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Generative AI and Self-Regulated Learning in Higher Education: A Narrative Review with Implications for Physics Education

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ABSTRACT

The rapid development of generative artificial intelligence (generative AI) is reshaping how students access information, complete academic tasks, and regulate learning in higher education. This narrative literature review synthesizes and critically interprets evidence on the role of generative AI in learning strategies and learning independence, with provisional implications for physics education. Searches were conducted in SINTA, Scopus, Web of Science, ScienceDirect, and SpringerLink for publications from 2020 to 2026, with Google Scholar used as a supplementary source. Twelve peer-reviewed publications were included in the main thematic synthesis and interpreted through Zimmerman's self-regulated learning framework, Bandura's social cognitive theory, and cognitive load theory as an additional perspective. The findings indicate that generative AI may support goal setting, feedback, motivation, strategy development, self-efficacy, and reflection. However, its benefits depend on active engagement, self-regulation capacity, output quality, and metacognitive guidance. Unguided use may encourage cognitive offloading, weaken self-monitoring, and improve task performance without equivalent conceptual understanding. Because only one study directly involved university students in physics or physics education, the implications remain provisional. Physics education programs should therefore promote independent problem solving, critical evaluation, transparent AI use, and structured metacognitive guidance.

Keywords: Generative Artificial Intelligence; Self-Regulated Learning; Learning Strategies; Educational Psychology; Physics Education.

INTRODUCTION

The rapid development of generative artificial intelligence (generative AI) has introduced new forms of interaction in higher education. Generative AI systems can generate explanations, respond to questions, provide immediate feedback, summarize information, and adapt responses to users' prompts, thereby creating new opportunities for supporting students' learning processes (Hwang & Chen, 2023). In physics education, these capabilities may be particularly relevant because students are frequently required to understand abstract concepts, integrate mathematical and conceptual representations, and solve multistep quantitative problems. Nevertheless, the educational value of generative AI depends not only on its technological capabilities but also on how students incorporate it into their own learning processes.

Unlike earlier educational technologies that primarily delivered predetermined content or structured learning activities, conversational generative AI enables students to request alternative explanations, ask follow-up questions, and obtain step-by-step assistance. These features may help students organize learning activities, identify errors, and explore difficult material. At the same time, immediate access to generated answers raises concerns about whether generative AI strengthens students' learning independence or gradually replaces cognitive and metacognitive processes that students should perform themselves.

This issue is closely related to self-regulated learning, which refers to students' capacity to set learning goals, select appropriate strategies, monitor their performance, and evaluate their learning outcomes (Zimmerman, 2002). When generative AI is used reflectively, it may support these processes by offering feedback, alternative explanations, and prompts for further evaluation. However, when students consult AI-generated responses before attempting to reason independently, the technology may contribute to cognitive offloading and reduced self-monitoring. Previous studies have indicated that generative AI can improve immediate task performance while producing more limited benefits for metacognitive engagement and independent regulation, particularly when its use is not accompanied by explicit instructional guidance (Fan et al., 2025; Xu et al., 2025).

These opportunities and risks may be especially relevant to physics learning. Physics requires students to integrate prerequisite concepts, mathematical operations, graphical representations, and explanations of physical phenomena. Students may obtain a correct numerical answer from generative AI without understanding the assumptions, conceptual relationships, or derivation processes underlying the answer. Consequently, apparently successful task completion may coexist with incomplete conceptual understanding. This possibility highlights the importance of distinguishing learning efficiency and task performance from the development of independent reasoning and self-regulated learning.

Evidence directly related to physics education remains limited. Al Farizi et al. (2024) reported that ChatGPT-supported project-based learning improved higher-order thinking skills in direct-current physics. However, the participants were secondary-school students, and learning independence was not directly measured. Mulvia (2026), the only source identified in this review that directly involved university students in physics or physics education, found that students perceived AI as useful and easy to use while also expressing concerns about plagiarism and declining critical-thinking ability. Because the latter study relied on students' perceptions rather than direct observations of self-regulated learning behavior, the existing evidence does not yet establish how generative AI influences the learning independence of physics education students.

The broader higher-education literature has examined generative AI in academic writing, research-skills development, online learning, science education, and general university learning. However, three important limitations remain. First, direct empirical evidence involving physics education students is extremely limited, making it difficult to determine whether findings from other disciplines can be transferred to physics learning. Second, relatively few studies have examined the role of generative AI across the forethought, performance or self-monitoring, and self-reflection phases of self-regulated learning. Third, the literature frequently uses the terms self-regulated learning, self-directed learning, learning autonomy, and learning independence without sufficient conceptual distinction, potentially obscuring differences among these related constructs.

These limitations provide the rationale for the present narrative literature review. Rather than claiming to establish direct empirical effects among physics education students, this review synthesizes conceptual and empirical evidence from broader educational contexts, distinguishes direct physics-related evidence from indirect evidence, and interprets recurring findings through Zimmerman's self-regulated learning framework and Bandura's social cognitive theory. The review is intended to develop provisional conceptual implications for physics education and identify priorities for future empirical investigation.

Physics education students are a particularly relevant population because they are expected not only to master physics concepts and problem-solving processes but also to develop the pedagogical competence required to teach these concepts to future learners. Their capacity to use generative AI critically, ethically, and reflectively may therefore have implications for both their current learning and their professional preparation as prospective teachers. Nevertheless, because direct evidence from physics teacher-education contexts remains scarce, these implications should be treated as provisional rather than as established empirical conclusions.

