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Descriptive Analysis of Self-Regulated Learning among Physics Education Students in AI-Assisted Learning Contexts

Andi Reski[1], Elisabeth Tuto Lamataro[1], Jeffri Parrangan[1]
[1]Physics Education Department, Universitas Musamus Merauke, Indonesia

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*Corresponding author: andireski_fkip@unmus.ac.id

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ABSTRACT

Artificial intelligence (AI) is increasingly used in higher education to support learning activities, including information seeking, concept exploration, and problem-solving. Understanding students' self-regulated learning (SRL) characteristics in AI-assisted learning contexts can provide insights into their reported learning practices and inform pedagogical design. This study aimed to describe SRL characteristics among Physics Education students in AI-assisted learning contexts. A quantitative descriptive survey was conducted involving 28 Physics Education students, using a saturated sampling technique. Data were collected through a 27-item questionnaire using a four-point Likert scale. Content validity was assessed by two experts using Gregory's formula, yielding a coefficient of 0.90, indicating high content validity. Data were analyzed descriptively by calculating percentage scores across five SRL indicators: self-efficacy, initiative, responsibility, learning resources, and learning strategies. The results showed that all five indicators were classified as high according to the study's interpretation criteria. Learning resources obtained the highest percentage (81.25%), followed by initiative (80.95%), self-efficacy (79.17%), responsibility (78.57%), and learning strategies (75.74%). These findings indicate relatively positive self-reported SRL characteristics across all five indicators, although differences were observed between them. The comparatively lower percentage for learning strategies suggests an opportunity to strengthen students' strategy selection, progress monitoring, and reflection on learning processes. Pedagogically, students may benefit from structured activities that encourage critical evaluation of AI-generated information, verification against credible sources, and reflection on problem-solving strategies. However, the findings represent students' self-reported responses and do not establish that AI use improves SRL. Further research using observational, longitudinal, or experimental designs is needed to examine students' actual SRL practices and the relationship between AI use and SRL.

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INTRODUCTION

The development of technology in the 21st century has brought significant changes in various aspects of life, including the field of education. The integration of digital technology in the learning process is growing as an effort to expand access to information, support learning activities, and create a more interactive learning experience. Various educational applications, platforms, and software have been developed to facilitate the learning process and encourage students to use technology effectively (Hidayat et al., 2022; Wahyuni et al., 2022). One of the technological developments that is increasingly receiving attention in the world of education is artificial intelligence (AI), which has the potential to provide learning support flexibly and according to user needs.

AI-based applications can help students access and process information, understand learning materials, complete academic assignments, and explore alternative problem-solving((Jo, 2024; Miao & Holmes, 2023). Through its ability to generate explanations, present examples, summarize information, and respond to questions, AI can be used as a learning assistant to support students' academic activities. The use of AI has become relevant in physics education because physics learning requires the ability to understand abstract concepts, perform mathematical reasoning, interpret physical phenomena, and solve problems systematically (Al-Kamzari & Alias, 2026; Roziqin et al., 2026). In this context, AI has the potential to help students explore alternative explanations, clarify difficult concepts that are difficult to understand, and obtain feedback during the problem-solving process. In addition, AI allows students to obtain learning support outside of lectures according to their individual needs (Rienties et al., 2025; Sandu et al., 2024). However, the availability of AI-based support does not necessarily guarantee that students are able to use information appropriately or be actively involved in managing the learning process.

The use of AI in learning thus needs to be studied not only in terms of the availability of technology, but also in terms of the characteristics of students in organizing their learning process. Access to AI-generated explanations and problem-solving alternatives can open up learning opportunities, but students still need to identify their learning needs, manage learning activities, evaluate information, and determine appropriate strategies. AI can support such processes, but excessive reliance on AI-generated answers without independent evaluation has the potential to limit students' involvement in reasoning, critical thinking, and decision-making (Lee et al., 2024). Therefore, self-regulated learning (SRL) is an important aspect to be studied in the context of AI-assisted learning. This assessment is needed to obtain an overview of the characteristics of learning settings that students report when AI is used as a learning assistant, without assuming that the use of the technology automatically improves SRL capabilities.

