Artificial Intelligence for Science Learning: A Systematic Review of Self-Regulation and Conceptual Understanding

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ABSTRACT

Purpose of the study: This study systematically reviews and synthesises the empirical literature on the role of Artificial Intelligence (AI) in science education, focusing specifically on how distinct AI features support the phases of students' self-regulated learning (SRL) and the construction of conceptual understanding in science.

Methodology: A qualitative systematic literature review reported in line with PRISMA principles was combined with bibliometric mapping. Peer-reviewed articles were retrieved from the Scopus and Sinta databases (2020–2026). Metadata and keyword co-occurrence were analysed using VOSviewer, followed by a thematic synthesis of 25 eligible articles structured around an AI-feature × SRL-phase × conceptual-understanding extraction matrix.

Main Findings: AI research in science education has grown sharply since 2022. Intelligent tutoring systems, learning analytics, adaptive simulations, and generative AI predominantly scaffold the forethought and performance phases of SRL, enhance conceptual understanding, reduce misconceptions, and raise motivation through personalised interaction. Support for the self-reflection phase remains comparatively weak, evidence is concentrated in higher education, and longitudinal and developing-country studies are scarce.

Novelty/Originality: The review advances an integrative framework that explicitly links specific AI affordances to individual SRL phases and to conceptual change in science, repositioning AI as a cognitive and metacognitive mediator rather than a content-delivery aid, and derives an evidence-based agenda that foregrounds the reflection phase, K–12 science, and Global South contexts.

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1. INTRODUCTION

Few questions are as pressing for contemporary science education as how to move learners from the fragile accumulation of factual knowledge towards the durable, transferable conceptual understanding that scientific literacy demands. International benchmarking continues to expose the size of this gap. In the most recent Programme for International Student Assessment, the mean science score in Indonesia was 383 points against an Organisation for Economic Co-operation and Development (OECD) average of 485, a result that declined relative to the previous cycle and that mirrors persistently low science-literacy levels across many education systems [1]. Such figures signal not merely a deficit in content coverage but a deeper difficulty in helping students reason scientifically and regulate their own learning of abstract, counter-intuitive ideas.

Two intertwined competencies sit at the heart of this challenge. The first is self-regulated learning (SRL), conceptualised as a multidimensional process involving learners' cognitive, metacognitive, motivational, and behavioural regulation during learning activities. Recent reviews highlight that SRL operates through cyclical processes of planning, monitoring, strategy use, and reflection, with Zimmerman's and Winne–Hadwin's frameworks remaining influential foundations for contemporary SRL research [2]. In science learning, SRL is particularly important because learners must actively regulate their understanding when engaging with complex and abstract scientific concepts, and evidence indicates that effective self-regulatory processes contribute to improved learning performance and deeper engagement [2]-[5]. The second competency is conceptual understanding itself, referring to learners' ability to construct meaningful connections among scientific concepts rather than merely recall factual information. Recent research on science learning continues to demonstrate that students frequently maintain alternative conceptions that are resistant to change, requiring instructional approaches that facilitate conceptual restructuring and knowledge integration [6].

Against this backdrop, Artificial Intelligence in Education (AIEd) has emerged as one of the most rapidly expanding fields in educational technology. Early systematic mapping showed that applications in higher education clustered around profiling and prediction, intelligent tutoring, assessment, and adaptive systems, yet were strikingly disconnected from pedagogical theory and ethical reflection prompting the now-familiar question of "where are the educators" [7]. Subsequent reviews have charted the maturation of the field across administration, instruction, and learning [8], traced two decades of scholarship [9], and articulated three evolving paradigms in which the learner shifts from recipient of AI-directed instruction to collaborator and finally to leader of AI-empowered learning [10], [11]. The arrival of generative AI has accelerated this trajectory, generating an extensive but fragmented body of work on tools such as ChatGPT in education and research [12]-[15].

The pedagogical promise is considerable. Intelligent tutoring systems (ITS) can provide personalised instruction, adaptive feedback, and scaffolding by modelling learners' knowledge states and regulating learning pathways. Similarly, learning analytics can transform learner-generated data into actionable insights by making cognitive and regulatory processes more visible, while AI-supported adaptive environments and simulations can facilitate exploratory learning and the development of scientific understanding through interactive representations [16]-[19]. In principle, these affordances align closely with self-regulated learning (SRL): AI technologies can support goal setting, monitor learners' progress, recommend learning strategies, and provide reflective feedback, whereas adaptive simulations and visualisations can assist learners in constructing more accurate mental models of complex scientific phenomena [20].

