

Review paper

Technology and Instructional Approaches to Support Self-Regulated Learning in STEM Education: A Systematic Literature Review

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ABSTRACT

In recent years, the importance of self-regulated learning (SRL) has become increasingly prominent in STEM education, encompassing science, technology, engineering, and mathematics. Self-regulated learning is regarded as a key competency for students to engage in autonomous learning and achieve sustainable development, particularly in complex and dynamic learning environments. However, there remains a lack of systematic and comprehensive research on how to foster self-regulated learning in STEM education. Following the PRISMA guidelines, this study conducts a systematic literature review to explore self-regulated learning in STEM education and learning contexts, rigorously selecting and analyzing relevant studies published between 2016 and 2025, and ultimately including 23 studies in the review. This review focuses on the primary pathways through which self-regulated learning is promoted in STEM education, including the technological tools that support and scaffold SRL, the instructional approaches to foster SRL, and the cognitive, affective, and behavioral outcomes associated with SRL and SRL-related interventions. As the study results show, a variety of modern technological tools support the development of self-regulated learning in STEM, including AI-powered learning systems, digital learning platforms, computer simulation technology, etc. Furthermore, the instructional approaches, such as innovative modules, game-based instructional approaches, and instructional methods, were found to contribute to the development of SRL. In addition, the review reveals that SRL and SRL-related interventions were associated with a range of cognitive, affective, and behavioral outcomes, with particularly notable associations reported for academic achievement and strategy use.

Keywords: self-regulated learning (SRL), STEM education, technological tools, instructional approaches, learning outcomes, systematic review

Self-Regulated Learning (SRL) refers to the active process of setting goals, selecting appropriate strategies, monitoring progress, and evaluating outcomes throughout the learning journey, emphasizing self-direction and control across cognitive, motivational, and behavioral dimensions (ElSayed et al., 2024). Specifically, SRL encompasses metacognitive processes (awareness and regulation of cognition) and intrinsic motivation and is manifested through strategic learning behaviors (goal setting, progress monitoring, and outcome evaluation), thereby enabling learners to actively regulate their learning processes. Self-regulated learners are more likely to embrace challenging tasks, attain deeper mastery of learning materials, and strive for academic success (Eilts, 2025). Extensive educational research has consistently demonstrated a strong association between SRL and academic achievement, a relationship observed across multiple educational stages, from secondary to higher education,

underscoring the pivotal role of SRL in optimizing learning outcomes (Xu et al., 2023). With the ongoing advancement of digital learning environments and learner-centered pedagogical approaches, effectively supporting learners' self-regulated learning has become a major focus of international educational research.

STEM education encompasses the disciplines of science, technology, engineering, and mathematics, including both learning within individual STEM disciplines and interdisciplinary learning activities that integrate two or more of these fields (Breiner et al., 2012; Sanders, 2008). In this study, STEM education refers to educational activities explicitly situated within these disciplinary or interdisciplinary contexts; studies addressing general educational settings without identifiable STEM learning content are excluded. Compared with traditional knowledge-transmission approaches, STEM learning typically involves open-ended problems, complex tasks, and interdisciplinary knowledge integration, requiring learners to engage in task planning, learning monitoring, strategy adjustment, and outcome evaluation in contexts characterized by uncertainty (Tytler, 2023; Zheng, 2024). Consequently, as a core competence that enables learners to effectively manage complex learning tasks, SRL provides essential support for the development of STEM literacy by fostering intrinsic motivation and facilitating the effective use of learning strategies.

In recent years, the increasing convergence of educational technologies, including artificial intelligence, digital games, gamification, and adaptive learning, has progressively transformed learning environments from conventional technology-assisted models into more interactive, responsive, and personalized learning ecosystems, creating new possibilities for addressing diverse learner needs and reshaping STEM learning experiences (Blumberg et al., 2024; Papadakis & Karakose, 2025; Zourmpakis et al., 2024). However, existing reviews have tended to focus on specific aspects of SRL or STEM education. Some have examined the cognitive and executive function mechanisms underlying SRL (Dörrenbächer-Ulrich & Bregulla, 2024), whereas others have investigated learning analytics and intervention indicators in higher education (Acevedo et al., 2024). Still others have concentrated on flipped classrooms and smart learning environments (Silverajah et al., 2022; Gambo & Shakir, 2021). Meanwhile, reviews of STEM education have primarily addressed interdisciplinary instruction, problem- and project-based learning, teacher practices, and the development of 21st-century competencies (Ilma et al., 2023; Sahito & Wassan, 2024). Although these reviews have advanced research on SRL and STEM education independently, systematic integration at the intersection of these two fields remains limited.

In particular, a comprehensive synthesis remains lacking regarding how technologies support SRL in STEM education, how instructional approaches foster SRL, and how SRL and related interventions are associated with learning outcomes. These three dimensions are inherently interconnected: technologies provide opportunities and scaffolds for learners' self-regulatory processes, instructional approaches shape how such support is enacted, and the effectiveness of these supports is ultimately reflected in cognitive, affective, and behavioral outcomes. Therefore, unlike previous reviews that have primarily focused on specific digital learning environments, flipped classrooms, smart learning environments, or particular instructional models in STEM education, this review integrates technological tools, instructional approaches, and multidimensional learning outcomes within a unified STEM-SRL analytical framework. In doing so, it provides a systematic account of how SRL is supported and enacted in STEM education and of the outcomes associated with such support.

