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AI-Based Information-Seeking Behavior as a Mediator between Metacognition and Students' Academic Achievement

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Abstract:
The use of Artificial Intelligence (AI) in learning has become widespread among university students to enhance material comprehension. How deeply and effectively students search for information using AI is largely determined by their metacognitive abilities. This study aims to examine: (1) the effect of metacognition on AI-based information-seeking behavior, (2) the effect of AI-based information-seeking behavior on academic achievement (GPA), (3) the effect of metacognition on GPA, and (4) the mediating role of AI-based information-seeking behavior in the relationship between metacognition and GPA. A quantitative approach was employed using Partial Least Squares Structural Equation Modeling (PLS-SEM) executed via the *seminr* package in R. The study population comprised students at UIN Syekh Wasil Kediri, using a cluster sampling technique representing all faculties (n = 273). The findings revealed that metacognition has a positive and significant effect on AI-based information-seeking behavior (β = 0.472, t = 10.856). However, metacognition did not significantly affect GPA (β = 0.116, t = 0.971), and AI-based information-seeking behavior likewise showed no significant effect on GPA (β = 0.040, t = 0.907). Consequently, AI-based information-seeking behavior does not mediate the relationship between metacognition and academic achievement. Therefore, higher education institutions should design AI literacy initiatives that focus on higher-order information processing to ensure technology utilization translates directly into enhanced academic outcomes.

Keywords: Metacognition; AI-Based Information-Seeking Behavior; Academic Achievement; GPA; PLS-SEM

Introduction

In the current era of digital transformation, the utilization of Artificial Intelligence (AI) has undergone a paradigm shift from a mere operational tool to a crucial strategic instrument across various sectors, including higher education (Borges et al., 2021). Specifically, this phenomenon is driven by the emergence of Generative AI (GenAI)—a technology based on deep learning models capable of generating novel, human-like content in response to complex prompts (Lim et al., 2023).

The use of Generative AI (GenAI) is growing quickly in higher education, and it is making sense with institutions striving to put the necessary skills into the hands of the next generation of workers. The use of GenAI in higher education is not just technology adaptation, but a pressing need to equip students with the competences and competitiveness demanded in the digital age (Jin et al., 2025). This technology can facilitate the access to information and promote flexibility in adaptive, student-centered teaching and learning processes (Bidry et al., 2025). Moreover, the emphasis of GenAI in learning is on strengthening students' cognitive and personal aspects. Specifically, GenAI is used to provide personalized teaching, increase the motivation of learning, and promote the autonomy of the students with flexible and dynamic information access (Garzón et al., 2025).

The use of Artificial Intelligence (AI) in academic settings is now aiding in the improvement of literature searches and data analysis, and it is also changing the way patterns of learning engagement are conducted. AI signals a shift in the nature of teaching and information handling, shifting from traditional teaching to becoming a facilitator of digital literacy and AI ethics. This novel function is crucial in helping students to learn how to use AI to critically, ethically, and purposefully incorporate AI as a tool for scientific inquiry to accomplish academic tasks.

The application of AI as an information seeking tool plays a significant role in the educational outcomes of students (Singh et al., 2025; Song et al., 2025; Vieriu & Petrea, 2025). In Higher education, the systematic use of AI can contribute to the effectiveness of learning through the development of adaptive learning systems, ITs (Intelligent Tutoring Systems), and automated feedback to assessments at high speed (Zawacki-Richter et al., 2019). Evidence in the form of a meta-analysis even shows that the implementation of ChatGPT in academic settings leads to enhanced higher-order thinking skills and effective learning (Wang & Fan, 2025). Hence, the application of Generative AI in education should be applied effectively, so that students can effectively use Generative AI in their learning process.