Accordingly, this narrative review aims to synthesize and critically interpret evidence concerning the role of generative AI in learning strategies and learning independence and to formulate provisional implications for physics education. Specifically, the review addresses three questions: (1) how does the reviewed literature describe the role of generative AI across the phases of self-regulated learning; (2) what conditions are associated with its supportive or potentially disruptive role; and (3) what provisional pedagogical implications can be formulated for physics education?

LITERATURE REVIEW

Conceptual Boundaries of Learning Independence

Because this review draws on several closely related constructs, their conceptual boundaries need to be clarified. Self-regulated learning, self-directed learning, learning autonomy, and independent learning are related concepts, but they are not conceptually identical and should not be used interchangeably without qualification.

In this review, self-regulated learning refers to the cyclical processes through which learners plan, monitor, control, and evaluate their learning activities. Zimmerman's (2002) model organizes self-regulated learning into three phases: forethought, performance or self-monitoring, and self-reflection. The forethought phase involves goal setting, strategic planning, and motivational beliefs. The performance phase concerns the implementation of strategies, attention control, and monitoring of ongoing learning. The self-reflection phase involves evaluating performance, interpreting outcomes, and adjusting subsequent learning strategies.

Self-directed learning places greater emphasis on learners' initiative in identifying learning needs, selecting resources, determining appropriate strategies, and evaluating learning outcomes. Learning autonomy and independent learning are used in this review as broader descriptions of learners' capacity to assume responsibility for their learning with reduced dependence on continuous external direction. Although these constructs overlap, the present synthesis uses Zimmerman's self-regulated learning model as its principal analytical framework because it provides clearly differentiated phases for examining the potentially supportive and disruptive roles of generative AI.

Self-Regulation and Social Cognitive Theory

Zimmerman's framework is closely connected to Bandura's (1997) social cognitive theory, which explains learning through reciprocal relationships among personal factors, behavior, and the learning environment. From this perspective, students' use of generative AI is shaped not only by the characteristics of the technology but also by their motivation, prior knowledge, self-efficacy, learning strategies, and instructional context.

Self-efficacy is particularly relevant because students' beliefs about their ability to complete learning tasks influence persistence, strategy selection, and willingness to engage with difficult material. Generative AI may support perceived competence by providing feedback, examples, and guided explanations. However, confidence based primarily on accepting AI-generated answers may not represent genuine mastery. The contribution of generative AI to self-efficacy is therefore likely to depend on whether students remain actively involved in attempting, evaluating, and revising their work.

Technological Support for Self-Regulated Learning

Technological support for self-regulated learning predates the emergence of generative AI. Open learner models, for example, have been used to make students' learning progress visible and to support monitoring and reflection (Hooshyar et al., 2020). Generative AI extends this form of support by enabling conversational interaction, immediate feedback, alternative explanations, task decomposition, and responses adapted to students' prompts.

Nevertheless, conversational responsiveness does not automatically produce stronger self-regulation. Xu et al. (2025) found that explicit metacognitive guidance was important for strengthening students' learning regulation and self-evaluation in generative AI-supported environments. Without appropriate guidance, access to AI-generated explanations may reduce students' independent monitoring and evaluation of their own understanding.

Related evidence also demonstrates a distinction between improved task performance and improved learning independence. Fan et al. (2025) showed that generative AI could enhance immediate task performance while producing more limited benefits for genuine understanding and intrinsic motivation. This pattern suggests that learners may complete tasks more efficiently without necessarily developing the metacognitive processes needed to regulate future learning independently.

Motivation, Engagement, and Interaction Quality

The educational role of generative AI is also shaped by motivational and interactional factors. Li et al. (2025) found that autonomous motivation, engagement, and self-directed learning contributed to the relationship between ChatGPT-supported instruction and students' research skills. These findings indicate that generative AI is more likely to support learning when students remain actively engaged rather than using it merely to obtain completed answers.

The quality of interaction and AI-generated output is another important condition. Bai and Wang (2025) reported positive relationships between interaction or output quality, learning motivation, and creative self-efficacy. However, Tam (2025) showed that high-quality AI feedback was beneficial only when students critically interpreted and acted on it. Thus, the effectiveness of feedback depends not only on the quality of the generated response but also on the learner's capacity to evaluate and apply it reflectively.

The social organization of AI-supported learning may also influence its effectiveness. Younis (2024) found that paired and group-based ChatGPT-supported learning was associated with stronger self-regulation and confidence than individual use. This finding suggests that discussion, comparison, and collaborative evaluation may prevent students from relying passively on a single AI-generated response.

Generative AI, Cognitive Load, and Cognitive Offloading

Cognitive load theory provides an additional interpretive perspective for understanding the role of generative AI in complex learning activities. According to Sweller (1988), instructional support can improve learning when it reduces cognitive demands that do not contribute directly to knowledge construction. Generative AI may reduce unnecessary difficulty by clarifying notation, reorganizing information, or presenting complex explanations in more manageable steps.

However, reducing unnecessary cognitive load is different from replacing the cognitive effort required for learning. When generative AI performs the entire reasoning or problem-solving process, students may engage less deeply in schema construction, strategy monitoring, and conceptual integration. This possibility is closely related to cognitive offloading, in which cognitive operations are transferred to an external tool.