Previous empirical studies have provided initial evidence regarding the contribution of AI-based learning environments to cognitive and metacognitive development. Research on intelligent tutoring systems has demonstrated that adaptive feedback and personalised guidance can improve student achievement by identifying individual knowledge gaps and providing targeted instructional support [18]-[20]. In relation to self-regulated learning, AI-supported learning analytics and adaptive systems have shown potential in assisting learners to monitor their progress, recognise learning difficulties, and adjust learning strategies through real-time feedback [21]-[24]. Furthermore, studies involving simulation-based and AI-enhanced science learning environments indicate that interactive representations, modelling tools, and adaptive scaffolding can facilitate conceptual understanding by enabling students to explore scientific phenomena, test explanations, and revise misconceptions [28]. However, these studies have generally examined AI effectiveness from specific technological perspectives, with limited attention to how AI-driven affordances interact with learners' regulatory processes to produce conceptual change in science learning

Yet the empirical picture is far from settled, and the inconsistencies are instructive. Meta-analytic evidence on ITS is positive but heterogeneous: median gains of roughly 0.66 standard deviations have been reported, but effects shrink sharply on standardised as opposed to locally aligned measures, and comparisons with human tutoring yield smaller advantages than once assumed [21]. Simulation-based learning shows large average effects yet is strongly moderated by the quality of scaffolding [25]-[27]. Reviews of AI-supported SRL converge on a recurring asymmetry technologies scaffold the forethought and performance phases far more readily than the reflection phase, and they raise unresolved questions about whether agency remains human-centred or drifts towards the system [26]-[28]. These divergent findings cannot be reconciled by counting effect sizes alone; they call for a synthesis that asks which AI features support which regulatory and conceptual processes, under what conditions, and at what cost to learner autonomy.

Three gaps follow from this state of the art. First, the majority of studies evaluate the general effectiveness of AI on learning outcomes without disaggregating how specific AI features map onto distinct SRL phases, leaving the mechanism of benefit underspecified [7], [24]. Second, the two literatures that this review brings together, AI for SRL, and AI for conceptual change in science have developed largely in parallel, so that the relationship between regulatory support and conceptual understanding remains theoretically underdeveloped. Third, the evidence base is skewed: it is concentrated in higher education, dominated by short-term quasi-experiments, sparse at the primary and secondary levels in science, and markedly under-representative of developing-country and Global South contexts in which infrastructure, teacher readiness, and the digital divide shape what AI can realistically deliver [34], [35].

Unlike previous reviews that have primarily focused on classifying AI applications, evaluating overall learning effectiveness, or examining individual technological interventions, this review adopts a more integrated perspective by examining the mechanisms through which AI supports learning regulation and conceptual development simultaneously. Previous studies have provided valuable insights into AI-supported tutoring, adaptive learning, learning analytics, and conceptual scaffolding; however, they have rarely explained how specific AI affordances correspond with the phases of self-regulated learning and how these regulatory processes contribute to conceptual understanding and conceptual change in science. Therefore, the distinctive contribution of this review is its attempt to connect technological affordances with cognitive and metacognitive learning mechanisms, positioning AI as a mediator of scientific knowledge construction rather than merely as an instructional delivery system.

The novelty of this review lies in addressing these gaps through an integrative lens. Rather than cataloguing AI tools, it explicitly aligns specific AI affordances with individual SRL phases and with the construction of conceptual understanding in science, and it consolidates this alignment into a conceptual framework that positions AI as a cognitive and metacognitive mediator rather than a mere instructional aid. In doing so the study makes a twofold contribution: theoretically, it extends Zimmerman's SRL model and conceptual-change theory into the AI era by specifying mediating mechanisms; practically, it offers educators, designers, and policymakers an evidence-informed map of where AI currently adds value and where it does not.

This review is important because the rapid expansion of AI adoption in education requires a stronger theoretical and empirical foundation to ensure that technological implementation contributes to meaningful learning rather than simply increasing access to digital tools. Understanding how AI influences learners' regulatory processes and conceptual development is particularly important in science education, where successful learning depends not only on information acquisition but also on the ability to construct, evaluate, and revise scientific explanations. By synthesising current evidence, this study provides guidance for researchers, educators, instructional designers, and policymakers in developing AI-supported learning environments that maintain learner agency, pedagogical alignment, and equitable access.

Accordingly, the purpose of this review is to systematically examine the role of AI in science education by integrating perspectives from self-regulated learning and conceptual understanding. Specifically, this study aims to analyse the development of AI research in science education, identify how AI affordances support different phases of self-regulated learning, synthesise evidence regarding AI contributions to conceptual understanding and conceptual change, and formulate theoretical, practical, and methodological implications for future research and educational practice.

Accordingly, the review is guided by four questions: (RQ1) How has research on AI in science education developed, thematically and bibliometrically, between 2020 and 2026? (RQ2) Which AI features support which phases of self-regulated learning, and where are the gaps? (RQ3) How does AI contribute to conceptual understanding and conceptual change in science? (RQ4) What theoretical, practical, and methodological implications and future directions emerge from the synthesis?

2. RESEARCH METHOD

2.1. Research Design and Protocol

This study adopted a qualitative systematic literature review (SLR) complemented by bibliometric analysis. The SLR component enables an in-depth, theory-driven synthesis of how AI supports SRL and conceptual understanding, while the bibliometric component provides an objective, quantitative map of the intellectual structure and growth of the field. The review process was organised around the four PRISMA stages identification, screening, eligibility, and inclusion to ensure transparency and reproducibility.