While there are benefits to AI, it also poses significant risks, including the potential for misinformation, algorithmic bias, and limited understanding of the complex human pedagogical considerations (Cardona et al., 2023). The complexity is further highlighted by Barus et al. (2025), who point out emerging ethical issues in higher education, especially the threat of academic integrity, vulnerabilities to student data privacy, and the potential for cognitive dependency. This poses significant ethical questions—both for students and teachers—and demands that students and teachers have the ability to critically assess the outputs of AI tools (Singh et al., 2025). Finally, adopting GenAI is highly reliant on each student's metacognitive skills, which refers to their self-awareness and control of their thinking processes in relation to AI, their ability to assess the integrity of AI-generated answers, and their understanding of how to incorporate AI into academic work (Tankelevitch et al., 2024). Thus, the level of metacognition exhibited by the user is one of the main factors in determining the optimal use of this technology.

According to Chen et al. (2025), metacognition is "deliberate awareness and analysis of thinking and learning processes. Metacognitive strategies are learning strategy which focus on increasing learning awareness of the learners' thinking processes. Learners implement these strategies to plan, monitor, and evaluate their own learning to develop their knowledge and understanding intentionally and deliberately.

In addition to its effect on student's GenAI information seeking, metacognition is one of the direct predictors that can affect student's learning outcome (Akpur, 2024; Pradhan & Das, 2021; Sawhney & Bansal, 2015). Metacognition is a process where learners can plan, monitor and assess their own comprehension as effective learning strategies (Xie et al., 2024). This will enhance metacognitive monitoring and cognitive regulation, enabling students to effectively regulate their working memory capacity, mitigate academic anxiety, and adjust learning approaches as needed (Agrawal et al., 2025; Musullulu et al., 2025). This neurocognitive process improves the accuracy of problem solving and retention of knowledge, leading to overall sustained improvements in academic performance (GPA).

The study of factors that affect the use of Artificial Intelligence (AI) in higher education has rapidly grown in recent years (Almoslamani & Arabia, 2025; Lau, 2026; Ramadan & Prasetio, 2024). Most of the previous studies, however, have primarily examined only behavioural intention or the decision to use AI, which can be triggered by a range of variables, including pedagogical-ethical understanding (IE-TPACK), self-efficacy, social norms, and technology anxiety, among others (Milutinović et al., 2025). This method usually views the use of AI as the final goal of research, neglecting the cognitive processes of users in the context of their actual interactions with AI. Therefore, there is still limited and insufficient understanding of the extent to which metacognitive capacity influences AI information-seeking strategies and the resulting impact on learning outcome indicators for tangible learning outcomes, such as Grade Point Average (GPA).

Based on this conceptualization, the following four main hypotheses are tested: (1) Depth of information seeking (using GenAI) will increase student GPA, (2) Metacognition will increase information seeking (using GenAI), (3) Metacognition will increase student GPA, and (4) GenAI-based information seeking will mediate the relationship between metacognition and GPA.

The results of this research are important both theoretically and practically for the progress of higher education in the digital age. With regard to the theoretical implications, the results build on the Self-Regulated Learning (SRL) framework and the theories of technology adoption, providing empirical evidence of the importance of internal cognitive regulation for the success of the integration of AI. This study is an important contribution to the research field because it moves beyond merely examining the intention to use AI and examines the impact of AI on students' objective academic performance metric (GPA), and validates the mediation effect of the AI-information-seeking depth. In practice, the results provide a scientific basis for the formulation of humanistic and ethical guidelines in adopting AI in higher education, rather than adopting prohibitive and protective measures. The results provide the educators with a reference point to redesign the instruction and assessment strategies that help develop the metacognition of students and their higher-order thinking process. This research shifts the paradigm for students from Generative AI as a tool for getting quick answers to one of a thinking partner, supporting independent learning and long-term academic success.

