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Tracing the Role of Artificial Intelligence in Self-Regulated Learning: A Systematic Review Using the Winne and Hadwin Framework (2007–2025)

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ABSTRACT

Self-regulated learning (SRL) is a vital 21st-century educational competency that allows learners to plan, monitor, and evaluate their own progress. As artificial intelligence (AI) tools, such as chatbots, intelligent tutoring systems, and generative AI, become more prevalent in educational settings, the role these tools play in supporting SRL requires further investigation. This study presents a systematic review of 22 peer-reviewed articles published between 2007 and May 2025 and retrieved from multiple academic databases including Scopus, ERIC, SpringerLink, and ScienceDirect, resulting 109 relevant records. Using Winne and Hadwin's (1998, updated 2018) COPES framework, which offers a microanalytic view of SRL processes, this review maps how AI technologies support different phases of SRL. The findings show that most AI tools assist learners during the strategy enactment phase, while fewer address the phases of planning, understanding the task, and metacognitive monitoring. The reflective adaptation phase, central to the cyclical nature of SRL, is notably underrepresented. Cognitive and metacognitive aspects dominate in terms of dimensions, whereas motivational and emotional components are less frequently targeted. Over 80% of the studies reported positive impacts of AI on SRL behaviors, and approximately 65% linked AI usage with improved academic performance. These results underscore the necessity of intelligent, responsive, and empathetic AI systems. Future development should focus on multi-phase, emotionally aware AI tools, particularly chatbots, that can offer personalized, continuous support throughout the entire SRL cycle.

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1. INTRODUCTION

Self-regulated learning (SRL) is increasingly recognized as a fundamental concept in contemporary education. SRL embodies learners' capacity to take charge of their learning by setting goals, selecting appropriate strategies, monitoring progress, and reflecting on outcomes (Panadero, 2017). These processes enhance academic performance and equip learners with lifelong learning skills necessary for navigating a rapidly evolving, complex world (Blaschke, 2021; Vieriu & Petrea, 2025).

Several theoretical frameworks have been proposed to conceptualize the dynamics of self-regulated learning (SRL). Two of the most influential are Zimmerman's three-phase model (2000) and Winne and Hadwin's COPES model (1998), both of which emphasize the cyclical nature of self-regulation. These models illustrate how learners interpret tasks, plan strategically, execute learning activities, and adapt their approaches through self-evaluation (Winne, 2023). Unlike Zimmerman's cyclical model, COPES provides a microanalytic perspective on the dynamic interplay between cognitive and metacognitive processes. This makes COPES more suitable for mapping the functionalities of AI tools (Parra-Gavilánez & Totoy, 2024). AI's role in SRL is more than just using static tools like LMS or video lectures; it provides real-time, adaptive support that traditional EdTech doesn't offer (Du, 2025). Despite the theoretical clarity, however, learners often struggle to master Self-Regulated Learning (SRL), particularly in setting meaningful goals, maintaining motivation, and effectively implementing metacognitive strategies (Diddee, n.d.; S. Li & Lajoie, 2022).

In response to these challenges, the field of educational technology has undergone transformative shifts, particularly with the integration of artificial intelligence (AI). AI has evolved from merely enhancing administrative efficiency to playing a pivotal role in facilitating personalized, adaptive, and data-driven learning environments (Vieriu & Petrea, 2025). In the context of SRL, AI has significant potential to support learners in independently planning, monitoring, and evaluating their learning (Azevedo et al., 2022; T. Li, Yan, et al., 2025).

Recent studies have shown that various AI tools, including intelligent tutoring systems, generative AI platforms, and AI-driven chatbots, are being used to support key components of self-regulated learning (SRL), such as goal setting, time management, self-reflection, and data-informed decision-making (Chang et al., 2023; Sun et al., 2025). For instance, educational chatbots can provide real-time feedback and guide learners through contextualized conversations tailored to their needs (Han et al., 2025). However, no systematic review has yet explicitly mapped how AI technologies support the various SRL phases as defined by well-established frameworks.

The present study aims to address this gap by conducting a systematic review of how AI supports self-regulated learning (SRL) across different educational levels and learning contexts. Guided by the COPES model (Winne & Hadwin, 1998), the review will analyze how AI applications contribute to the development of SRL competencies. The findings are expected to provide theoretical insights and practical guidance for designing AI-based educational tools that support learner autonomy and self-regulation more effectively.

1.1 Theoretical Framework for Guiding This Systematic Review

Over the last three decades, various theoretical models have been developed to understand and promote self-regulated learning (SRL). These models define the stages of autonomous learning and serve as conceptual tools that enable researchers and practitioners to design interventions that systematically strengthen students' SRL competencies (Cleary et al., 2013; Panadero, 2017). One of the most widely adopted frameworks is the COPES model, proposed by Winne and Hadwin (1998). This model remains particularly relevant in technology-supported learning environments (Panadero, 2017; Winne, 2023).

