



Self-Regulated Learning in Generative Artificial Intelligence-Assisted Science Learning: A Factor Structure Analysis

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Abstract: This study examines students' self-regulated learning (SRL) in Generative Artificial Intelligence (GenAI)-assisted science learning. The purpose of this study was to identify the characteristics of students' SRL and examine the empirically established factor structure of SRL in a GenAI-assisted learning environment. This study employed a quantitative survey design involving 154 students. Data were analyzed using descriptive statistics, Exploratory Factor Analysis (EFA), and Confirmatory Factor Analysis (CFA). The results showed that students exhibited moderate to high levels of SRL, with the motivation dimension showing stronger performance compared to the metacognitive aspect. EFA identified six initial factors, while CFA confirmed the final five dimensions: metacognitive planning and goal setting, help-seeking and resource management, self-regulation difficulties, intrinsic motivation, and self-monitoring and evaluation. The measurement model demonstrated satisfactory validity, reliability, and model fit. Other findings also showed that science learning can support students' SRL development, but still requires structured support to strengthen metacognitive skills. This study contributes to the development of SRL measurement in GenAI-based science learning.

Keywords: confirmatory factor analysis; factor structure; generative artificial intelligence; science learning; self-regulated learning

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INTRODUCTION

The development of GenAI offers new opportunities in science learning, where concept exploration, instant feedback, and independent idea development are now easily possible (Bahroun et al., 2023; Cooper, 2023; Mao et al., 2024; Rahim & Widodo, 2024). However, GenAI also increases the complexity of the learning process, as students are required to actively manage interactions with intelligent systems through processes such as formulating questions, evaluating responses, and verifying the accuracy of information (Memon & Kwan, 2025; Nathaniel et al., 2025; Yang et al., 2025). Thus, the effectiveness of GenAI depends not only on the availability of the technology but is also largely determined by students' SRL abilities in managing their learning process. Despite this, various studies indicate that students still experience difficulties in optimally utilizing GenAI (Azevedo et al., 2022; Cai & Tian, 2026). Students tend to use GenAI passively, lacking critical evaluation of the information they receive, and experiencing difficulties designing effective prompts and monitoring learning strategies. These findings indicate that interacting with GenAI demands a more complex form of self-regulation than conventional or digital learning in general. In the context of inquiry-based science learning, these demands are even greater because students are expected to plan, monitor, and reflect on their scientific thinking processes independently (Omarchevska et al., 2022; Zhou et al., 2025). Without adequate SRL skills, GenAI's potential to improve learning quality risks being underutilized.

However, currently developed SRL models and instruments are still dominated by conventional or online learning contexts in general (Broadbent et al., 2023; Edisherashvili et al., 2022). Classic SRL models emphasize metacognitive, motivational, and behavioral dimensions, but do not fully accommodate the iterative, adaptive, and dialogue-based characteristics of human interaction with AI systems. Several recent studies have developed SRL instruments in various contexts, such as the validation of the CEMOR in elementary school students (Ebbes et al., 2024) and the development of the SRLI-U in college students (López-Angulo et al., 2024), and have begun to explore the use of AI in SRL (X. Liu et al., 2025). Theoretically, the integration of SRL in human-computer interaction contexts has also been proposed (Azevedo & Gašević, 2019; Ifenthaler & Yau, 2020). However, research specifically examining how SRL processes manifest and structure in direct interactions with GenAI in science learning remains very limited (Xu et al., 2025; Zhang et al., 2025; Zhang & Chen, 2026). These limitations highlight the gap between existing SRL theory and its practice in GenAI-based learning. This gap

becomes even more apparent when examined within the context of Indonesian education, which has a teacher-centered approach and uneven development of student learning independence. Inquiry-based learning has begun, but many obstacles remain for teachers and students.

Meanwhile, GenAI is developing rapidly without consistently strengthening students' critical thinking and self-regulation skills. This can lead to inequities, as students, in addition to facing the demands of inquiry-based learning, also need to improve their ability to interact with GenAI. Therefore, SRL in this context needs to be understood as a contextual process, influenced by local social, cultural, and educational practices. Based on this gap, this study aims to examine in depth the characteristics and manifestations of students' SRL in the context of GenAI-assisted science learning, and to analyze how the SRL factor structure is empirically formed based on students' interactions with GenAI. In contrast to previous research that tends to focus on developing instruments or partial measurements, this research emphasizes understanding the self-regulatory processes that emerge directly in human-AI interactions, including activities such as prompt formulation, response evaluation, and information verification. Thus, this research is expected to contribute to 1) developing a theoretical framework for SRL in the context of interactions with GenAI; 2) providing empirical evidence regarding the structure of SRL in AI-based learning environments, and; 3) strengthening contextual understanding of the dynamics of SRL in science education in Indonesia. In line with these objectives, this research is formulated in two main questions: 1) What are the characteristics and manifestations of students' SRL in the context of GenAI-assisted science learning? and 2) How is the structure of SRL factors empirically formed based on students' interactions with GenAI in science learning?