Cognitive offloading is not necessarily harmful when technology assists limited aspects of a task while learners retain responsibility for planning, monitoring, and evaluating their work. It becomes educationally problematic when AI substitutes for the cognitive and metacognitive processes that students are expected to develop independently.

Evidence Relevant to Physics Education

Direct evidence concerning generative AI and the learning independence of physics education students remains highly limited. Mulvia (2026) directly investigated university students in physics or physics education and found that students perceived AI as useful while also recognizing risks related to plagiarism and declining critical-thinking ability. However, the study relied on perceptions rather than direct observations of self-regulated learning behavior.

Al Farizi et al. (2024) provided discipline-specific evidence from secondary-school physics learning. The study reported improved higher-order thinking performance through ChatGPT-supported project-based learning in direct-current physics. Nevertheless, the participants were secondary-school students, and learning independence was not directly measured. Ng et al. (2024) also provided supporting evidence from secondary-school science education, but not specifically from university physics education.

The remaining evidence comes primarily from broader higher-education contexts, including academic writing, research-skills development, general university learning, and online education. Therefore, findings from these studies cannot be treated as direct evidence concerning physics education students. Instead, they provide a conceptual basis for examining how similar mechanisms may operate in physics learning.

Conceptual Synthesis

Based on the reviewed literature, the role of generative AI in learning independence can be understood as conditional rather than uniformly positive or negative. Its contribution appears to depend on the interaction among technological affordances, students' motivation and self-regulation, the quality of AI-generated feedback, and the instructional environment.

Within Zimmerman's framework, generative AI may support the forethought phase through planning and strategy generation, the performance phase through feedback and error identification, and the self-reflection phase through alternative explanations and evaluative prompts. At the same time, each phase carries a corresponding risk when students delegate goal setting, monitoring, or reflection entirely to AI.

Bandura's social cognitive theory complements this analysis by highlighting the role of self-efficacy, behavioral engagement, and environmental guidance. Cognitive load theory further explains how AI may either reduce unnecessary difficulty or replace productive cognitive effort. Together, these perspectives provide the theoretical basis for interpreting the reviewed findings and formulating provisional implications for physics education.

METHOD

This study employed a narrative literature review with a qualitative thematic synthesis to examine the role of generative artificial intelligence in students' learning strategies and learning independence, with particular attention to its potential implications for physics education. A narrative review was selected because the study sought to integrate empirical and conceptual findings derived from diverse research designs and educational contexts rather than conduct a formal systematic review or meta-analysis.

The literature search was conducted from 1 January to 3 April 2026 using SINTA, Scopus, Web of Science, ScienceDirect, and SpringerLink. Google Scholar was used only as a supplementary search engine to identify additional potentially relevant publications, although the exact date of this supplementary search was not retained. The metadata of the selected publications, including authorship, publication year, journal information, page numbers, publication type, and DOI, were verified on 10 April 2026.

The search terms covered three main conceptual areas: generative artificial intelligence, self-regulated learning, and educational context. The principal search structure was: ("generative artificial intelligence" OR "generative AI" OR ChatGPT OR Gemini) AND ("self-regulated learning" OR "self-directed learning" OR "learning autonomy" OR "independent learning" OR "learning strategies") AND ("higher education" OR university OR "physics education" OR "physics students"). Indonesian equivalents of the terms were also used in the SINTA search. Search terms and Boolean combinations were adjusted to the technical requirements of each search platform.

Because the initial search results were not recorded prospectively using a systematic-review protocol, the numbers reported are approximate. The searches identified approximately 262 records across the six sources. After duplicate checking based on DOI, title, first-author name, and publication year, approximately 142 unique records remained. The records were then manually examined for thematic relevance. Seventeen sources were retained for different purposes: 12 peer-reviewed publications formed the principal evidence base, one professional blog article was used only as an illustrative source, and four publications were used as theoretical or historical background.

Sources were included when they: (1) were published between 2020 and 2026, except for classical theoretical publications; (2) addressed ChatGPT, Gemini, or another form of generative AI in an educational context; (3) examined learning strategies, self-regulation, learning independence, motivation, or related learning outcomes; (4) involved higher-education students or, as supporting evidence, investigated relevant learning mechanisms in physics or science education; (5) were published in English or Indonesian; and (6) were peer-reviewed empirical studies, reviews, meta-analyses, or conceptual journal articles. Sources were excluded from the principal synthesis when they did not examine generative AI, focused only on earlier educational technologies, were duplicates, lacked verifiable publication information, or did not provide sufficient information for thematic analysis. Non-peer-reviewed materials were retained only as supplementary illustrations and were not used independently to support the conclusions.

Among the 12 peer-reviewed sources included in the principal synthesis, only one directly examined university students in physics or physics education. One additional study investigated physics learning among secondary-school students. The remaining studies were conducted in broader higher-education, science-education, academic-writing, or online-learning contexts. Accordingly, findings derived from the broader literature were interpreted as potential conceptual implications for physics education rather than as direct empirical evidence concerning physics education students.

The relevance and methodological quality of the selected publications were examined qualitatively. The assessment considered the clarity of the research objectives, appropriateness of the research design, description of participants and educational context, transparency of data-collection and analytical procedures, correspondence between the reported evidence and conclusions, and acknowledgement of study limitations. No standardized risk-of-bias instrument was applied because the review was narrative rather than systematic. Nevertheless, the methodological limitations and contextual boundaries of each publication were recorded and considered during the synthesis.