The COPES model conceptualizes SRL as a recursive, dynamic process unfolding in four phases: defining the task; setting goals and planning learning strategies; executing those strategies while monitoring their effectiveness; and adapting future approaches based on reflective evaluations. Each phase is shaped by five interrelated elements: Conditions, Operations, Products, Evaluations, and Standards. "Conditions" refers to internal factors, such as learners' prior knowledge, motivation, and interests, as well as external factors, such as task instructions or available resources. Operations describe a set of cognitive and metacognitive processes summarized by the acronym SMART: searching, monitoring, assembling, rehearsing, and translating (Winne & Hadwin, 1998). Products are the tangible outputs of learning, such as notes, essays, or visual representations. Evaluations occur when learners assess the quality of their work. Standards represent the criteria or goals used to judge those outcomes (Bowen et al., 2022; Hooda et al., 2022).

The COPES model stands out due to its adaptability in accommodating a wide range of variables that influence self-regulated learning and its ability to provide timely, context-sensitive educational support through technology (Chansa Thelma et al., 2024). For these reasons, this review adopts the COPES framework as its central analytical lens to examine how artificial intelligence contributes to learners' engagement in self-regulated learning (SRL).

1.2 Artificial Intelligence in Educational and SRL Contexts

Artificial intelligence (AI) is broadly understood as the ability of computer systems to mimic human cognitive functions, such as reasoning, decision-making, and natural language understanding (Zawacki-Richter et al., 2019). In recent years, AI has emerged as a major driver of transformation in education, enabling the design of more personalized, adaptive, and data-informed learning environments (Chen et al., 2024; Uden & Ching, 2024).

One of AI's most notable contributions to learning is its ability to enhance SRL through technologies like adaptive learning systems, recommender tools, and generative AI applications. These systems assist learners by helping them design personalized learning plans, providing real-time feedback, automatically monitoring their progress, and suggesting alternative strategies when difficulties arise (Xu et al., 2025; Zhu, 2025). Intelligent tutoring systems (ITS), for example, can analyze patterns of learner behavior and offer targeted, predictive interventions to support self-regulated learning (SRL) components such as goal setting and self-reflection. Similarly, platforms powered by generative AI, such as ChatGPT, have been used to facilitate meaningful dialogue that promotes critical thinking and self-evaluation during the learning process (L. Zhang & Hew, 2025).

Nevertheless, the effectiveness of AI in supporting self-regulated learning (SRL) depends on more than just the technological sophistication of these systems; it also depends on how well they align with established pedagogical principles and theoretical models. As Weber et al., (2025) noted, AI systems that overlook metacognitive functions are often less effective in fostering learner autonomy. In contrast, systems grounded in SRL frameworks, such as COPES, are more likely to provide timely, meaningful support tailored to individual learning needs. However, some AI systems may lack contextual sensitivity and create learner dependency (Simpson, 2025). This highlights the need for adaptive, learner-centered designs. Additionally, much of the literature published prior to 2020 may not reflect recent advancements in generative AI. Therefore, this review prioritizes studies from the last five years to capture the most relevant and current developments.

While the integration of AI into education shows considerable promise, our understanding of how these systems function across all SRL phases and dimensions is incomplete. This systematic review aims to answer the following research questions: First, how have artificial intelligence technologies been applied to support SRL processes by the phases and constructs defined by Winne and Hadwin (1998) and later expanded by Winne (2018)? Second, to what extent has the use of AI improved students' SRL capabilities and academic outcomes? This study will review the most recent empirical evidence in the field to provide a clearer understanding of AI's potential in supporting SRL and offer recommendations for designing more human-centered and pedagogically informed educational technologies.

2. METHOD

2.1. Literature Search

This review's literature search was designed using the SPIDER framework, which is particularly effective for identifying qualitative and mixed-method empirical studies in education due to its focus on study design and evaluation outcomes (Cooke et al., 2012). The framework helped define and refine the scope of the review by focusing on five core elements: sample, phenomenon of interest, study design, evaluation outcomes, and research type. The target sample in this study consisted of students enrolled in formal education settings ranging from primary school to higher education. The main phenomenon of interest was the use of artificial intelligence to support self-regulated learning (SRL). Studies employing experimental, quasi-experimental, or exploratory designs were considered as long as they reported measurable outcomes related to SRL or academic performance. Qualitative, quantitative, and mixed-methods studies were included to capture a comprehensive picture of current practices and evidence.

To identify relevant studies, several major academic databases were searched in May 2025, including Scopus, IEEE Xplore, SpringerLink, Wiley, ERIC, Taylor & Francis, Emerald, MDPI, and ProQuest. A carefully constructed keyword string was used to maximize the relevance of the search results. The search terms, written in English, included variations and synonyms of key concepts: "artificial intelligence," "AI tutor," "AI-driven learning," and "intelligent tutoring systems," combined with "self-regulated learning" and constrained to formal or higher education contexts using Boolean operators. The publication window was set from January 2007 to May 2025 to capture foundational studies and recent developments in the field. The extended timeframe is justified by foundational works published in the late 2000s that established the conceptual basis for AI-SRL research, particularly with regard to intelligent tutoring systems and early learning analytics.