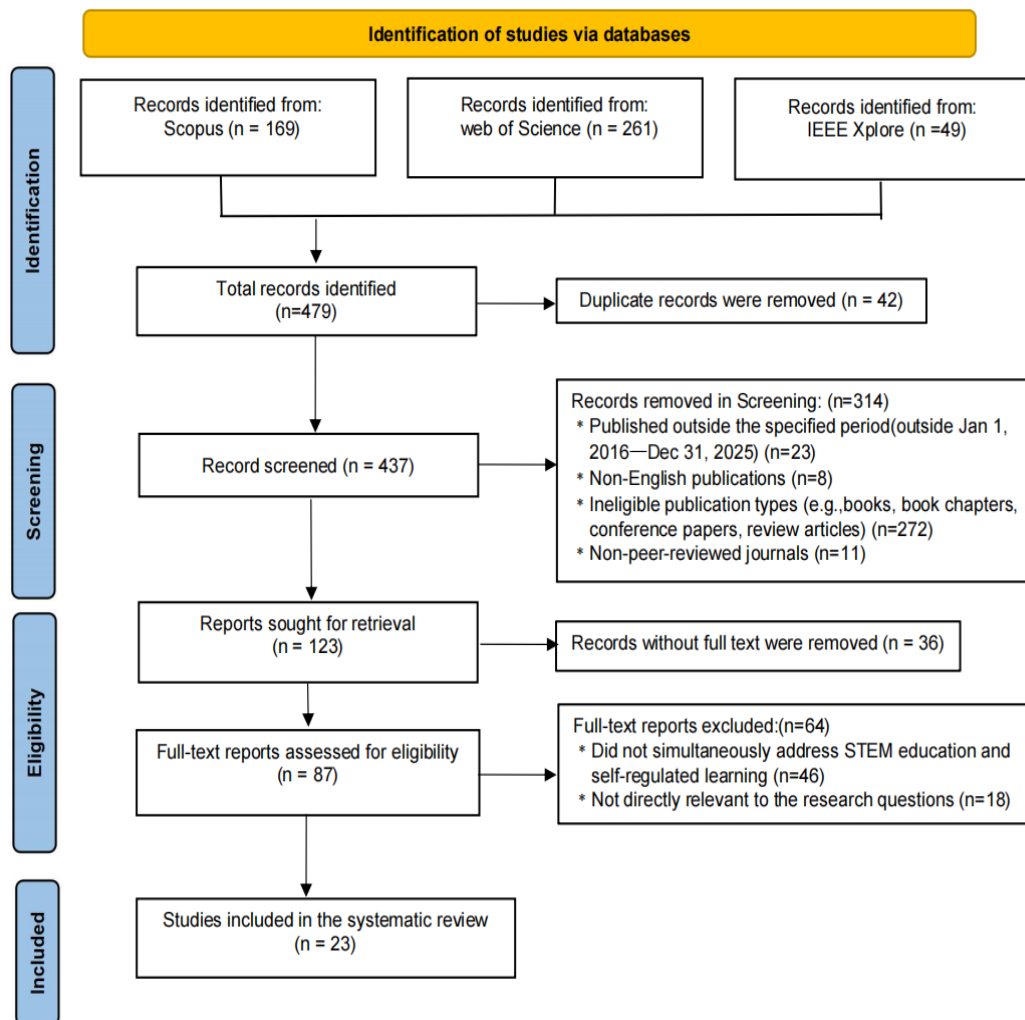
This review focuses on studies published between 2016 and 2025 to capture recent developments in SRL research within the context of the rapid integration of technologies such as virtual simulation, mobile learning, and artificial intelligence into STEM education over the past decade, rather than to establish the historical origins of SRL theory. The literature search was conducted using the Web of Science, Scopus, and IEEE Xplore databases to ensure comprehensive coverage of educational and interdisciplinary research. Based on the above conceptualization and the identified research gaps, this study addresses the following three research questions (RQs):

1. RQ1: How have technological tools been utilized to support and scaffold self-regulated learning in STEM education?
2. RQ2: How have instructional approaches been employed to foster self-regulated learning in STEM education?
3. RQ3: What cognitive, affective, and behavioral outcomes are associated with self-regulated learning and SRL-related interventions in STEM education?

METHODOLOGY

Systematic Searching Procedures

This study follows the PRISMA 2020 review process, which comprises four stages: identification, screening, eligibility, and included, as illustrated in [Figure 1](#). In this study, a review protocol was developed before conducting the systematic review; however, it was not prospectively registered in any publicly accessible registry.

Figure 1*Adapted PRISMA systematic selection process.*

Identification phase

This study selected three databases: Scopus, Web of Science (WoS), and IEEE Xplore. All database searches were conducted between March 15 and March 20, 2026, with the search restricted to studies published between January 1, 2016, and December 31, 2025. To account for differences in search syntax and indexing across databases, the search strategies were adapted to each database's requirements. The detailed search strategies are presented in [Table 1](#). Specifically, searches were conducted using the "TITLE-ABS-KEY" field in Scopus, the "Topic (TS)" field in Web of Science, and the 'All Metadata' field in IEEE Xplore.

Table 1*Search Strategies Used in Scopus, Web of Science, and IEEE Xplore*

Databases	Search field	Title/Abstract/Keywords
Scopus	TITLE-ABS-KEY	TITLE-ABS-KEY ('Self-regulated learning' OR 'Self regulated learning') AND TITLE-ABS-KEY ('STEM education' OR 'STEM learning' OR 'Science education in STEM' OR 'Technology education in STEM' OR 'Engineering education in STEM' OR 'Mathematics education in STEM')
Web of Science	Topic (TS)	TS= ('Self-regulated learning' OR 'Self regulated learning') AND TS= ('STEM education' OR 'STEM learning' OR 'Science education in STEM' OR 'Technology education in STEM' OR 'Engineering education in STEM' OR 'Mathematics education in STEM')

IEEE Xplore	Metadata	(‘Self-regulated learning’ OR ‘Self regulated learning’) AND (‘STEM education’ OR ‘STEM learning’ OR ‘Science education in STEM’ OR ‘Technology education in STEM’ OR ‘Engineering education in STEM’ OR ‘Mathematics education in STEM’)
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The search strategy was deliberately aligned with the conceptual scope of this review, which focuses on self-regulated learning in explicitly STEM education and learning contexts. Specifically, the review targeted studies that explicitly situated their educational contexts within a STEM education and learning, rather than studies that broadly encompassed science, technology, engineering, or mathematics as separate disciplinary settings without an explicit connection to STEM education and learning contexts. Similarly, ‘self-regulated learning’ and its spelling variant were used to identify studies explicitly grounded in the SRL construct. Related processes, such as metacognition, monitoring, planning, help-seeking, and learning strategies, were not searched independently because, when examined outside an explicit SRL framework, they may represent distinct theoretical constructs. These boundaries ensured that the retrieved studies remained conceptually consistent with the review’s intended focus on explicitly framed SRL research within STEM education.

The initial search yielded 479 records, comprising 169 records from Scopus, 261 from Web of Science, and 49 from IEEE Xplore. Before the screening, 42 duplicate records were identified and removed, leaving 437 unique records for screening.

Screening phase

Following duplicate removal, 437 unique records underwent screening against the predefined inclusion and exclusion criteria presented in Table 2. Eligible studies were required to be peer-reviewed journal articles published in English between January 1, 2016, and December 31, 2025. Ineligible publication types, including books, book chapters, conference papers, review articles, were excluded.

Table 2

Inclusion and Exclusion Criteria

Inclusion criteria	Exclusion criteria
Peer-reviewed journal papers	Not Peer-reviewed journal papers
Published between January 1, 2016 and December 31, 2025	Other years
English articles	Not English articles
Published journal articles	books, book chapters, conference papers, review articles

During the screening, 314 records were excluded because they were published outside the specified period (n =23), were not published in English (n = 8), were ineligible publication types (n =272), or were not peer-reviewed journal articles (n = 11). Consequently, 123 reports were retained for full-text retrieval. The screening was conducted independently by two reviewers. Any disagreements between the two researchers were resolved through discussion and consensus. If consensus could not be reached, a third reviewer was consulted to make the final decision.

Eligibility phase and inclusion phase

During the eligibility phase, a systematic review was conducted for the 123 remaining articles. Of these, the full texts of 36 reports could not be obtained, leaving 87 reports for full-text eligibility assessment. The inclusion criteria were as follows: (1) the article needed to include STEM education and self-regulated learning simultaneously; and (2) the article was directly relevant to the research questions of this study. Following the eligibility assessment, 64 studies were excluded for failing to meet the predefined inclusion criteria. Among these, 46 studies did not simultaneously address STEM education and self-regulated learning, while 18 studies were not directly relevant to the research questions.