Self-regulated learning is a process when individuals actively manage their cognitive, motivational, and behavioral aspects to achieve learning goals (Panadero, 2017; Zimmerman, 2002). In this study, SRL was examined through five indicators, namely self-efficacy, initiative, responsibility, learning resources, and learning strategies. Self-efficacy refers to students' confidence in their ability to complete learning tasks; initiative is related to the willingness to initiate and develop learning activities; responsibility is related to responsibility in managing learning processes and outcomes; learning resources refers to the ability to identify and utilize relevant learning resources; while learning strategies are related to the selection and use of strategies that support the achievement of learning objectives. These five indicators are relevant in the context of AI-assisted learning because students need to have confidence in their own abilities, take the initiative in learning, take responsibility for the learning process, evaluate the information obtained, and choose appropriate learning strategies. Although AI can provide additional explanations, examples, and sources of information, students are still responsible for assessing the relevance and accuracy of the information generated by AI and determining how to use it appropriately (Albadarin et al., 2024; Lee et al., 2024; Ng et al., 2024). Thus, the assessment of these five indicators can provide a more detailed picture of the characteristics of SRL reported by students in the context of using AI as a learning assistant.

The relevance of the SRL assessment is also supported by the results of preliminary interviews with several Physics Education students at Musamus University. The interviews indicate that there are problems in the management of learning activities, especially delays in completing and collecting assignments given by lecturers. These initial findings show that the aspects of responsibility, initiative,

and regulation of learning activities need further attention. However, the interviews are exploratory so they cannot be used to describe the condition of all Physics Education students. In the midst of increasing access to AI, it is also necessary to understand the characteristics of SRL reported by students when using AI as a learning assistant. This condition provides a contextual basis to examine the SRL of Physics Education students without assuming that the use of AI always has a positive or negative impact on their ability to manage the learning process.

Previous research has examined the use of AI in education, among others related to the application of technology, user acceptance, and learning outcomes. A number of studies have also begun to explore the relationship between generative AI and SRL (Hey et al., 2024; Jin et al., 2023; Reski et al., 2025). However, further descriptive studies are still needed to understand the characteristics of certain SRL indicators in students in the context of specific disciplines and institutions. In Physics Education students, the assessment of self-efficacy, initiative, responsibility, learning resources, and learning strategies separately can provide a more detailed picture of the aspects of learning settings that they report in the context of AI-assisted learning. This is important because access to AI-generated explanations and solutions does not automatically show how students perceive their learning abilities, initiate learning activities, manage responsibilities, utilize learning resources, or choose learning strategies. Therefore, mapping of the five indicators is needed to identify variations in the characteristics of SRL reported by students as well as aspects that have the potential to be of concern in the development of AI-assisted physics learning.

Based on this description, this study aims to describe five indicators of self-regulated learning, namely self-efficacy, initiative, responsibility, learning resources, and learning strategies, in Physics Education students at Musamus University who use AI as a learning assistant. Using a quantitative approach through a descriptive survey, this study presents a profile of students' SRL characteristics based on responses to the five indicators measured. The contribution of this research lies in providing a contextually specific descriptive picture of the five indicators, as well as being the basis for pedagogical considerations to support the responsible, critical, and reflective use of AI in physics learning.

METHOD

This study uses a quantitative approach with a descriptive survey design to examine the use of artificial intelligence (AI) and self-regulated learning among Physics Education students at Musamus University. Respondents were selected using a saturated sampling technique, which involves all members of the population who meet the predetermined inclusion criteria. The participants involved were active students of Physics Education who had studied for more than three semesters and had experience using at least one application from each of the following six categories: text processing (ChatGPT, Perplexity, Grammarly, and Gemini), reference management (Mendeley and Zotero), learning evaluation (Kahoot! and Quizizz), data analysis (Tableau and IBM Watson), plagiarism detection (Turnitin and Copyscape), and computation and scientific simulation (Wolfram Alpha and MATLAB). The categories and examples of applications were compiled by referring to the use of digital devices and AI-related applications in academic learning, as well as guidelines for the use of generative artificial intelligence in higher education published by the Directorate General of Higher Education, Research, and Technology (Directorate General of Higher Education, Research, and Technology, 2024). These inclusion criteria were set to ensure that participants have experience using various devices that support various academic learning activities. Based on these criteria, as many as 28 students participated in this study.