METHODS

This study adopted a quantitative exploratory research design (Lim, 2025). This design is appropriate for investigating emerging phenomena where theoretical structures are not yet established, particularly in the context of human-AI interaction in learning. This study integrated conceptual and empirical analyses to ensure alignment between theoretical constructs and observed data, thereby strengthening construct validity. Conceptual analysis was used to identify the characteristics and manifestations of SRL based on a literature review, while empirical analysis was conducted using a multivariate statistical approach to uncover the latent structure of SRL based on actual student data. Thus, this design directly supports the research questions by 1) identifying the characteristics of SRL through conceptual analysis and 2) examining its empirical structure through multivariate modeling.

The respondents were 154 junior high school students aged 12-15 from various regions in Indonesia, studying grades seven through nine in public and Islamic schools. This diverse background was intentionally selected to capture a broad spectrum of learning experiences using GenAI in Indonesia. To ensure the data's relevance to the research objectives, strict inclusion criteria were established: participants had to have experience using GenAI tools (such as ChatGPT or Gemini) while studying science for at least one semester. Furthermore, the entire learning process was supervised by science teachers with between 5 and 20 years of teaching experience to ensure consistent teaching quality. The sample selection technique is convenience sampling, which is appropriate for exploratory studies focusing on specific populations with defined characteristics, such as students with prior experience using GenAI in learning contexts. Although this technique limits generalizability, it is suitable for capturing initial empirical patterns in underexplored contexts, which is consistent with the exploratory nature of this study. To enhance internal consistency, all participants were drawn from schools implementing the same national curriculum framework. This aimed to maintain consistency in the learning context, ensuring that the data remained representative of the phenomenon of human-AI interaction in the school environment.

The sample size of 154 participants was deemed to meet the sample adequacy criteria for the planned statistical analysis. The sample size was considered adequate for exploratory factor analysis, meeting minimum thresholds recommended in educational research, and was further evaluated using KMO and communality criteria to ensure factorability. To ensure the stability of the factor structure and empirical validity, researchers will conduct a Kaiser-Meyer-Olkin (KMO) test and ensure that the communality value is at an acceptable level before further analysis. Furthermore, the sample size used in this study is sufficient to achieve 80% statistical power for models of moderate complexity in PLS-SEM. This study has received ethical clearance from the relevant institutional review board. Furthermore, all participants and their guardians provided written informed consent before data collection began. Participation was voluntary, and all data were anonymized to ensure confidentiality and compliance with ethical standards in educational research.

The instrument in this study was developed to capture and empirically represent students' SRL in the context of GenAI-assisted science learning. The instrument was developed to operationalize SRL constructs within GenAI-assisted science learning contexts. Each item reflects observable self-regulatory behaviors during interaction with GenAI. The instrument development process adhered to basic psychometric measurement principles to ensure construct clarity and indicator consistency. This approach enabled the link between the SRL conceptual framework and empirical data obtained from student responses. The initial stage of instrument

development was conducted through an in-depth literature review of various established SRL theories, particularly those encompassing metacognitive, motivational, and behavioral dimensions. Indicators were derived from established SRL frameworks covering metacognitive, motivational, and behavioral dimensions (Cho & Jonassen, 2009; Cleary & Zimmerman, 2012; Kaplan, 2008; Mokhtari & Reichard, 2002; Nguyen & Gu, 2013; Pekrun et al., 2002; Pintrich, 2004; Pintrich & De Groot, 1990; Teng & Zhang, 2016). Each dimension was analyzed to identify key components such as planning, monitoring, evaluation, motivational control, and learning strategies. These components were then mapped to the context of students' interactions with GenAI as a learning partner. This mapping process ensured content validity by aligning SRL constructs with context-specific behaviors in GenAI interaction. The result of this stage is conceptual indicators that have been contextualized and are ready for operationalization.

The next stage was to operationalize the indicators into measurable instrument items. Each indicator was developed into a statement describing student behavior when interacting with GenAI in science learning. The initial instrument consisted of 48 statements using a 7-point Likert scale (1 = does not describe me very well to 7 = describes me very well). The use of a 7-point scale aimed to increase measurement sensitivity and capture variations in students' levels of self-regulation. Each item was designed using contextual and understandable language without compromising construct accuracy. The resulting instrument enabled exploration of the SRL structure through factor analysis. Overall, this process contributed to the development of an SRL framework relevant to GenAI-assisted science learning. Data collection was conducted in two stages: instrument validation and field administration. The initial stage involved a comprehensive literature review to identify relevant SRL dimensions and indicators, which served as the basis for instrument development. Content validity was then assessed through expert judgment involving experts in science education, learning technology, and educational psychology. The experts evaluated the relevance and clarity of each item to ensure alignment with the intended constructs. Based on expert feedback, several items were revised to improve conceptual clarity and wording. This process ensured that the instrument was conceptually appropriate before empirical data collection.

The revised instrument was subsequently administered to students using a digital questionnaire distributed through an online platform such as Google Forms. Data collection was conducted in science learning contexts that explicitly involved the use of GenAI, ensuring that responses reflected students' actual learning experiences. Participants were informed about the study purpose, and confidentiality was assured to reduce response bias. The questionnaire was completed in a structured manner with guidance from teachers or researchers to ensure item comprehension. Data quality was ensured through screening for invalid response patterns. The collected data used a 7-point Likert scale and were exported to a spreadsheet for further statistical analysis. Data analysis was conducted in alignment with the research questions. Descriptive statistical analysis was used to describe students' SRL levels in general and across each dimension. Descriptive statistics (mean, standard deviation, skewness, and kurtosis) were used to characterize SRL patterns. Internal consistency was assessed using Cronbach's alpha (≥ 0.70), and item validity was evaluated using corrected item-total correlation (≥ 0.30). Items that did not meet this criterion were considered for removal before further analysis.