Research Methodology

This study is quantitative in nature. Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to analyze the data to examine the complex relationships among the latent constructs by combining factor analysis and multiple regression simultaneously (Chinnaraju, 2025). The PLS-SEM was chosen as the non-parametric statistics tool for maximizing the variance explained (R^2) of the dependent variables and handle both reflective and formative constructs without normally distributed data or small sample size (Hair et al., 2014). All data processing and model testing of the structural model was done in R software with the SEMinR package (Hair et al., 2021). Figure 1 shows the conceptual model.

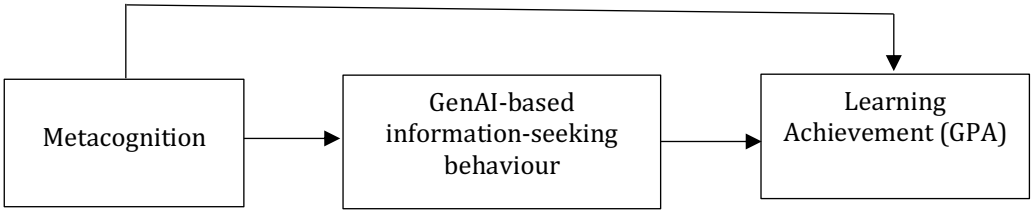

Figure 1. Conceptual Model of the Relationships Among Metacognition, Generative AI-Based Information Seeking, and Learning Achievement (GPA)

The population in this study was all active students at UIN Syekh Wasil Kediri in undergraduate degree. The sampling was done by cluster random sampling method in which the faculties in UIN Syekh Wasil Kediri were taken as cluster units. The sample obtained in this procedure was made up of 272 students from the different faculties. This size proved to be very adequate to test the structural model following the minimum sample size estimation criteria for PLS-SEM by Kock and Hadaya (2016).

The research variables used in this study were metacognition, AI-based information seeking, and academic achievement (GPA). The metacognition was assessed by a questionnaire that was based on the metacognition theory of Flavell (1979) and modified by Schraw (1998). This instrument consists of two main dimensions: (1) Knowledge of Cognition, with indicators of declarative and conditional knowledge; and (2) Regulation of Cognition, with indicators of planning, monitoring and evaluation. There were 15 items in the metacognition scale.

A short instrument was adapted from Kuhlthau's (1990) Information Search Process (ISP) framework to assess the Generative AI-based information-seeking variable. This construct includes four major components: (1) Iterative Querying (information exploration stage), (2) Prompt Refinement (search focus formulation stage), (3) Source Expansion (initiation and source triangulation stage), and (4) Critical Evaluation (collection and critical evaluation stage of academic information). This instrument contained 12 items.

In this study, academic achievement was objectively assessed by using Cumulative Grade Point Average (GPA). GPA is the most representative and valid quantitative measurement that indicates the cumulative academic performance of the student, which depends on a number of cognitive processes and the use of learning technologies (Meepradit et al., 2022).

Results and Discussion

The analysis started with the evaluation of the measurement model (outer model) in order to examine the internal consistency reliability and convergent validity of the measured constructs before testing the proposed structural model. Table 1 summarizes the results of internal consistency reliability for each latent variable measured (Metacognition, GenAI-Based Information Seeking, and Academic Achievement (GPA)), which were obtained by Cronbach's alpha (α), ρA, and Composite Reliability (ρC), and convergent validity assessed by Average Variance Extracted (AVE).

Table 1. Measurement Model Evaluation: Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha (α)	ρA	ρC (CR)	AVE
Metacognition	0.892	0.892	0.908	0.52
GenAI-Based Information Seeking	0.883	0.893	0.903	0.56
Academic Achievement (GPA)	1.000	1.000	1.000	1.000

The assessment of the measurement model was carried out to test the validity and reliability of the measurement models in the research. The reliability tests for the Metacognition construct and the GenAI-Based Information Seeking construct are also conducted in this study, and the internal consistency testing shows that both constructs have a high degree of reliability, which is higher than the criterion of 0.70 (Hair et al., 2021) as seen in Table 1. In terms of convergent validity, the Average Variance Extracted (AVE) indices of Metacognition and GenAI-Based Information Seeking were 0.52 and 0.56, respectively. The convergent validity for both constructs is considered acceptable with these AVE values resolving beyond the ideal value of 0.50. This is consistent with Fornell and Larcker (1981) who concluded that Composite Reliability (ρC) greater than 0.60 shows that the convergent validity of the construct is acceptable. So all measurement items in the instrument were maintained. Overall, the outer model evaluation shows that all the reliability and validity conditions have been met, which is good news and means that the model is robust and can be used in structural model (inner model) analysis.