The initial search yielded 109 records. After removing 43 duplicate entries, 66 publications remained for further screening. The remaining 66 publications proceeded to the next stage of the review process, which involved screening the abstracts and evaluating the full texts based on predetermined inclusion and exclusion criteria.

2.2. Screening and Study Selection

Study selection was conducted in two stages, in alignment with the PRISMA systematic approach. First, two independent reviewers screened the titles and abstracts of the remaining 66 records. The inclusion criteria were: (1) studies involving the use of AI technologies (e.g., chatbots, intelligent tutoring systems, or generative AI) in formal educational settings, (2) research examining the role of AI in supporting one or more SRL phases (e.g., goal setting, monitoring, reflection), (3) studies describing the architecture, functionality, or learner interaction with AI, (4) empirical studies reporting learning or SRL-related outcomes, and (5) articles published in English in peer-reviewed journals or conference proceedings. Exclusion criteria included studies that applied AI solely for administrative purposes; studies that lacked an explicit link between AI and SRL; and articles that did not provide outcome-based evaluations or system descriptions (e.g., editorials, concept papers, or abstracts).

Following this screening, 43 records were excluded. The remaining 66 articles were reviewed in full text. The two reviewers reached an agreement of 87% (Fleiss' Kappa = 0.76, $p < .001$), indicating a high level of consistency in applying the selection criteria.

In the second stage, 20 articles were randomly selected to further assess inter-rater reliability during the full-text review. The reviewers reached a consensus on 16 out of 20 studies (Fleiss's kappa = 0.60, $p = .03$), with most disagreements arising from a lack of information about the interaction between AI and learners. After final deliberation, 22 articles were included in the review and moved forward for systematic analysis. Figure 1 summarizes our review process.