To answer the second research question, factor analysis was conducted to identify and confirm the empirical structure of SRL in GenAI-assisted science learning. EFA using Principal Axis Factoring with Promax rotation was conducted to identify the underlying factor structure, with factorability assessed using KMO and Bartlett's test. The extraction method used was Principal Axis Factoring (PAF) with Promax rotation. The factor selection criteria were based on factor loading values ≥ 0.50 and communality ≥ 0.40 . Furthermore, CFA using PLS-SEM was conducted to confirm the measurement model and strengthen construct validity through convergent and discriminant validity assessment. Convergent validity was assessed through outer loading values ≥ 0.70 , Average Variance Extracted (AVE) ≥ 0.50 , and Composite Reliability (CR) ≥ 0.70 , while discriminant validity was tested using the Fornell-Larcker criteria. Model fit was also evaluated using the Standardized Root Mean Square Residual (SRMR) value ≤ 0.08 to ensure the model has a good level of fit.

RESULT AND DISCUSSION

A descriptive analysis was conducted on 154 respondents using a 7-point Likert scale (1 = does not describe me very well to 7 = describes me very well). This analysis aimed to map the general trend of students' SRL levels in the context of GenAI-assisted science learning. Statistics calculated included the mean, standard deviation, minimum, maximum, skewness, and kurtosis. An evaluation of the data distribution was conducted to ensure that there were no extreme deviations that could affect the interpretation of the results. The results of the total SRL score analysis are presented in Table 1.

Table 1. Descriptive Statistics of

Total SRL Scores	
Statistics	Value
N	154
Mean	4.8007
Standard Deviation	1.8503
Minimum	1
Maximum	7
Skewness	-0.5154
Kurtosis	-0.8811

Based on Table 1, the average total SRL score indicates that students generally have a moderate to high level of self-regulation. The standard deviation indicates significant variation in responses between students, but still within reasonable limits. The skewness value indicates a slightly left-skewed distribution, meaning more students have SRL scores above the average than below the average. The kurtosis value indicates a relatively flat distribution (platykurtic), but still within the acceptable range of normality (± 2). Overall, the data distribution meets the assumption of univariate normality and is suitable for further analysis. These findings indicate that in the context of GenAI-assisted science learning, students' SRL characteristics tend to develop positively. The finding that students' SRL characteristics tend to develop positively indicates that most students have acquired basic skills in managing their learning process independently. The average score in the moderate to high category indicates that students are beginning to plan, monitor, and evaluate their learning process more systematically. This situation may be influenced by the use of GenAI-assisted learning technology, which allows students to receive rapid and flexible feedback (Z. Liu et al., 2025; Lu et al., 2026). With this support, students have a greater opportunity to develop learning strategies tailored to their needs. Furthermore, the left-skewed distribution of scores indicates that most students demonstrated relatively good levels of self-regulation. This indicates that GenAI-assisted learning has the potential to strengthen students' SRL characteristics in science learning.

These findings align with research that stated that SRL develops when students have the opportunity to control their learning process independently (Hatala et al., 2023; Heaysman & Kramarski, 2022). Furthermore, prior studies highlight the important role of intrinsic motivation and metacognitive strategies in enhancing students' self-regulation abilities (Kwarikunda et al., 2022; Urban & Urban, 2023). However, several previous studies have shown that not all students can develop SRL optimally without adequate scaffolding (Dever et al., 2024; van der Graaf et al., 2023). For example, Monique Boekaerts' and others' research showed that students with low motivation tended to have difficulty self-regulating their learning process (Boekaerts, 1995; Ilishkina et al., 2022; Zhu & Doo, 2021). This suggests that although the SRL characteristics of the students in this study developed positively, there may still be groups of students who require additional support. Therefore, the use of GenAI in learning needs to be accompanied by a structured pedagogical strategy so that students' SRL development can take place more evenly. To understand the specific manifestations of SRL, descriptive analysis was also conducted on each SRL dimension. This analysis aimed to identify the most dominant and relatively weaker dimensions in GenAI-based learning interactions. The results are presented in Table 2.

Table 2. Descriptive Statistics per SRL Dimension

Dimension	N	Minimum	Maximum	Mean	Std. Dev	Skewness	Kurtosis
M1	154	2.00	7.00	4.4535	1.05641	-0.072	-0.327
M2	154	1.00	7.00	4.5130	1.42021	-0.089	-0.441
M3	154	2.00	7.00	4.4610	1.04945	0.070	-0.523
M4	154	1.50	7.00	4.8166	1.08391	-0.105	-0.179
MO1	154	1.60	7.00	4.8299	0.99798	-0.416	-0.101
MO2	154	2.20	6.60	4.7571	0.80390	-0.699	0.626
MO3	154	1.00	7.00	5.1753	1.32106	-0.600	-0.288
MO4	154	2.00	7.00	5.4459	1.23153	-0.780	-0.031
B1	154	2.43	7.00	4.8312	0.94697	-0.485	-0.325
B2	154	2.00	7.00	4.9818	1.10433	-0.478	-0.269

Based on Table 2, all SRL dimensions had mean scores above 4.45, indicating that student self-regulation emerged consistently across various aspects of learning. The dimensions with the highest scores were MO3 (intrinsic task interest) and MO4 (self-reinforcement), indicating that students' motivational aspects were relatively strong in GenAI-assisted learning. High scores on MO3 indicate that students have an intrinsic interest in the learning tasks they undertake. Meanwhile, high scores on MO4 indicate that students can control their emotions and motivate themselves during the learning process. This indicates that students learn not only due to external demands but also due to strong internal motivation. Thus, GenAI-assisted learning appears to

encourage more independent learning engagement and intrinsic motivation in students.

