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A Systematic Review-Based Conceptual SR-AI Model Integrating Self-Regulated and Personalized Learning for Critical Thinking in Higher Education

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Abstract

High-frequency use of artificial intelligence (AI) in higher education does not by itself establish critical or reflective engagement. This study examined how self-regulated learning (SRL) and personalized learning can inform a conceptual architecture for critical thinking in AI-enhanced higher education. Using PRISMA 2020 reporting guidance, the review screened 552 records from Scopus and 14 records identified through citation searching; 42 peer-reviewed studies published between 2022 and 2026 were included and coded through thematic synthesis. The synthesis generated four recurrent patterns: SRL was associated with the quality of AI engagement; personalized and adaptive systems were most useful when paired with pedagogical scaffolding; metacognition and critical thinking emerged as explicit target outcomes; and six studies identified an emerging concern regarding overreliance and reduced independent cognitive engagement. Across the reviewed corpus, comparison with established SRL, learning-analytics, chatbot-design, and generative-AI frameworks did not identify a model that placed SRL as a proposed regulatory link between structured AI interaction and higher-order outcomes under personalized entry conditions. The resulting SR-AI Model comprises an Input Layer, Core Process Layer, Self-Regulation Mechanism, and Cognitive Outcome Layer. It is a provisional conceptual model, not an empirically validated intervention. Interpretation is limited by a Scopus-centered, English-language corpus supplemented by 14 citation-search records screened under the same eligibility criteria, by the absence of a formal risk-of-bias appraisal, and by the lack of a retained inter-rater coefficient.

KEYWORDS
artificial intelligence; self-regulated learning; personalized learning; critical thinking.

Introduction

The integration of Artificial Intelligence (AI) into higher education has fundamentally transformed the landscape of teaching and learning, positioning intelligent technology as an integral component of academic activity rather than a peripheral tool (Wang et al., 2024; Taheri et al., 2025). Universities are no longer solely tasked with producing graduates who possess theoretical mastery, but increasingly with cultivating individuals who can interact effectively with intelligent systems and leverage technology as a productive cognitive instrument. This shift has become particularly urgent in the context of rapidly evolving labor markets, where demand for AI-related competencies such as machine learning, big data, and cybersecurity continues to outpace the supply of qualified graduates (Ahdiat, 2025).

In Indonesia, labor-market mismatch and rapid student adoption of AI provide relevant but analytically separate context. Reported unemployment and AI-use figures describe the environment in which higher education operates; they do not demonstrate that frequent AI use causes weak critical thinking or that all frequent users engage

uncritically (Ahdiat, 2025). Evidence of shallow processing, reduced monitoring, and overreliance instead comes from studies that directly examine learning processes and metacognitive behavior (Fan et al., 2025; Galindo-Domínguez et al., 2026). These figures establish context but do not demonstrate the pedagogical mechanism investigated in this review.

Frequent AI use and critical engagement are analytically distinct. Studies of unscaffolded AI-assisted learning report answer retrieval, shallow processing, and reduced evaluative monitoring, whereas guided inquiry, metacognitive prompts, and SRL scaffolds are associated with deeper engagement (Liu & Zhong, 2025; Fan et al., 2025; Vendrell & Johnston, 2026; Xia et al., 2026). The pedagogical problem is therefore not AI access itself but the absence of an instructional architecture that makes planning, monitoring, evaluation, and critique part of AI interaction.

Existing frameworks address parts of this problem but differ in scope. Zimmerman's (2000) model specifies cyclical self-regulation without an AI or personalization architecture; Ifenthaler and Yau (2020) use learning analytics to support study success but do not make critical thinking an explicit outcome; Chang et al. (2023) specify chatbot design principles for goal setting, feedback, and personalization without proposing SRL as a cross-layer regulatory link; and Schorr et al. (2026) conceptualize learning-to-learn in the generative-AI era without the four-layer instructional specification proposed here. The reviewed corpus did not identify a framework that simultaneously specifies personalized entry conditions, structured AI interaction, SRL processes, and metacognition and critical thinking as explicit outcomes.