2.2. Information Sources and Search Strategy

Two complementary databases were searched: Scopus, as the primary source of internationally indexed peer-reviewed literature, and Sinta, to capture regionally relevant Indonesian scholarship. The search window spanned January 2020 to 2026, reflecting the period in which AIEd research, and generative AI in particular, expanded most rapidly. The search combined controlled and free-text terms using Boolean operators: ("Artificial Intelligence" OR "AI" OR "intelligent tutoring" OR "adaptive learning" OR "learning analytics" OR "generative AI") AND ("science education" OR "STEM") AND ("self-regulated learning" OR "metacognition" OR "conceptual understanding" OR "misconception").

2.3. Eligibility Criteria
Inclusion and exclusion criteria were defined a priori and are summarised in Table 1.

Table 1. Inclusion and exclusion criteria

Criterion	Inclusion	Exclusion
Period	Published 2020–2026	Published before 2020
Language	Written in English	Other languages
Source	Peer-reviewed journal articles (Scopus/Sinta indexed)	Editorials, abstracts, non-peer-reviewed items
Focus	AI applied to science/STEM learning addressing SRL and/or conceptual understanding	AI used purely for administration or unrelated domains
Evidence	Empirical studies or systematic reviews/meta-analyses	Opinion pieces without data or synthesis

The eligibility criteria were established to ensure the relevance and quality of the selected studies. The 2020–2026 publication period was chosen to capture recent advances in AI applications in science education, particularly the rapid development of adaptive learning, intelligent tutoring systems, and AI-based learning analytics. Only English-language, peer-reviewed journal articles indexed in Scopus or Sinta were included to ensure academic rigor. Studies were selected if they investigated AI implementation in science/STEM learning related to self-regulated learning (SRL) and/or conceptual understanding. Articles focusing on non-pedagogical AI applications, unrelated domains, opinion papers, and publications without empirical evidence or systematic synthesis were excluded. These criteria ensured that the reviewed literature provided recent and evidence-based insights into the cognitive and metacognitive roles of AI in science education.

2.4. Selection Process
Records identified through database searching were de-duplicated and screened by title and abstract against the eligibility criteria, after which full texts were assessed for eligibility. Twenty-five articles met all criteria and formed the corpus for synthesis. Screening decisions and reasons for exclusion were documented to support reproducibility.

2.5. Data Extraction and Analysis
A structured extraction matrix was used to record, for each study, the authors and year, country/context, research design, sample, key variables, the specific AI feature(s) examined, the SRL phase(s) supported, the conceptual-understanding outcome, reported limitations, and stated future directions. Analysis proceeded in two strands. First, bibliometric analysis in VOSviewer used keyword co-occurrence to identify thematic clusters and co-authorship analysis to characterise collaboration. Second, a thematic synthesis organised findings around three analytic dimensions AI support for SRL phases, AI support for conceptual understanding, and the mediating role of motivation and personalization rather than around individual authors, enabling cross-study comparison and the identification of convergences, divergences, and gaps.

2.6. Methodological Limitations of the Review
Three limitations should be borne in mind when interpreting the findings. The restriction to Scopus and Sinta and to English-language articles may have excluded relevant work indexed elsewhere; the qualitative thematic synthesis, while well suited to mechanism-level questions, does not yield pooled effect sizes; and the relatively small corpus reflects the deliberately narrow intersection of AI, SRL, and conceptual understanding in science rather than the breadth of AIEd as a whole.

3. RESULTS AND DISCUSSION
3.1. Publication Trends and Thematic Structure (RQ1)
The analysis of publication trends provides an overview of the evolution and maturity of research on Artificial Intelligence (AI) in science education. Across the reviewed corpus, publications demonstrated a gradual increase from 2020 onward, followed by a substantial acceleration after 2022. This growth corresponds with the rapid adoption of AI-driven educational technologies, including learning analytics, intelligent tutoring systems, adaptive learning platforms, and generative AI applications. The increasing volume of publications reflects not only technological advancement but also a conceptual shift in educational research, where AI is increasingly viewed as a mechanism for supporting cognitive engagement, learner autonomy, and metacognitive development rather than merely as a tool for content delivery. This transition aligns with the movement from AI-directed learning toward AI-empowered learning, in which intelligent systems function as adaptive partners that

facilitate students' active construction of knowledge [11]. The distribution of reviewed studies by publication year is presented in Table 2.

Table 2. Distribution of reviewed studies by year (2020–2026)

Year	No. of Articles	Characterisation of the Period
2010	1	Foundational framing of AI in education
2021	2	Early implementation of intelligent tutoring systems
2022	3	Growing emphasis on learning analytics
2023	4	Expansion of adaptive simulations in science
2024	5	Tighter integration of AI with science learning
2025	5	Rising focus on AI support for SRL
2026	5	Convergence on conceptual change and SRL

The publication pattern indicates that AI research in science education has evolved through several stages. Early studies primarily explored the feasibility and implementation of intelligent learning systems, whereas more recent investigations have shifted toward understanding how AI influences learning processes and psychological mechanisms. The increasing attention to self-regulated learning after 2025 suggests that researchers are moving beyond measuring general learning outcomes toward examining how AI facilitates planning, monitoring, and reflection. Similarly, the growing emphasis on conceptual change indicates a shift from evaluating achievement gains alone toward investigating whether AI can support deeper scientific understanding and the restructuring of misconceptions.