Data from the selected publications were entered into an extraction matrix containing the author and publication year, country or educational context, participant characteristics, research design, form of generative AI use, principal findings, methodological limitations, thematic relevance, and relationship to physics education.

The review tasks were divided among the authors. Abdul Walid conducted the literature search and documented the initial search records; Ishak applied the eligibility criteria and checked duplicate publications; Andi Kamal Ahmad conducted data extraction and thematic categorization; and Juniar Rasyid coordinated the narrative synthesis, manuscript preparation, and integration of revisions.

The extracted findings were analyzed using a combination of deductive and inductive thematic analysis. Deductive analysis was guided by Zimmerman's three phases of self-regulated learning: forethought, performance or self-monitoring, and self-reflection. Inductive analysis was used to identify recurring patterns that were not fully represented by the theoretical framework. Four principal themes were developed: (1) generative AI as support for learning strategies; (2) risks of cognitive dependence and reduced self-regulation; (3) contextual, motivational, technological, and instructional factors influencing the effectiveness of generative AI; and (4) differences in the role of generative AI across the phases of self-regulated learning. The more detailed categorization of dependence into functional, substitutive, and total dependence was treated as a conceptual interpretation developed by the authors rather than as a classification directly measured in all reviewed studies.

To strengthen the credibility of the synthesis, findings were compared across geographical, disciplinary, and educational contexts to identify recurring patterns, contextual differences, and limitations in their transferability to Indonesian physics education. Theoretical consistency was examined by comparing the thematic interpretation with Zimmerman's self-regulation framework and Bandura's social cognitive theory. Search records, eligibility decisions, source-characteristic tables, extraction matrices, methodological notes, and theme-development records were maintained as an audit trail to enhance the transparency and traceability of the review process. However, because the initial search counts were recorded retrospectively and approximately, the review does not claim the level of reproducibility expected from a formal systematic review.

RESULTS

Characteristics and Scope of the Reviewed Publications

The principal narrative synthesis was based on 12 peer-reviewed publications published between 2020 and 2026. These publications comprised nine empirical studies, one systematic review and meta-analysis, and two conceptual articles. One professional blog commentary was consulted only as a supplementary illustration and was not included in the principal evidence synthesis or used independently to support the conclusions.

The reviewed publications represented diverse educational contexts, research designs, and participant groups. Only one study directly investigated university students in physics or physics education (Mulvia, 2026). One additional study examined the use of ChatGPT in secondary-school physics learning (Al Farizi et al., 2024), while another examined self-regulated learning in secondary-school science education (Ng et al., 2024). The remaining publications addressed broader higher-education contexts, including academic writing, research-skills development, online learning, and general university learning. Consequently, findings derived from the broader literature are interpreted as potential conceptual implications for physics education rather than as direct empirical evidence concerning physics education students.

Table 1. Characteristics of the Peer-Reviewed Publications Included in the Main Synthesis

No.	Author and year	Participants/ context	Research design	Main finding	Relevance to physics education
1	Al Farizi et al. (2024)	40 Grade 12 science students studying direct-current physics in Indonesia	Quasi-experimental classroom intervention	ChatGPT-supported project-based learning produced a greater improvement in higher-order thinking skills than instruction without ChatGPT	Direct physics-learning evidence, but from secondary education
2	Mulvia (2026)	93 physics or physics-education students in Indonesia	Quantitative descriptive survey	Students perceived AI as useful and easy to use but expressed concerns about plagiarism and declining critical-thinking ability	Direct higher-education physics evidence
3	Hwang and Chen (2023)	General educational context; no participants	Conceptual/narrative article	Identified the potential of generative AI to provide feedback, break down tasks, and support personalized learning, while also identifying educational risks	Conceptual foundation
4	Alemdag (2025)	Meta-analysis of 57 studies involving university students	Systematic review and meta-analysis	Generative AI was associated with improved learning outcomes, although its effect on metacognitive and self-regulatory outcomes was limited	General higher-education evidence

5	Chiu (2024)	General educational context; no participants	Conceptual article	Emphasized the importance of instructional guidance, institutional policy, and ethical practices in generative AI use	Conceptual and policy foundation
6	Xu et al. (2025)	68 university students receiving guided or unguided generative AI support	Controlled empirical study	Metacognitive guidance strengthened students' learning regulation and self-evaluation, whereas unguided use was associated with weaker self-regulatory processes	Indirect higher-education evidence
7	Ng et al. (2024)	74 secondary-school students in a science-learning intervention in Hong Kong	Quasi-experimental pilot study	A generative AI-supported chatbot improved knowledge, engagement, motivation, and aspects of self-regulated learning	Supporting science-education evidence at a different educational level
8	Fan et al. (2025)	117 university students	Laboratory experiment	Generative AI improved task performance, but improvements in genuine understanding and intrinsic motivation were limited, indicating possible metacognitive laziness	Indirect higher-education evidence
9	Li et al. (2025)	366 university students majoring in education	Quasi-experimental study	ChatGPT-supported instruction improved research skills through autonomous	Indirect higher-education evidence

				motivation, engagement, and self-directed learning	
10	Bai and Wang (2025)	323 university students in China	Two-wave longitudinal survey	Higher interaction and output quality were associated with stronger learning motivation and creative self-efficacy	Indirect higher-education evidence
11	Tam (2025)	48 university students in an academic-writing course in Hong Kong	Qualitative/mixed-methods study	The benefits of ChatGPT-generated feedback depended on students' ability to evaluate and act on the feedback reflectively	Indirect higher-education evidence
12	Younis (2024)	100 university students in three ChatGPT-supported online-learning formats	Quasi-experimental pretest–posttest study	Paired and group learning formats were associated with stronger self-regulation and confidence than individual ChatGPT-supported learning	Indirect higher-education evidence

Generative AI as Support for Learning Strategies

The reviewed literature identified three recurring mechanisms through which generative AI may support students' learning strategies: immediate feedback, cognitive scaffolding, and motivational or social support.