Data was collected using a non-test instrument in the form of a questionnaire which at the initial stage consisted of 30 statements with a four-point Likert scale, namely strongly disagree, disagree, agree, and strongly agree. The mapping of self-regulated learning (SRL) indicators in this study is based on a theoretical framework of learning regulation that emphasizes the involvement of motivational, cognitive, metacognitive, and behavioral aspects in the learning process (Panadero, 2017; Zimmerman, 2000). The development of indicators also considers the dimensions of learning process management, information search, and the use of learning strategies discussed by (Erdogan & Senemoglu, 2016).

Based on this foundation, SRL in this study is operationalized through five indicators, namely self-efficacy, initiative, responsibility, learning resources, and learning strategies. The five indicators are used to organize students' responses to the questionnaire and describe the characteristics of SRL reported by students in the context of AI-assisted learning. This mapping is an operationalization of constructs that are adjusted to the research context, not a direct reproduction of one standard SRL instrument. (Panadero, 2017; Roll & Barhak-Rabinowitz, 2023; Zimmerman, 2002). The instrument blueprint used in this study is presented in Table 1.

Table 1. Instrument Grid Before Validation

No.	Indicator	Item Number	Quantity
1	Self-efficacy	1,2,3,4,5,6	6
2	Initiative	7,8,9,10,11,12	6
3	Responsibility	13,14,15,16,17,18	6
4	Learning resources	19,20,21,22,23,24	6
5	Learning strategies	25,26,27,28,29,30	6

Before being used in the research, the instrument first underwent content validation by two validators who had a background in Physics Education. According to Gregory (2007), content validity indicates the extent to which the items in an instrument are able to represent the measured aspects comprehensively and proportionally. In this study, content validation aims to ensure the suitability of each statement item with the measured self-regulated learning indicator. The validator assessment includes linguistic aspects, the suitability of the content with the indicators, and the readability of the instrument by potential respondents. The assessment of linguistic and readability aspects is used as a basis for providing improvement input, while the calculation of the content validity coefficient using the Gregory formula is based on the level of agreement between the two validators in assessing the relevance of each statement item. Based on the results of the assessment, several statements are revised to be more concise, clear, and do not cause double interpretation. The results of the assessment of the validity of the instrument's contents by the two validators are presented in Table 2.

Table 2. Validation Results

Assessment Tabulation Expert Validation		Validator I	
		Irrelevant (Skor 1-2)	Relevant (Skor 3-4)
Validator II	Irrelevant (Skor 1-2)	A 0	B 1
	Relevant (Skor 3-4)	C 2	D 27

Gregory's (2007) formula is used to calculate the content validity coefficient based on the agreement between the two validators on the relevance of each statement item. The results of the assessment are grouped into four categories, namely A (both validators assess the item as irrelevant), B (the first validator assesses it relevant and the second validator does not relevant), C (the first validator assesses it irrelevant and the second validator relevant), and D (the two validators assess the item relevant). The content validity coefficient is calculated using the following formula, as presented in equation (1).

$$V = \frac{D}{A+B+C+D} = \frac{27}{0+1+2+27} = 0{,}9 \quad (1)$$

The content validity coefficient was interpreted based on the following criteria: 0.80–1.00 (very high), 0.60–0.79 (high), 0.40–0.59 (medium), 0.20–0.39 (low), and 0.00–0.19 (very low). Based on the results of the calculation using the Gregory formula, a content validity coefficient of 0.90 was obtained which was included in the very high category. However, the three statements indicating disagreement

between the two validators (categories B and C) were not maintained because after the revision, the two validators still did not reach an agreement on the relevance of the item. Therefore, the final instrument used in the study consisted of 27 statements with a distribution of six items in the first indicator (self-confidence), three items in the second indicator (initiative), six items in the third indicator (responsibility), six items in the fourth indicator (learning resources), and six items in the fifth indicator (learning strategies). However, testing the reliability of the instrument has not yet become part of the procedure of this study. Therefore, the findings of the study are interpreted based on the results of descriptive analysis and evidence of the validity of the content obtained through expert assessment while the internal consistency of the instrument can be the focus of further testing in future research.