The MO3 and MO4 dimensions reflect students' ability to develop intrinsic motivation and self-reinforcement during the learning process. Students with high scores on the intrinsic task interest dimension typically demonstrate high curiosity, active engagement in tasks, and a tendency to explore material independently. Meanwhile, students with high scores on the self-reinforcement dimension tend to manage negative emotions, maintain learning focus, and motivate themselves when facing difficulties. This finding aligns with research stating that intrinsic motivation and emotional regulation are important components in the development of SRL (Van Pham, 2024; Schunk & Zimmerman, 2013; Urban & Urban, 2023). Furthermore, students with high intrinsic motivation tend to be more persistent and active in the learning process (Kamberi, 2025; Pintrich, 2004). Teachers can identify students with high scores on this dimension through indicators such as enthusiasm when working on assignments, the ability to maintain learning focus, and the willingness to complete tasks without external encouragement. Therefore, this motivational dimension is an important indicator in understanding student engagement in GenAI-assisted learning.

On the other hand, dimensions M1 (plan) and M3 (self-monitor) showed relatively lower mean scores compared to the other dimensions, although they were still in the moderate to high category. Dimension M1 relates to students' ability to develop a learning plan that includes goals, strategies, and learning steps. Meanwhile, dimension M3 relates to students' ability to monitor learning progress and adjust strategies. The relatively lower mean scores indicate that students' learning planning and monitoring abilities are not as strong as the motivational aspect. This indicates that students may have high learning motivation but are not yet fully capable of systematically planning and monitoring their learning process. Therefore, students' metacognitive aspects still require strengthening in GenAI-assisted learning.

The planning and monitoring dimensions of learning are important components of self-regulation, requiring more complex metacognitive skills (Chang et al., 2023; Sharma et al., 2024). Students with high scores on the planning dimension are typically able to set learning goals, determine appropriate strategies, and manage study time effectively. Meanwhile, students with high scores on the self-monitoring dimension can evaluate their learning progress and adjust their strategies. However, previous research indicates that metacognitive skills often develop more slowly than the motivational aspects. Planning and monitoring are advanced stages in the SRL cycle that require ongoing practice. Teachers can identify students with low scores on this dimension through indicators such as a lack of learning planning, difficulty managing time, and an inability to evaluate learning outcomes. Therefore, strengthening metacognitive strategies needs to be a priority in GenAI-assisted learning.

The findings of this study can be further analyzed based on Barry J. Zimmerman's SRL theory. Zimmerman explains that SRL consists of three main phases: planning, implementation, and reflection. In the context of this study, dimensions MO3 and MO4 relate to the implementation and reflection phases, indicating a high level of learning engagement. Meanwhile, dimensions M1 and M3 relate to the planning and monitoring phases, which require advanced metacognitive skills. The difference in strength between these dimensions indicates that students are stronger in the motivational aspect than in the metacognitive aspect. This indicates that students have a high drive to learn, but still need support in developing systematic learning strategies.

This finding can also be explained by the SRL model proposed by Paul R. Pintrich, which emphasizes the interaction between motivational, cognitive, and behavioral aspects. Pintrich stated that intrinsic motivation is often the initial factor that drives students to engage in self-regulation (Garcia & Pintrich, 1994). In this study, high scores on the motivational dimension indicate that students have an internal readiness to learn independently. However, low scores on the planning and monitoring dimensions indicate that students still need scaffolding in developing learning strategies (Shao et al., 2023; van der Graaf et al., 2023). This suggests that GenAI-assisted learning can be utilized to strengthen students' metacognitive skills. Thus, integrating GenAI into learning can help balance students' motivational and metacognitive aspects.

Holistically, the results of this study indicate that students' SRL in GenAI-assisted science learning develops unevenly across dimensions. The motivational aspect demonstrated higher strength than the metacognitive and behavioral aspects. This suggests that students are psychologically ready for independent learning, but still require support in systematic learning strategies. These findings imply that teachers need to design learning that not only increases motivation but also strengthens students' planning and monitoring abilities. GenAI can be utilized as a tool to provide automated feedback and help students plan their learning (Haindl & Weinberger, 2024; Kubsch et al., 2025). This way, students' SRL development can be carried out more comprehensively and sustainably.