First, generative AI can provide rapid and individualized feedback that allows students to identify errors and reconsider their understanding. Tam (2025) found that the effectiveness of ChatGPT-generated feedback depended substantially on whether students critically evaluated and followed up on the feedback rather than accepting it passively. Similarly, Xu et al. (2025) showed that generative AI was more effective in supporting self-regulation when students received explicit metacognitive guidance.

Second, generative AI can function as cognitive scaffolding by breaking complex tasks into smaller and more manageable steps. This mechanism was conceptually identified by Hwang and Chen (2023) and was supported by studies showing that structured AI assistance can improve students' engagement with difficult learning tasks (Ng et al., 2024; Xu et al., 2025). In physics education, this general mechanism may be relevant to the analysis of quantitative problems and the identification of conceptual or procedural errors. However, direct evidence concerning its application among university physics students remains limited.

Third, generative AI may contribute to motivation, engagement, and confidence. Li et al. (2025) found that autonomous motivation, engagement, and self-directed learning helped explain the relationship between ChatGPT-supported instruction and students' research skills. Bai and Wang (2025) similarly reported that the quality of generative AI interaction and output was positively associated with students' learning motivation and creative self-efficacy. Younis (2024) further found that social interaction around ChatGPT use, particularly in paired and group-learning formats, was associated with stronger self-regulation and confidence than individual use.

The physics-related evidence showed both potential benefits and important limitations. Al Farizi et al. (2024) reported that ChatGPT-supported project-based learning improved higher-order thinking skills in secondary-school direct-current physics. Mulvia (2026) found that physics and physics-education students perceived AI as useful for supporting their learning. Nevertheless, Al Farizi et al. did not investigate university students or directly measure learning independence, while Mulvia relied on students' perceptions rather than direct observations of their learning behavior. These findings should therefore be interpreted cautiously.

The reviewed evidence also suggests that improved performance does not necessarily indicate improved learning independence. Although the meta-analysis reviewed by Chen & Cheung (2025) reported positive effects of generative AI on learning outcomes, its effects on metacognitive and self-regulatory outcomes were considerably more limited. This distinction indicates that increases in task scores or efficiency should not automatically be interpreted as improvements in students' ability to regulate their own learning.

Risks of Cognitive Dependence and Reduced Self-Regulation

The literature also identified risks associated with unguided or excessive generative AI use. The most consistent concern was the possibility that students would transfer essential cognitive and metacognitive processes to the AI system rather than engaging in those processes independently.

Xu et al. (2025) found that students who received explicit metacognitive guidance demonstrated stronger learning regulation and self-evaluation than students who used generative AI without such guidance. This finding indicates that access to AI-generated explanations alone may not strengthen self-regulation unless students are also encouraged to plan, monitor, and evaluate their learning.

Fan et al. (2025) similarly found that generative AI could improve immediate task performance without producing equivalent improvements in genuine understanding or intrinsic motivation. The authors described this pattern as metacognitive laziness, in which students obtain acceptable task outcomes while reducing the effort devoted to independent reasoning and self-monitoring. Mulvia (2026) also reported that physics and physics-education students recognized the potential risks of plagiarism and declining critical-thinking ability when AI was used without sufficient control.

Based on the recurring patterns across these studies, cognitive dependence can be provisionally interpreted at three levels. Functional dependence refers to the occasional use of generative AI as assistance without replacing the overall independent learning process. Substitutive dependence occurs when students begin to replace part of their reasoning or monitoring process with AI-generated responses. Total dependence refers to a more extensive reliance in which students may lose confidence in completing academic tasks without AI assistance. These levels constitute an author-developed conceptual categorization and were not directly measured as a standardized classification across the reviewed studies.

Overall, the findings indicate that generative AI may strengthen performance while simultaneously weakening self-monitoring when students use it primarily to obtain answers rather than to examine their own reasoning. The risk appears particularly relevant to the performance or monitoring phase of self-regulated learning.

Conditions Shaping the Effectiveness of Generative AI

The synthesis identified four recurring conditions associated with the effectiveness of generative AI in supporting learning independence: metacognitive guidance, autonomous motivation and engagement, the quality of AI interaction and output, and instructional or social design.

First, metacognitive guidance was consistently identified as an important condition. Xu et al. (2025) showed that structured prompts and guidance strengthened students' regulation and evaluation of their learning. Without such guidance, generative AI use was more likely to replace rather than support independent cognitive processes.

Second, autonomous motivation and engagement influenced how students used generative AI. Li et al. (2025) found that these factors contributed to the relationship between ChatGPT-supported instruction and research-skill development. Students who remained actively engaged were more likely to use AI as a learning resource rather than as a substitute for effort.