To further examine the intellectual structure of the field, bibliometric keyword analysis was conducted to identify dominant research themes and their conceptual relationships. The mapping revealed four interconnected clusters: AI technology, self-regulated learning, conceptual understanding, and science education contexts. These clusters demonstrate that AI research in science education is not solely driven by technological innovation but is increasingly connected with established educational theories, cognitive processes, and disciplinary learning demands. The dominant keyword clusters and their analytical focus are summarised in Table 3.

Table 3. Dominant keyword clusters in AI–science-education research

Cluster	Representative Keywords	Analytic Focus
AI technology	Machine learning, adaptive systems, chatbot tutoring	Design of intelligent and adaptive learning systems
Self-regulated learning	Self-regulation, metacognition, monitoring	Support for autonomous learning strategies
Conceptual understanding	Conceptual change, misconceptions, scientific reasoning	Construction and repair of scientific representations
Science education	Science education, STEM, inquiry	Integration of AI in disciplinary contexts

The thematic structure highlights the multidimensional nature of AI integration in science education. The AI technology cluster represents the technological foundation that enables personalization, adaptation, and automated feedback. However, the presence of SRL and conceptual understanding clusters indicates that current research increasingly focuses on the pedagogical mechanisms through which AI influences learning. In particular, the connection between AI-supported monitoring systems and SRL-related constructs suggests that AI is increasingly positioned as a metacognitive scaffold that helps learners regulate their own learning processes.

Furthermore, the conceptual understanding cluster reveals that AI applications are expanding beyond efficiency-oriented learning support toward deeper cognitive outcomes, such as conceptual reconstruction and scientific reasoning. Nevertheless, the clustering also indicates that empirical connections between specific AI functionalities and particular learning mechanisms remain insufficiently explored. Future research should therefore move toward theory-driven investigations that clarify how different AI features contribute to specific phases of self-regulated learning and long-term conceptual development in diverse science education contexts.

Compared with previous bibliometric reviews of AIEd [7], [9], the present synthesis reveals a further theoretical maturation of the field. Earlier research primarily positioned AI as a technological innovation for prediction, assessment, and adaptive delivery, whereas the current evidence indicates a transition toward AI as a mechanism for supporting cognitive regulation and conceptual development. This shift represents an important difference from previous research because it highlights not only what AI technologies are used, but also how they influence learning mechanisms in science education.

3.2. AI Features and the Phases of Self-Regulated Learning (RQ2)

Read through Zimmerman's cyclical model, the corpus reveals a clear and consequential asymmetry [36]. AI features map readily onto the forethought and performance phases but only weakly onto self-reflection. In the forethought phase, recommendation systems and dashboards support goal setting and the planning of learning pathways; in the performance phase, real-time feedback, automated error analysis, and progress monitoring scaffold strategy enactment and control. The self-reflection phase self-evaluation, causal attribution, and adaptive adjustment receives comparatively little dedicated support, even though it is precisely this phase that sustains long-term, transferable learning. This pattern is corroborated across recent syntheses: AI-supported SRL studies report robust scaffolding of planning and performance but persistent thinness at the reflective end of the cycle, alongside concern that poorly designed automation can displace rather than cultivate learner agency [24].

The mechanism behind these benefits is most credible where AI provides timely, individualised feedback. Meta-analytic evidence indicates that ITS can raise attainment substantially relative to conventional instruction, with median effects near 0.66 standard deviations, although the magnitude depends heavily on the alignment between assessment and instruction and is more modest on standardised measures [21]. Recent systematic reviews further indicate that fine-grained adaptive feedback, learner modelling, and scaffolding are key mechanisms through which ITS approaches the effectiveness of human tutoring [7]. The implication for SRL is direct: AI is most effective when it externalises and prompts regulatory processes that learners would otherwise leave implicit.

This interpretation is consistent with previous meta-analytic evidence showing positive effects of ITS on achievement [21]. Nevertheless, the present synthesis differs from these earlier studies because achievement improvement alone does not explain the mechanism of learning. The current findings suggest that the educational value of ITS depends on whether adaptive feedback stimulates learners' own monitoring and strategic adjustment rather than simply providing correct answers. Therefore, AI effectiveness should be interpreted through the quality of cognitive engagement it generates.

3.3. AI, Simulation, and Conceptual Change in Science (RQ3)

The second analytic dimension concerns conceptual understanding. Here the corpus points to adaptive simulations and virtual laboratories as the most consequential AI-adjacent affordance, allowing learners to manipulate variables, observe otherwise inaccessible phenomena, and iterate experiments without constraints of equipment, time, or safety. Such environments facilitate the development and refinement of scientific mental models by providing dynamic representations, opportunities for inquiry, and immediate interaction with complex phenomena. Recent studies indicate that technology-enhanced simulations and virtual laboratory environments can promote conceptual change by helping learners confront alternative conceptions, test hypotheses, and construct more coherent scientific explanations [34]-[36]. Meta-analytic evidence confirms that simulation-based learning yields large average effects in higher education, while emphasising that scaffolding quality is the decisive moderator unscaffolded exploration is markedly less productive [28]. Reviews focused specifically on interactive physics simulations reach a similar conclusion, reporting gains in conceptual understanding when simulations are embedded in guided inquiry rather than used as stand-alone demonstrations [40].