Eligibility was primarily based on empirical relevance to the review questions. Studies involving learners were included to provide evidence on learning-related outcomes and experiences. Design-oriented studies without direct learner participation were also considered eligible when they provided relevant evidence on the design and technological feasibility of educational applications. Such evidence was treated as complementary and was not interpreted as demonstrating effects on learners. Ultimately, 23 studies were included in the systematic review.

Data extraction and quality assessment

For studies meeting the inclusion criteria, two researchers independently extracted and coded the data using a predesigned data extraction form. The extracted information included study characteristics, sample characteristics,

study design, technological tools or instructional approaches, the SRL theoretical framework and measurement methods, and cognitive, affective, and behavioral outcomes. Any discrepancies were resolved through discussion and, when necessary, adjudicated by a third researcher. Subsequently, the methodological quality of the included studies was assessed using the Mixed Methods Appraisal Tool (MMAT 2018) (Hong et al., 2018), with the appropriate appraisal criteria applied according to each study design. Quality assessment was conducted independently by two researchers. The appraisal results were used to compare the quality of the evidence and identify methodological limitations rather than to determine study eligibility for inclusion. Detailed quality assessment results are provided in Appendix A.

Data coding and analysis

To address the three research questions, data concerning technology applications, instructional approaches, and learning outcomes were extracted from the included studies and analyzed using a combination of inductive and theory-informed coding. For RQ1, technological applications were inductively categorized according to similarities in their functions and modes of implementation. For RQ2, instructional approaches were first inductively categorized by their instructional design characteristics and were subsequently mapped onto the phases and subprocesses of Zimmerman's (2002) three-phase SRL model, comprising forethought, performance, and self-reflection. For RQ3, a theory-informed coding approach was used to synthesize the learning outcomes reported in the included studies. SRL was conceptualized as a multidimensional process involving cognitive/metacognitive, motivational/affective, and behavioral regulation (Pintrich, 2000; Panadero, 2017). To distinguish these underlying regulatory processes from their associated learning outcomes, this study's outcomes were organized into three analytical categories: cognitive, affective, and behavioral, consistent with previous research synthesizing SRL-related learning outcomes (Zheng & Sun, 2025). In interpreting behavioral outcomes, a distinction was made between underlying self-regulatory processes, observable learning behaviors, and platform-recorded interaction data. Behavioral indicators such as repeated practice, feedback access, and hint use were not treated as direct evidence of effective self-regulation, as similar behavioral patterns may reflect different underlying regulatory processes or learning conditions. Instead, these indicators were interpreted in relation to their operational definitions and specific learning contexts in the original studies.

RESULTS

Through a systematic search and rigorous screening process, this study identified 23 articles that met the established research criteria. However, these studies display a certain degree of overlap across dimensions such as technological applications, instructional strategies, and implementation effects. The included studies exhibited substantial heterogeneity in research design, sample size, and measurement approaches, encompassing randomized and quasi-experimental interventions, observational studies, process-tracing analyses, small-scale course evaluations, and technology design and simulation studies. Sample sizes ranged from exploratory studies involving 25 participants to large-scale course-based studies with more than 1,000 students. However, most studies remained confined to a single school, course, or technological context, indicating that larger sample sizes do not necessarily translate into greater representativeness of the findings.

The MMAT appraisal indicated variability in the overall methodological quality of the included empirical studies. Most studies addressed clearly defined research questions and employed data that were appropriate for answering those questions. The principal methodological limitations included convenience sampling, non-randomized group allocation, inadequate control of confounding variables, insufficient reporting of missing data, and reliance on self-report measures. Randomized intervention studies or studies incorporating comparison groups provided relatively stronger evidence regarding intervention effects, whereas single-group course evaluations and observational studies were more suitable for elucidating SRL processes or associations among variables and were insufficient to support definitive causal inferences. It should be noted that Yan et al. (2024) was a technology design and simulation-based validation study. Its contribution lies in elucidating the design mechanisms through which an AI-supported adaptive practice system facilitates SRL; however, because the system has not yet been evaluated in authentic classroom settings, the study was considered evidence of technological feasibility only and was not used to infer its actual effects on SRL or learning outcomes. The complete MMAT appraisal results and the rationale underlying each assessment are presented in Appendix A.

Technological tools supporting self-regulated learning in STEM education

This systematic literature review identified 18 studies that investigated the use of technological tools to facilitate or support the development of SRL in STEM education, primarily involving Artificial Intelligence (AI), digital learning platforms, Computer-based virtual technology, human-computer interaction technologies, and mobile internet technologies, as shown in [Table 3](#). Overall, technology is no longer used merely as a medium for

knowledge delivery; rather, it has increasingly assumed the functions in self-regulated learning, including learning planning, process monitoring, strategy adjustment, feedback utilization, and self-reflection.

Table 3

Synthesis of technological tools and their support for self-regulated learning

Technology application	Articles	SRL Support Mechanism	Evidence Base and Interpretive Limitations
Artificial intelligence (AI)	Glick et al. (2024); Yan et al. (2024);	Support planning, self-monitoring, reflection, confidence judgement, and adaptive strategy adjustment through virtual-agent training and intelligent practice systems.	Evidence comprises a section-level randomized training study and a system-design study evaluated through simulation. The intervention provides preliminary behavioral evidence, but low module completion and limited baseline information constrain causal interpretation. The simulation study demonstrates technical feasibility rather than effectiveness with STEM learners.
Digital platforms (Moodle, Blockly Games, Learning management system, Tech-enhanced environments, etc.)	Sung et al. (2025); Duran et al. (2025); Manzanares et al. (2020); Bernacki et al. (2020); Huang et al. (2022); Schettig et al. (2022); Asher et al. (2025); Hou et al. (2025); Kurniawan et al. (2025)	Support goal setting, behavioral tracking, self-monitoring, strategy selection and adjustment, feedback use, repeated practice, and self-evaluation.	Evidence includes digital-training interventions, course implementations, quasi-experimental research, observational studies, and multimodal or process-trace analyses. Platform records strengthen the observation of SRL in authentic learning contexts; however, non-randomized designs, single-course settings, incomplete participation, and the ambiguous meaning of some digital actions limit causal and generalizable conclusions.
Computer-based virtual technology (Energy3D, Computer-supported collaborative learning, etc.)	Li, Du, et al. (2020); Zheng et al. (2019); Zheng et al. (2020); Li et al. (2022); Li, Chen, et al. (2020)	Provide contexts for goal setting, strategic planning, task execution, self-monitoring, adaptive adjustment, experimentation, reflection, and visualization of SRL processes.	Evidence is predominantly observational and process-oriented, using behavioral logs, interaction records, clustering, network analysis, and temporal modelling. These studies offer detailed accounts of how SRL unfolds over time, but their concentration on specific simulation tasks, schools, and learner groups prevents attribution of SRL improvement to the virtual technology itself.
Human-Computer Interaction (HCI)	Johnson (2019)	Integrate goal planning, progress monitoring, immediate feedback, bodily interaction, and reflection.	Evidence derives from a small mixed-methods study combining pre-post assessment with discourse analysis. The design provides useful mechanism-level evidence, but convenience sampling, self-selected partners, and the highly specific laboratory context substantially limit causal inference and generalizability.
Mobile Internet Technology	Tsamago and Bayaga (2023)	Facilitate autonomous inquiry, information seeking, collaboration, self-monitoring, feedback, and reflection.	Evidence is based on a non-equivalent-group quasi-experimental study. The comparison-group design provides more direct evidence than a single-group evaluation; however, non-random assignment means that school context, teacher effects, prior ability, and access to technology may have contributed to the observed differences.