Third, the quality of AI-generated output and students' responses to that output shaped the learning process. Bai and Wang (2025) found that higher interaction and output quality were associated with stronger motivation and creative self-efficacy. Tam (2025), however, demonstrated that high-quality feedback was beneficial only when students critically interpreted and acted on it.

Fourth, instructional and social design affected the direction of AI-supported learning. Younis (2024) found that students using ChatGPT in paired or group formats demonstrated stronger self-regulation and confidence than those learning individually. Chiu (2024) also emphasized conceptually that clear institutional policies and instructional guidance are necessary to support responsible and transparent use. In the context of physics education, Mulvia (2026) further indicated that ethical concerns, particularly plagiarism and the possible decline of critical thinking, need to be addressed through explicit guidance.

These conditions suggest that the benefits of generative AI are not automatic. They depend on how AI is integrated into learning activities, how actively students evaluate its output, and whether educators provide sufficient cognitive, ethical, and instructional guidance.

Synthesis Across the Phases of Self-Regulated Learning

The reviewed findings were further organized according to Zimmerman's three phases of self-regulated learning: forethought, performance or self-monitoring, and self-reflection. Because most of the reviewed studies did not measure all three phases directly, the synthesis presented in Table 2 represents a theory-informed interpretation of recurring findings rather than a standardized comparison across studies.

Table 2. Theory-Informed Synthesis of Generative AI Across the Phases of Self-Regulated Learning

Self-regulated learning phase	Evidence from the reviewed literature	Potential implication for physics education	Potential risk	Primary supporting sources
Forethought	Generative AI may support goal setting, learning planning, strategy selection, and preparation for learning tasks	AI may assist students in identifying prerequisite concepts, organizing topics, and planning approaches to physics problems	Students may delegate the entire planning process to AI without independently defining goals or strategies	Ng et al. (2024); Li et al. (2025); Younis (2024)
Performance/self-monitoring	Immediate feedback may help students detect errors and adjust their strategies while completing tasks	AI may help students identify conceptual or procedural errors during physics problem solving	Cognitive offloading, reduced independent monitoring, and reliance on AI-generated answers	Mulvia (2026); Xu et al. (2025); Fan et al. (2025); Tam (2025)
Self-reflection	Generative AI may provide alternative explanations and prompts that support self-evaluation	AI may assist students in reviewing their reasoning and comparing alternative explanations of physics concepts	Reflection may remain superficial when students accept AI responses without evaluating or internalizing them	Xu et al. (2025); Ng et al. (2024); Tam (2025); Younis (2024)

The synthesis indicates that generative AI may support all three phases of self-regulated learning, but its contribution differs across phases. The reviewed evidence suggests that generative AI is potentially useful for planning, feedback, and reflection, while the performance or self-monitoring phase appears to be the most vulnerable to cognitive substitution. Nevertheless, because only one study directly examined university students in physics or physics education, these phase-based implications should be interpreted as a provisional conceptual framework for physics education rather than as established empirical conclusions about physics education students.

DISCUSSION

The Dual Role of Generative AI in Learning Strategies and Learning Independence

The broader higher-education evidence synthesized in this review suggests that generative AI may play a dual role in students' learning strategies and learning independence. On the one hand, it can provide immediate feedback, structured explanations, motivational support, and opportunities for students to reconsider their understanding. On the other hand, excessive or unguided use may reduce students' independent cognitive engagement and weaken their monitoring of the learning process. Therefore, the educational value of generative AI does not appear to result from access to the technology alone, but from how students and lecturers incorporate it into learning activities.

The positive role of generative AI is supported by several studies conducted in broader higher-education contexts. Li et al. (2025) found that autonomous motivation, engagement, and self-directed learning contributed to the relationship between ChatGPT-supported instruction and students' research skills. Bai and Wang (2025) similarly reported that the quality of generative AI interaction and output was positively associated with learning motivation and creative self-efficacy. Tam (2025), however, demonstrated that the effectiveness of AI-generated feedback depended on whether students actively evaluated, interpreted, and acted on the feedback rather than receiving it passively. Together, these findings indicate that generative AI is more likely to support learning when students remain cognitively and metacognitively engaged.

These findings can be interpreted through Bandura's (1997) social cognitive theory. Feedback, guided problem solving, and opportunities to revise responses may strengthen students' perceptions of competence and self-efficacy. Nevertheless, AI-generated explanations should not automatically be regarded as mastery experiences. Their contribution to self-efficacy is more likely to be constructive when students attempt a task, evaluate the AI response, correct misunderstandings, and recognize their own progress. By contrast, confidence based primarily on accepting AI-generated answers may not reflect genuine improvement in students' knowledge or independent problem-solving ability.

The reviewed evidence also shows that improved task performance does not necessarily indicate stronger learning independence. Fan et al. (2024) found that generative AI could improve immediate task performance without producing equivalent gains in genuine understanding or intrinsic motivation. Similarly, the meta-analysis included in the review reported stronger effects on general learning outcomes than on metacognitive and self-regulatory outcomes (Alemdag, 2025). These findings qualify the more positive results reported by Li et al. (2025) and Bai and Wang (2025), suggesting that efficiency, motivation, performance, and self-regulation should be treated as related but distinct educational outcomes.