The review objective was to characterize the evidence linking SRL with AI use (RQ1), examine how personalization has been incorporated into AI-based instruction (RQ2), and identify recurrent conceptual gaps (RQ3). The model-construction objective was distinct: recurrent findings were translated into a layer only when multiple included studies supported a common function, the function addressed one of the three gaps, and its placement could be traced to an established theoretical perspective. The resulting contribution is therefore a synthesis-based proposition, not a claim that existing models are universally inapplicable.

To address these objectives, the study conducted a systematic literature review of 42 peer-reviewed studies retrieved from Scopus and citation searching and proposed the Self-Regulated AI Learning Model (SR-AI Model). The model comprises an Input Layer, Core Process Layer, Self-Regulation Mechanism, and Cognitive Outcome Layer. Its relationships are classified as corpus-supported associations, synthesis-level inferences, or propositions requiring empirical validation.

Self-Regulated Learning in AI-Based Learning Contexts

Self-regulated learning (SRL) refers to the capacity of individuals to plan, monitor, and evaluate their own learning processes independently (Zimmerman, 2000). Within AI-based learning environments, SRL is proposed in this review as a regulatory mechanism that may shape the quality of student interaction with intelligent systems. He (2025) reported that AI-supported SRL predicted learner autonomy, while Jin et al. (2025) found that SRL was associated with writing quality and learning outcomes in AI-assisted academic tasks. Anders and Dux Speltz (2025) further argued that integrating SRL within a human-centered AI literacy framework promotes more reflective and responsible AI use among students. Collectively, these findings indicate that SRL is consistently associated with the quality of AI-assisted learning outcomes. The evidential basis for this claim is, however, heterogeneous. Liu (2026) tested a mediated pathway in which SRL ability reduced AI dependence both directly and indirectly through lower AIGC usage frequency; in that model, usage frequency rather than SRL was the mediator. He (2025), Jin et al. (2025), and Anders and Dux Speltz (2025) reported associations, predictive relationships, or conceptual linkages, and Xia et al. (2026) argued from a design perspective that generative-AI learning environments must explicitly incorporate SRL mechanisms because unguided use tends to produce surface-level rather than deep engagement. No included study tested SRL itself as the mediator between AI interaction and higher-order outcomes. Positioning SRL as a general regulatory infrastructure through which AI interaction produces meaningful outcomes is therefore a synthesis-level inference drawn from associational and design-oriented evidence. Despite this growing body of evidence, SRL remains underutilized as a design principle in AI-based instructional frameworks, with most existing models focusing on technological features rather than the regulatory mechanisms that govern how students learn.

Personalized Learning and Adaptive Learning Systems

Personalized learning refers to an instructional approach that tailors content, strategies, and learning experiences to the individual characteristics, preferences, and prior knowledge of each learner. Ingkavara et al. (2022) demonstrated that personalized learning significantly enhances the effectiveness of SRL in digital environments by providing learners with appropriately calibrated challenges and support. Luo et al. (2026) extended this finding by showing that a generative AI-based personalized recommender system can simultaneously improve academic performance and the quality of student self-regulation. Adaptive learning, as a technological enabler of personalized learning, allows systems to dynamically adjust content difficulty and instructional scaffolding based on real-time interaction data, thereby creating a responsive learning environment that evolves with the learner (Ifenthaler & Yau, 2020). The convergence of personalized and adaptive learning with AI-based systems represents a significant advancement in instructional design, yet most implementations remain algorithmically driven without sufficient integration of the cognitive and metacognitive dimensions of learning. Anders and Dux Speltz (2025) caution that personalization must extend beyond content recommendation to encompass the development of learner agency and reflective capacity, a dimension that current adaptive systems largely neglect.

Metacognition and Critical Thinking as Cognitive Outcomes

Metacognition, defined as the capacity to understand and regulate one's own thinking processes (Flavell, 1979), has emerged as a central construct in the design of AI-based learning environments. In contexts where students interact with generative AI, metacognitive ability determines whether they can evaluate the validity, relevance, and limitations of AI-generated outputs rather than accepting them uncritically. Schorr et al. (2026) argue that the age of generative AI demands a new form of learning-to-learn, one that is fundamentally metacognitive in character, enabling students to adapt their cognitive strategies in response to rapidly evolving technological capabilities. Critical thinking, defined as the capacity to analyze, evaluate, and construct judgments based on evidence and reasoning, represents the behavioral manifestation of metacognitive competence in applied contexts. Salido et al. (2025) conducted