Generative AI introduces a distinct and still-emerging contribution. Unlike the static content of conventional simulations, dialogic tools can surface and address misconceptions in real time through adaptive explanation, offering a complementary route to conceptual change [12]. The evidence base, however, remains exploratory and fragmented, with reviews cautioning that enthusiasm currently outpaces rigorous outcome data and that risks of inaccuracy and over-reliance are non-trivial [13]. The synthesis therefore positions generative AI as promising but unproven for conceptual change in science, and as an important priority for controlled study.

These findings are largely consistent with Chernikova et al. and Banda and Nzabahimana, who demonstrated that simulation-based environments can enhance conceptual understanding when supported by appropriate scaffolding. However, the present review identifies a further dimension that has received limited attention in previous studies: the interaction between simulation-based conceptual change and learners' self-regulatory processes. While earlier research mainly examined whether simulations improve understanding, this synthesis highlights that AI-supported simulations may become more powerful when they encourage learners to predict, monitor evidence, evaluate explanations, and revise mental models.

3.4. Motivation and Personalisation as Mediating Mechanisms

Across both dimensions, motivation and personalisation recur as mediating mechanisms rather than outcomes in their own right. Personalised pathways, adaptive difficulty, and responsive feedback are reported to raise engagement and intrinsic motivation, which in turn sustain the effortful monitoring and reflection that SRL and conceptual change require. This positions affective-motivational support as a hinge between AI affordances and cognitive outcomes a relationship that the present framework makes explicit and that remains insufficiently theorised in the primary literature.

Previous research on adaptive learning environments has frequently identified personalisation as a mechanism for increasing engagement and persistence. However, most studies have treated motivation as an outcome variable rather than as a mediating mechanism. The present review contributes a different interpretation by positioning motivation as a bridge connecting AI affordances, SRL processes, and conceptual understanding. In this framework, personalisation is not valuable merely because it makes learning easier, but because it encourages sustained cognitive effort required for scientific reasoning and conceptual restructuring.

3.5. An Integrative Conceptual Framework

Synthesising the three dimensions yields the integrative framework shown in Figure 1. The framework reads from left to right: AI features and affordances (intelligent tutoring, learning analytics, adaptive simulations, and generative AI) support the phases of self-regulated learning, which in turn enable conceptual understanding (mental-model construction, conceptual change, and scientific reasoning), yielding learning outcomes of autonomy, durable science learning, and scientific literacy. A data-driven feedback loop returns performance information to the AI layer, enabling adaptive personalisation. Crucially, the entire mediating pathway is bounded by moderating conditions teacher pedagogical readiness, AI and data literacy, institutional support and policy, ethics and student agency, and infrastructure and equity that determine whether the potential of AI is realised in practice. The framework thus operationalises the central claim of this review: that AI functions as a cognitive and metacognitive mediator, interpreted through the joint lens of Zimmerman’s SRL model and conceptual-change theory.

Previous conceptual models of AI in education have generally focused on AI adoption, learner–AI interaction, or pedagogical paradigms [10], [11]. In contrast, the framework developed in this review provides a mechanism-oriented explanation by positioning AI between technological affordances and learning outcomes through SRL processes. This represents the central novelty of the study, as it explains not only whether AI improves science learning but also through which regulatory and cognitive pathways such improvement occurs.