Data analysis was carried out descriptively by calculating students' self-regulated learning (SRL) scores on each indicator, then converting them into percentage form to describe the level of achievement of each indicator. This study involved 28 students who filled in 27 statements using a four-point Likert scale. The percentage for each indicator is calculated by comparing the actual scores of all respondents for that indicator against the maximum possible score, using the formula in equation (2).

$$P_j = \frac{S_j}{28 \; x \; k_j \; x \; 4} \; x \; 100\% \quad (2)$$

With, P_j is the percentage for each indicator, S_j is the actual score of all respondents on each indicator and k_j is the number of statement items on the indicator. Furthermore, the percentages obtained are interpreted into three categories, namely low, medium, and high. The interpretation criteria were adapted from (Mahama et al., 2022) and adjusted to the characteristics of the research instrument. The determination of categories refers to the percentage range based on the minimum and maximum scores of the Likert scale with a minimum score of 1 for each item and a maximum score of 4. The interpretation criteria used to categorize the results of each indicator are presented in Table 3.

Table 3. Percentage-Based Interpretation Criteria

Level	Percentage Range
Low	25,00 - 49,97
Moderate	50,00 - 74,97
High	75,00 – 100

It was processed based on the number of respondents, the number of items, and the Likert scale in this study; the categorization foundation was adapted from Mahama et al. (2022).

RESULTS AND DISCUSSION

Instrument Validation Results

Instrument Validation Results The research instrument in the form of a self-regulated learning (SRL) questionnaire in the initial stage consisted of 30 statements. Content validation was carried out by two validators who had a background in Physics Education to assess the suitability of the items with the measured indicators, linguistic aspects, and readability of the instruments. Based on the results of the assessment, several items were revised to increase clarity and reduce the potential for double interpretation. The content validity analysis using the Gregory formula resulted in a coefficient of 0.90, which is included in the very high category based on the interpretation criteria used in this study. However, the three statements in the initiative indicator were not maintained because the two validators had not reached an agreement on the relevance of the items after the revision process. Thus, the final instrument used in data collection consisted of 27 statements. The Gregory coefficient of 0.90 indicates the level of agreement of validators in assessing the relevance of the item, but it cannot be used as evidence of the reliability or internal consistency of the instrument. Therefore, the findings of the study are interpreted based on the results of the descriptive analysis and the evidence of the validity of the content obtained through expert assessment.

Descriptive Results of Student Self-Regulated Learning

Descriptive analysis was conducted to identify the characteristics of self-regulated learning (SRL) reported by 28 Physics Education students in the context of artificial intelligence (AI)-assisted learning. The analysis focused on five indicators, namely self-efficacy, initiative, responsibility, learning resources, and learning strategies. The response score for each indicator was converted into a percentage of the maximum score that could be obtained, then interpreted based on the low, medium, and high category criteria as presented in Table 2. The results of the analysis showed that the percentage of the five indicators was in the range of 75.74%–81.25% and all of them were in the high category based on the research interpretation criteria. Descriptively, the findings showed that student responses were relatively positive on all SRL indicators measured by percentage variations between indicators. Details of scores, percentages, and categories of each indicator are presented in Table 4.

Table 4. Descriptive Statistics of Students' Self-Regulated Learning Indicators in AI-Assisted Learning

No.	Indicator	S_j	$28\ x\ K_j\ x\ 4$	P_j	Category
1	Self-efficacy	535	672	79.17%	High
2	Initiative	272	336	80.95%	High
3	Responsibility	528	672	78.57%	High
4	Learning resources	546	672	81.25%	High
5	Learning strategies	509	672	75.74%	High

Based on Table 4 above, it can be seen that the highest percentage of learning resources indicates that the aspect of learning resource use gets a relatively higher score compared to other indicators. On the other hand, a relatively lower percentage of learning strategies indicates a difference in students' response to aspects of learning strategies. However, this difference cannot be directly interpreted as a difference in actual ability or as evidence of the influence of the use of AI on SRL, because the data was obtained through self-report questionnaires and the study was not designed to test the cause-and-effect relationship.