After the measurement model evaluation, the bootstrapping procedure was used to test the four hypotheses proposed in this study in the structural model (inner model) evaluation process. The estimated values of the path coefficients (β), t-statistics, p-values and the 95% confidence intervals are summarized in Table 2.

Table 2. Structural Model Evaluation and Hypothesis Testing Results

Hypothesis	Path	β	t-statistic	p-value	95% CI	Decision
H1	Metacognition → GenAI-Based Information Seeking	0.49	11.16	< 0.001	[0.41, 0.58]	Significant
H2	Metacognition → GPA	0.12	0.94	0.690	[-0.20, 0.23]	Not Significant
H3	GenAI-Based Information Seeking → GPA	0.03	0.78	0.240	[-0.07, 0.13]	Not Significant

Hypothesis	Path	β	t-statistic	p-value	95% CI	Decision
H4	Metacognition → GenAI-Based Information Seeking → GPA	0.02	0.76	0.240	[-0.03, 0.06]	Not Significant

Hypothesis 1: There is a significant impact of students' metacognition on their information-seeking behavior when using GenAI in learning.

The data in Table 2 shows that there is a strong positive relationship between metacognition and GenAI-based information-seeking behavior, with a path coefficient (β = 0.49). This effect is strongly supported by a t-statistic (t = 11.16) much higher than the critical level of t = 1.96 and a high level of significance (p < 0.001), which means that there is very little likelihood of a statistical error. In addition, the 95 percent CI (95% CI [0.41, 0.58]) is entirely above zero, which provides evidence of the reliability and stability of this effect in the target population. Together, these statistical parameters give a reliable and solid empirical ground for a definite conclusion that metacognitive ability is indeed and significantly a driving predictor of AI based information-seeking behavior.

This result is consistent with those of Zhou and Lam (2019) who showed that metacognition in information discovery and information utilization in digital environments should involve process planning, process monitoring and process evaluation. Metacognitive regulation prompts users to formulate prompts independently, critically examine the reasonableness and rationality of AI-generated responses, and reflectively transfer and integrate the results into their existing cognitive systems (Wu et al., 2025). Learners can use metacognitive strategies to orient, monitor, comprehend, broaden their perspective, and consolidate, thus moving them away from being passive receivers of information to active, persistent inquiry, independent thinking, and assessment of and validation of information sources (source engagement) (Singh et al., 2025). Metacognitive awareness is a cognitive upstream antecedent that influences the usefulness and ease of using AI technology in the eyes of students (Alshammari et al., 2026). Failure to have metacognitive monitoring can lead to surface learning and a dependence on algorithmic outputs when using GenAI.

Hypothesis 2: Metacognition affects the students' Grade Point Average (GPA).

The path coefficient (β = 0.12) shows a very low relationship between Metacognition and GPA. The t-statistic (t = 0.94) is also far below the critical t value of 1.96 and the significance value (p = 0.690) is far above the 0.05 threshold, providing further evidence of the lack of meaningful effect. Furthermore, the 95% confidence interval (95% CI [-0.20, 0.23]) contains the null value, which again suggests that there is no definite direction or significant effect at the population level. Collectively, these statistics suggest that there is a strong empirical foundation indicating that metacognition is not a direct predictor of students' GPAs.