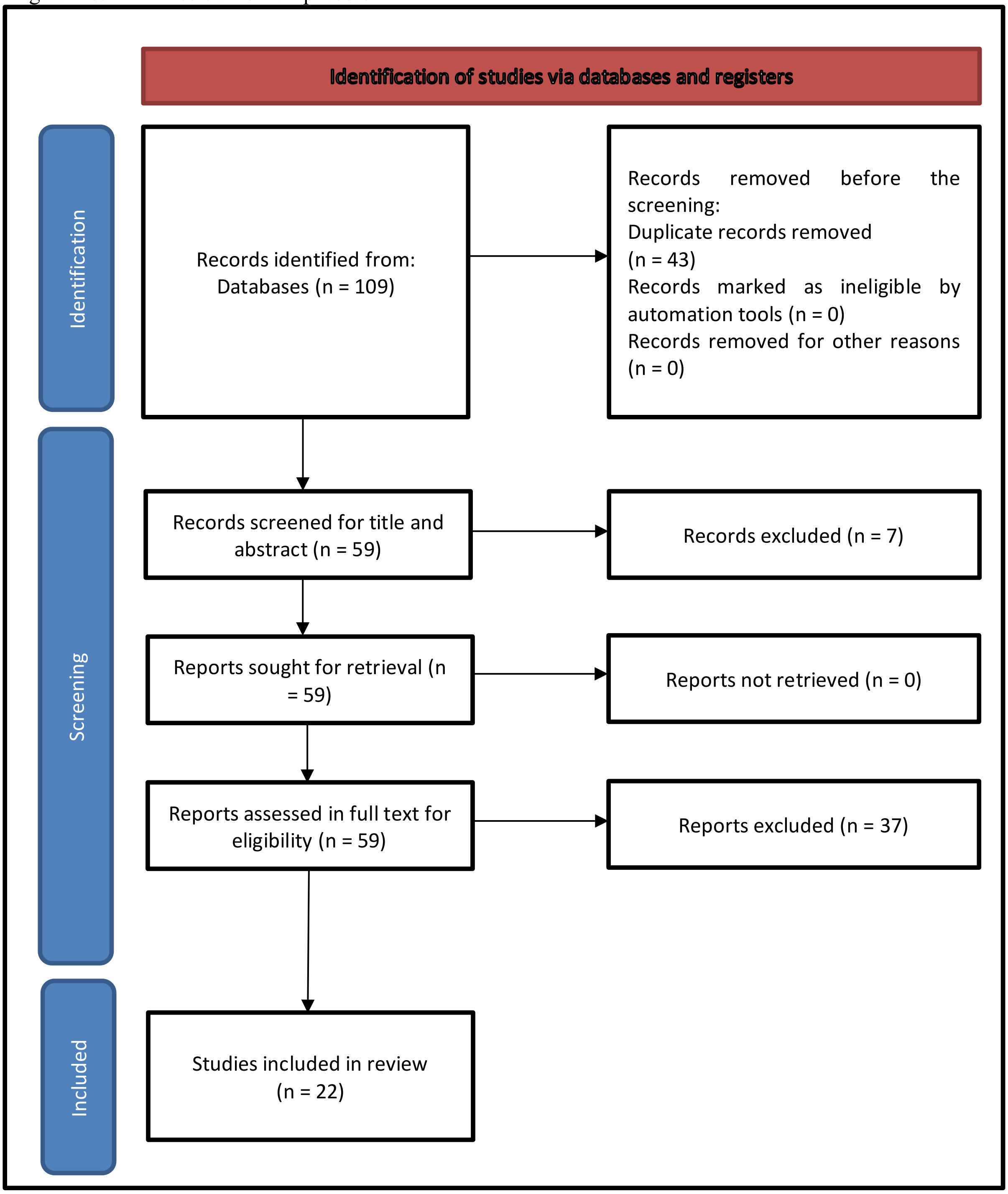

Figure 1. PRISMA Flowchart

2.3. Data Extraction and Analysis

A thorough analysis was conducted by systematically extracting data from each selected publication using a coding framework based on the theoretical model proposed by Winne and Hadwin (1998) and later refined by Winne (2018, 2023). The first author performed the initial data extraction by reviewing the full texts of all 22 included articles. Each study was analyzed to capture relevant information across several dimensions: general bibliographic data (including title, authors, year of publication, educational domain, and participant level); the type and function of the AI intervention (e.g., adaptive tutor, chatbot, generative AI, or recommendation system); and the specific SRL components addressed.

The analysis focused on two levels of SRL integration: the five COPES elements (Conditions, Operations, Products, Evaluations, and Standards) and the four primary SRL phases (task definition, planning and goal setting, strategy enactment, and adaptation through reflection). Additionally, the outcomes reported by each study were reviewed in terms of their effects on SRL development and academic achievement. The extracted data were organized thematically and coded to facilitate cross-study comparisons and pattern identification. Disagreements about coding or interpretation were resolved through iterative discussion. When necessary, a third reviewer was involved to reach a consensus.

This analytical framework was designed to address the two central research questions of the review: the extent to which AI-supported interventions address the different phases and dimensions of SRL (RQ1) and the extent to which these interventions influence students' learning performance and metacognitive regulation (RQ2). A PRISMA flow diagram was constructed to visually present the study selection process, from identifying 109 studies initially to including 22 empirical articles finally.

3. RESULTS AND DISCUSSION

3.1. General Characteristics of the Reviewed Studies

For this review, a total of 22 peer-reviewed, empirical articles were systematically analyzed. All of the selected publications were published in internationally indexed journals or reputable conference proceedings and were directly relevant to the intersection of artificial intelligence (AI) and self-regulated learning (SRL) in educational contexts. Most of the studies were published between 2023 and 2025, reflecting the growing academic interest in integrating AI into education and its potential to enhance learner autonomy and self-management.

Most of the studies were conducted in higher education settings, particularly at the university level. The remainder spanned various levels of formal education, including primary and secondary schools, as well as online and hybrid learning environments.

In the Indonesian context, familial and sociocultural factors also shape students' capacity for SRL. Saputra et al., (2019) found that family support and parental involvement significantly influenced SRL behaviors among vocational high school students, underscoring the importance of contextual variables when applying AI-based interventions in diverse settings.

Across the corpus, a common theme emerged: the focus on integrating AI, primarily in the form of chatbots and intelligent agents, into self-directed learning scenarios. These tools were generally used to guide students through planning, monitoring, and reflective processes within individualized learning pathways.

The dominance of recent publications from 2023–2025 signals a rapid acceleration of interest in applying AI to support self-regulated learning (SRL), particularly as generative and adaptive technologies have become more accessible and pedagogically sophisticated. This trend highlights an ongoing shift in educational research toward leveraging AI to foster deeper cognitive and metacognitive engagement in learners, not just for content delivery.

