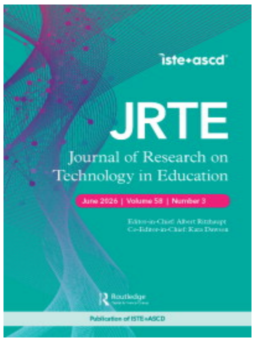

Journal of Research on Technology in Education

ISSN: 1539-1523 (Print) 1945-0818 (Online) Journal homepage: www.tandfonline.com/journals/ujrt20

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To cite this article: Junsheng Wu, Jiahe Gu, Sun Dan, Xiong Yuhan, Hexiang He , Peiyao Zhang & Zi Yan (01 May 2026): The potential of artificial intelligence to enhance self-regulated learning: A three-level meta-analysis, Journal of Research on Technology in Education, DOI: 10.1080/15391523.2026.2643171

To link to this article: https://doi.org/10.1080/15391523.2026.2643171

Published online: 01 May 2026.

JOURNAL OF RESEARCH ON TECHNOLOGY IN EDUCATION
https://doi.org/10.1080/15391523.2026.2643171

The potential of artificial intelligence to enhance self-regulated learning: A three-level meta-analysis

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ABSTRACT

As artificial intelligence (AI) technologies rapidly advance in education, their potential to support learners' self-regulated learning (SRL) has gained increasing attention. This meta-analysis synthesized 95 effect sizes from 28 empirical studies to evaluate the overall impact of AI interventions on SRL and examine moderating variables. The results showed that AI interventions significantly improved learners' SRL. Further analysis indicated that intervention duration and subject domain moderated effectiveness. A multiple-moderator model within the three-level framework also showed that these two variables significantly affect outcomes. Overall, the findings offer guidance for educators and policymakers and support integrating AI technologies into educational practice to enhance learners' SRL strategies.

ARTICLE HISTORY

Received 8 December 2025
Revised 2 March 2026
Accepted 6 March 2026

KEYWORDS

Meta-analysis; artificial intelligence; self-regulated learning; intervention

Introduction

Self-regulated learning (SRL), which enhances learners' metacognitive awareness, motivation, and strategic learning, has long garnered attention for its vital role in fostering students' academic, social, emotional, and career development (Brenner, 2022). It is generally defined as an active process where the learner sets goals, monitors progress, and regulates cognition, motivation, and behavior based on internal goals and external contexts (Pintrich, 2000; Zimmerman, 1990).

SRL has been widely promoted across K-12 and higher education contexts, and its positive influence on academic performance has been well established in empirical research (Dignath et al., 2008; Theobald, 2021; Zheng, 2016). However, many students continue to face difficulties in applying SRL strategies effectively (Chitra et al., 2022), often due to limited mastery of key skills. For instance, a lack of metacognitive ability may hinder learners from understanding problems, selecting suitable strategies, and arriving at correct solutions (Güner & Erbay, 2021), while poor time management skills are linked to increased levels of anxiety (Scherer et al., 2017). Therefore, fostering students' SRL abilities remains a central concern in current educational research and practice.

To overcome these issues, researchers have increasingly adopted artificial intelligence (AI) interventions to support SRL development (Liao et al., 2024; Su et al., 2024; Yusuf et al., 2024). AI has been applied in diverse forms within the domain of education, ranging from intelligent tutoring systems to contemporary chatbots and humanoid robots that support or perform instructional functions (Chen et al., 2020).

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A fast-growing body of literature has investigated the effectiveness of AI in supporting various learning outcomes related to SRL. For instance, Saritepeci and Durak (2024) reported that the use of AI tools (e.g. ChatGPT) in design-based learning significantly enhanced students' creative self-efficacy, critical reflection, and overall reflective development. Wei (2023) found that AI-assisted language instruction (Duolingo) not only improved the SRL ability of English as a Foreign Language learners but also promoted learner engagement and autonomy through personalized feedback. Similarly, Essien et al. (2024) demonstrated that generative AI tools (ChatGPT) could improve graduate students' critical thinking skills, particularly at the foundational levels of Bloom's taxonomy (e.g. understanding and application).

Despite these promising findings, the overall effect of AI on SRL has yet to be systematically quantified. Existing literature reviews (e.g. Chang & Sun, 2024) have provided descriptive overviews, but meta-analytic evidence remains limited. Accordingly, this study employs a three-level meta-analytic framework that accounts for sampling error, within-study variance, and between-study heterogeneity (Harrer et al., 2021). Therefore, this work aims to systematically evaluate the overall effect of AI-supported interventions on students' SRL and examine potential moderating factors using a three-level meta-analytic framework.

Literature review

AI in education

Defining AI precisely remains challenging because its technical scope continues to expand and intersect with multiple disciplines, including neuroscience, psychology, and linguistics (Chen et al., 2020). Nevertheless, various researchers have proposed their own conceptualizations. According to Coppin (2004), AI is a discipline that explores and develops systems and methods capable of imitating or drawing upon the intelligent behavior of organisms to solve complex problems or deliver practical functions through behaviors such as problem-solving, adapting to novel situations, answering questions, and planning. Kaplan and Haenlein (2019) define AI as a system's capability to accomplish specific goals and tasks by interpreting external data and adapting flexibly. Sheikh et al. (2023) describe AI as autonomous systems that analyze environmental data and take actions to achieve goals. This definition distinguishes AI from traditional algorithms while remaining inclusive of future developments. Generative artificial intelligence (GenAI), represented by tools such as ChatGPT and DeepSeek, has recently expanded educational applications of AI. As a technological breakthrough, GenAI has evolved beyond simple pattern recognition to generating complex content (Sun & Zhou, 2024). It encompasses technologies capable of producing text, images, audio, software code, and other sophisticated or creative outputs (Storey et al., 2025). In general, GenAI is characterized by four key features: "(multi-)modality," "interaction," "flexibility," and "productivity" (Ronge et al., 2025). In this review, "AI" mainly refers to AI-enabled educational systems and tools rather than to artificial intelligence as a scientific discipline. Given recent developments, we pay particular attention to LLM (Large Language Model)-based generative AI, while also recognizing earlier forms of AI used in educational settings.

Despite differences in form, an expanding body of empirical evidence highlights the educational value of AI (e.g. Liao et al., 2024; Liu et al., 2023; Su et al., 2024; Yusuf et al., 2024; Zahra & Parisa, 2024). A meta-analysis by Gu and Yan (2025) indicated that GenAI has a positive impact on students' academic performance in educational settings. Many national education policies have acknowledged the potential of AI. For example, the United Kingdom, the United States, China, and Canada have called for accelerated reforms in STEM education, aiming to introduce students to foundational AI concepts at an early stage, countries such as Hungary have emphasized the cultivation of high-level AI talent by incorporating mandatory AI-related courses into higher education curricula to advance students' awareness and understanding of the field (Saheb & Saheb, 2023). Chiu et al. (2023)'s systematic review emphasizes that AI supports multiple aspects of education, including instruction, learning, evaluation, and administration, by enabling personalized teaching, enhancing teachers' competencies, and supporting their professional development. AI not only alleviates teacher burden but also offers learners a more individualized and interactive experience (Harry & Sayudin, 2023).