Generative AI Across the Phases of Self-Regulated Learning

Zimmerman's (2002) cyclical model provides a useful framework for explaining why generative AI may produce different effects across the forethought, performance or self-monitoring, and self-reflection phases. During the forethought phase, generative AI may assist students in setting goals, identifying relevant learning resources, and organizing strategies. This support may be particularly useful when students are beginning an unfamiliar or complex task. However, its educational value decreases when students delegate the entire planning process to AI without independently defining their goals or considering appropriate strategies.

The performance or self-monitoring phase appears to be the most vulnerable to cognitive substitution. Immediate AI-generated feedback may help students identify errors and adjust their approaches, but the same accessibility may encourage them to consult AI before attempting to monitor their own reasoning. Xu et al. (2025) found that explicit metacognitive guidance strengthened students' learning regulation and self-evaluation, whereas unguided AI use was associated with weaker self-regulatory processes. Fan et al. (2025) similarly showed that improved task performance could coexist with reduced independent cognitive engagement. These findings indicate that the educational effect of AI-generated feedback depends on whether it stimulates students' monitoring or replaces it.

During the self-reflection phase, generative AI may offer alternative explanations, follow-up questions, and feedback that help students reconsider their performance. Tam (2025) showed that students benefited from AI-generated feedback when they critically interpreted and followed up on it. Reflection may remain superficial, however, when students merely accept an AI response as correct without comparing it with their own reasoning, learning objectives, or other credible sources. Generative AI therefore has the potential to support reflection, but only when students are required to evaluate its output rather than simply consume it.

The provisional categorization of dependence into functional, substitutive, and total dependence can also be understood through these self-regulatory phases. Functional dependence may occur when AI assists particular activities while students retain responsibility for planning, monitoring, and reflection. Substitutive dependence may emerge when AI begins to replace one or more of these processes. Total dependence represents a more extensive condition in which students may lose confidence in completing learning tasks without AI assistance. These categories were developed by the authors from recurring patterns in the literature and should be treated as a conceptual framework for future empirical testing rather than as an established classification.

Conceptual Implications for Physics Education

The relevance of these findings to physics education must be interpreted cautiously. Among the peer-reviewed publications included in the main synthesis, only Mulvia (2026) directly investigated university students in physics or physics education. Al Farizi et al. (2024) provided discipline-specific evidence from secondary-school physics learning, while the remaining publications were conducted in broader higher-education, science-education, academic-writing, research-skills, or online-learning contexts. Consequently, the present review does not establish how generative AI affects the learning independence of physics education students empirically. Instead, it develops provisional implications by connecting broader educational findings with the characteristics of physics learning.

Al Farizi et al. (2024) found that ChatGPT-supported project-based learning improved higher-order thinking performance in secondary-school direct-current physics. However, the study did not involve university students or directly measure self-regulated learning. Mulvia (2026) reported that physics and physics-education students perceived AI as useful, while also recognizing risks related to plagiarism and declining critical-thinking ability. Because this evidence is based on student perceptions rather than direct observations of learning behavior, it should not be used to conclude that generative AI necessarily strengthens or weakens learning independence.

Conceptually, physics learning may provide a particularly relevant context for examining the balance between AI support and independent reasoning. Physics frequently requires students to integrate prerequisite concepts, mathematical procedures, graphical representations, and explanations of physical phenomena. Generative AI may assist students by clarifying instructions, providing alternative explanations, or identifying possible procedural errors. However, students who use AI to obtain final answers without examining the underlying derivation may display acceptable procedural performance while retaining an incomplete conceptual understanding.

This interpretation can also be examined through cognitive load theory (Sweller, 1988), which serves as an additional interpretive perspective rather than the principal analytical framework of the review. Generative AI may reduce extraneous cognitive load when it clarifies unfamiliar notation, reorganizes complex information, or provides structured explanations. Such support may allow students to allocate greater attention to relevant conceptual relationships. Conversely, when AI replaces the reasoning process itself, students may devote less cognitive effort to schema construction and conceptual integration. The result may be efficient task completion without correspondingly deep learning.

The reviewed studies did not directly compare cognitive offloading across academic disciplines. Therefore, the possibility that cognitive substitution is especially consequential in physics should be treated as a hypothesis requiring empirical investigation rather than as an established comparative finding. Future research should directly examine how physics education students use generative AI during conceptual reasoning, mathematical derivation, problem representation, and reflection on problem-solving errors.

Physics education students also occupy a distinctive position as prospective teachers. In addition to developing content knowledge, they are expected to model effective learning strategies and eventually guide their own students in the responsible use of educational technologies. Generative AI use during teacher preparation may therefore have implications for their future pedagogical practice. However, none of the reviewed studies directly investigated whether patterns of AI dependence during university study subsequently influence teaching behavior. This issue should consequently be regarded as an important direction for future longitudinal and teacher-education research.

Pedagogical Implications

The synthesis indicates that the benefits of generative AI depend primarily on metacognitive guidance, autonomous motivation and engagement, the quality of AI interaction and output, and instructional or social design. These conditions suggest that lecturers should not merely permit or prohibit AI use. Instead, they should design activities that require students to demonstrate how AI contributes to, rather than substitutes for, their reasoning.

First, students may be required to make an initial independent attempt before consulting generative AI. In physics learning, this may involve identifying known and unknown variables, selecting relevant principles, representing the problem, and proposing an initial solution strategy. Students can then use generative AI to compare approaches, identify possible errors, or request alternative explanations. This sequence may help preserve the self-monitoring process while still allowing students to benefit from AI-supported feedback.