Research on artificial intelligence (AI) reflects a shift in technology-supported learning from providing general feedback to enabling personalized regulation. However, the current evidence base varies substantially in methodological strength. Among the included studies, Glick et al. (2024) provided comparatively stronger intervention evidence by using a randomized design to examine AI-driven virtual agents designed to train students in planning, monitoring, and reflection strategies, while using learning tool log data to track self-regulated learning

(SRL) behaviors. By evaluating intervention outcomes with objective behavioral data, rather than relying solely on self-report measures, the study reduced potential measurement bias. However, the relatively low training completion rate, together with the absence of baseline measurements and controls for demographic variables, limited the internal validity of the findings and weakened causal inferences. Therefore, although the study provides relatively direct intervention evidence for the potential of AI-driven virtual agents to support SRL, the magnitude and causal interpretation of the observed effects should remain cautious. In contrast, Yan et al. (2024) proposed an AI-based adaptive practice system (CAP) that integrates learners' confidence assessment, knowledge tracing, dynamic item sequencing, and an AI-learner shared-control mechanism. By continuously monitoring learners' progress and dynamically adjusting practice content, the system provides technological scaffolding for self-monitoring, autonomous decision-making, and self-regulation. Nevertheless, because the system was evaluated through simulation rather than an eligible human empirical design, it provides design and feasibility evidence rather than evidence of effects on learners' SRL in authentic classroom settings.

Digital learning platforms primarily promote self-regulated learning (SRL) through process tracking, immediate feedback, and adaptive support. The comparatively stronger evidence comes from intervention studies, which suggest that digital platforms can function as process-oriented scaffolds for self-regulated learning by embedding learning-strategy training, gamified feedback, active-learning modules, and differentiated learning pathways within learning management systems (LMSs) or personalized digital learning environments. Through features such as self-paced learning, immediate feedback, progress monitoring, and adaptive support, these platforms create more structured conditions for learners to plan, monitor, strategically adjust their learning, and sustain engagement throughout the learning process (Bernacki et al., 2020; Duran et al., 2025; Schettig et al., 2022; Kurniawan et al., 2025). However, methodological limitations, including class-level allocation, non-probability or course-based sampling, and uncontrolled pretest-posttest designs, constrain causal inference. In contrast, Huang et al. (2022), Sung et al. (2025), Manzanares et al. (2020), and Hou et al. (2025) employed serious games, online self-assessments, platform-generated log data, multimodal learning traces, and process mining techniques to demonstrate how digital learning platforms support learners' self-monitoring, feedback utilization, repeated practice, and help-seeking. These studies have strengthened the understanding of the dynamic processes underlying SRL; however, platform-generated behavioral data alone cannot fully explain learners' regulatory intentions. The same observable behavior may reflect effective adaptation of strategy, but it may also indicate confusion, trial and error, or reliance on external prompts.

Research on computer-based virtual technology primarily elucidates the dynamic processes underlying self-regulated learning. Using Energy3D, collaborative interaction records, and behavioral sequence analysis, Li et al. (2020) and Zheng et al. (2020) revealed the temporal relationships among planning, execution, monitoring, and reflection. Such process-oriented studies provide valuable insights into how SRL unfolds; however, they generally do not establish that simulation technologies themselves are responsible for improvements in SRL. Research on human-computer interaction and mobile internet technologies further extends the range of approaches available to support SRL. Johnson (2019) integrated embodied interaction through Kinect with immediate feedback and reflective prompts, although the small sample size renders the findings primarily exploratory. Tsamago and Bayaga (2023) adopted a nonequivalent quasi-experimental design to integrate mobile internet technologies into Self-Organized Learning Environment (SOLE) pedagogy, supporting self-regulated learning by promoting students' autonomous inquiry and collaborative learning. Nevertheless, the use of non-random group assignment means that the findings may still be confounded by pre-existing differences among schools, teachers, and students.

Instructional approaches for self-regulated learning in STEM education

This review included 13 studies that employed instructional approaches to promote self-regulated learning (SRL) in STEM education and further examined how these approaches were implemented to support the development of SRL. Based on their instructional design characteristics, the approaches were categorized into three types: instructional models, game-related instructional approaches, and specific instructional methods. Zimmerman's three-phase model of SRL was used as the analytical framework to examine how these strategies supported the forethought, performance, and self-reflection phases (Zimmerman, 2002). As shown in [Table 4](#), task analysis and self-judgment were the most frequently addressed SRL components across the included studies, whereas self-motivational beliefs and self-reactions received comparatively less attention. This distribution suggests that existing instructional designs place greater emphasis on goal setting, strategic planning, and outcome evaluation, while paying relatively less attention to learners' interests, outcome expectations, and adaptive regulation. It should be noted that the frequency with which the SRL components were examined reflects patterns of research attention rather than the effectiveness of the corresponding instructional strategies.

Table 4

Distribution of Zimmerman's SRL Components across the included Instructional Studies

Phase	Dimensionality	Number of studies
Forethought Phase	Task Analysis: Goal Setting, strategic planning	11
	Self-motivation belief: self-efficacy, outcome expectations, intrinsic interest, learning goal orientation.	5
Performance Phase	Self-Control: imagery, self-instruction, attention focusing, task strategies;	8
	Self-Observation: self-recording and self-experimentation.	10
Self-Reflection Phase	Self-judgment: self-evaluation, causal attribution;	11
	Self-reaction: self-satisfaction/ affect/Adaptive/defensive	6

Instructional models primarily supported self-regulated learning (SRL) by establishing clear learning goals, providing strategic guidance, and organizing reflective activities. However, the evidence was more informative about the implementation and potential benefits of structured instructional approaches than about their causal effectiveness. Kreider (2018) and Schettig (2022) examined SRL development through a multi-tiered support model and active learning modules, respectively, providing related empirical evidence for the practical implementation of structured instructional models. However, methodological limitations, including single-group pretest-posttest designs, missing data, and inadequate control of confounding variables, restricted the strength of causal inferences. Accordingly, these studies provide suggestive rather than robust causal evidence of effectiveness. Evidence from the remaining studies was more exploratory or design-oriented. Picho-Kiroga et al. (2025) designed a metacognitive instructional intervention based on Pintrich's model of self-regulated learning to explore its potential for enhancing SRL among engineering students. However, because of the small sample size and the absence of a comparison group, the findings remain exploratory. In contrast, Bordin et al. (2023) contributed primarily to the conceptualization and implementation of an interdisciplinary instructional model incorporating SRL strategies. Given its qualitative orientation and limitations in the reported evidentiary chain, this study is more appropriately interpreted as evidence concerning instructional design and implementation than as evidence of intervention effectiveness. Further details are provided in [Table 5](#).