Self-regulated learning

SRL refers to a dynamic process whereby learners apply strategies, respond to self-generated feedback, and regulate motivation to achieve learning goals (Zimmerman, 1990). According to Panadero (2017), numerous theoretical models of SRL have been developed over time (e.g. Boekaerts, 2011; Winne, 2011; Zimmerman, 1989; Zimmerman & Campillo, 2003; Zimmerman & Moylan, 2009). Many of these models conceptualize SRL as a multi-phase process (Panadero, 2017; Theobald, 2021; Xu et al., 2023), which is broadly divided into preparation, performance, and evaluation phases (Panadero, 2017).

Throughout this process, learners employ a variety of strategies, which are typically categorized into cognitive, metacognitive, and resource management strategies, as presented in Table 1 (Donker et al., 2014; Pintrich & de Groot, 1990; Theobald, 2021). Cognitive strategies include techniques such as rehearsal, elaboration, and organization (Pintrich & de Groot, 1990; Weinstein & Mayer, 1985). Metacognitive strategies involve planning, monitoring, and regulating cognitive activities. These strategies draw upon declarative knowledge (available strategies), procedural knowledge (how to use them), and conditional knowledge (when and why they should be applied effectively in different learning contexts) (Pintrich, 2000; Xu et al., 2023). Resource management strategies address learners' regulation of time, learning environments, and social support, including help-seeking behaviors (Pintrich, 1999).

Following Panadero's (2017) framework, cognitive and metacognitive strategies are combined in this study. Studies that broadly address "SRL" or "SRL strategies" as dependent variables are classified under the category of "General Regulatory Strategies." Thus, we define the following classification scheme: (1) General regulatory strategies; (2) (Meta) cognitive strategies; (3) Resource management strategies (see Table 2).

Effect of AI on SRL

Integrating AI into educational settings holds great potential for helping learners acquire essential SRL competencies, e.g. goal setting, planning, and monitoring progress (Ng et al., 2024). This connection is especially salient in digital learning environments. Kitsantas and Dabbagh (2009) pointed out that technology-supported learning environments can be intentionally designed to facilitate core processes of SRL, such as goal setting, task strategy use, and self-monitoring. In a related vein, Winne (2018) emphasized that SRL processes are often difficult to observe directly

Table 1. Classifications of SRL

Reference	SRL strategy categories
Pintrich and de Groot (1990)	Metacognitive; effort management and control; actual cognitive
Theobald (2021)	Cognitive; metacognitive; resource management
Donker et al. (2014)	Cognitive; metacognitive; management

Table 2. Categories of SRL Strategy Outcomes

Category	Example outcomes
General regulatory strategies	Self-regulated learning; self-directed learning; learning regulation
(Meta) cognitive strategies	Metacognition; goal setting; task analysis; self-monitoring; self-assessment; self-evaluation
Resource management strategies	Motivation regulation; resource management strategies; collaboration; peer interaction

and that real-time, multi-channel trace data can help researchers and educators better identify learners' monitoring and control activities as they unfold. Taken together, these perspectives help explain how AI-supported tools and learning analytics can both support and capture learners' self-regulatory behaviors in digital environments. AI-powered systems and tools, including intelligent tutoring systems (Araújo et al., 2024), learning analytics dashboards (Kim et al., 2016), and adaptive learning platforms (Liu, 2022), can offer scaffolding support throughout each phase of the SRL cycle, including setting learning objectives, tracking academic progress, and reflecting on outcomes. Research has shown that these tools are effective in promoting students' SRL and scientific understanding, particularly by providing instant feedback, suggestions, and examples (e.g. Deveci Topal et al., 2021; Durall & Kapros, 2020; Salvagno et al., 2023). AI tools can also foster learning experiences by delivering individualized prompts that enhance students' metacognitive reflection and critical thinking skills (Hutson & Plate, 2023). In addition, AI has been found to support student motivation (Hmoud et al., 2024), learning engagement (Schönberger, 2024), and self-efficacy (Wang et al., 2023), as well as to promote collaborative interactions and peer-supported learning (Hashim et al., 2021).

These findings demonstrate that AI has the capacity to support the cognitive and metacognitive aspects of SRL as well as the motivational and resource management dimensions. To comprehensively understand the effects of AI interventions on education, our study includes various AI intervention forms, e.g. adaptive learning platforms, chatbots, GenAI applications, and learning analytics platforms.

Prior meta-analysis of AI's impact on SRL

Existing meta-analyses on AI have primarily focused on its effects on academic performance (e.g. Dong et al., 2025; Sun & Zhou, 2024; Wu & Yu, 2024; Zheng et al., 2023). Regarding outcomes beyond academic achievement, narrative reviews have generally suggested that AI has a positive influence on SRL, learning motivation, cognitive engagement, critical thinking, self-efficacy, and learning participation (e.g. Chang & Sun, 2024; Chen et al., 2025; Javaid et al., 2024). Meta-analyses investigating the impact of AI on SRL are still quite limited.

Moderator

In this study, moderators refer to factors that may influence the effectiveness of AI interventions in promoting SRL. Identifying these variables is essential for explaining variations in intervention effects and for informing the optimization of future AI-supported instructional designs. As meta-analytic research specifically examining AI interventions on SRL strategies remains limited, the present study draws on findings from existing meta-analyses addressing related learning outcomes, such as academic performance, to inform moderator selection (Li et al., 2024). Moderators are categorized into three domains: sample characteristics, intervention characteristics, and methodological features.

Regarding sample characteristics, prior research indicates that educational stage, subject domain, sample size, and geographic region may moderate the effects of AI interventions. For example, studies have reported differential impacts of AI across education levels and subject areas (Dong et al., 2025; Zheng et al., 2023). Regional factors have also been shown to influence intervention outcomes, reflecting differences in the implementation and perception of AI across cultural contexts (Tlili et al., 2025).

Intervention characteristics constitute the second category of moderators. These include intervention duration, which may affect learning outcomes depending on the intervention lasts (Dong et al., 2025), as well as variations in instructional support, such as AI hardware types (Zheng et al., 2023), learner training (Vázquez-Parra et al., 2024), and the inclusion of GenAI tools. Differences in these elements may lead to heterogeneous intervention effects.