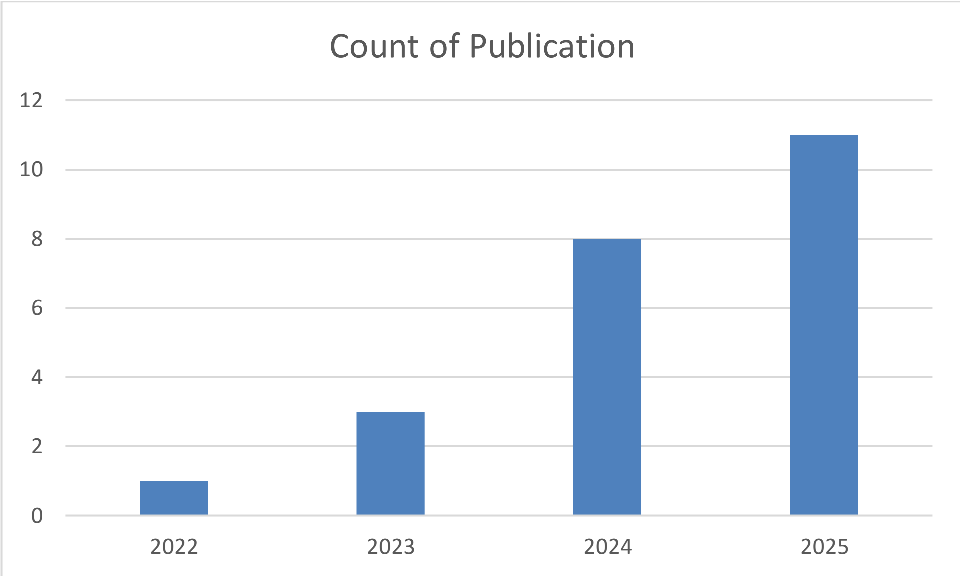

Figure 2. Count of 22 Publications

Most studies were conducted in higher education settings, primarily at the university level. A smaller number of studies explored the implementation of AI-based chatbots in secondary education and online learning environments. The primary areas of focus across these studies included second language acquisition (L2 learning), STEM disciplines (especially science and information technology), educational psychology, instructional technology, and emotional visualization tools. Several studies investigated using generative AI systems to scaffold learning through personalized interaction.

Of the 22 studies reviewed, 16 specifically evaluated chatbots as interactive learning agents designed to facilitate various components of self-regulated learning. These chatbots were often integrated into digital platforms to assist with goal setting, strategy selection, and providing reflective feedback. The remaining seven studies concentrated on the motivational and metacognitive dimensions of AI integration. These studies examined the use of large language models, such as GPT, to support learners' emotional regulation, cognitive monitoring, and self-directed planning.

The design and implementation of these chatbots generally followed two dominant approaches, summarized and compared in Table 1.

Table 1. Design Approaches in AI-Based Chatbot Development

Design Approach	Number of Studies	Key Characteristics
Rule-based	9	Operates on pre-defined scripts with limited, fixed-response capabilities
NLP-driven (AI-based)	14	Utilizes machine learning and natural language processing for adaptive interactions

Several studies incorporated generative AI technologies, such as GPT-3, into chatbot systems to enable adaptive, context-sensitive responses tailored to students' learning states and behaviors (Lin et al., 2024; K. Wang et al., 2025). These models enabled the chatbots to adjust their feedback dynamically based on learners' inputs, emotional cues, and progress patterns. This made the chatbots more responsive and effective in facilitating self-regulated learning (SRL).

Of the 22 studies analyzed, the majority of AI implementations supported specific phases of self-regulated learning as defined by the Winne and Hadwin (1998) model. Eighteen studies focused on the strategy enactment phase, helping students execute learning tasks with guided support. Twelve studies addressed the planning phase, particularly goal-setting and task management. Nine studies provided features that aligned with metacognitive monitoring, such as real-time progress tracking or prompting learners to reflect on their learning. However, only three studies targeted the adaptive reflection phase, which involves reevaluating learning strategies based on feedback and outcomes.

A complete summary of the reviewed studies, including their targeted self-regulated learning (SRL) phases and AI design features, is presented in Table 2.

Table 2. Summary of the Reviewed Studies

No	First Author & Year	Level of Education	AI Type	SRL Stage	Conditions	Operations	Products	Evaluations	Standards	SRL Process	Learning Achievement
1	(K. Wang et al., 2025)	Higher Education	General AI Tools	Performance	✓	✓	✓	✗	✗	Raised awareness in SRL	Improved academic outcomes
2	(Shafiee Rad, 2025)	Secondary/College	Intelligent Tutor	Monitoring	✗	✓	✓	✓	✗	Better comprehension process	Enhanced reading performance
3	(Z. Zhang, 2025)	General Students	ChatGPT, Copilot	Preparation	✓	✓	✗	✗	✗	Stimulated metacognition	Indirect gain via reflection
4	(Al-Abri, 2025)	Undergraduate	ChatGPT	Feedback	✗	✓	✓	✓	✗	Increased engagement	Support for learning tasks
5	(Ji et al., 2025)	College	AI Literacy	Goal-setting	✓	✗	✗	✗	✓	Triggered innovation drive	Increased learning motivation
6	(Xu et al., 2025)	Adult/Managers	AI Integration	Strategic	✓	✗	✗	✓	✓	Managerial SRL traits	Boosted intention to use AI
7	(Liao et al., 2024)	Not Specified	Visual Recognition AI	Planning	✓	✓	✗	✓	✗	Aided in planning	Better visualization use
8	(Hartley et al., 2024)	Independent Learners	AI Tutor, ChatGPT	Execution	✗	✓	✓	✓	✓	Guided autonomous learning	Helped structure study behavior
9	(Hartley et al., 2024)	University	Adaptive Learning	Feedback	✗	✓	✓	✓	✗	Personalized learning paths	Tailored performance improvement