Table 5

Instructional Approaches and Evidence Categories for SRL in STEM education

Instructional Strategy Category	SRL Support Mechanism	Articles	Evidence Base and Interpretive Limitations
Instructional models (GPD Model, CS3LD Model, etc.)	Support SRL through explicit goal setting, strategic guidance, formative feedback, and reflective activities.	Bordin et al. (2023); Kreider et al. (2018); Schettig et al. (2022); Picho-Kiroga et al. (2025)	Evidence includes curriculum-design and reflective studies, mixed-methods implementation evaluations, quasi-experimental research, and small-scale exploratory interventions. These studies demonstrate how SRL principles can be integrated into instructional practice; however, the lack of rigorous control groups, relatively small sample sizes, and limited control of confounding variables constrain causal inference.
Game-based instructional approaches (Gamification; Serious Games; A whole-body educational game)	Foster monitoring, persistence, and reflection through challenging tasks, immediate feedback, peer interaction, and opportunities for repeated practice	Duran et al. (2025); Manzanares et al. (2020); Johnson (2019)	Evidence from curriculum implementation, quantitative studies, and small-scale mixed-methods research consistently indicates improvements in learner engagement and self-regulatory behaviors. Nevertheless, convenience sampling and context-specific implementations limit the generalizability of the findings.
Instructional method (SOLEs method, mastery-based testing method, etc.)	Promote planning, monitoring, and strategic adaptation through inquiry-based learning, mastery-oriented assessments, performance rubrics, and	Tsamago and Bayaga (2023); Asher et al. (2025); Shumaker et al. (2025); Kurniawan et al. (2025); Glick et al. (2024);	Evidence includes quasi-experimental studies, randomized controlled trials, classroom-based observational studies, and single-group mixed-methods research. Randomized controlled trials provide relatively strong evidence of behavioral effects, whereas the remaining studies are limited by non-randomized group assignment or the absence of appropriate control groups.

differentiated instruction.	Bernacki et al. (2020)
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Game-related instructional approaches provided contextualized support for self-regulated learning processes, particularly self-monitoring, persistence, and reflection, through challenge, immediate feedback, collaborative activities, and structured prompts (Duran et al., 2025; Manzanares et al., 2020; Johnson, 2019). However, the studies differed in both the focus and weight of their evidence. Duran et al. (2025) reported high levels of learner engagement and satisfaction, although their single-course cohort design and limited control of confounding precluded attribution of these outcomes to gamification itself. Manzanares et al. (2020) found generally favorable performance and satisfaction within a serious-game environment incorporating SRL instruction, but convenience sampling and the absence of an intervention comparison group limited claims of effectiveness. Johnson (2019) provided more direct evidence of planning, monitoring, and reflection elicited by game-based scaffolds, although its small sample and uncontrolled design similarly constrained causal interpretation. Collectively, the evidence more strongly supports the feasibility of game-related environments for promoting engagement and eliciting observable SRL processes than their effectiveness in producing sustained or transferable improvements in learners' SRL.

Instructional methods were primarily reflected in four ways: explicit strategy instruction, inquiry-based learning, assessment support, and personalized instruction. Bernacki et al. (2020) and Glick et al. (2024) implemented digital learning skills training and SRL strategy training, respectively, treating planning, self-monitoring, and reflection as learning competencies that can be explicitly taught. These interventions promoted the use of learning strategies and self-regulated learning behaviors; however, class-level assignment, voluntary participation, and relatively low training completion rates limited the attribution of the observed effects to the interventions themselves. With respect to assessment support, the randomized experiment by Shumaker et al. (2025) provided comparatively stronger evidence. It demonstrated that point values embedded in scoring rubrics guided learners to prioritize higher-value content during learning, providing strong behavioral evidence that scoring rubrics can influence self-regulated learning decision-making. Meanwhile, Tsamago and Bayaga (2023), Asher et al. (2025), and Kurniawan et al. (2025) supported self-directed inquiry, iterative feedback, and adaptive learning through Self-Organized Learning Environments (SOLE), mastery-based assessment, and personalized instruction, respectively, reflecting a gradual shift in SRL support from teacher-directed instruction toward learner-centered approaches. Nevertheless, causal inference remains constrained by methodological limitations, including non-randomized designs, context-specific settings, and potential teacher-related confounding. Evidence is comparatively stronger for the quasi-experimental SOLE study, whereas evidence for mastery-based assessment and personalized instruction remains primarily associative or exploratory.

Cognitive, affective, and behavioral outcomes of self-regulated learning in STEM education

This study synthesizes learning outcomes associated with self-regulated learning (SRL) and SRL-related interventions in STEM education across three dimensions: cognitive, affective, and behavioral (Pintrich, 2000; Panadero, 2017; Zheng & Sun, 2025). Overall, the available evidence is concentrated primarily on cognitive and behavioral outcomes, whereas affective outcomes have received comparatively limited attention. This distribution suggests that existing research has placed greater emphasis on the relationship between SRL and measurable learning performance as well as observable regulatory behaviors, while learners' affective experiences remain underexplored. Further details are provided in [Table 6](#).

Table 6

Cognitive, Affective, and Behavioral Outcomes Associated with Self-Regulated Learning and SRL-Related Interventions in STEM Education

Outcome Dimension	Main Outcomes	Articles	Evidence Base and Interpretive Limitations
Cognitive outcomes (n = 19)	Academic achievement, examination performance, knowledge acquisition, conceptual understanding, learning gains, academic task performance, and metacognitive monitoring	Zheng et al. (2020); Tsamago and Bayaga (2023); Bernacki et al. (2020); Manzanares et al. (2020); Huang et al. (2022); Sung et al. (2025); Li, Du, et al. (2020); Zheng et al. (2019); Sebesta and Bray Speth (2023); Li et al. (2022); Li, Chen, et al. (2020); Johnson (2019); Asher et al. (2025); Hou et al. (2025); Picho-Kiroga et al. (2025); Duran et al. (2025); Schettig et al. (2022); Kurniawan et al. (2025); Shumaker et al. (2025)	Evidence includes digital-training interventions, quasi-experimental studies, observational course research, process-trace analyses, and small exploratory interventions. Findings generally associate monitoring, strategy adaptation, and reflective regulation with more favorable cognitive outcomes. However, variation in Outcome measures, non-randomized designs, context-specific tasks, and limited control of confounding variables constrain causal interpretation.
Affective outcomes (n = 5)	Self-efficacy, learning motivation, satisfaction, and confidence in learning	Manzanares et al. (2020); Huang et al. (2022); Kreider et al. (2018); Duran et al. (2025); Schettig et al. (2022)	Evidence for affective outcomes is comparatively limited and relies substantially on questionnaire data. Self-efficacy, motivation, satisfaction, and confidence were reported either in association with SRL engagement or following SRL-related support. However, self-report bias, common-method variance, and the limited use of rigorous comparison groups constrain conclusions regarding the direction, durability, and causal nature of these outcomes.
Behavioral outcomes (n = 18)	Monitoring, strategy use, help-seeking, revision, repeated practice, task persistence, collaborative regulation, and engagement with learning resources	Zheng et al. (2020); Manzanares et al. (2020); Huang et al. (2022); Sung et al. (2025); Glick et al. (2024); Li, Du, et al. (2020); Zheng et al. (2019); Kreider et al. (2018); Sebesta and Bray Speth (2023); Li et al. (2022); Li, Chen, et al. (2020); Johnson (2019); Asher et al. (2025); Hou et al. (2025); Duran et al. (2025); Bernacki et al. (2020); Kurniawan et al. (2025); Shumaker et al. (2025)	Behavioral evidence is strengthened by platform logs, multimodal traces, interaction records, and process-mining techniques, which reduce dependence on retrospective self-report. Nevertheless, observable actions do not always reveal learners' regulatory intentions: repeated attempts or feedback access may indicate adaptive monitoring, confusion, or task dependence. Most findings are therefore better interpreted as process or associational evidence rather than generalizable causal effects.