The third category involves methodological characteristics that may contribute to variability in reported outcomes (Cooper, 2010). These include research design (experimental versus quasi-experimental; Zheng et al., 2023; Wang et al., 2024), sampling methods, the quality of measurement instruments, reporting and control of confounding variables, response rates, and levels of participant attrition.

Drawing on prior meta-analyses and empirical studies, the present research systematically examines these moderator categories to deepen understanding of how sample features, intervention design, and methodological approaches influence the effectiveness of AI interventions in enhancing learners' SRL.

Research question

Although research on AI applications in education has grown recently, comprehensive analyses of its role in supporting learners' SRL remain limited, particularly regarding its impact on different SRL strategies. To narrow this research gap, the present study adopts a three-level meta-analysis approach to systematically synthesize and evaluate the effects of AI interventions on promoting learners' SRL. This approach aims to gain a comprehensive and accurate understanding of how AI influences learners' self-regulation across different dimensions, including general regulatory, (meta) cognitive, and resource management strategies. The findings also contribute to both theoretical advancement and practical implications in the field.

This work seeks to address the two research questions:

1. What is the overall effect of AI interventions on learners' SRL?
2. Do the effects of AI interventions on SRL vary with the characteristics of the sample, intervention, or methodology?

Method

Literature search strategy

This meta-analysis strictly followed the PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) guidelines (Page et al., 2021) to ensure the scientific rigor and reproducibility of the research results. In order to systematically and comprehensively obtain relevant research results on the effect of AI interventions on promoting SRL, we implemented structured searches in three high-quality databases, including Web of Science, ERIC, and PsycINFO. This study limited the time range of the literature search to January 2011 to October 2024. Following the rationale of Xu et al. (2023), 2011 was selected as the start year to capture relevant research conducted after the release of the *Handbook of Self-Regulation of Learning and Performance* (Zimmerman & Schunk, 2011). Boolean logic was used to combine keyword groups to ensure both coverage and relevance. In addition, backward snowballing was conducted by screening reference lists of relevant review studies to complement database searches.

The search keywords were categorized into three main groups:

The first group included terms associated with AI, such as "artificial intelligence," "machine learning," "deep learning," "neural networks," "robotics," "generative artificial intelligence," "ChatGPT," "Gemini," "chatbots," and "large language models." The second group covered SRL strategies, including terms like "self-regulated learning," "self-directed learning," "metacognition," "goal setting," "task analysis," "self-monitoring," "self-assessment," "motivation regulation," "resource management strategies," "collaboration," and "peer interaction." The third group consisted of terms indicating learning effects, such as "effect," "impact," "outcome," "result," "influence," and "change." Keywords from different groups were combined using the Boolean operator "AND" to ensure that the results focused on the influence of AI on SRL strategies. Within each group, keywords were connected using "OR" to broaden the search scope. To further improve search quality and relevance, the search was limited to English-language, peer-reviewed journal papers, and keywords were restricted to appear in the title, abstract, or keyword fields.

Inclusion and exclusion criteria and screening process

Two categories of inclusion criteria were established during the screening process: methodological criteria and content-related criteria.

Studies included were required to meet both methodological and content-related criteria. Methodological criteria were as follows: (1) The study must be written in English and published in a peer-reviewed journal; (2) The study must employ an experimental, quasi-experimental, or repeated measures design; (3) Sufficient statistical information must be reported to allow for effect size calculation. Content-related criteria were as follows: (1) The work focuses on the effects of AI tools (e.g. GPT, AI assistants, chatbots) on at least one SRL-related strategy, such as cognitive/metacognitive strategies, motivation regulation, or resource management; (2) The participants are learners within mainstream educational systems, ranging from K-12 to higher education (e.g. studies involving students in special education contexts were excluded under this criterion).

The initial search identified a total of 1,940 records, 1,646 of which remained after removing duplicates and retracted articles. Two independent researchers conducted a pilot screening of 10% of the articles, comprising 165 studies randomly selected from the initial pool, to evaluate consistency in inclusion decisions based on titles and abstracts. The inter-rater agreement coefficient reached 0.94, indicating high consistency. Following consensus on the inclusion criteria, the remaining articles were screened accordingly.

Screening of the titles and abstracts eliminated 1,569 studies, leaving 77 articles for full-text review. Among these, 49 records were further excluded owing to the lack of relevant outcome variables, inappropriate methodology, or non-eligible samples. Ultimately, 28 studies met all inclusion criteria and were included in the meta-analysis (Figure 1).

Data extraction and coding procedure

Data about bibliographic information, sample characteristics, study design, intervention characteristics, and outcome variables were systematically extracted. Moderator variables were coded along three dimensions: sample characteristics (e.g. educational level, subject, region), AI intervention characteristics (e.g. duration, platform, use of GenAI), and methodological characteristics (e.g. design type, sampling method, source of outcome measures).

All included studies were independently coded by the first author. To ensure the accuracy of the coding, a preliminary check was conducted on a randomly selected 20% subset of the included studies in order to identify potential interpretative biases (Krippendorff, 2018). During the preliminary check, both researchers independently coded the studies based on the predefined criteria and compared their decisions. The inter-rater agreement reached 91%, with Cohen's Kappa coefficient exceeding 0.80, reflecting substantial agreement between the two coders following the benchmarks by Landis and Koch (1977). Discrepancies were resolved through discussion before proceeding with the full-scale screening of the remaining studies.

Study quality assessment

To mitigate the potential bias introduced by low-quality studies on the overall effect estimates, a study-level quality assessment was conducted using five core indicators adapted from the Effective Public Health Practice Project (EPHPP) tool proposed by Thomas et al. (2004). These included sampling strategy, study design, confounder control, measurement tool validity, and participant attrition. Each indicator was scored on a 3-point scale (1 = weak, 2 = moderate,