Self-Efficacy

The self-efficacy indicator obtained a score of 535, with a percentage of 79.17% and was in the high category. These findings indicate that students report relatively positive beliefs about their abilities in the context of the learning being studied. In a social-cognitive perspective, self-efficacy refers to an individual's belief in his or her ability to organize and carry out the necessary actions to achieve certain goals. Zimmerman (2000) explained that self-efficacy is related to learning motivation, activity choices, effort, and perseverance in the face of difficulties. Thus, confidence in one's ability is one of the important aspects in the learning regulatory process.

In the context of artificial intelligence-assisted learning (AI), access to alternative explanations and problem-solving examples has the potential to provide support for students when facing difficulties in understanding physics concepts. This potential is in line with the findings of (Wang et al., 2023), which show a positive relationship between AI capabilities in college and student self-efficacy. An experimental study by Urban et al. (2024) also found that the use of ChatGPT increased students' self-efficacy in completing creative problem-solving tasks compared to conditions without the help of ChatGPT. However, the results of the study were obtained through a different design and context of this study. Therefore, a score of 79.17% in this study cannot be used to conclude that the use of AI increases self-efficacy. These findings are more appropriately understood as an overview of student beliefs reported through questionnaires.

The pedagogical implication is that AI-assisted learning needs to be designed so that students not only receive answers, but also build confidence based on conceptual understanding and successful completion of assignments independently. Lecturers can provide physics problems gradually, ask students to explain the reasons behind each completion step, and use feedback to help students evaluate their learning progress. Although AI can provide assistance during the problem-solving process, students still need to be given the opportunity to complete assignments without the help of AI and

reflect on their understanding. This is important so that the confidence formed does not only depend on the existence of technology, but also reflects students' perception of their own abilities.

Initiative

The initiative indicator obtained a score of 272 with a percentage of 80.95% and was included in the high category. These results show that students report a relatively positive tendency in the aspect of learning initiative measured in this study. In the framework of self-regulated learning (SRL), initiative can be understood as the tendency to initiate learning activities, formulate learning needs, seek information, and take action when facing difficulties. This aspect is related to the process of goal setting and planning in Zimmerman's SRL model (2000), although initiative is not a dimension that is used uniformly in all SRL models.

In the context of artificial intelligence (AI)-assisted learning, students have the opportunity to explore questions, ask for additional explanations, and consider alternative approaches to learning physics concepts. Ng et al. (2024) through a pilot study in science learning, found that ChatGPT-based chatbots designed to support SRL have the potential to support students' behavioral engagement and learning motivation. The findings provide an idea that AI can be leveraged to facilitate a more targeted learning process. However, (Darvishi et al., 2024) show that students may also tend to rely on AI assistance without fully learning from the feedback provided. Thus, the availability of AI does not necessarily indicate that students have developed independent learning initiatives. Continuous initiatives involve students' ability to determine what needs to be learned, ask relevant questions, and assess the usefulness of the information obtained.

From a pedagogical perspective, lecturers can encourage initiative through open-ended assignments that require students to formulate questions, determine the information needed, and explain the reasons for choosing problem-solving strategies. AI can be used as a means of exploration, while students remain responsible for the direction of the investigation and the validity of its conclusions. For example, in physics learning, students may be asked to identify conceptual problems, formulate questions to explore these problems through AI, and then verify answers with textbooks or other scientific sources. Although the percentage of these indicators is relatively high, self-report data does not show how often students actually initiate learning activities or seek information without external encouragement. Therefore, these results need to be interpreted as the tendency of learning initiatives reported by students, rather than as direct evidence of actual learning behavior or the causal influence of AI use.

Responsibility

In artificial intelligence (AI)-assisted learning, learning responsibility is also related to students' ability to evaluate AI outputs, check the accuracy of information, and use technology assistance ethically. A study on generative AI literacy in higher education students (Chen et al., 2025) shows the importance of being able to evaluate AI outputs as well as understanding the ethical aspects of their use in academic contexts. These findings are relevant to learning responsibility because the use of AI involves not only the ability to obtain information, but also critical consideration of the quality and feasibility of the information. However, the high score on the responsibility indicator in this study does not in itself prove that students always verify information or use AI responsibly in every learning situation.