No	First Author & Year	Level of Education	AI Type	SRL Stage	Conditions	Operations	Products	Evaluations	Standards	SRL Process	Learning Achievement
10	(Ferreira da Rocha et al., 2024)	College	Gamification + OLM	Evaluation	✓	✓	✓	✓	✓	Encouraged self-monitoring	Improved academic achievement
11	(Harvey, 2024)	Secondary	AI-based Platform	Monitoring	✓	✓	✓	✓	✗	Better learner awareness	Improved test performance
12	(Chen et al., 2024)	College/ Grad	AI Chatbot	Regulation	✗	✓	✓	✓	✓	Strengthened metacognition	Improved writing skills
13	(Ortega-Ochoa et al., 2024)	High School	Educational AI System	Evaluation	✓	✓	✗	✓	✗	Reflection and adjustments	Partial improvement
14	(Lin et al., 2024)	Higher Education	Chatbot, GPT	Planning	✓	✓	✗	✗	✓	Structured goal-setting	Improved learning efficiency
15	(Barberis & Jin, 2023)	High School	AI Assistant	Execution	✗	✓	✓	✗	✗	Helped manage tasks	Helped students stay on track
16	(Xia et al., 2023)	University	AI for Writing Feedback	Feedback	✓	✓	✓	✓	✓	Reflection and revision	Better writing performance
17	(Kay, 2023)	Undergraduate	Dashboards + AI Feedback	Monitoring	✓	✓	✓	✓	✓	Enhanced self-tracking	Higher motivation and grades
18	(J. Wang et al., 2022)	University	AI-supported MOOCs	Evaluation	✗	✓	✓	✓	✗	Reinforced evaluation skills	Performance slightly improved
19	(T. Li, Yan, et al., 2025)	K-12	AI + Learning Analytics	Planning	✓	✓	✗	✗	✗	Better preparedness	Not specified

No	First Author & Year	Level of Education	AI Type	SRL Stage	Conditions	Operations	Products	Evaluations	Standards	SRL Process	Learning Achievement
20	(T. Li, Nath, et al., 2025)	College	GPT Tutor	Execution	✗	✓	✓	✗	✗	Direct task support	Limited learning gains
21	(Martín-Rodríguez & Madrigal-Cerezo, 2025)	Pre-Service Teachers	AI-Coaching System	Feedback	✓	✓	✓	✓	✓	Growth in reflection	Strong performance improvement
22	(Wong & Viberg, 2024)	Secondary	AI-Personalized Feedback	Monitoring	✓	✓	✓	✓	✗	Ongoing adaptation	Helped lower-performing students

3.2. RQ1: The Role of AI Across SRL Phases and Dimensions

The self-regulated learning (SRL) model, first proposed by Winne and Hadwin (1998) and later refined by Winne (2018), conceptualizes learning as a cyclical process consisting of four interconnected phases. (1) Task definition: Learners interpret and understand the nature of the task. (2) Goal setting and planning: Learners formulate objectives and develop learning plans. (3) Strategy enactment: Learners execute and adjust selected strategies as needed. (4) Adaptation: Learners reflect on and modify strategies based on outcomes. These phases reflect a complex interplay of cognitive, metacognitive, and motivational processes that require active learner engagement and autonomy.

In the digital era, artificial intelligence (AI) has emerged as a promising tool for supporting various components of SRL. However, an analysis of 22 selected studies revealed uneven distribution of AI support across the four phases. The Strategy Enactment phase received the most attention, with 19 out of 22 studies using AI to help students execute learning strategies. In this phase, AI typically functions as a virtual guide, delivering step-by-step feedback and prompting learners with targeted suggestions. It also sustains motivation through chatbot-based interactions and intelligent tutoring systems (D'Mello & Graesser, 2023). These technologies enabled learners to stay engaged and implement learning strategies more effectively and independently.

The planning and goal-setting phase was addressed in 12 studies. In this context, AI applications frequently Provided assistance in time management, task segmentation, and formulating specific, measurable, and achievable learning goals (C. Zhang, 2023). Well-structured planning has been shown to improve subsequent strategy implementation, making this type of AI support essential to the SRL cycle.

In contrast, the adaptation phase, central to reflective learning, was explored in only five studies. These interventions often involved emotion detection technologies, such as facial recognition or sensor-based systems, automated learning journals, and adaptive feedback mechanisms that respond to student performance in real time (Ortega-Ochoa et al., 2024). The scarcity of AI support in this phase is concerning, given that reflection and strategic adjustment are vital for long-term learning growth.

The Task Definition phase received the least attention, with only three studies reporting AI tools that help students clarify and interpret task instructions. This lack of attention is significant because a clear understanding of task requirements is foundational to the rest of the SRL process. Some promising approaches have emerged, including natural language processing (NLP)-based systems designed to help students interpret assignment prompts more accurately (Alqahtani et al., 2023). However, these systems remain underutilized in educational settings.

From a dimensional perspective, the cognitive aspects of SRL, such as information processing, elaboration, and the use of learning strategies, received the most AI support, appearing in 18 studies. The metacognitive dimension, which includes monitoring and regulating one's learning processes, was addressed in 15 studies. The motivational dimension, which covers self-efficacy and goal orientation, was examined in 12 studies. However, only four studies explicitly incorporated affective support, such as recognizing and responding to learners' emotional states during study sessions.