In the context of GenAI-assisted science learning, the SRL characteristics found in this study indicate that students are beginning to develop self-regulation skills related to scientific thinking processes and the investigation of scientific concepts. Science learning requires students to understand abstract concepts, conduct scientific reasoning, and connect phenomena to theoretical concepts, thus requiring more complex self-regulation skills than general learning (Hartelt & Martens, 2024; Ho et al., 2022). The use of GenAI allows students to ask exploratory questions, receive instant feedback, and independently revise their understanding

throughout the learning process (Perifanou & Economides, 2025). Recent research has shown that GenAI can support SRL processes by providing personalized learning goals, problem-solving strategies, and adaptive feedback that help students develop deeper conceptual understanding (Ma et al., 2026; Wang et al., 2026; Xu et al., 2025). Furthermore, recent studies in science learning have shown that the use of AI-based chatbots with metacognitive feedback can improve students' ability to monitor conceptual understanding and correct misconceptions during science learning (Yin et al., 2024). Therefore, the SRL characteristics emerging in this study can be interpreted as indicating that GenAI plays a role in strengthening student engagement in the scientific inquiry process and independent exploration of scientific concepts.

In addition to SRL characteristics, SRL in science learning is also evident in students' ability to manage problem-solving processes and reflect on their understanding of scientific concepts (Ho et al., 2022; Wang et al., 2023). Science learning generally involves investigative activities, data analysis, and concept evaluation, which require strong monitoring and reflection skills. Research over the past five years has shown that integrating GenAI into learning can enhance critical thinking and problem-solving skills through more adaptive self-regulation mechanisms (Rahim et al., 2024; Zhou et al., 2024). Furthermore, recent systematic research has shown that the use of AI in learning helps students develop independent learning strategies through collaborative interactions between humans and technology (Järvelä et al., 2023). However, several studies have also emphasized that the development of SRL in AI-based learning is often uneven, with students tending to be stronger at the implementation stage than at the planning and reflection stages (Samsonovich et al., 2024; Xu et al., 2026). This finding is consistent with the results of this study, which showed that the motivational dimension is stronger than the metacognitive dimension. Thus, the manifestation of SRL in GenAI-assisted science learning indicates that students have high motivational readiness but still need pedagogical support to develop metacognitive abilities more systematically.

Before further interpretation, the instrument was tested for validity and reliability. The validity test used item-total correlation with a criterion of ≥ 0.30 . One statement was found not to meet the criteria and was therefore removed from further analysis. After this refinement, the final instrument consisted of 47 items. The Cronbach's alpha value (0.938) indicates that the instrument has very high internal consistency. This value far exceeds the minimum threshold of 0.70 recommended in educational research. This indicates that the SRL indicators consistently measure the same construct. Thus, interpretation of students' SRL characteristics and manifestations is based on a psychometrically valid instrument. The results indicate that students exhibit moderate to high levels of SRL. SRL manifestations were strongest in dimensions MO3 (intrinsic interest in the task) and MO4 (self-reinforcement), indicating the strength of students' internal motivation and regulation. Furthermore, high scores on the intrinsic interest in the task dimension indicate that students have an intrinsic interest in learning the task, allowing them to engage in learning activities without relying on external stimuli. Meanwhile, high scores on the self-enhancement dimension indicate that students can control negative emotions, maintain motivation, and strengthen themselves throughout the learning process. These findings suggest that students are not only motivated to learn but also able to manage their emotional and motivational states independently. Therefore, integrating GenAI into science learning has the potential to facilitate more adaptive learning engagement and support the development of student self-regulation more comprehensively.

The implications of these findings for instrument development indicate that the motivational dimension, particularly intrinsic task interest and self-reinforcement, is an important component that needs to be maintained in the structure of SRL instruments. High scores on both dimensions indicate that the indicators used can consistently capture students' motivational characteristics. This suggests that intrinsic motivation and emotional regulation are relevant components in the context of GenAI-assisted learning. Furthermore, the stability of scores on both dimensions also indicates that the indicators used have good sensitivity in measuring variations in students' self-regulation abilities. These findings reinforce the importance of incorporating emotional regulation and motivational aspects in the development of modern SRL instruments. Therefore, the instrument developed in this study has the potential to be used in technology-based learning contexts more broadly.

On the other hand, the relatively lower scores on the planning and monitoring dimensions offer important implications for instrument development. Dimensions M1 (plan) and M3 (self-monitor) indicate that metacognitive indicators still need to be strengthened to more optimally capture variations in student abilities. This suggests that further instrument development should consider adding more specific indicators related to learning planning and monitoring. Furthermore, the variation in scores on these dimensions indicates that students' metacognitive abilities are still developing and require more sensitive measurement. Strengthening indicators in the metacognitive dimension can also help produce a more balanced instrument across dimensions. Thus, the results of this study provide an important contribution to the improvement of SRL instruments based on GenAI-assisted learning.

To answer the second research question, the analysis was conducted through two main stages: Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). These two stages aim to identify and confirm the factor structure of SRL in the context of GenAI-assisted science learning. Prior to the factor analysis, a data feasibility test was conducted using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and

Bartlett's Test of Sphericity. The KMO test was used to determine the adequacy of the sample and the suitability of the data for factor analysis, while Bartlett's Test was used to test whether there was a correlation between items in the instrument. The KMO value is 0.905. This indicates that the sample size is in the excellent (valuable) category and meets the requirements for factor analysis. Furthermore, the Bartlett's Sphericity Test shows a chi-square value of 4929.345 with a significance level of 0.000 (less than 0.05), indicating a significant correlation between items. Thus, the data are considered valid and meet the assumptions for proceeding to the factor analysis stage.