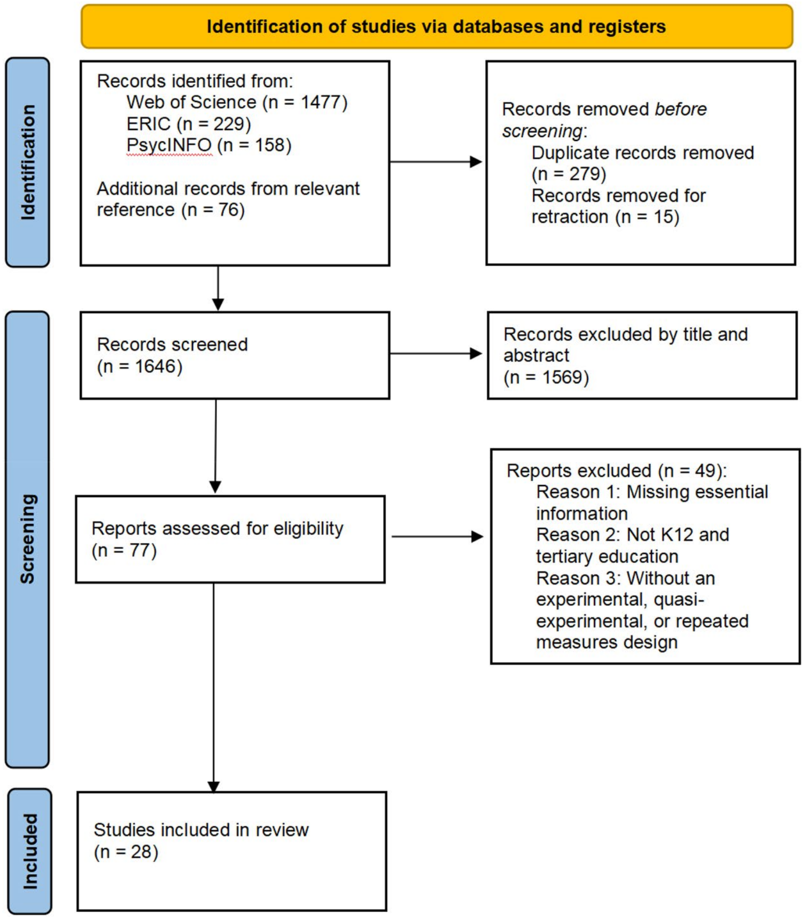

Figure 1. PRISMA flow diagram.

3 = strong), and the mean score was calculated to classify overall study quality as weak (1.0–1.6), moderate (1.7–2.3), or strong (2.4–3.0), following Li et al. (2024) and Yan et al. (2023). Composite scores were used in subgroup and sensitivity analyses.

Data analyses

An overall meta-analysis was conducted to synthesize three types of outcomes related to SRL, including general regulation strategies, (meta) cognitive strategies, and resource management strategies. Effect size and corresponding 95% confidence intervals (CI), variance estimate, and standard error were calculated for both independent-group and repeated-measures designs. Additional analyses included moderator tests and assessments of publication bias. For independent-group designs, standardized mean differences (Cohen's d) were computed as the mean difference between experimental (AI intervention) and control groups divided by the pooled standard deviation. Posttest-only comparisons were calculated using the posttest mean difference and pooled standard deviation, reflecting intervention-related learning gains. For repeated-measures designs, effect sizes were computed as the mean change score divided by the standard deviation of paired differences. Difference score variances were estimated using pretest and posttest standard deviations adjusted by the pre–post correlation. Because most studies did not report this correlation, a conservative value of $r = 0.50$ was adopted to estimate standard errors and variances, consistent with previous meta-analytic practice. To examine robustness, we repeated the analyses using $r = 0.30$ and $r = 0.70$. Because clustering information was not consistently available in the studies, potential design effects in clustered interventions may not have been fully accounted for. To correct small-sample bias associated with Cohen's *d*, all effect sizes were transformed into Hedges' g (Hedges, 1981). Effect magnitude was interpreted using the classification proposed by Thalheimer and Cook (2002), with values of 0.15–0.40 considered small, 0.40–0.75 moderate, and >0.75 large. Because single studies often contributed multiple effect sizes, which violate assumptions of statistical independence, a three-level meta-analytic model was applied (Cheung, 2014). This model partitions variance into sampling variance (Level 1), within-study variance (Level 2), and between-study variance (Level 3). Likelihood ratio tests (LRT) were conducted to assess the significance of variance at Levels 2 and 3. Moderator variables were then entered individually to examine sources of heterogeneity. When several moderators were found to significantly influence the overall effect size, multiple-moderator models were constructed. Sensitivity analyses were performed using studentized deleted residuals to identify outlying effect sizes (|residual| > 1.96). Identified outliers were removed and analyses re-run to evaluate the robustness of results.

Meta-analytic models were implemented in R using the metafor package (Viechtbauer, 2010) following the procedures outlined by Assink and Wibbelink (2016). Effect sizes were initially calculated using Comprehensive Meta-Analysis (CMA) 3.0, and variance components were evaluated *via* one-tailed log-likelihood ratio tests. All moderators were coded as dummy variables.

To assess publication bias, we employed several commonly used statistical methods, including the visual inspection of funnel plots (Egger et al., 1997), the three-level Egger's regression test (Egger et al., 1997; Fernández-Castilla et al., 2021; Rodgers & Pustejovsky, 2021), and the trim-and-fill method (Duval & Tweedie, 2000).

Results

In this review, we synthesized 28 independent studies and extracted 103 effect sizes. Most included studies were conducted in tertiary education settings, primarily in Eastern cultural contexts, focusing on Natural Sciences (NS) and Humanities, Arts, and Social Sciences (HASS). Interventions were generally short with small-to-medium samples, relying mainly on traditional computing devices or robots, while Gen AI applications were limited (see Table 3).

We calculated the overall effect size and the separate effect sizes based on three different types of SRL strategies, i.e. general regulatory strategies ($k = 15$), (meta) cognitive strategies ($k = 39$), and resource management strategies ($k = 49$). Sensitivity analyses identified eight outliers ($g = -1.448$, $g = 2.860$, $g = 1.961$, $g = -0.607$ from Lee et al. (2024); $g = 2.100$, $g = 2.009$, $g = 2.187$, $g = 2.285$ from Hsieh and Maritz (2023)), resulting in 95 effect sizes in the final analysis (see Figure 2).

Table 3. Summary of Characteristics of Included Studies

Category		*n*	%	Category		*n*	%
Education level	Tertiary	16	57.14%	Sample size	≤ 50	8	28.57%
	Secondary school	6	21.43%		51–100	9	32.14%
	Elementary school	4	14.29%		101–300	8	28.57%
	Kindergarten	2	7.14%		> 300	3	10.71%
Cultural context	Eastern	21	75.00%	AI-supported hardware	Traditional computing devices	6	21.43%
	Western	7	25.00%		Robots	6	21.43%
Subject domain	NS	14	50.00%		Smartphones/ Tablets	5	17.86%
	HASS	13	46.43%		Mixed devices	1	3.57%
	Both subjects	1	3.57%		Not specified	10	35.71%
Intervention duration	≤ 10 wk	17	60.71%	Inclusion of GenAI	With GenAI	7	25.00%
	> 10 wk	10	35.71%		Without GenAI	21	75.00%
	Not reported	1	3.57%				