a bibliometric and systematic review demonstrating that while the integration of critical thinking and AI in higher education has gained growing scholarly attention, most studies address these constructs in isolation rather than as integrated instructional targets. Vendrell and Johnston (2026) provide direct evidence that well-designed AI scaffolding can promote critical thinking, but only when the scaffolding is intentionally structured to prompt evaluative reasoning rather than answer retrieval. Zheng et al. (2026) further demonstrated that socially shared regulation of learning enhances critical thinking development, suggesting that metacognitive and critical thinking outcomes are best cultivated within structured, regulated learning processes.

Theoretical Synthesis: Five Perspectives as the Foundation of the SR-AI Model

The five perspectives were retained because each maps to a necessary model function identified in the synthesis: cognitive learning theory explains processing and cognitive-load constraints in AI-based tasks (Mayer, 2014; Peltzer et al., 2026); constructivism explains active knowledge construction during interaction (Vygotsky, 1978; Liu & Zhong, 2025); SRL theory specifies planning, monitoring, and evaluation (Zimmerman, 2000); metacognition theory specifies monitoring and regulation of thinking (Flavell, 1979; Zheng et al., 2026); and adaptive learning and learning analytics explain personalization based on learner data (Ifenthaler & Yau, 2020; Luo et al., 2026). Selection required a direct mapping to at least one layer and support from the reviewed corpus. Overlap is acknowledged between SRL and metacognition, while a tension remains between system-driven adaptation and learner agency. The synthesis therefore uses these perspectives as a design rationale and source of testable propositions rather than treating their combination as proof of a new theory.

Conceptual Gaps in Existing Literature

Three gaps recur within the reviewed corpus. First, AI-integration studies often emphasize technological affordances without specifying the regulatory process through which students evaluate AI output. Second, personalization and SRL are frequently examined as related features but are not consistently represented as a coordinated instructional sequence. Third, metacognition and critical thinking are often measured as outcomes but remain underspecified as explicit design targets. These claims are bounded to the search strategy and corpus; they do not imply that no framework outside the review addresses the same relationships. The SR-AI Model is proposed as one traceable response to these recurrent gaps.

Methods

This study employed a Systematic Literature Review (SLR) and was reported in accordance with PRISMA 2020 (Page et al., 2021). PRISMA was used as a reporting framework for identification, screening, eligibility, and inclusion; it was not treated as a substitute for quality appraisal. The review protocol, including the research questions, search concepts, eligibility rules, extraction fields, and coding stages, was established internally before screening but was not prospectively registered. The review addressed three questions:

RQ1: How does existing literature characterize the relationship between self-regulated learning and AI use in higher education contexts?

RQ2: How has personalized learning been integrated with AI-based instructional systems in higher education?

RQ3: What conceptual gaps exist in the current literature that a new integrative model of AI-based learning could address?

Search Strategy

The final Scopus search was conducted on 5 June 2026. Scopus was selected because it indexes peer-reviewed literature across education, psychology, computer science, and social science in a single exportable database, supporting transparent deduplication and bibliometric analysis. No Scopus subject-area filter was applied. Web of Science, ERIC, PsycINFO, and IEEE Xplore were not searched; this decision improves procedural consistency but limits coverage and is treated as a review limitation. Citation searching of highly cited and framework-defining studies was recorded separately from the Scopus search. The search was executed as one compound query:

(((TITLE-ABS-KEY ("artificial intelligence" OR "generative AI" OR "large language model" OR "AI-assisted learning") AND TITLE-ABS-KEY ("self-regulated learning" OR "self-regulation" OR "learner autonomy") AND TITLE-ABS-KEY ("higher education" OR "university" OR "college")) OR (TITLE-ABS-KEY ("personalized learning" OR "adaptive learning") AND TITLE-ABS-KEY ("artificial intelligence" OR "machine learning") AND TITLE-ABS-KEY ("critical thinking" OR "metacognition" OR "higher-order thinking"))) AND PUBYEAR > 2019 AND (LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "ch")) AND LIMIT-TO (LANGUAGE, "English"))

Explicit outer parentheses ensure that the year, document-type, and language limits apply to both concept blocks. The query returned 552 Scopus records. The document-type filter permitted both journal articles (DOCTYPE "ar") and book chapters (DOCTYPE "ch") to avoid prematurely excluding framework-defining edited-volume chapters at the search stage. Review of the 42 included studies confirms that all are journal articles; no book chapter met the full-text eligibility criteria, and none is included in the final synthesis. The term "peer-reviewed studies" used elsewhere in this manuscript refers to this all-journal-article corpus. Fourteen additional records were identified through backward and forward citation searching, producing 566 records before deduplication.