The pedagogical implication is that lecturers need to integrate activities that require students to be accountable for their learning processes and outcomes. In physics problem-solving tasks. For example, students may be asked to explain the conceptual basis of AI-provided answers, compare them with relevant references, and identify possible reasoning errors. This activity is in line with the importance of assessment and reflection in learning regulation, while supporting the development of critical AI literacy. Panadero et al. (2017) through a meta-analysis of self-assessment, also showed that self-assessment activities have the potential to support SRL. Thus, students need to be given the opportunity to evaluate the results of their own work, review the problem-solving process, and explain how AI is used in the process. However, the effectiveness of this approach needs to be tested through research that observes the learning process directly, not just based on questionnaire responses.

Learning Resources

The learning resources indicator obtained a score of 546 with a percentage of 81.25%, making it the indicator with the highest percentage in this study. These findings show that students report a relatively positive tendency in the aspect of using the learning resources measured. The management of learning resources is a relevant aspect of self-regulated learning (SRL), because students need to identify, obtain, and utilize information to support their learning goals. Panadero (2017) explained that various SRL models include aspects of environmental management and learning resources. In this context, learning resources indicators are used to describe students' responses to aspects of learning resource use measured in research instruments.

In artificial intelligence (AI)-assisted learning, the technology can provide access to additional explanations. For example, in the application of concepts and alternative representations of physics materials. Chen et al. (2025) found that students use generative AI to support various academic tasks, while showing concern for the evaluation of AI outputs and the need for ethical use guidelines. Meanwhile, Choi et al (2025) identified various factors and strategies that students use when assessing the credibility of AI-generated information. Both studies emphasize the importance of distinguishing access to information from the ability to evaluate information quality. Thus, the highest percentage of learning resources indicators in this study cannot be interpreted as evidence that students already have strong resource evaluation skills or that AI directly improves learning resource management skills.

Pedagogically, these results can be the basis for developing activities that not only emphasize access to information, but also evaluation of its quality. Lecturers can ask students to compare AI answers with textbooks or scientific articles, check the suitability of explanations with physics principles, and provide reasons for the choice of sources used. For example, in learning thermodynamics concepts, students can compare AI explanations of heat transfer with explanations in physics textbooks, then identify the suitability of concepts, the accuracy of terms, and supporting evidence. This strategy is in line with the recommendations of McGrew et al. (2024) regarding the need for explicit learning to help students evaluate the credibility of online information sources. Thus, the use of learning resources can be directed at developing information literacy and critical assessment, rather than simply obtaining answers quickly. The interpretation of results still needs to be limited to the perceptions reported by students because this study does not directly measure the quality of the sources they use.

Pedagogically, these results can be the basis for developing activities that not only emphasize access to information, but also evaluation of its quality. Lecturers can ask students to compare AI answers with textbooks or scientific articles, check the suitability of explanations with physics principles, and provide reasons for the choice of sources used. For example, in learning thermodynamics concepts, students can compare AI explanations of heat transfer with explanations in physics textbooks, then identify the suitability of concepts, the accuracy of terms, and supporting evidence. This strategy is in line with the recommendations of McGrew et al. (2024) regarding the need for explicit learning to help students evaluate the credibility of online information sources. Thus, the use of learning resources can be directed at developing information literacy and critical assessment, rather than simply obtaining answers quickly. The interpretation of the results still needs to be limited to the perceptions reported by students because this study does not directly measure the quality of the sources used.

Learning Strategies

The learning strategies indicator obtained a score of 509 with a percentage of 75.74%, which is the lowest score compared to the other four indicators. However, the percentage is still in the high category based on the interpretation criteria used in this study. Descriptively, these results show a relative variation in student responses to the five self-regulated learning (SRL) indicators, with the learning strategy aspect obtaining a relatively lower percentage. These findings can be the basis for identifying aspects of learning strategies that need more attention in learning design. However, the percentage difference between the indicators cannot be directly interpreted as a difference in the actual level of students' ability, because the results of the study are based on questionnaire responses and predetermined percentage categories.

