007/s11409-017-9174-1

Yan, L., Sha, L., Zhao, L., Li, Y., Martinez-Maldonado, R., Chen, G., Li, X., Jin, Y., & Gašević, D. (2023). *Practical and Ethical Challenges of Large Language Models in Education: A Systematic Scoping Review*. https://doi.org/10.1111/bjet.13370

Zhang, F., Gou, J., SHEN, K. N., Camarinha-Matos, L. M., & Wang, Z. (2025). Effects of AI teammates on learning behavior in Human-AI collaboration environments: a perspective on self-regulated learning. *Education and Information Technologies*, *30*(18), 26801–26825. https://doi.org/10.1007/s10639-025-13717-z

Zheng, L., Fan, Y., Chen, B., Huang, Z., Gao, L., & Long, M. (2024). An AI-enabled feedback-feedforward approach to promoting online collaborative learning. *Education and Information Technologies*, *29*(9), 11385–11406. https://doi.org/10.1007/s10639-023-12292-5

Zheng, L., Long, M., Chen, B., & Fan, Y. (2023). Promoting knowledge elaboration, socially shared regulation, and group performance in collaborative learning: An automated assessment and feedback approach based on knowledge graphs. *International Journal of Educational Technology in Higher Education*, *20*, 46. https://doi.org/10.1186/s41239-023-00415-4

Zhu, G., Professor, A., Fan Senior Lecturer, X., Hou Student, C., Zhong Student, T., Seow, P., Chen Shen-Hsing Professor, A., & Rajalingam Director, P. (2023). *Embrace Opportunities and Face Challenges: Using ChatGPT in Undergraduate Students' Collaborative Interdisciplinary Learning*.