Inclusion and Exclusion Criteria

Eligibility required a higher-education study to examine AI-based learning together with at least one regulatory or cognitive construct relevant to RQ1-RQ3. Studies had to be peer reviewed, published in English between 2020 and 2026, and report a discernible empirical, theoretical, or review design. Full texts were excluded for an exclusive K-12 or vocational focus without transferability to higher education, peripheral administrative use of AI, absence of a cognitive, metacognitive, or regulatory outcome, methodologically insufficient reporting, or insufficient construct linkage to the review questions. The former conceptually redundant criterion was removed because conceptual similarity alone is not an objective basis for exclusion.

Selection Process

The PRISMA 2020 flow comprised 552 Scopus records and 14 records from citation searching. The citation-search records were merged with the Scopus records before deduplication and were screened at the title/abstract and full-text stages against the same eligibility criteria; no separate or relaxed rule was applied to them. After 38 duplicates were removed, 528 records were screened; 312 were excluded at title/abstract stage, leaving 216 full texts. Full-text exclusions totaled 174: K-12 or vocational-only focus (41), peripheral treatment of AI (38),

absence of cognitive or metacognitive outcomes (35), methodologically insufficient reporting (29), and insufficient construct linkage to RQ1-RQ3 (31). Forty-two studies were included. Title/abstract and full-text screening were conducted by the first and second authors, with disagreements resolved through discussion and, when required, review by the third author. A formal inter-rater coefficient and a record-level list of excluded full texts were not retained; these omissions are reported as limitations. Figure 1 separates database records from citation-search records in accordance with PRISMA 2020.