Learning strategies are an important aspect of self-regulated learning (SRL) because they include the selection and application of cognitive and metacognitive approaches to achieve learning goals. Panadero (2017) explained that SRL models emphasize the process of planning, monitoring, control, and reflection that help students set strategies according to the demands of the task. In physics learning, this process can be seen when students determine relevant principles, develop problem-solving steps, examine units, evaluate the fairness of results, and revise strategies if the initial approach is unsuccessful.

In the context of artificial intelligence (AI)-assisted learning, Xu et al (2025) found that metacognitive support explicitly provided in a generative AI-based learning environment can support students' SRL abilities, especially in the use of learning strategies and self-evaluation. These findings suggest that the existence of AI needs to be accompanied by a learning design that helps students organize and evaluate their thinking processes. In contrast, Krupp et al. (2024), in a ChatGPT-assisted physics problem-solving study, found that some students received incorrect AI answers as correct answers and showed limited reflective involvement. These results are relevant to physics learning because the final answer that seems reasonable is not necessarily supported by reasoning or the application of proper physics principles. However, this study does not measure the process of using AI directly, so it cannot determine whether the pattern occurs in respondents.

The pedagogical implication is that lecturers can design assignments that require students to explain the initial strategies before using AI, compare the strategies with AI-generated alternatives, and reflect on the strengths and limitations of each approach. In physics problem-solving, students can also be asked to examine the consistency of equations, units, and final results with relevant conceptual principles. This approach is in line with the results of Xu et al. (2025), which emphasize the importance of metacognitive support to help students strategize and evaluate their learning processes in a generative AI environment. Therefore, a relatively lower percentage of indicators than other indicators may be a consideration to pay more attention to learning strategy monitoring and evaluation activities. However, these findings do not suggest that AI fails to support students' learning strategies; conclusions about the role of AI require research designs that specifically examine their relationships or influences.

CONCLUSION AND SUGGESTION

This study describes the characteristics of self-regulated learning (SRL) reported by 28 Physics Education students in the context of artificial intelligence (AI)-assisted learning. The results of the descriptive analysis showed that the five SRL indicators were in the high category, with percentages ranging from 75.74% to 81.25%. The learning resources indicator obtained the highest percentage (81.25%), followed by initiative (80.95%), self-efficacy (79.17%), responsibility (78.57%), and learning strategies (75.74%). These results showed that student responses were relatively positive in all indicators measured, although there were variations in the percentage of indicators. Relatively speaking, the aspect of using learning resources obtained the highest score, while learning strategies obtained the lowest scores and can be considered in designing learning that emphasizes the selection of cognitive strategies, monitoring understanding, evaluation of problem-solving, and learning reflection.

In the context of AI-assisted learning, these findings confirm the importance of a pedagogical approach that not only facilitates access to information, but also encourages students to verify AI outputs, evaluate the credibility of sources, explain conceptual reasons, and account for the strategies used in solving physics problems. However, the results need to be interpreted by considering the descriptive design and the use of self-report questionnaires. The percentages obtained represent students' responses to the measured indicators, rather than direct observations of their learning behaviors, so they cannot be used to conclude that the use of AI directly improves SRL. Further research is recommended to combine questionnaires with interviews, observations, or analysis of learning activities, as well as to use longitudinal or experimental designs to further examine the relationship between AI use and SRL of Physics Education students.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

AUTHOR CONTRIBUTIONS STATEMENT

Conceptualization, A.R. and E.T.L.; methodology, A.R. and J.P..; instrument development and validation, A.R., E.T.L. and J.P.; data collection, E.T.L; formal analysis, A.R; writing—original draft preparation, A.R., E.T.L., J.P.; writing—review and editing, A.R.; supervision, E.T.L. and J.P. All authors have read and approved the final version of the manuscript.

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DECLARATION OF GENERATIVE AI SOURCES

During the preparation of this manuscript, the authors used ChatGPT (OpenAI) to assist with language refinement, academic writing improvement, and the organization and revision of certain sections of the manuscript. The use of this tool was limited to writing assistance and did not involve the generation or manipulation of research data, statistical results, or research findings. All AI-assisted content was critically reviewed, revised, and verified by the authors. The authors take full responsibility for the accuracy, originality, and integrity of the final content of this manuscript.

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