First, cognitive outcomes constituted the most extensively investigated dimension, encompassing 19 studies. These outcomes primarily included academic achievement, conceptual understanding, learning gains, academic task performance, and metacognitive monitoring. With respect to academic achievement, digital learning skills training, online monitoring, strategy adjustment, and mastery-based assessment were generally associated with improved test scores or course performance. Intervention studies documented improvements in academic performance following the implementation of SRL support (Bernacki et al., 2020), whereas complementary observational evidence indicated that greater engagement in metacognitive monitoring, adaptive strategy use, and SRL-related learning activities was associated with stronger academic performance (Asher et al., 2025; Huang et al., 2022; Sebesta & Bray Speth, 2023).

In the conceptual understanding, Self-Organized Learning Environments (SOLE), serious games, and full-body interactive educational games provided contextualized support for the understanding and construction of STEM concepts through self-directed inquiry, immediate feedback, and reflective activities (Tsamago & Bayaga, 2023; Manzanares et al., 2020; Johnson, 2019). However, compared with stronger experimental evidence, the evidence base in this domain remains relatively limited, drawing primarily on descriptive or mixed-methods studies with methodological constraints. Accordingly, these findings are more appropriately interpreted as supporting the potential educational value of SRL-supportive learning environments for conceptual learning, rather than demonstrating that SRL support itself directly improves conceptual understanding. Furthermore, studies based on Energy3D, Computer-simulated learning environments, and multimodal learning trajectories demonstrated that more coherent and adaptive SRL processes, including advanced planning, ongoing monitoring, strategy revision, and outcome evaluation, were generally associated with higher task success rates, stronger engineering design performance, and greater knowledge gains (Zheng et al., 2020; Sung et al., 2025; Li et al., 2020; Li et al., 2022). However, as these studies primarily employed descriptive or process-tracing designs, their evidence is better suited to elucidating the associations and potential mechanisms linking SRL processes to learning performance than to supporting causal inferences. In terms of metacognition, Picho-Kiroga et al. (2025) found that instructional support targeting monitoring and judgments of performance may improve the accuracy of learners' performance judgments, thereby reducing the discrepancy between perceived and actual performance.

Second, the behavioral dimension was addressed in 18 studies and primarily encompassed self-monitoring, strategy use, feedback utilization, help-seeking, repeated practice, task persistence, collaborative regulation, and learning resource use. Studies conducted in digital platforms and simulation environments indicated that SRL is manifested through a sequence of observable behaviors, including monitoring task progress, revising solutions, switching learning strategies, and adjusting subsequent actions based on feedback (Huang et al., 2022; Sung et al., 2025; Li et al., 2020; Li et al., 2022).

In collaborative learning environments, successful groups typically exhibited more diverse and well-organized sequences of individual regulation and socially shared regulation (Zheng et al., 2019). In the specific regulatory behaviors, comparatively stronger intervention evidence indicated that SRL training was associated with increased use of planning and self-monitoring tools (Glick et al., 2024). Complementing the intervention evidence, observational and process-tracing studies further elucidated the associations between SRL support and students' learning behaviors. Asher et al. (2025) found that engagement in repeated testing within a mastery-based testing system was associated with students' renewed engagement with previously studied content and increased out-of-class practice, whereas Hou et al. (2025) reported substantial differences between high- and low-performing students in patterns of hint access, answer viewing, and transitions among help-seeking strategies. Furthermore, the findings of Sebesta and Bray Speth (2023) further suggest that the ability to modify existing learning methods and adopt more adaptive learning strategies is a key factor in the improved examination performance of some students.

Finally, the affective dimension was addressed in only 5 studies and primarily encompassed self-efficacy, learning motivation, satisfaction, and learning confidence. Self-efficacy was the most frequently reported affective outcome, with intervention studies demonstrating that SRL-related interventions enhanced students' self-efficacy, confidence in learning, and self-advocacy (Kreider et al., 2018; Schettig et al., 2022). Complementary observational evidence from Huang et al. (2022) further demonstrated that self-efficacy and metacognitive monitoring behaviors were closely intertwined within the SRL process, jointly characterizing distinct learner profiles that were differentially associated with academic performance. In the learning motivation and satisfaction, learner-centered instructional approaches, such as gamification, active learning, and serious games, were found to enhance learning motivation, learning satisfaction, learner engagement, and intentions for continued participation, thereby fostering more positive learning experiences (Manzanares et al., 2020; Duran et al., 2025). However, compared with the evidence for cognitive and behavioral outcomes, evidence regarding affective outcomes remains relatively limited and relies predominantly on self-report measures to assess learners' subjective perceptions. Only a small number of studies triangulated these findings with learning analytics data or academic performance.

DISCUSSION

This review identified three key areas of research concerning SRL in STEM education: technological tools designed to support and facilitate SRL, instructional approaches aimed at fostering SRL, and cognitive, affective, and behavioral outcomes associated with self-regulated learning and SRL-related interventions. Importantly, these findings should be interpreted within the defined scope of this review, which focuses specifically on research explicitly framed around SRL within STEM education or learning contexts. Accordingly, the patterns identified provide a focused understanding of this particular body of literature rather than a comprehensive representation of self-regulation research across individual STEM disciplines.

Technology-supported SRL in STEM

This review indicates that technology serves three primary functions in research on self-regulated learning (SRL) within STEM education. First, it functions as a direct scaffold by providing support for learners' planning, monitoring, feedback, and reflection (Glick et al., 2024). Second, it serves as a learning environment that promotes the development of SRL through self-directed inquiry, collaborative learning, and task design (Tsamago & Bayaga, 2023). Third, it functions as an analytical tool by leveraging digital learning traces to reveal the dynamic processes underlying SRL (Sung et al., 2025). Correspondingly, scaffold-based technologies have primarily been evaluated through intervention studies that examine their effectiveness in promoting SRL, whereas learning environments have mainly been investigated to understand how SRL support can be embedded within authentic classroom contexts. By contrast, analytical tools have been used predominantly in process-oriented studies to explain the developmental mechanisms of SRL. Therefore, these technological approaches serve distinct research purposes. Although digital platforms appeared most frequently among the included studies, this should not be interpreted as evidence that they are more effective than artificial intelligence, virtual environments, or human-computer interaction technologies.