Second, generative AI output should be treated as an object of critical evaluation. Students may be asked to identify assumptions, verify equations, compare AI explanations with textbooks or other credible sources, and explain whether a response is conceptually and mathematically justified. Such tasks align with the findings of Tam (2025), which showed that the usefulness of AI-generated feedback depended on students' active interpretation, and with Xu et al. (2025), which emphasized the importance of explicit metacognitive support.

Third, transparency regarding AI use should be incorporated into academic assignments. Students may be required to document the prompts used, the parts of the assignment supported by AI, the revisions they made, and the limitations or errors they identified in the generated output. This approach may help address the ethical concerns reported by Mulvia (2026) while shifting attention from merely detecting AI use to evaluating the quality of students' engagement with it.

Fourth, the findings of Younis (2024) suggest that social interaction may strengthen AI-supported learning. Paired or group-based activities can require students to compare AI-generated responses, discuss differences, and justify a final solution collectively. Such interaction may reduce passive reliance on a single AI response and encourage students to articulate and defend their reasoning.

Based on this synthesis, three related strategies may be considered in physics education: requiring an initial independent attempt before AI consultation, incorporating AI-use disclosure and reflection, and providing practice in critical prompting and response verification. These strategies are conceptual recommendations developed from the reviewed evidence. They were not evaluated as a combined pedagogical intervention in the included studies and therefore require empirical testing before their effectiveness can be established.

Provisional Implications for the Physics Education Curriculum

The synthesis offers several provisional implications for physics education curricula. At the course level, lecturers may integrate brief learning units on AI literacy, academic ethics, prompt formulation, output verification, and reflective AI use. AI literacy should not be limited to technical knowledge of how to generate responses. It should also include awareness of hallucination, bias, incomplete reasoning, unverifiable claims, and the distinction between obtaining an answer and understanding a concept.

At the program level, physics education programs may develop clear guidelines regarding acceptable and unacceptable uses of generative AI in coursework, laboratory reports, lesson planning, and undergraduate research. These guidelines should address disclosure requirements, responsibility for verifying generated information, appropriate citation or acknowledgement, and consequences for academic misconduct. Clear guidelines may reduce uncertainty among students while enabling lecturers to guide AI use openly and constructively.

At the institutional level, lecturer readiness is essential because metacognitive scaffolding depends on instructors' ability to design tasks that require independent reasoning and critical evaluation. Physics education programs may therefore collaborate with academic development or educational technology units to provide training on AI-supported assessment, ethical use, critical prompting, and the evaluation of AI-generated scientific explanations.

These recommendations should not be interpreted as empirically validated curriculum interventions for physics education students. They represent provisional implications derived primarily from broader higher-education evidence. Their feasibility and effectiveness need to be examined through studies involving physics education students, lecturers, and institutional contexts.

Boundaries of the Interpretation

The discussion must be interpreted in relation to the scope of the evidence. The reviewed publications differed in participant characteristics, educational level, disciplinary context, research design, and learning outcomes. Several studies relied on self-reported perceptions, while others examined short-term interventions or task performance rather than long-term learning independence. In addition, only one study directly involved university students in physics or physics education.

Accordingly, the synthesis supports a preliminary conceptual framework rather than definitive claims about physics education students. The most defensible conclusion is that generative AI may support planning, feedback, motivation, and reflection when accompanied by active engagement and metacognitive guidance, but may weaken self-monitoring when used to replace independent reasoning. Whether these mechanisms operate in the same way within university physics education remains an empirical question requiring further investigation.

CONCLUSION

The reviewed literature suggests that generative AI may play a dual role in students' learning strategies and learning independence. It can support learning through immediate feedback, structured explanations, cognitive scaffolding, motivation, and opportunities for planning and reflection. However, when used without adequate metacognitive guidance, generative AI may encourage cognitive offloading and reduce students' independent monitoring of their reasoning. Its educational role therefore appears to depend on students' active engagement, self-regulation capacity, the quality of AI-generated output, and the instructional design surrounding its use.

Within Zimmerman's self-regulated learning framework, generative AI may support the forethought, performance or self-monitoring, and self-reflection phases in different ways. The self-monitoring phase appears conceptually to be the most vulnerable when students use AI-generated responses to replace rather than evaluate their own reasoning. Nevertheless, these implications for physics education remain provisional because only one peer-reviewed study directly involved university students in physics or physics education, while most of the evidence was drawn from broader educational contexts. The findings should therefore be interpreted as a preliminary conceptual framework rather than as direct empirical conclusions about physics education students.

This narrative review has several limitations. The initial search counts were recorded retrospectively and approximately, the review did not apply a formal PRISMA procedure or standardized risk-of-bias instrument, and the included publications differed in population, discipline, research design, and learning outcomes. Several studies also relied on self-reported perceptions or short-term interventions. Consequently, the synthesis cannot establish causal relationships between generative AI use and students' learning independence.

Future research should directly examine how physics education students use generative AI during conceptual reasoning, mathematical problem solving, self-monitoring, and reflection. Quantitative, qualitative, and mixed-methods studies are needed to test the proposed relationships among AI use, self-regulated learning, motivation, and conceptual understanding. Quasi-experimental studies may also evaluate strategies such as requiring an initial independent attempt before AI consultation, providing structured metacognitive prompts, critically evaluating AI-generated solutions, and documenting AI use transparently in academic assignments.

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