The analysis reveals a consistent pattern: the dominance of chatbot-based AI interventions in the strategy enactment phase. Chatbots can deliver real-time feedback and guidance, making them ideal for supporting learners during task execution, which is likely why they dominate this phase. In contrast, far fewer studies have examined the use of AI in the earlier task definition phase or the later adaptive reflection phase, where more complex reasoning and emotional support are often necessary. Furthermore, NLP-driven chatbots appear to offer broader support across SRL phases due to their capacity for adaptive interaction. Unlike rule-based systems, which are limited to static, predefined responses, NLP-driven chatbots can adapt to the user's needs. This uneven distribution underscores a significant design gap that must be addressed in future AI-powered educational tools.

In summary, although AI technologies have demonstrated considerable potential in supporting self-regulated learning (SRL), existing applications tend to prioritize certain phases and dimensions over others. There is a notable concentration of AI functionality in the enactment and cognitive domains, with limited emphasis on initial task comprehension, reflective adaptation, and affective regulation. To advance the development of AI-assisted learning environments, future research and design should strive for greater balance, ensuring all phases and dimensions of SRL are supported. A more holistic approach would better equip students to become adaptive, reflective, and resilient learners.

A cross-study comparison reveals that, although many AI interventions—especially NLP-driven chatbots and intelligent tutors are effective in facilitating the strategy enactment phase, limited progress has been made in supporting the earlier task definition and later adaptation phases. This suggests that design efforts are concentrated on action-based guidance rather than reflective or preparatory processes. For example, Xu et al. (2025) found that learners using a GPT-powered chatbot exhibited a "marked improvement in self-monitoring frequency and goal adjustment accuracy," demonstrating how AI can bridge the gap between cognitive and metacognitive demands during the enactment phase. However, Barberis and Jin (2023) noted that, although students used AI to manage tasks, "the system's fixed feedback loop limited deeper reflective engagement," highlighting a core design limitation of rule-based systems. This imbalance in AI functionality across SRL phases indicates the necessity of more integrative AI designs that can support learners holistically.

In conclusion, the analysis of the reviewed studies answers RQ1 by confirming that AI tools are concentrated primarily in the middle phases of the SRL cycle, especially in the strategy enactment phase, while offering limited scaffolding in task comprehension and reflective adaptation. This uneven distribution suggests that future AI development must expand beyond task execution to provide full-cycle SRL support.

3.3. RQ2: The Impact of AI on SRL Processes and Academic Performance

The integration of AI in education is increasingly recognized as a transformative influence that reshapes how students engage in self-regulated learning (SRL). Of the 22 studies reviewed, 20 reported measurable improvements in students' SRL behaviors. These improvements included more structured planning, increased progress monitoring frequency, and an enhanced ability to reflect on learning outcomes. These results imply that AI interventions, particularly those employing chatbots, adaptive tutoring systems, and intelligent feedback engines, can effectively foster autonomous learning behaviors. For instance, Chen et al. (2024) showed that a GPT-powered chatbot promoted deeper reflective processes and enhanced learners' metacognitive self-awareness. Additionally, Martín-Rodríguez and Madrigal-Cerezo (2025) noted improved strategy regulation among pre-service teachers via emotion-sensitive AI feedback.

In terms of academic performance, 15 studies found statistically significant gains in metrics such as test scores, writing quality, and completion rates. For instance, Liao et al. (2024) found that students receiving AI-supported SRL guidance outperformed their peers in traditional learning environments. However, four studies reported improved SRL behaviors without corresponding academic gains. These discrepancies were often attributed to short intervention durations or the limited adaptability of AI tools. For instance, Wang et al. (2025) found that, while learners became more aware of their SRL processes, the chatbot system failed to dynamically adjust its feedback, potentially weakening its instructional impact.

These results support RQ2, indicating that AI tools can significantly strengthen SRL processes and lead to academic improvement. However, the effectiveness of these tools depends heavily on their adaptability, personalization, and emotional sensitivity. Poorly optimized systems may result in surface-level engagement or passive reliance on the tool itself. Therefore, future AI developments must prioritize pedagogically informed, human-centered design to ensure long-term efficacy in SRL growth and learning performance.

3.4. Integrative Analysis of AI's Role in Self-Regulated Learning (SRL)

The findings of this review confirm the growing role of artificial intelligence (AI) particularly NLP-driven chatbots and intelligent tutors as a strategic tool that supports various aspects of self-regulated learning (SRL). AI is no longer limited to delivering content or automating instruction. Rather, it increasingly functions as a cognitive and metacognitive scaffold that enables students to plan, monitor, and regulate their own learning. This transformation aligns with the SRL model proposed by Winne and Hadwin (1998) and refined by Winne (2018). This model frames SRL as a cyclical process of understanding tasks, planning strategies, executing those strategies, and reflecting adaptively.