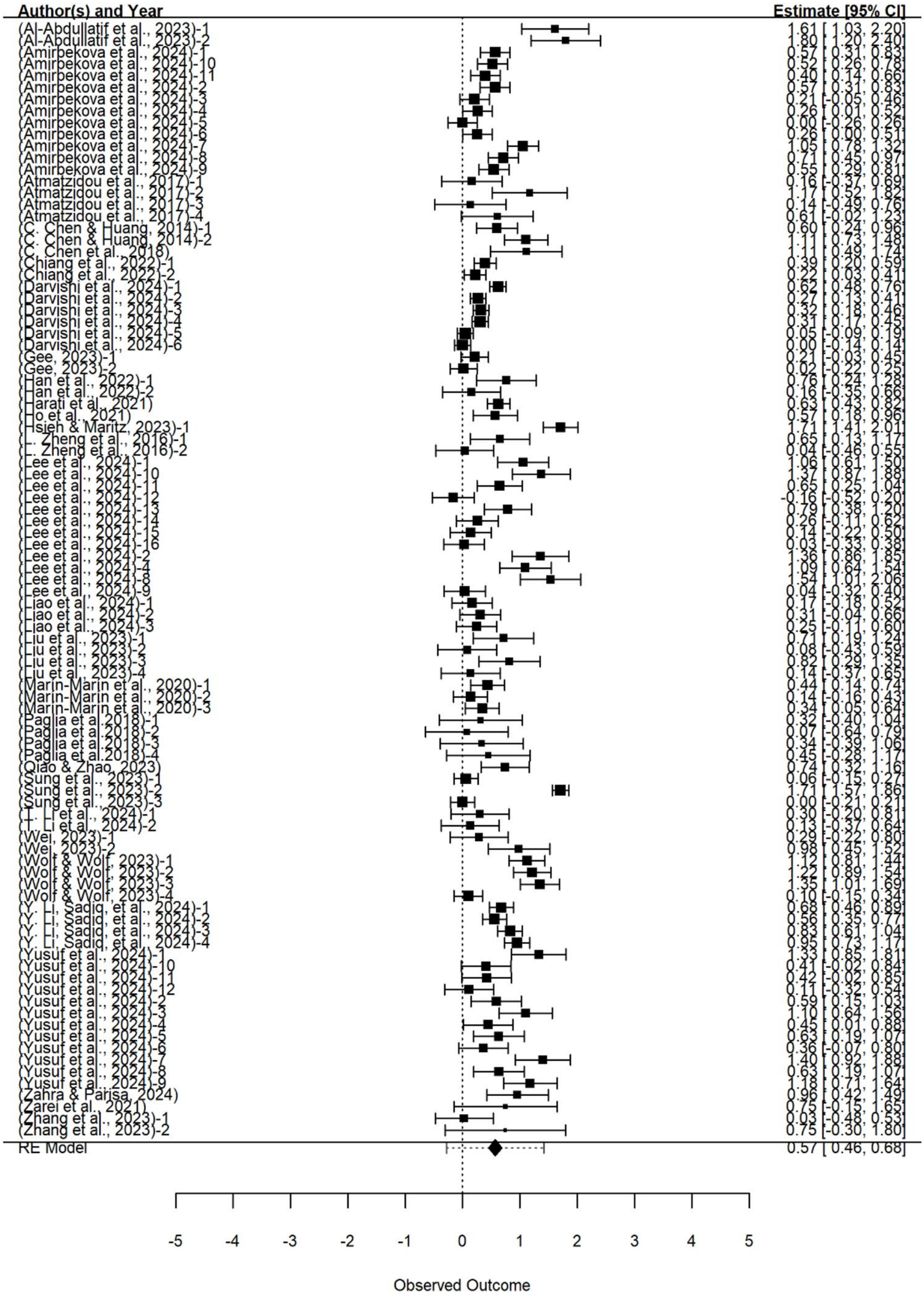

Figure 2. Forest plot (without outliers).

Overall effect size

After removing outlier effect sizes, a two-level random-effects model was applied, yielding a significant overall effect of AI interventions on SRL ($g = 0.567$, 95% CI [0.472, 0.662], PI [−0.269, 1.403], $p < .0001$). The heterogeneity test yielded $Q\ (94) = 885.47$, $p < 0.0001$, suggesting substantial variability among the effect sizes, which is unlikely to be caused solely by sampling error. This finding indicates the potential presence of moderator variables or between-study differences.

To account for dependent effect sizes within studies, a three-level meta-analytic model was implemented. Results remained significant ($g = 0.570$, 95% CI [0.456, 0.683], PI [−0.276, 1.416], $p < .0001$). Variance decomposition showed that within-study variance (Level 2) accounted for 78.80% of total variance, followed by between-study variance (Level 3) at 10.10%, and sampling variance (Level 1) at 11.11%, indicating that heterogeneity primarily arose from differences among multiple outcomes within individual studies. Sensitivity analyses showed that the pooled effect was stable across plausible pre–post correlations ($g = 0.552$–0.597) and remained statistically significant in all cases (all $p < .0001$), indicating that the findings are not overly dependent on the $r = .50$ assumption.

The necessity of each variance component was evaluated using LRT. Removing Level 2 significantly worsened model fit (LRT = 377.93, $p < 0.0001$), confirming its critical role. In contrast, excluding Level 3 did not significantly affect fit (LRT = 0.78, $p = 0.38$), indicating a comparatively small and statistically non-significant contribution.

Despite this, retaining the full three-level structure is theoretically justified given the nested nature of the data, with multiple effect sizes reported within studies. This structure better reflects the data-generating mechanism and improves model precision (Harrer et al., 2021).

Finally, based on Hunter and Schmidt (1990) guideline that heterogeneity is substantial when sampling variance explains less than 75% of total variance, the present value of 11.28% provides strong support for moderator analyses to further explain variability among effect sizes.

Follow-up analyses found that AI interventions had significant positive effects on all three types of SRL strategies. Specifically, the effect size was largest for general regulatory strategies ($k = 13$), $g = 0.654$, 95% CI [0.400, 0.909], $p < .0001$; followed by (meta) cognitive strategies ($k = 39$), $g = 0.602$, 95% CI [0.426, 0.779], $p < .0001$; and resource management strategies ($k = 43$), $g = 0.510$, 95% CI [0.343, 0.678], $p < .0001$.

Moderator analyses

This study examined three key categories of moderator variables: sample, intervention, and methodology. Table 4 presents the subgroup analysis results for each moderator and its specific categories, while Table 5 summarizes the subsequent meta-regression findings. The analysis indicates that two moderator variables had a statistically significant impact on the overall effect size: intervention duration and subject domain.