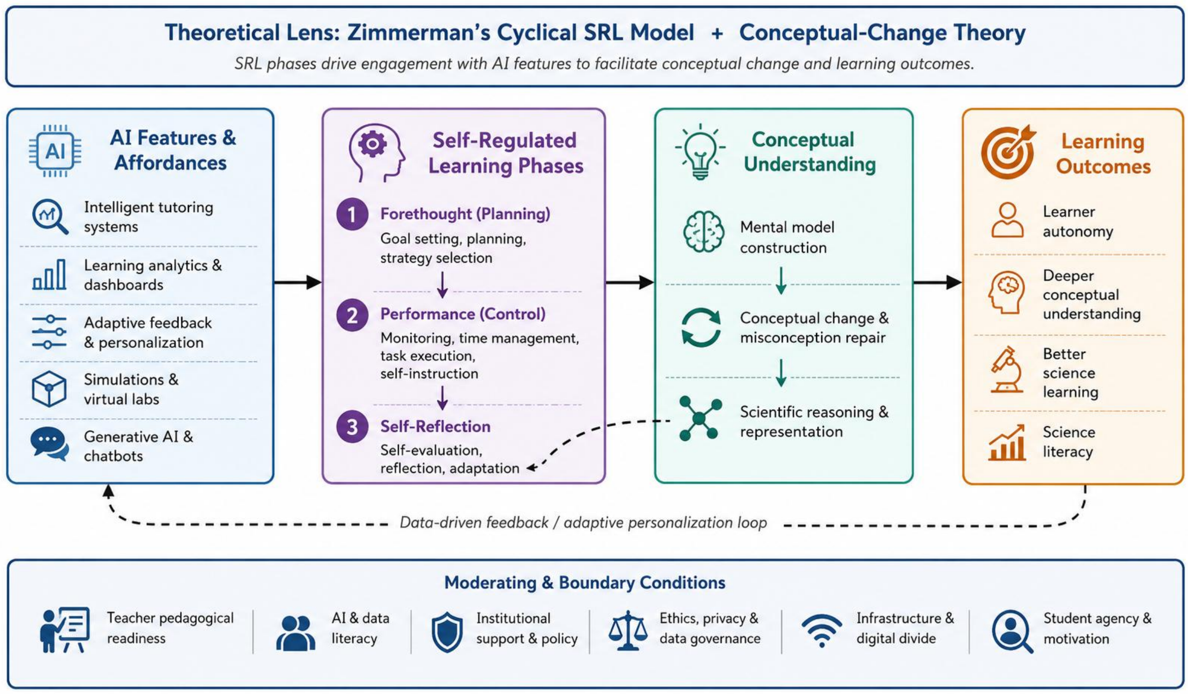

Figure 1. Integrative framework: AI as cognitive and metacognitive mediator of SRL and conceptual understanding in science.

Figure 1 illustrates the proposed conceptual framework explaining how Artificial Intelligence (AI) contributes to science learning through the interaction between technological affordances, self-regulated learning processes, and conceptual understanding. The framework is theoretically grounded in Zimmerman’s cyclical self-regulated learning (SRL) model and conceptual-change theory, positioning AI as a cognitive and metacognitive mediator rather than merely an instructional tool.

The framework proposes that AI features, including intelligent tutoring systems, learning analytics, adaptive feedback, simulations, virtual laboratories, and generative AI applications, provide learners with personalized support throughout the learning process. These technological affordances interact with the three phases of SRL: forethought, performance, and self-reflection. During the forethought phase, AI supports goal setting and learning strategy selection through adaptive recommendations. During the performance phase, AI facilitates monitoring and task regulation through real-time feedback and analytics. During the self-reflection phase, AI assists learners in evaluating their progress and adjusting subsequent learning strategies.

Through these SRL processes, AI contributes to conceptual understanding by supporting mental model construction, conceptual change, and the correction of scientific misconceptions. Rather than producing learning gains directly, AI influences outcomes by shaping how learners process, monitor, and reconstruct scientific knowledge. Consequently, improved conceptual understanding is expected to contribute to broader learning outcomes, including learner autonomy, deeper science learning, and enhanced scientific literacy.

However, the effectiveness of AI-supported learning is not determined solely by technological capability. The framework highlights several moderating and boundary conditions, including teacher pedagogical readiness, AI and data literacy, institutional support, ethical governance, digital infrastructure, and student motivation. These factors determine whether AI can be meaningfully integrated into educational practices and whether its potential benefits can be achieved across diverse learning contexts.

Overall, this framework extends existing perspectives on AI in education by conceptualizing AI as an adaptive learning partner that mediates the relationship between technological affordances, self-regulated learning, and conceptual development. It provides an analytical foundation for understanding not only whether AI improves science learning outcomes, but also how and under what conditions such improvements occur.

3.6. Synthesis of Representative Studies

To make the development of the field legible at a glance, Table 4 synthesises representative high-quality studies along the extraction dimensions, juxtaposing their designs, findings, limitations, and proposed directions. The table foregrounds both the convergence on planning/performance support and the recurring limitations short durations, non-standardised measures, and higher-education samples that frame the agenda below.

Table 4. Synthesis of representative studies on AI, SRL, and conceptual understanding

Author	Year	Country	Design	Sample	Variables	Main Findings	Limitations	Future Research
Zawacki-Richter et al.	2019	Germany/ Intl.	Systematic review (146 studies)	HE literature	AI applications; pedagogy	AIEd clusters in profiling, ITS, assessment, adaptive systems; weak pedagogical/ethical grounding	HE only; pre-2019; descriptive	Connect AIEd to learning theory and ethics
VanLehn	2011	USA	Meta-review	ITS evaluations	Tutoring granularity; achievement	Step-based ITS approach human-tutoring effectiveness (d≈.76)	Domain-specific; lab-leaning	Fine-grained adaptive tutoring across domains
Ma et al.	2014	USA/Canada	Meta-analysis	107 comparisons	ITS vs other instruction	ITS outperform most instruction except small-group human tutoring	Heterogeneous outcomes	Moderator and design analysis
Kulik & Fletcher	2016	USA	Meta-analysis (50)	Controlled evaluations	ITS effect on test scores	Median 0.66 SD gain; weaker on standardised tests	Test–instruction alignment confounds	Standardised-outcome and K–12 studies
Chernikova et al.	2020	Germany	Meta-analysis (145)	HE learners	Simulation-based learning; scaffolding	Large effects; scaffolding is the key moderator	HE focus; varied scaffolds	Optimise scaffolding design
Ouyang & Jiao	2021	USA/China	Conceptual review	AIEd literature	Pedagogical paradigms	Three paradigms: learner as recipient, collaborator, leader	Conceptual, not empirical	Empirical tests of learner-as-leader designs
Cooper	2023	Australia	Exploratory study	ChatGPT in science	Generative AI; prompting	GenAI can surface and address misconceptions via dialogue	Single tool; exploratory	Controlled GenAI conceptual-change studies