The primary value of digital learning platforms lies in their ability to transform self-regulated learning processes, which are inherently difficult to observe, into learning behaviors that can be systematically recorded and analyzed. By providing goal prompts, immediate feedback, strategic guidance, and personalized support, these platforms offer continuous scaffolding for learners' planning, monitoring, and self-reflection while simultaneously leveraging behavioral logs and learning analytics to capture the dynamic nature of SRL, thereby providing teachers with data-informed evidence to support instructional decision-making (Bernacki et al., 2020; Huang et al., 2022). This finding is consistent with previous research showing that the pedagogical value of digital platforms extends beyond resource integration and feedback provision to their capacity to support continuous monitoring and adaptive instruction (Makhno, 2022; Elmabaredy & Gencel, 2024). However, digital behavioral data reflect learners' activities rather than the quality of their self-regulation, and high frequencies of platform interactions do not necessarily indicate higher levels of SRL. For example, frequent access to feedback may reflect proactive monitoring, but it may also indicate learning difficulties or dependence on external support (Hou et al., 2025). Likewise, repeated practice may arise from persistence but may equally be driven by assessment requirements (Asher et al., 2025). Therefore, the contribution of digital platforms to SRL should be interpreted by considering learning tasks, behavioral sequences, and learning outcomes in combination, rather than inferring learners' self-regulatory competence solely from the frequency of platform activities.

This review found that technological support for self-regulated learning in STEM education has evolved from providing external learning scaffolds to making SRL processes visible and delivering adaptive support. Computer simulations and collaborative learning environments can capture the temporal trajectories of planning, monitoring, strategy revision, and evaluation, thereby providing fine-grained evidence for understanding how SRL unfolds during complex learning tasks (Zheng et al., 2019; Li et al., 2022). However, because these studies are predominantly observational and conducted within specific task contexts, they can reveal regulatory processes but cannot establish that the technologies themselves improve learners' SRL capabilities. In contrast, artificial intelligence, human-computer interaction technologies, and mobile technologies have further advanced SRL support toward greater personalization, contextualization, and real-time feedback by extending the forms of scaffolding through adaptive guidance, immersive interaction, and mobile learning (Glick et al., 2024; Johnson, 2019; Tsamago & Bayaga, 2023). Nevertheless, the current evidence is still largely derived from small-sample studies, non-randomized designs, or simulation-based evaluations, such as Yan et al. (2024), which address technological feasibility through simulation-based validation rather than empirically demonstrating effects on learners. Consequently, the educational value of these technologies lies primarily in demonstrating their potential rather than providing robust evidence of sustained effectiveness. Furthermore, the implementation of these technologies remains constrained by practical factors, including teachers' digital competence, technological infrastructure, learners' capabilities, and the availability of instructional resources (Celik, 2023; Won, 2023; Ahiaku, 2025). Future research should further explore the deep integration of artificial intelligence, mobile technologies, and digital learning platforms and combine long-term interventions in authentic classroom settings with multi-source learning analytics to examine the sustained effects of technology-supported SRL and the mechanisms through which these effects are achieved.

Instructional approaches for SRL in STEM

This review found that different instructional approaches can all support self-regulated learning (SRL) through mechanisms such as goal setting, immediate feedback, task engagement, and reflective activities. However, their effectiveness does not stem from the instructional approach itself but depends on how well these mechanisms align with learners' characteristics and the learning context. In other words, no single instructional approach is universally superior. Rather, its educational value is jointly shaped by multiple factors, including scaffold design,

implementation quality, learners' capabilities, and task characteristics. This finding is consistent with the argument of Zhang and Zou (2024) that the effectiveness of instructional approaches in promoting SRL depends on their ability to provide appropriate scaffolding that responds to learners' developmental needs and to progressively shift responsibility for regulation from external support to learners themselves as their self-regulatory competence develops.

Structured instructional models are typically grounded in theories of self-regulated learning and organize learning activities around Zimmerman's cyclical phases of forethought, performance, and self-reflection, thereby providing learners with a clear learning pathway and systematic regulatory support (Bordin et al., 2023). However, the effectiveness of these instructional models depends not on the quantity of scaffolding provided but on the dynamic alignment between scaffolding and learners' capabilities. Insufficient scaffolding may fail to stimulate effective self-regulation, whereas excessive structuring may reduce learners' opportunities to set their own goals, select learning strategies, and monitor their learning independently (Mamun, 2022). Therefore, the design of structured instructional models should follow the principle of progressive scaffolding by dynamically adjusting the level of support as learners' capabilities develop. Such models should also gradually reduce learners' dependence on external scaffolds, facilitating the transfer of regulatory responsibility from teachers to learners and ultimately promoting the internalization and transfer of SRL strategies.

In contrast, gamified instruction enhances learner engagement through challenging tasks, immediate feedback, and peer interaction while providing authentic, contextualized opportunities for learners to enact self-regulated learning processes (Duran et al., 2025; Manzanares et al., 2020). However, high levels of engagement or satisfaction should not be regarded as direct evidence of SRL development, as learner engagement may be driven by reward mechanisms, competitive pressure, or novelty effects rather than by the genuine internalization and transfer of self-regulatory strategies across learning contexts. Therefore, the evaluation of gamified instruction should extend beyond learner engagement and immediate learning performance to examine whether learners can continue to apply SRL strategies autonomously after external incentives and the game environment are removed, and whether these strategies can be transferred to new learning tasks and problem-solving contexts.

Specific instructional methods offer greater contextual flexibility and can support self-regulated learning through self-directed inquiry, feedback cycles, and reflective activities (Bernacki et al., 2020; Tsamago & Bayaga, 2023). However, the existing evidence primarily demonstrates how different instructional methods support specific phases or components of SRL, rather than providing sufficient evidence that any single instructional method can systematically promote the development of SRL across its entire regulatory cycle. Although different instructional methods exhibit distinct strengths in supporting planning, monitoring, feedback utilization, or reflection, none is capable of comprehensively addressing the multi-phase and multidimensional regulatory demands of SRL. Therefore, differences among instructional methods should be understood primarily as differences in their conditions of applicability and underlying mechanisms, rather than as evidence of the superiority of one instructional method over another.