Moderator analyses showed that most variables did not significantly moderate the effect of AI on SRL. Cultural context was non-significant ($F(1,93) = 2.45$, $p = 0.121$), although effects were higher in Eastern ($g = 0.623$) than Western contexts ($g = 0.430$). Education stage was also non-significant ($F(3,91) = 0.970$, $p = 0.431$), with the largest effect at the tertiary level ($g = 0.644$), followed by kindergarten ($g = 0.463$) and elementary levels ($g = 0.450$), and the smallest at secondary level ($g = 0.424$). Sample size did not moderate outcomes ($F(3,91) = 0.303$, $p = 0.814$), though smaller samples (≤50) showed larger effects ($g = 0.647$) than larger ones ($g = 0.509$–0.562). The presence of a control group was not a significant moderator ($F(1,93) = 2.577$, $p = 0.107$). Studies with controls showed a significant effect ($g = 0.599$), whereas those without controls were non-significant ($g = 0.296$). Sampling method ($F(1,37) = 1.905$, $p = 0.176$) and random assignment ($F(1,83) = 3.812$, $p = 0.054$) were also non-significant. Random sampling produced higher effects than convenience sampling ($g = 0.820$ vs. 0.535), and non-randomized designs exceeded randomized ones ($g = 0.749$ vs. 0.505). Pre-intervention training ($F(1,94) = 0.041$, $p = 0.841$) and study quality ($F(2,92) = 1.950$, $p = 0.148$) were non-significant, though high-quality studies showed the largest effects ($g = 0.744$). Subject domain was a significant moderator ($F(2,92) = 3.835$, $p = 0.025$): HASS showed the highest effect ($g = 0.754$), followed by NS ($g = 0.496$), while both-subject studies were non-significant ($g = 0.262$). Intervention duration also significantly moderated outcomes ($F(1,90) = 4.594$, $p = 0.035$), with longer interventions (≥10 wk; $g = 0.734$) reported a higher effect size than shorter ones (< 10 wk; $g = 0.488$). AI hardware did not significantly moderate effects ($F(3,61) = 1.509$, $p = 0.221$). Traditional computers/devices ($g = 0.631$), smartphones/tablets

Table 4. Analysis of Moderator Variables

Moderator	*k*	Hedges' g	95% CI	*F*	*df*	*p*	Level 2 variance	Level 3 variance
Culture				**2.45**	**1, 93**	**0.121**	**0.158**	**0.016**
Eastern	71	0.6225***	[0.494, 0.752]			< 0.001		
Western	24	0.4299***	[0.222, 0.637]			< 0.001		
Education stage				**0.970**	**3, 91**	**0.431**	**0.156**	**0.024**
Kindergarten (≈4–6)	5	0.462*	[0.017, 0.908]			0.042		
Elementary school (≈6–12)	11	0.450**	[0.112, 0.788]			0.010		
Secondary school (≈12–18)	12	0.424**	[0.141, 0.707]			0.004		
Tertiary (18+)	67	0.644***	[0.498, 0.789]			< 0.001		
Sample size				**0.303**	**3, 91**	**0.814**	**0.161**	**0.023**
≤ 50	24	0.647***	[0.446, 0.849]			< 0.001		
51–100	18	0.562***	[0.316, 0.808]			< 0.001		
101–300	40	0.522***	[0.300, 0.743]			< 0.001		
≥ 300	13	0.509**	[0.220, 0.798]			0.0012		
Control group				**2.577**	**1, 93**	**0.107**	**0.156**	**0.018**
With control	88	0.599***	[0.482, 0.716]			< 0.001		
Without control	7	0.296	[−0.061, 0.652]			0.101		
Sampling method				**1.905**	**1, 37**	**0.176**	**0.193**	**0.025**
Convenient	19	0.535**	[0.234, 0.836]			0.001		
Random	20	0.820***	[0.530, 1.109]			< 0.001		
Random assignment				**3.812**	**1, 83**	**0.054**	**0.159**	**0.0234**
With random assignment	57	0.505***	[0.342, 0.668]			< 0.001		
Without random assignment	27	0.749***	[0.554, 0.945]			< 0.001		
Train before experiment				**0.041**	**1, 94**	**0.841**	**0.157**	**0.025**
With training	11	0.604***	[0.275, 0.933]			< 0.001		
Without training	84	0.566***	[0.441, 0.691]			< 0.001		
Study quality				**1.950**	**2, 92**	**0.148**	**0.158**	**0.015**
Moderate	60	0.493***	[0.356, 0.630]			< 0.001		
High	26	0.744***	[0.532, 0.956]			< 0.001		
Low	9	0.578***	[0.255, 0.899]			0.001		
Subject				**3.835**	**2, 92**	**0.025**	**0.15**	**0.013**
HASS	29	0.754***	[0.575, 0.931]			< 0.001		
NS	60	0.496***	[0.368, 0.637]			< 0.001		
Both	6	0.262	[−0.132, 0.655]			0.191		
Intervention duration				**4.594**	**1, 90**	**0.035**	**0.159**	**0.014**
< 10 wk	58	0.488***	[0.350, 0.625]			< 0.001		
≥ 10 wk	35	0.734***	[0.558, 0.910]			< 0.001		
AI hardware				**1.509**	**3, 61**	**0.221**	**0.158**	**~0**
Robot	18	0.369**	[0.151, 0.586]			0.001		
Smartphone/ tablet computer	18	0.599***	[0.380, 0.818]			< 0.001		
Traditional computers/ devices	27	0.631***	[0.458, 0.805]			< 0.001		
Hybrid	2	0.307	[−0.272, 0.886]			0.293		
Inclusion of GenAI				**0.054**	**1, 93**	**0.816**	**0.155**	**0.029**
With GenAI	41	0.553***	[0.354, 0.752]			< 0.001		
Without GenAI	54	0.582***	[0.432, 0.733]			< 0.001		

Note. HASS: humanities, arts, and social sciences; NS: natural sciences; *k*: number of effect sizes; CI: confidence interval.
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

($g = 0.599$), and robots ($g = 0.369$) showed significant effects, whereas hybrid devices were non-significant ($g = 0.307$). The inclusion of GenAI did not significantly moderate outcomes ($F(1,93) = 0.054$, $p = 0.816$), indicating no meaningful difference between GenAI ($g = 0.553$) and non-GenAI studies ($g = 0.582$).

Table 5. Results of the Meta-Regression Analysis

Moderator	*k*	Estimate [95% CI]	*t*	*F* (df1, df2)
Multiple moderator model	92			*F*(3, 88) = 3.94, *p* < .05
Intercept		0.262 [−0.114, 0.637]	1.385	
>10 wk (vs. ≤10 wk)		0.145 [−0.083, 0.372]	1.261	
HASS (vs. both)		0.466 [0.027, 0.905]	2.107*	
NS (vs. both)		0.193 [−0.211, 0.598]	0.951	

Note. HASS: humanities, arts, and social sciences; NS: natural sciences; k: number of effect sizes; CI: confidence interval; **p* < .05.