The next step was factor extraction using the Principal Axis Factoring (PAF) method. This method focused on identifying latent constructs based on shared variance between indicators. The number of factors was determined by considering eigenvalues greater than 1, scree plot analysis, and conceptual interpretation of each formed factor. Given that SRL dimensions are theoretically correlated, factor rotation used the oblique Promax method to allow for correlations between latent constructs. Item selection criteria were based on factor loadings ≥ 0.50 , communalities ≥ 0.40 , and the absence of significant cross-loadings between factors. Based on the results of the exploratory factor analysis, not all items showed adequate loadings on the formed factors. Some items did not have significant factor loadings on any factor or showed loadings below the established minimum threshold. Therefore, these items were eliminated from the model to obtain a more stable and interpretable factor structure. After the elimination process, six factors formed the SRL structure in GenAI-assisted science learning. These factors reflect the cognitive, motivational, and self-regulation dimensions of students.

Exploratory factor analysis yielded an initial six-factor structure representing key dimensions of students' SRL in GenAI-assisted science learning. These factors are 1) metacognitive planning and goal setting; 2) help-seeking and resource management; 3) self-regulation difficulties; 4) intrinsic motivation; 5) environmental structuring; and 6) self-monitoring and evaluation. These factors capture cognitive, motivational, and behavioral aspects of students' regulation when interacting with GenAI. However, this initial structure is considered tentative and requires further validation to ensure construct stability and measurement validity. Several items were removed due to low factor loadings (<0.50), weak communalities (<0.40), or substantial cross-loadings, resulting in a more parsimonious and interpretable factor structure. The refined factor structure resulting from the EFA was then tested using Confirmatory Factor Analysis (CFA). This step was carried out to verify construct validity and determine how well the model fit the field data (model fit). CFA results indicated that several indicators did not meet validity criteria. Specifically, item SRL23 exhibited a negative loading and was removed. In addition, the Environmental Structuring construct demonstrated insufficient convergent validity (low AVE) and reliability, leading to its exclusion from the final model. Following model refinement, a final five-factor structure was established, representing a more robust and empirically supported model of SRL in GenAI-assisted science learning. The final factor structure, including retained items and constructs, is presented in [Table 3](#).

Table 3. Final Factor Structure of SRL

Factor	Factor Name	Item
F1	Metacognitive Planning and Goal Setting	1, 2, 3, 4, 5, 7, 8, 9, 10, 15
F2	Help-Seeking and Resource Management	26, 34, 37, 44, 45, 46
F3	Self-Regulation Difficulties	6, 14, 19, 48
F4	Intrinsic Motivation	31, 33
F5	Self-Monitoring and Evaluation	11, 16

Based on [Table 4](#), the final SRL structure consists of five main dimensions. This structure demonstrates that SRL in GenAI-assisted science learning comprehensively encompasses metacognitive, motivational, behavioral, and self-regulatory aspects of students. To provide a clearer interpretation of each dimension, examples of statements representing each factor are presented in [Table 5](#). These examples provide a more concrete picture of how each dimension of SRL is represented in the context of GenAI-assisted science learning.

Table 4. Examples of Statement Items for Each Dimension

Factor	Factor Name	Example of Statement Items
F1	Metacognitive Planning and Goal Setting	I plan my approach before I start learning with GenAI. I manage my time and deadlines when completing tasks using GenAI as a learning support. I choose the most appropriate learning method before starting, including when to use GenAI.
F2	Help-Seeking and Resource Management	I organize my study space to be comfortable when using GenAI. When I do not understand, I seek help from teachers, peers, or GenAI. When facing difficulties, I immediately seek help, including through AI.
F3	Self-Regulation Difficulties	I find it difficult to plan appropriate learning strategies when using GenAI. I do not realize that my learning strategies are ineffective when using GenAI. I tend to ignore self-evaluation even after using GenAI in learning.
F4	Intrinsic Motivation	I am interested in exploring science topics beyond the classroom using AI. I am interested in learning science through experiments or AI-based exploration.
F5	Self-Monitoring and Evaluation	I check whether I understand the material during learning, including after receiving explanations from GenAI. I review my learning outcomes, including information obtained from GenAI.

These five dimensions were then further analyzed to ensure that each construct has good measurement quality and can empirically represent the SRL concept. Therefore, after the final factor structure is obtained, the next step is to test the measurement model through convergent validity. This test aims to ensure that each indicator within the construct adequately and consistently explains the construct's variance. The Average Variance Extracted (AVE) value indicates how much of the indicator's variance is explained by the latent construct, while composite reliability measures the internal consistency of the indicators within each construct. A construct is considered to have convergent validity if the AVE value is greater than 0.50 and the composite reliability value is greater than 0.70. The results of the convergent validity and construct reliability tests in this study are presented in [Table 5](#).