Crompton & Burke	2023	USA	Systematic review	HE AIEd	Roles and applications of AI	Maps state of the field; uneven theory use	HE only	K–12 and discipline-specific reviews
Crompton et al.	2024	USA	Systematic review	K–12 AIEd	Affordances and challenges	Benefits tempered by readiness, equity, and ethics gaps	Few rigorous K–12 trials	Rigorous K–12 science studies
Zhou	2025	China	Qualitative SLR (14, PRISMA)	HE SRL	AI support across SRL phases	Forethought/performance well supported; reflection weak; agency at risk	Small corpus; HE	Reflection-phase and agency-preserving designs
Yusuf et al.	2024	Multi-country	Systematic mapping (407)	GenAI in education	GenAI themes and applications	Eight themes; benefits with ethical and rigour gaps	Mapping, not outcome synthesis	Outcome-focused GenAI evaluations

Note. HE = higher education; ITS = intelligent tutoring system; SLR = systematic literature review; SD = standard deviation. Reported effect sizes are drawn from the cited syntheses.

Table 4 reveals several consistent patterns in the emerging literature on AI, self-regulated learning (SRL), and conceptual understanding. First, existing studies demonstrate a strong convergence regarding the capacity of AI-based learning environments to support cognitive and regulatory processes through adaptive feedback, intelligent tutoring, simulation, and personalised learning pathways. Meta-analytic evidence on intelligent tutoring systems indicates that AI-supported tutoring can produce meaningful improvements in learning outcomes, particularly when feedback is timely, domain-specific, and aligned with instructional objectives [21]. Similarly, research on simulation-based learning highlights that scaffolding and interactive representations are critical mechanisms for promoting deeper conceptual understanding rather than merely increasing access to digital resources [28].

However, the synthesis also identifies several unresolved issues. Most empirical studies have evaluated AI applications from a technology-centred perspective, focusing on effectiveness indicators such as achievement gains, system performance, or learner interaction patterns. Relatively fewer studies have examined how AI affordances interact with learners' self-regulatory mechanisms, particularly how AI supports the complete SRL cycle from forethought, performance monitoring, to self-reflection. Recent reviews suggest that while AI is increasingly capable of supporting planning and performance phases, the reflection phase and preservation of learner agency remain insufficiently explored [24].

Furthermore, methodological limitations remain evident across the reviewed studies. Many investigations rely on short intervention periods, heterogeneous outcome measures, and samples concentrated in higher education contexts, limiting the generalisability of findings across educational levels and disciplines. The literature also indicates a need for more rigorous empirical designs that integrate AI capabilities with established learning theories and examine not only whether AI improves outcomes, but also how and under what conditions AI facilitates conceptual change and self-regulated learning.

Therefore, future research should move beyond evaluating AI as an instructional tool and investigate AI as a regulatory learning partner that can dynamically support learners' cognitive, metacognitive, and motivational processes. Such an approach is particularly relevant for science education, where conceptual understanding requires learners to construct, evaluate, and revise mental models through sustained interaction with representations, feedback, and inquiry-based experiences.

3.7. Critical Discussion: Convergences, Inconsistencies, and Weaknesses

Overall, the findings demonstrate that AI in science education should not be understood as a direct determinant of learning outcomes, but as a mediating system that influences how learners regulate, construct, and transform scientific knowledge. Across the reviewed studies, AI consistently supports planning, monitoring, feedback, and personalised learning; however, its contribution to reflection, learner agency, and long-term conceptual change remains underdeveloped.

Compared with previous reviews that examined AI applications broadly [7], [8] or focused specifically on SRL support [24], this review advances the field by integrating technological, regulatory, and conceptual perspectives into a single explanatory framework. The synthesis indicates that the effectiveness of AI depends less on technological sophistication and more on the extent to which AI facilitates meaningful cognitive engagement, encourages learner autonomy, and supports the reconstruction of scientific understanding.

Therefore, a general conclusion can be drawn that AI has the greatest educational potential when functioning as a cognitive and metacognitive partner rather than as an automated replacement for human teaching. Future AI-supported science education should prioritise designs that strengthen the complete SRL cycle, particularly reflection, while maintaining teacher mediation, ethical governance, and equitable access.

The main novelty of this review lies in integrating three perspectives that have previously been examined separately: AI affordances, self-regulated learning processes, and conceptual understanding in science education. Previous reviews have predominantly investigated AI adoption patterns, technological effectiveness, or specific learning outcomes. In contrast, this study provides a mechanism-based explanation of how AI influences science learning through regulatory and cognitive pathways. By positioning AI as a cognitive and metacognitive mediator, the present review extends existing AIEd perspectives and provides a more comprehensive explanation of when and why AI contributes to meaningful science learning.

3.8. Implications of the Study

The findings of this review provide several theoretical and practical implications for the development of AI-supported science education. Theoretically, this study extends existing perspectives on Artificial Intelligence in Education by conceptualising AI not merely as a technological intervention but as a cognitive and metacognitive mediator that influences learning through self-regulated learning processes. By integrating Zimmerman's self-regulated learning model with conceptual-change theory, this review provides a mechanism-oriented explanation of how AI affordances contribute to scientific understanding. This perspective advances previous AIEd research, which has often focused on technological adoption, effectiveness, or learning outcomes without sufficiently explaining the underlying learning mechanisms.