The coding results based on Zimmerman's SRL framework further revealed a structural imbalance in current instructional support for self-regulated learning. Task analysis, self-judgment, and self-observation received substantially greater attention than self-motivational beliefs and self-reactions. On the one hand, this distribution may reflect a stronger emphasis in instructional practice on supporting goal setting, learning monitoring, and outcome evaluation. On the other hand, it also suggests that these cognitive processes are more readily observable, measurable, and amenable to instructional intervention. Notably, the most frequently addressed components, including task analysis, self-observation, and self-judgment, all involve metacognitive processes related to planning, monitoring, and evaluation, indicating that current instructional designs primarily focus on supporting learners' metacognitive regulation. However, strengthening metacognitive regulation alone is insufficient to sustain the development of SRL. Without adequate support for self-efficacy, learning interest, emotion regulation, and adaptive responses, learners may acquire self-regulatory strategies but struggle to apply them consistently, autonomously, and across different learning contexts (Ghaleb & Sundram, 2024). Therefore, the design of future instructional approaches should move beyond supporting isolated components of SRL and instead place greater emphasis on the interplay among cognitive, motivational, and emotional regulation in order to promote the internalization, transfer, and sustainable development of SRL strategies.

Outcomes of SRL in STEM education

This review examined the relationships between self-regulated learning (SRL) and SRL-related interventions and cognitive, affective, and behavioral learning outcomes. The findings indicate that existing research has focused predominantly on cognitive and behavioral outcomes, whereas affective outcomes have received relatively limited systematic attention and support. At the same time, only a small number of intervention studies have evaluated changes in learning outcomes following the implementation of SRL support. Most of the available evidence is derived from analyses of associations among questionnaire measures, academic performance, and digital behavioral

data. Consequently, the current evidence primarily reflects associations between SRL and learning outcomes rather than robust causal effects.

In the cognitive domain, academic achievement was the most frequently adopted outcome indicator, and most studies reported that self-regulated learning was associated with better academic performance. This finding is consistent with those of Song et al. (2025) and Theobald et al. (2021), who argued that learners with higher levels of SRL are more likely to effectively plan, continuously monitor, and flexibly regulate their learning processes, thereby achieving superior academic outcomes. At the same time, improvements in academic achievement were often accompanied by gains in conceptual understanding, learning gains, and strategy use (Manzanares et al., 2020; Sebesta & Bray Speth, 2023), suggesting that SRL-related outcomes are inherently multidimensional and that the development of different learning outcomes may reinforce one another to jointly support improved learning performance. However, learners differ substantially in their developmental stage, prior knowledge, learning needs, and self-regulatory competence, and the priorities and developmental trajectories of cognitive, behavioral, and affective outcomes likewise vary across learning contexts. Therefore, SRL interventions should not adopt a uniform or standardized design; instead, they should provide differentiated support tailored to learners' characteristics and specific learning contexts, while dynamically adjusting the forms and intensity of scaffolding.

At the behavioral level, this review found that self-regulated learning and SRL-related interventions were generally associated with positive behavioral outcomes, particularly in terms of task execution efficiency and strategy implementation. This finding is consistent with Zheng (2020), who reported that effective SRL strategies significantly improved both the efficiency and quality of task completion. Existing behavioral evidence is derived primarily from digital behavioral data, including learning platform logs, chat records, and process mining, which continuously capture behaviors such as monitoring, help-seeking, repeated practice, feedback utilization, and strategy switching, thereby providing a more objective basis for understanding the dynamic processes of SRL (Sung et al., 2025; Asher et al., 2025). However, digital behavioral data may reflect only learners' observable behaviors rather than their underlying regulatory intentions, and the same behavior may correspond to different SRL processes. Therefore, future research should integrate multiple data sources, including behavioral logs, self-report measures, interviews, and learning outcomes, to triangulate SRL behaviors and elucidate the mechanisms through which they operate across different learning contexts.

Compared with cognitive and behavioral outcomes, affective outcomes remain substantially underexplored in the existing literature, with only a small number of studies examining self-efficacy, motivation, satisfaction, and learning confidence. However, affective outcomes should not be regarded as mere by-products of self-regulated learning; rather, they are critical factors that influence learners' sustained use of SRL strategies and their capacity to maintain autonomous learning. As Bakhtiar and Hadwin (2022) argued, SRL enhances learners' agency by supporting the maintenance of motivation, the regulation of emotions, and the ability to cope with academic challenges. At the same time, affective outcomes are dynamically interconnected. For example, greater self-efficacy can foster stronger learning interest and sustained engagement, while the development of learning interest can, in turn, reinforce learners' positive evaluations of their own capabilities, thereby creating a mutually reinforcing cycle (Schweder & Raufelder, 2022). Therefore, future research should adopt longitudinal and multi-source measurement designs to further elucidate the mechanisms through which SRL strategies shape affective development and to advance understanding of the interrelationships among affective, cognitive, and behavioral outcomes.

LIMITATION AND CONCLUSION

Although this review systematically synthesized some studies on SRL in STEM education, several limitations should be acknowledged. Firstly, this review employed a deliberately bounded search strategy, focusing on studies explicitly framed around SRL within STEM education and learning contexts. Consequently, studies addressing related self-regulatory processes without an explicit SRL framework, as well as research situated within individual STEM disciplines without explicit reference to STEM education or learning, may have been overlooked. Therefore, the findings were interpreted within this delimited scope, which necessarily constrains their broader applicability. Future reviews may adopt broader construct- and discipline-based search strategies to capture the wider research landscape. Secondly, it primarily focused on technological applications, instructional strategies, and learning outcomes, while the underlying mechanisms of SRL were less explored. In addition, only peer-reviewed journal articles were included, potentially excluding valuable theoretical and practical insights from other academic sources. Finally, the review was limited to formal STEM education settings, overlooking informal and non-traditional learning contexts. Therefore, future research should investigate SRL mechanisms and implementation across diverse STEM learning environments to provide a more comprehensive understanding of SRL in STEM education.

This review systematically synthesized research on self-regulated learning (SRL) in STEM education published between 2016 and 2025, examining technological tools, instructional approaches, and associated learning outcomes. First, technological tools primarily promoted SRL by supporting learners' planning, monitoring, and reflection,

with digital learning platforms representing the most widely adopted technology. Future research should focus on integrating and optimizing diverse technological support functions to develop more intelligent and adaptive SRL support systems. Second, this review synthesized three instructional approaches to foster SRL in STEM education. The effectiveness of different approaches depended largely on the alignment between instructional scaffolding and learners' characteristics and learning needs. Future instructional approaches should emphasize optimizing dynamic scaffolding and the gradual transfer of regulatory responsibility to learners. Finally, SRL and related interventions were generally associated with cognitive and behavioral outcomes, particularly improved academic achievement and strategy use, whereas affective outcomes have received comparatively limited attention. Future research should further investigate the mechanisms through which SRL promotes learners' affective development.

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Ethical statement

This study was conducted as a systematic literature review of previously published research. No primary data were collected from human participants or animals. Therefore, ethical approval from an Institutional Review Board (IRB) and informed consent were not required.

Competing interests

The authors declare that they have no competing interests.

Author contributions

Y.J. contributed to the conceptualization, methodology, literature search, study selection, data extraction, data synthesis, original draft writing, and review and editing of the manuscript. N.M.A. contributed to the literature search, study selection, data extraction, and data synthesis. K.O. contributed to the supervision and academic guidance of the research. All authors read and approved the final manuscript.

Data availability

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

AI disclosure

During the preparation of this manuscript, the authors used ChatGPT solely for language editing purposes.

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