Table 5. Convergent Validity and Construct Reliability Results

Construct	AVE	Composite Reliability
Metacognitive Planning and Goal Setting	0.527	0.917
Help-Seeking and Resource Management	0.622	0.907
Self-Regulation Difficulties	0.576	0.842
Intrinsic Motivation	0.823	0.903
Self-Monitoring and Evaluation	0.835	0.910

Based on [Table 5](#), all constructs in the SRL model demonstrate adequate convergent validity. This indicates that the indicators forming each construct can represent the latent variables consistently and measurably. The Metacognitive Planning and Goal Setting dimensions demonstrate strong internal consistency, thus reliably describing students' ability to plan and set learning goals. Similarly, the Help-Seeking and Resource Management and Self-Regulation Difficulties dimensions demonstrate good measurement quality, indicating that the indicators within these two constructs accurately capture variations in student learning behavior. These findings demonstrate that behavioral aspects and barriers to self-regulation can be reliably measured in the context of GenAI-assisted learning.

Furthermore, the Intrinsic Motivation and Self-Monitoring and Evaluation dimensions demonstrate very strong construct quality in explaining their constituent indicators. This indicates that intrinsic motivation and self-monitoring abilities are relatively stable components of students' SRL structure. Strength in these two dimensions also indicates that students tend to have high internal drive and strong learning reflection skills in GenAI-assisted learning. Overall, these results indicate that the developed measurement model has good convergent validity and reliability. Therefore, the developed SRL instrument can be used to comprehensively and consistently measure student self-regulation in the context of artificial intelligence-based learning.

After all constructs met the convergent validity and reliability criteria, the next step was to test discriminant validity to ensure that each construct had clear conceptual distinctions. Discriminant validity is necessary to ensure that the measured constructs truly represent distinct concepts and do not overlap. Discriminant validity testing in this study was conducted using the Fornell-Larcker criterion, which compares the square root of the Average Variance Extracted (AVE) with the correlation between constructs. A construct is

considered to have discriminant validity if the square root of the AVE is greater than the correlation between the other constructs. This test is crucial to ensure the quality of the measurement model before further interpretation of the relationships between constructs. The results of the discriminant validity test using the Fornell-Larcker criterion are presented in [Table 6](#).

Table 6. Discriminant Validity (Fornell-Larcker)

Construct	MPGS	HSRM	SRD	IM	SME
Metacognitive Planning and Goal Setting	0.726	0.485	-0.380	0.532	0.627
Help-Seeking and Resource Management	0.485	0.789	-0.221	0.468	0.527
Self-Regulation Difficulties	-0.380	-0.221	0.759	-0.205	-0.172
Intrinsic Motivation	0.532	0.468	-0.205	0.907	0.423
Self-Monitoring and Evaluation	0.627	0.527	-0.172	0.423	0.914

Note: Diagonal values (bold) = $\sqrt{\text{AVE}}$ AND Off-diagonal values = correlation between constructs

Discriminant validity testing was carried out using the Fornell-Larcker criteria. According to Table 9, the square root of the AVE for each construct is greater than the correlation between the other constructs. This indicates that each construct has a strong ability to differentiate itself from other constructs in the research model. The self-monitoring and intrinsic motivation constructs demonstrated the highest square root of the AVE values, indicating that they possess very strong discriminant validity. Furthermore, the self-regulation difficulties construct showed a negative correlation with the other constructs, indicating that self-regulation difficulties are inversely related to students' self-regulation abilities. In general, these findings show that the measurement model has fulfilled the requirements of discriminant validity, meaning that each construct empirically has a unique conceptual identity and differs from one another.

After convergent and discriminant validity have been met, the next step is to evaluate the overall model suitability through a model fit test. The model fit evaluation aims to ensure that the developed model has a good level of fit with the empirical data. In this study, model fit was evaluated using the Standardized Root Mean Square Residual (SRMR) value. The SRMR value is used to measure the difference between the observed covariance matrix and the covariance matrix predicted by the model. An SRMR value of 0.05 indicates that the model has an adequate level of fit (good fit). This suggests that the discrepancy between the observed and model-implied covariance matrices is minimal, confirming that the proposed SRL model provides an adequate representation of the empirical data. The satisfactory model fit further supports the structural validity and stability of the identified factors, indicating that the measurement model is robust and appropriate for subsequent analysis. After the measurement model is declared valid, reliable, and has a good level of fit, the next step is to interpret the relationships between constructs. This interpretation aims to understand how the SRL dimensions interact in GenAI-assisted science learning. Analysis of the relationships between constructs provides insight into the role of each dimension in supporting students' self-regulation abilities. Furthermore, this interpretation also helps explain the contribution of each construct to the overall development of SRL.

The findings of this study indicate that the metacognitive dimension of Planning and Goal Setting has a strong positive relationship with Self-Monitoring and Evaluation and Intrinsic Motivation. These results align with Zimmerman's SRL theory, which emphasizes that the effectiveness of the forethought phase is crucial for an individual's success in monitoring actions and engaging in self-reflection ([Najafinejad et al., 2021](#); [Zimmerman, 1990](#)). Students who can set clear goals and design learning strategies tend to be more active in monitoring their learning progress ([Lourenço & Paiva, 2024](#); [Radović et al., 2024](#)). However, the findings of this study provide a new perspective by demonstrating that in a GenAI-assisted learning ecosystem, this relationship shifts to a more dynamic and cyclical nature. The presence of GenAI allows students to continuously recalibrate their learning strategies thanks to real-time feedback, ultimately strengthening ongoing self-regulation processes. Furthermore, the correlation between metacognitive planning and intrinsic motivation indicates that precise goal setting can sharpen cognitive control and trigger stronger internal drives in students. This emphasizes that metacognitive capacity serves as a crucial foundation for developing adaptive self-regulation mechanisms in an AI-based educational environment ([Pratiwi et al., 2025](#)).