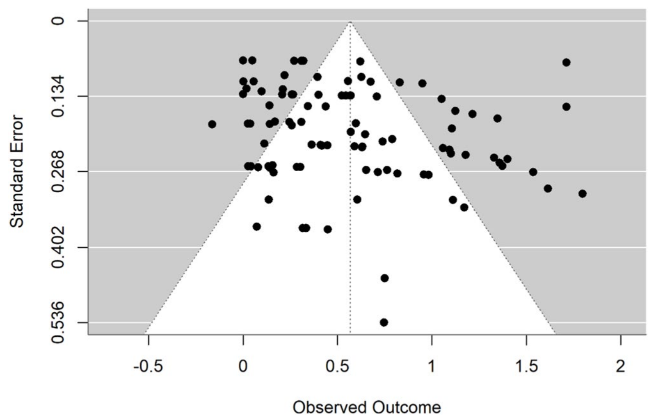

Figure 3. Funnel plot. *Note*. Publication bias analysis for AI on SRL after removing outliers.

Multiple moderator model

A multiple moderator meta-regression analysis was conducted to examine the effects of intervention duration and subject domain on effect sizes, while controlling for potential multicollinearity between moderator variables (Assink & Wibbelink, 2016). In the model, studies with an intervention duration of 10 wk or less were set as the reference group. For the subject domain variable, studies categorized as involving both HASS and NS subjects served as the reference group.

The overall model was statistically significant ($F[3, 88] = 3.94$, $p < .05$), indicating that at least one moderator had a regression coefficient significantly different from zero. Among the moderators, studies with intervention durations greater than 10 wk showed a slightly higher effect size compared to the reference group ($\beta = 0.145$). Regarding subject domain, studies in the HASS field exhibited a stronger estimated effect size ($\beta = 0.466$, $p < .05$) relative to the mixed-subject group, while the difference for studies in the NS field was smaller ($\beta = 0.193$). Although individual moderators did not all reach statistical significance, the overall model supports the potential moderating roles of intervention characteristics and disciplinary context in the meta-analysis.

Publication bias analysis

Funnel plot analysis, Egger's regression test, and the trim-and-fill method were combined to assess the potential presence of publication bias. First, the funnel plot generated based on the two-level model exhibited a degree of asymmetry (see Figure 3), which may suggest potential publication bias. Subsequently, Egger's regression test using the two-level model showed that the regression coefficient of the standard error as a predictor was statistically significant ($t = 2.0348$, $df = 93$, $p = 0.0447$). A follow-up three-level Egger regression, which accounted for the nested structure of effect sizes, yielded a borderline result ($p = 0.0551$), indicating that the standard error's predictive effect on effect size was not statistically significant.

Further analysis using the trim-and-fill method showed that seven effect sizes may be missing on the right of the mean effect size, suggesting slight asymmetry. After adjustment, the overall effect size increased slightly to $g = 0.6183$ (95% CI = [0.5240, 0.7126], $p < 0.001$), compared to the original unadjusted estimate of $g = 0.5670$ (95% CI = [0.4719, 0.6621], $p < 0.001$). The effect's direction and statistical significance remained unchanged. These findings suggest that the risk of publication bias in the present meta-analysis is relatively low and does not meaningfully affect the robustness of the results.

Discussion

Overall effect

Overall, AI appears to be an effective tool for improving learners' use of SRL strategies. The meta-analysis results indicate that AI interventions have a significant positive effect ($g = 0.567$) on SRL. The analysis also examined effect sizes across different SRL strategies (*General regulatory strategies,* (*Meta*) *cognitive strategies, Resource management strategies*), showing that AI interventions had significant and moderate positive effects on all three categories of SRL strategies. These findings align with previous research results. For instance, Li et al. (2025) reported that AI-supported learning improved students' research skills and enhanced their motivation, engagement, and autonomous learning behaviors. Similarly, studies have found positive effects on self-efficacy (Liao et al., 2024) and critical thinking skills (Saritepeci & Durak, 2024). Notably, most studies in this meta-analysis reported positive effects, with only a small number (two studies) showing negative outcomes. This pattern reinforces the overall effectiveness of AI interventions in promoting SRL.

Moderating effects

This study systematically explored how the effectiveness of AI interventions on SRL strategies may be moderated by factors across three dimensions: sample, intervention, and methodology. Through a multilevel meta-analysis ($k = 95$), two moderators were found to have statistically significant effects: intervention duration and subject domain. Additionally, the results of a multiple moderator regression model were examined. Although this meta-analysis included 95 effect sizes, some moderator analyses may still have been underpowered when subgroup sizes were small. The moderator findings should therefore be interpreted with appropriate caution.

Intervention duration emerged as a statistically significant moderator ($F(1, 90) = 4.594$, $p = 0.035$), indicating that interventions lasting more than 10 wk ($g = 0.734$, $p < .001$) produced significantly stronger effects than those lasting 10 wk or less ($g = 0.488$, $p < .001$). This finding suggests that continued practice may enhance the impact of AI on individuals' use of SRL strategies. This is partially consistent with Dong et al. (2025), whose meta-analysis revealed no statistically significant difference in duration on the whole, but effect sizes were noticeably larger for interventions over 8 wk ($g = 1.82$) compared to those lasting 5–8 wk ($g = 0.55$) or 1–4 wk ($g = 0.14$). Similarly, Cheung and Slavin (2013) reported that both the use and duration of educational technologies had significant effects on academic achievement.

This pattern may be attributed to sustained motivation and increased user familiarity over time. Based on Cognitive Load Theory (Sweller et al., 2011), initial use of AI tools can impose a high extraneous cognitive load (Yatani et al., 2024), due to interface navigation, tool operation, and conceptual orientation. However, with continued exposure, students may redirect their cognitive resources from handling external operations to processing core learning content, thus increasing germane load efficiency. This shift facilitates higher-quality and more sustained strategic learning. Longer intervention durations offer learners more opportunities to internalize AI tools within their personal learning processes (Dong et al., 2025), helping them to establish more consistent and autonomous behaviors during the planning, monitoring, and self-evaluation of their learning. In addition, intervention duration was divided into only two groups, which may have obscured more subtle differences across studies. We adopted this approach because the available effect sizes were unevenly distributed across duration intervals, and further subdivision would have left some groups too small for reliable comparison. Therefore, the findings related to duration should be interpreted with caution.