The result is consistent with Eriyani (2020) in the context of metacognitive awareness in Indonesian higher education where the result shows a very weak correlation between metacognitive awareness and students' GPA. When there is no significant difference between metacognitive ability and learning results, it is assumed that there is no metacognitive regulation by the learner in practice, yet. Despite being sensitive to their own confusion and being able to assess when they are not understanding what they are learning, students are generally passive in the monitoring, evaluation and

revision of ineffective learning strategies. This passive awareness also results in a failure to take action when there is confusion, which allows for the development of a learning gap that will negatively impact the overall assessment.

This result, however, differs from the results of Abdelrahman (2020), Alfaraj et al. (2026), and Musullulu et al. (2025) who showed that metacognition is one of the main predictors of academic achievement. The studies looked at metacognition as well as other factors that predicted GPA (cognitive control, confidence, grit, growth mindset, and appropriate task-execution beliefs). This is supported by the systematic review conducted by Tjalla and Dewi (2026) which indicated that metacognitive strategy to be used to get the maximum academic results needs to be integrated with other psychological factors such as motivational efficacy, grit, growth mindset, perseverance, and academic self-efficacy. However, metacognition is not an isolated entity but must work optimally with other supporting factors such as perseverance, a growth mindset and self-efficacy to enhance learning outcomes. Metacognitive awareness is combined with these psychological and environmental factors, which is a significant element to predict and optimize students' academic achievement.

Hypothesis 3: The use of AI in learning will impact student grade point averages..

This result suggests that the direct link between AI-based Information-Seeking Behavior and GPA is very small (path coefficient ($\beta = 0.03$)), and practically not explanatory. This is supported by the value of the t-statistic ($t = 0.78$) which is significantly lower than the critical t value of 1.96, and the value of the significance ($p = 0.24$) which is greater than 0.05. Moreover, the 95% confidence interval (95% CI [-0.07, 0.13]) which crosses zero, also supports the absence of a stable and significant direct effect at the population level. Combined, the statistical results can give a solid scientific answer to the question of whether there is a direct relationship between AI based Information Seeking Behavior and students' GPA.

This is congruent with Hassan (2026), who found that the use of AI without guidance and supervision does not always positively impact academic outcomes. Liu, et al. (2025) also noted that while ChatGPT incorporation enhances task-specific mastery, it also has a lesser effect on cumulative assessment outcomes like GPA, which are tightly linked to other external assessment factors. The findings indicate that the use of AI by students is not directly correlated with academic performance but rather, must be supported by other factors—such as academic self-efficacy and critical thinking (Yudhoyono et al., 2026), and cognitive load management or deep self-regulation (Iqbal et al., 2025)—which require further examination.

Hypothesis 4: AI information seeking behavior is a mediator between metacognition and GPA.

The path coefficient for the indirect effect (0.02) is very small and close to zero, suggesting a very small mediation effect in testing the indirect effect. This is confirmed by the t ($t = 0.76$) which is well below the critical value t ($t = 1.96$) and the significance value ($p = 0.24$) which is greater than the critical value p ($p = 0.05$). The lack of a mediating effect is well supported with a 95% CI for the indirect effect of zero (-0.03, 0.06), signifying that the indirect effect is not stable and is not statistically significant. Put together, these empirical indicators give a solid scientific foundation to the conclusion that the construct of AI-based Information-Seeking Behavior is not acting as a mediating variable in Metacognition — GPA relationship.

In fact, students who have high metacognitive awareness and regulation are more sensitive to their own learning needs, and are more active in using AI technology as an information exploration tool. But this cognitive process ends at the data gathering stage.

This activity with AI that is not followed by deep cognitive processing, critical thinking and substantive integration into the completion of academic tasks is not a demonstration of content knowledge that is reflected in an increased cumulative GPA. AI-based information-seeking behavior is not therefore considered to be an intervening variable that connects internal cognitive factors (metacognition) and external factors of success (GPA). The finding is consistent with the view that using AI does not necessarily lead to students' formal learning achievement. In this study, metacognitive awareness did not play a significant role in the GPA of the sample, suggesting that there are more dominant executive and psychological driving factors influencing the learning outcome, either directly or indirectly through interaction with AI.