However, despite this promise, AI applications remain disproportionately focused on the strategy enactment phase. Chatbots, in particular, are commonly used to deliver reminders, provide real-time feedback, and support learners during task execution. Few systems are designed to support the initial phase of task definition, in which learners interpret instructions and align them with prior knowledge, or the adaptation phase, in which learners review performance and revise approaches. This lack of comprehensive phase coverage limits the extent to which AI can support SRL in all its complexity.

The emotional and motivational aspects of SRL are also under-explored. While a few studies, such as those by Chen et al. (2024) and Ortega-Ochoa et al. (2024), incorporate emotion-sensitive features like sentiment tracking or adaptive feedback, most AI systems lack empathy-driven design principles. Consequently, these tools risk becoming mechanistic, offering transactional rather than transformative learning support.

A deeper synthesis suggests that future AI designs must evolve beyond task-level assistance to become phase-sensitive and emotionally responsive systems. These tools should dynamically adjust their interactions based on learners' cognitive states, emotional conditions, and personal learning goals. Only by embracing this holistic approach can AI fulfill its potential as a sustainable, equitable driver of self-regulated learning.

3.5. Potential and Limitations of AI in Enhancing Self-Regulated Learning

Artificial intelligence (AI) has substantial potential to enhance self-regulated learning (SRL), particularly by fostering learner autonomy, strategic planning, and self-monitoring. Nearly all of the reviewed studies acknowledged that AI, especially in the form of chatbots and adaptive systems, encouraged learners to set goals, monitor their progress, and evaluate their learning strategies more independently. These tools also provided consistent support that connected cognitive, metacognitive, and motivational processes. For instance, students who used personalized chatbot systems reported greater clarity in planning and more persistence when facing challenging tasks (Al-Abri, 2025; Hartley et al., 2024).

Despite these positive trends, the review also revealed several limitations. One issue is the novelty effect: learners initially engage enthusiastically with AI tools, but motivation can wane if interactions become repetitive or lack personal relevance (Zhang, 2025). Additionally, many systems are designed for short-term use and lack features that encourage sustained reflective practice. Without ongoing personalization, learners may become dependent on AI guidance rather than internalizing self-regulated learning (SRL) strategies.

Another critical limitation is the lack of longitudinal studies. Most of the reviewed interventions were short-term and did not examine whether improvements in SRL translated into lasting behavioral change. This raises questions about the long-term impact of AI-supported learning tools on students' academic resilience and autonomy. Furthermore, younger learners, such as those in K–12 settings, often require more gamified or visual interactions than are currently offered by most AI systems, which tend to be text-based and cognitively demanding.

Three design principles are essential to realizing AI's full potential in self-regulated learning (SRL): (1) integration of emotionally adaptive dialogue and feedback, (2) alignment with theoretical models such as COPES to ensure support across all SRL phases, and (3) long-term usability through dynamic updating, personalization, and multimodal interaction. AI tools that meet these criteria can act as reflective partners in learners' educational journeys, not merely as instructional agents.

4. CONCLUSION

This systematic review examined 22 empirical studies using the COPES framework as a guiding model to explore how artificial intelligence (AI) technologies support the phases and dimensions of self-regulated learning (SRL). Addressing RQ1, the findings show that most AI interventions, particularly chatbots and adaptive learning systems, focus on the strategy enactment and planning phases of SRL. However, fewer tools support the task definition and adaptive reflection phases, which are essential for initiating and sustaining meaningful learning cycles. Cognitive and metacognitive dimensions received the most support, while emotional and motivational components were underrepresented in most AI designs.

In answering RQ2, the review found that AI-enhanced tools generally improved students' SRL behaviors, including goal setting, strategy use, and reflective thinking. Furthermore, 15 of the 22 studies reported statistically significant gains in academic achievement. However, some studies also highlighted the limitations of rule-based or short-duration AI interventions, which may lead to superficial engagement or dependency without fostering deeper conceptual understanding.

This review recommends a conceptual framework for future SRL-supportive chatbots that emphasizes three pillars: emotionally adaptive interaction, phase-sensitive alignment with models like COPES, and sustainable, personalized engagement over time. These design principles can guide the development of intelligent learning companions that support SRL across its full cycle from task comprehension to reflective adaptation.

While the pedagogical benefits of AI are promising, ethical considerations must not be overlooked. Future developments should anticipate risks such as learner overdependence, data privacy concerns, and algorithmic bias. Addressing these issues requires transparent system design, clear consent mechanisms, and inclusive AI training datasets.

This review not only applies the COPES model but also makes a novel contribution by identifying underexplored emotional and motivational dimensions and proposing design-focused implications for future AI-enhanced SRL systems. These findings bridge the gap between theoretical SRL models and real-world AI implementations in education, thereby enriching the current literature.

For educators and instructional designers, the findings underscore the importance of critically evaluating and selecting AI tools that align with pedagogical objectives and self-regulated learning (SRL) theory. Teachers should be trained to not only use AI but also to meaningfully integrate it into lesson planning, student reflection activities, and formative assessment. Future research should explore the long-term impacts of AI on SRL persistence and investigate how affect-aware AI systems influence motivation, equity, and long-term learner autonomy across different age groups.

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