Significant differences were found in the effectiveness of AI interventions across different subject domains ($F(2, 92) = 3.835$, $p = 0.025$). The strongest effect was found in the HASS ($g = 0.754$, $p < .001$), which was significantly higher than in NS ($g = 0.496$, $p < .001$) and in both-subject contexts where both HASS and NS were present ($g = 0.262$, $p = 0.191$). However, only six effect sizes were included in the both-subject group, which may reduce statistical stability and increase the risk of bias. This finding aligns with Sun and Zhou (2024), who reported that GenAI had a greater impact on academic achievement in the humanities and social sciences than in the NS subjects. Similar patterns were also found in Dong et al. (2025), who discussed the effects of AI on the academic performance of students.

One possible explanation is that disciplines within HASS place greater emphasis on creativity, contextual understanding, flexible thinking, and adaptive reasoning (Faulconer et al., 2020; Li & Liu, 2025)—domains in which AI systems, particularly those focused on natural language processing, tend to excel. For example, AI can analyze literary texts, generate diverse perspectives, and prompt deeper reflective thinking processes.

In contrast, learning in the NS is often associated with a higher intrinsic cognitive load, requiring students to manage multiple interacting elements simultaneously (Sweller, 2024). Without sufficient prior knowledge, students may struggle to effectively use AI tools to support abstract reasoning or solve complex problems. The cognitive and regulatory demands differ across domains: in HASS contexts, AI-generated personalized feedback, question prompts, and suggestions may directly stimulate goal-setting, self-monitoring, and reflective behaviors, thereby facilitating the development and internalization of SRL strategies. On the other hand, NS learning often follows structured learning progressions (NRC, 2007), where mastery of one concept is typically a prerequisite for the next. These progressions may be linear, spiral, or integrated in nature, gradually building more complex and refined knowledge structures (Linn, 2005). If the output generated by AI fails to accurately align with students' knowledge connection points, the effectiveness of the strategy used may be limited.

The overall multiple moderator model was statistically significant ($F(3, 88) = 3.94$, $p < .05$), with the HASS subject domain showing a significant positive effect ($\beta = 0.466$, 95% CI [0.027, 0.905], $p < .05$). This suggests that the HASS subject domain had independent predictive value, even after controlling for other model variables. These findings suggest that, under the interplay of multiple factors, disciplinary context may be an important contributor to enhancing the efficacy of AI educational interventions. However, these conclusions should be interpreted with caution, as the current evidence base is still relatively limited and continues to evolve, particularly in relation to LLM-based generative AI interventions. As more studies become available, the pooled estimates may change.

Limitations and possible future research

First, the current meta-analysis included only peer-reviewed English-language journal articles, excluding grey literature and non-English publications. This restriction may have limited the generalizability of the findings and potentially affected statistical stability. Future research could broaden inclusion criteria to incorporate additional sources, such as dissertations, book chapters, conference proceedings, and non-English studies, to enhance representativeness and external validity.

Second, moderator analyses were conducted at the overall SRL level rather than distinguishing among specific SRL strategy types, because the number of effect sizes within each subgroup was insufficient for reliable categorical analyses. Consequently, differential moderating effects across (meta)cognitive, motivational, and resource management strategies could not be examined in depth, and the statistical power of some subgroup analyses was limited. Future meta-analyses could expand the literature base to increase effect sizes per moderator, thereby enabling more refined subgroup analyses.

Third, this review did not include studies conducted specifically in special education settings. As a result, the findings may be less applicable to learners receiving specialized services. Future meta-analyses could examine whether the effects differ in special education contexts.

Finally, although the present study examined a wide range of moderators (e.g., culture, education stage, study quality, subject domain, intervention duration, AI hardware, and GenAI inclusion), this list was not exhaustive. In particular, the cultural coding relied primarily on the country/region where the sample and intervention were situated as reported in the studies, which may not fully capture within-country heterogeneity (e.g., international schools adopting Western curricula in Eastern countries). Therefore, cultural moderator findings should be interpreted cautiously. Recent research suggests that AI tools may not effectively support SRL under certain conditions. For example, learners with low digital literacy may struggle to navigate AI interfaces or interpret AI-generated feedback, which can lead to frustration (Yifan et al., 2025). In addition, over-reliance on AI may hinder the development of self-regulatory abilities, especially once AI support is withdrawn (Darvishi et al., 2024; Rui et al., 2025). Furthermore, limited AI literacy among teachers may constrain the effective integration of AI into instruction (Bozkurt et al., 2023). These considerations suggest that the effects of AI should be interpreted within broader contextual and implementation constraints. Future reviews could continue to explore additional moderators and boundary conditions to deepen understanding of how contextual and methodological factors shape the relationship between AI interventions and SRL.

Implications

From a practical perspective, the findings carry important implications for educational practice. As AI becomes increasingly fused with educational settings, educators and policymakers should recognize its potential to support learners' self-regulation. It is recommended that AI tools be thoughtfully integrated into instructional design through personalized feedback, guided learning pathways, and mechanisms for autonomous goal setting to strategically enhance learners' SRL capabilities.

Additionally, when implementing AI-supported instructional interventions, careful consideration should be given to intervention duration and disciplinary context in order to optimize learning outcomes. Given that intervention duration emerged as a significant moderator, future implementations of AI-assisted SRL should consider maintaining interventions over longer periods to consolidate learners' self-regulatory skills. Moreover, differences across subject domains indicate that the effectiveness of AI tools in supporting SRL may vary depending on disciplinary characteristics, highlighting the need to tailor AI integration to specific learning contexts. This study also highlights the need for future research to further investigate the differential effects of AI on various SRL strategies, with the aim of uncovering more specific mechanisms through which AI enhances strategic learning. These findings also have implications for broader policy and institutional discussions about AI integration in formal education. The moderating effects of intervention duration and subject domain suggest that AI should not be treated as a one-size-fits-all solution, but instead aligned with instructional time, disciplinary demands, and learners' developmental needs. In practice, this means that curriculum planning may need to treat AI-supported learning as a sustained component of instruction rather than a short-term supplement, while assessment systems may also draw on AI-supported feedback and digital learning traces to better capture learners' self-regulatory processes. At the same time, differences in learner readiness, digital literacy, access to technological resources, and instructional support may shape who benefits most from AI-supported learning. This suggests that policy decisions should attend not only to adoption, but also to the equitable and effective conditions needed for implementation.

Conclusion

This study employed a three-level meta-analytic approach to systematically synthesize data from existing literature, with a focus on the effects of AI interventions on SRL strategies. These findings can deepen our understanding of the dynamic AI–SRL interplay and highlight the potential of AI as a means of fostering SRL across diverse educational contexts. By identifying key moderators, this work provides actionable insights for the design of targeted, evidence-based interventions. Future research can build on this foundation to refine AI-assisted SRL approaches, optimize implementation strategies, and ultimately enhance learners' autonomy and academic success.

Acknowledgement

During the preparation of this work, the authors used ChatGPT-5 in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

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