The findings in this study validate the use of Artificial Intelligence (AI) in the higher-education learning ecosystem as something well beyond the passive or non-engaged use of technology, and must instead be conducted wisely, systematically and purposefully. In this context, Adamakis and Rachiotis (2025) emphasize the need for deepening the overall AI literacy to guarantee the success of AI integration. While this literacy cannot be limited to the technical-operational level (from being able to build a prompt in technical terms), it must also include critical understanding and ethical considerations. The critical dimension calls for students to process information metacognitively (monitor, filter, analyze for possible algorithmic bias) and the ethical dimension checks the students' integrity and intellectual responsibility. This comprehensive literacy base is essential for enabling users to explore information in a meaningful way with AI tools.

This finding aligns with the findings of Fakhlina et al. (2025) who highlight the crucial role that human verification, critical evaluation and contextual adjustments play when dealing with AI-generated data. The failure to find a positive impact of AI on students' GPAs in this study is because there is no such "deep cognitive" intervention where information-seeking is transformed into a substantive understanding of the content. To put it another way, students' metacognition and potential for metacognitive ability will have a measurable effect on their GPA only if they are supported by other executive variables, such as critical capacity, cognitive evaluation, and comprehensive information-synthesis skills. However, the phenomenon requires a response from the higher education institution, namely by making curriculum changes so that graduates are prepared to deal with the dynamic information world (Srirahayu et al., 2026).

Finally, the AI-literacy review by Ng et al. (2021) provides further evidence that the integration of AI into education is a crucial aspect of shifting students' capabilities, rather than simply using AI as a means to operate and use the technology technically. However, the optimal application of AI demands an integrated approach, which involves learning about seven fundamental aspects, as proposed by Hackl et al. (2026): technical, applied, critical thinking, ethical, social, interdisciplinary integration, and legal. This is reaffirmed by Cern (2024), who highlights that the fundamentals of AI literacy are precisely in fortifying the ethical dimension, social reflection and moral consideration. Thus, the issue of incorporating AI literacy into the curriculum and the institutional policies of higher education is not just a matter of technological training for the competitive job market, but a crucial imperative to prepare students for the future with a critical consciousness and sense of social responsibility, so that they can wisely, humanely and ethically face the technological disruption.

Conclusion

The study found that metacognitive awareness is the most dominating predictor that significantly causes the Information-Seeking Behavior in students when using AI. However, neither Metacognition nor Information-Seeking Behavior was directly and indirectly shown to be a significant factor that influenced Cumulative GPA. The results show that in general, students' use of AI is limited to surface-level information exploration, meaning that the cognitive-regulation process only goes as far as gathering information, and does not automatically translate into formal academic achievement.

In theory, these findings add to the educational-technology literature by helping prove that the relationship between metacognition, the use of AI, and academic achievement is not linear. Having an impact on learning outcomes needs to bridge the variables of metacognitive capacity and interaction with AI technology, as well as other psychological drivers. In practice, universities and teachers are urged to create focused and scaffolded learning environments and programs rather than simply encouraging the use of AI in the classroom. These frameworks should steer students away from the easy retrieval of information, and towards the more advanced cognitive processing tasks, including critical analysis, problem-solving etc.

The limitation of this study is that it has focused on the general information-seeking behaviour, used only one achievement indicator (cumulative GPA) and the population scope is limited. The use of more than one higher education institution with various institutional features and academic-cultural backgrounds is therefore recommended for future research to expand population. Future research is also invited to include non-cognitive executive factors (e.g., academic self-efficacy, grit, growth mindset) and consider the effects of the use of AI on short term, task-specific performance, to gain a more holistic understanding of the true effect of AI technology on student learning outcomes.

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