The relationships between Help-Seeking and Resource Management with other dimensions, particularly Metacognitive Planning and Goal Setting and Self-Monitoring and Evaluation, also showed significant patterns. These findings support Pintrich's SRL model, which confirms that the ability to manage learning resources is a fundamental and integral element of the overall self-regulation mechanism ([Schunk, 2005](#); [Shamdas, 2023](#); [von Keyserlingk et al., 2025](#)). However, this study not only confirms existing theories but also extends them. In the context of GenAI-assisted learning, help-seeking behavior is no longer limited to social interactions with teachers or peers but expands to interactions with artificial intelligence systems ([Chen & Law, 2025](#)). In contrast to traditional help-seeking, which tends to be reactive, the AI-assisted help-seeking in this study demonstrated more proactive, iterative, and student-controlled characteristics. In this context, GenAI acts not merely as a data provider but rather as a co-regulator, facilitating the development of more adaptive and flexible learning

strategies. These findings redefine the concept of help-seeking within the SRL framework by incorporating artificial intelligence as part of an external regulatory system that students can internalize.

The Self-Regulation Difficulties dimension showed a negative correlation with all other constructs, indicating that the higher a student's self-regulation skills, the lower the level of difficulty they experienced. This pattern is consistent with Bandura's social cognitive theory, which emphasizes the interrelationship between self-regulation, self-efficacy, and control over the learning process (Aguilar & Kim, 2019; Bandura, 2010; Jaya & Sucipto, 2023). However, in the context of GenAI-assisted learning, these findings provide a more critical perspective. While previous research has shown that digital technology can support learning (Baidoo-Anu & Ansah, 2023), the results of this study indicate that these benefits are not universal. GenAI tends to reinforce existing differences in self-regulation skills, with students with high SRL experiencing greater benefits, while students with low SRL continue to experience difficulties. These findings challenge the assumption that AI technology automatically improves learning and also highlight the potential for new gaps in self-regulation skills to emerge.

Overall, the five-factor structure generated in this study provides an important contribution to the development of SRL theory in the context of AI-based learning. Unlike traditional SRL models that position teachers as the primary source of external regulation, the findings of this study demonstrate that GenAI can function as a distributed regulatory system, simultaneously supporting planning, monitoring, and evaluation processes. This expands the SRL conceptual framework from one centered on internal regulation to a hybrid regulatory model involving continuous interaction between humans and AI systems. Thus, SRL in this context can be understood not only as self-regulation but also as a form of co-regulation between humans and artificial intelligence. From a practical perspective, these findings have important implications for the implementation of learning, particularly in the context of education in Indonesia. The integration of GenAI into learning cannot focus solely on the technological aspect but must also be accompanied by the development of students' self-regulation skills. Given that learning practices in Indonesia are still heavily influenced by a teacher-centered approach, the use of GenAI without appropriate pedagogical strategies has the potential to produce less than optimal impact. Therefore, teachers need to design learning that explicitly trains skills such as formulating prompts, critically evaluating AI responses, and reflecting on the learning process. This suggests that the successful integration of GenAI depends heavily on the alignment between technological innovation and pedagogical transformation.

Furthermore, these findings underscore the importance of considering context in understanding SRL. In the Indonesian educational context, where the development of students' self-regulation skills varies, GenAI can serve as a supportive tool while also potentially widening the gap. Therefore, the implementation of AI in education needs to be accompanied by interventions specifically targeted at strengthening students' metacognitive and self-regulation skills. This reinforces the view that SRL is a contextual construct influenced by social, cultural, and learning practices. Finally, this research not only provides empirical contributions by identifying the structure of SRL in GenAI-assisted learning, but also offers theoretical refinements regarding how self-regulation develops in interactions with intelligent systems. GenAI can no longer be viewed simply as a learning tool, but rather as a transformational element that reshapes the dynamics of student self-regulation, while presenting new opportunities and challenges for future educational practices.

CONCLUSION

Based on the research results, students demonstrated moderate to high levels of SRL in the context of GenAI-assisted science learning, as indicated by a positive trend in students' motivational and self-regulation aspects. The empirically formed SRL structure consists of five main dimensions, namely metacognitive planning and goal setting, help-seeking and resource management, self-regulation difficulties, intrinsic motivation, and self-monitoring and evaluation, which illustrate the integration of metacognitive, motivational, and behavioral aspects in GenAI-based learning. All constructs in the measurement model were shown to have good convergent validity, discriminant validity, and reliability, and the model also showed an adequate fit with the empirical data based on the model fit value. The relationship between constructs indicates that metacognitive planning abilities play an important role in improving students' intrinsic motivation, self-monitoring, and help-seeking strategies in GenAI-assisted learning. In addition, the self-regulation difficulties dimension showed a negative relationship with other constructs, indicating that the better students' self-regulation, the lower the learning difficulties they experienced. Overall, these findings suggest that implementing GenAI in science learning has the potential to strengthen students' self-regulation skills by encouraging more independent, reflective, and adaptive learning engagement. The implications of this research suggest that GenAI integration serves not only as a source of information but also as a learning partner that can help students develop more effective and sustainable learning strategies.

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