Practically, the findings suggest that educators and instructional designers should move beyond using AI primarily for information delivery and automated assessment. Instead, AI applications should be designed to support the complete cycle of self-regulated learning, particularly the self-reflection phase, which remains the least developed area of current AI implementation. Teachers should maintain an active mediating role by guiding students in interpreting AI feedback, evaluating generated information, and developing independent learning strategies. For educational institutions and policymakers, the findings highlight the importance of strengthening teacher AI literacy, ethical governance, digital infrastructure, and equitable access to ensure that AI integration contributes to meaningful science learning rather than increasing existing educational disparities.

3.9. Limitations of the Study

Despite providing an integrative synthesis of AI, self-regulated learning, and conceptual understanding in science education, this review has several limitations. First, the reviewed literature remains dominated by higher education contexts and technologically developed educational environments, which may limit the transferability of findings to primary and secondary education settings, particularly in developing countries. Second, although this review integrates evidence from systematic reviews, meta-analyses, and empirical studies, the heterogeneity of research designs, learning measures, AI applications, and disciplinary contexts makes direct comparison across studies challenging. Third, the rapid evolution of generative AI technologies means that some recent applications are still supported mainly by exploratory studies rather than robust longitudinal evidence. Therefore, conclusions regarding the long-term effects of generative AI on conceptual change and learner autonomy should be interpreted cautiously.

Furthermore, as a review-based study, the proposed framework represents a theoretical synthesis derived from existing evidence rather than direct experimental validation. Future empirical investigations are required to test the causal relationships proposed between AI affordances, self-regulated learning processes, and conceptual understanding. These limitations indicate that while current evidence demonstrates substantial potential for AI in science education, further rigorous investigation is needed before broad generalisations can be established.

3.10. Recommendations for Future Research

Building on these findings and limitations, several directions for future research are recommended. First, future studies should investigate AI-supported reflection processes, as this phase represents the weakest area in current AI-supported self-regulated learning research. Research should examine how AI can encourage self-evaluation, causal reasoning, and strategic adjustment without reducing learner autonomy.

Second, future research should employ longitudinal, experimental, and mixed-method designs to examine not only whether AI improves learning outcomes but also how these improvements occur over time. Combining quantitative achievement measures with learning analytics, interviews, and observations may provide deeper insights into learners' regulatory processes and conceptual development.

Third, future studies should expand beyond higher education by examining AI-supported science learning in primary and secondary schools, especially in developing-country contexts where infrastructure, teacher readiness, and digital inequality influence implementation outcomes. Comparative cross-country studies are also needed to understand how contextual factors shape the effectiveness of AI integration.

Finally, research on generative AI should move beyond exploratory investigations toward rigorous evaluation of its contribution to conceptual change, misconception repair, scientific reasoning, and learner agency. Future AI systems should be developed not only to provide adaptive responses but also to cultivate learners' capacity for reflection, critical evaluation, and independent scientific thinking.

4. CONCLUSION

This systematic review examined how Artificial Intelligence (AI) supports students' self-regulated learning (SRL) and conceptual understanding in science education through a synthesis of 25 studies using bibliometric and thematic analyses. The findings indicate that AI-supported science learning has expanded rapidly, particularly since 2022, reflecting a shift from viewing AI as an instructional aid toward recognising its potential as a cognitive and metacognitive learning partner. AI affordances, including intelligent tutoring systems, learning analytics, adaptive simulations, and generative AI, consistently support the forethought and performance phases of SRL through personalised guidance, adaptive feedback, progress monitoring, and learning strategy support. Furthermore, AI-enhanced simulations and interactive environments contribute to conceptual understanding by enabling learners to explore scientific phenomena, construct mental models, and revise misconceptions. However, evidence remains limited regarding AI's role in supporting the reflection phase of SRL, and its effectiveness depends strongly on instructional design, assessment approaches, technological quality, and learning context.

The contribution of this review is the development of a mechanism-oriented understanding of AI in science education by connecting specific AI affordances with SRL processes and conceptual understanding outcomes. Rather than positioning AI as a replacement for human instruction, this review highlights AI as a mediator that can enhance learners' cognitive and metacognitive processes when aligned with sound pedagogical principles. The findings suggest that the educational value of AI depends less on technological sophistication and more on its capacity to promote learner agency, meaningful feedback, reflection, and knowledge reconstruction. Therefore, successful AI integration requires coordinated support from teachers, institutions, and educational systems through appropriate pedagogical design, teacher competence development, ethical guidelines, and equitable access.

Future research should further investigate how AI can strengthen the reflective phase of SRL through metacognitive prompts, self-assessment mechanisms, and reflective feedback. Longitudinal and mixed-methods studies are needed to examine how AI-supported learning influences self-regulation and conceptual change over time, while future investigations should expand beyond higher education by including K–12 settings, diverse scientific disciplines, and underrepresented regions. In addition, rigorous evaluation of generative AI applications is necessary to determine how these technologies can enhance conceptual understanding and learner agency while addressing challenges related to reliability, dependency, and ethical implementation.

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