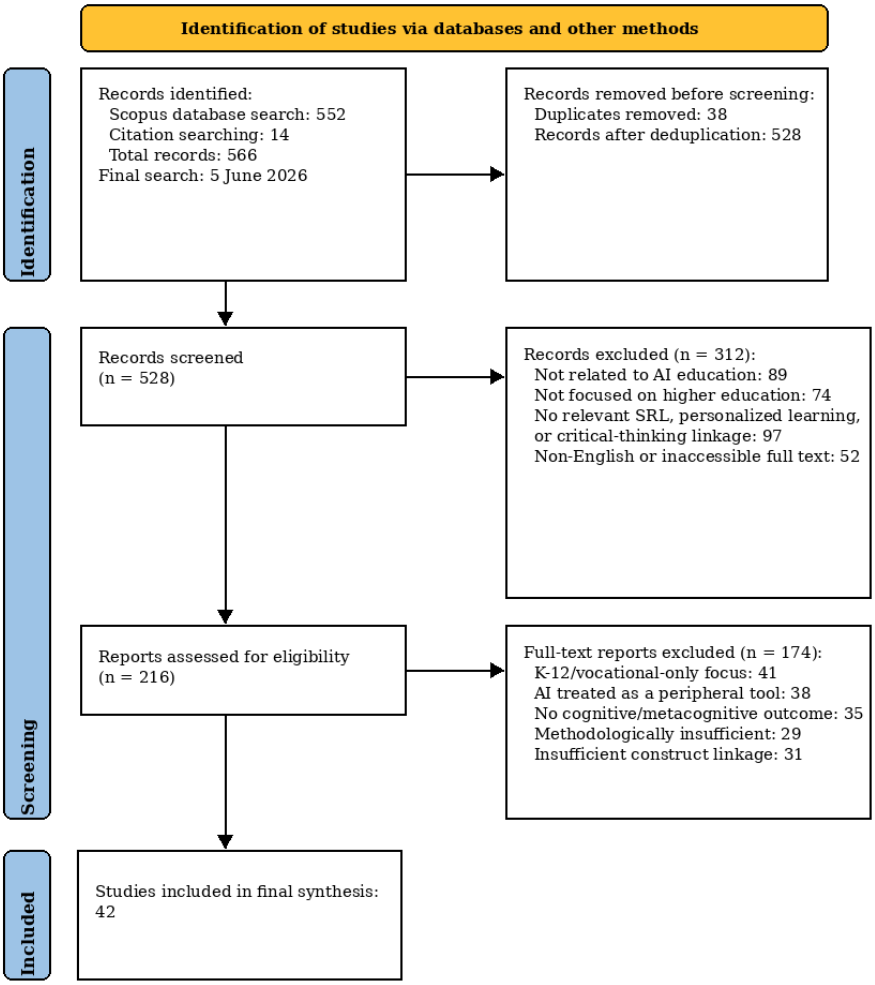

Figure 1. PRISMA 2020 Flow Diagram of the Systematic Literature Review Process

Data Extraction and Synthesis

Data were extracted to a standardized matrix containing citation, study design, sample or context when reported, focal constructs, measures, principal findings, and provisional theme assignment. Following the stages of thematic synthesis (Thomas & Harden, 2008), the coding framework linked first-order descriptive codes (for example, planning, monitoring, AI critique, adaptive feedback, overreliance, and critical evaluation) to analytical themes and then to model functions. The first author coded the corpus; the second author checked theme assignments and the third author reviewed the framework comparison. Disagreements were resolved by discussion. Theme codes were recorded at study level and were not mutually exclusive; no primary theme was designated for each study. All 42 studies were processed; the earlier claim of theoretical saturation was removed. No formal design-specific risk-of-bias appraisal was conducted across the heterogeneous empirical, conceptual, review, and meta-analytic designs. Consequently, the synthesis is not quality weighted, no retrospective ratings are invented, and causal interpretation is restricted to relations directly tested in primary studies. Appendix A provides the study-level audit table available from the retained extraction records.

Results and Discussions

Profile of Included Literature

The synthesis included 42 studies. Although the eligibility window was 2020–2026, the included studies were published between 2022 and 2026: one each in 2022, 2023, and 2024, 19 in 2025, and 20 in 2026, so that 40 studies (95.2%) were published in 2024–2026. Appendix A lists each included study, design or evidence type, construct focus, and theme assignment. Because no formal risk-of-bias appraisal was conducted, the profile supports transparency and traceability but not a quality-weighted confidence judgment. The 42 studies appeared in 34 journals, each of which is reported in its own row in Table 1 so that the distribution can be checked against the reference list. Six journals contributed more than one study: Computers and Education: Artificial Intelligence and British Journal of Educational Technology (three each), and Computers in Human Behavior, Interactive Learning Environments, International Journal of Educational Technology in Higher Education, and Journal of Computer Assisted Learning (two each). The remaining 28 journals contributed one study each.

Table 1. Distribution of Included Studies by Journal Source (n = 42)

Journal / Source	Number of Studies	Percentage (%)	Included Studies
Computers and Education: Artificial Intelligence	3	7.1	Anders & Dux Speltz (2025); Ingkavara et al. (2022); Schorr et al. (2026)
British Journal of Educational Technology	3	7.1	Fan et al. (2025); Lim et al. (2024); Neshaei et al. (2025)
Computers in Human Behavior	2	4.8	Galindo-Domínguez et al. (2026); Jin et al. (2025)
Interactive Learning Environments	2	4.8	Cheng & Cheung (2026); Chiu (2025)
International Journal of Educational Technology in Higher Education	2	4.8	Du et al. (2025); Liu et al. (2025)
Journal of Computer Assisted Learning	2	4.8	AlMuhaysh (2026); Chen & Alibakhshi (2026)
ACM Transactions on Computing Education	1	2.4	Jamil (2026)
Acta Psychologica	1	2.4	Fan & Gao (2026)
Assessment and Evaluation in Higher Education	1	2.4	Lu & Zeng (2026)
Computers & Education	1	2.4	Luo et al. (2026)
Discover Computing	1	2.4	Bećirović et al. (2026)
Discover Education	1	2.4	EL Hosayny et al. (2026)
Education Sciences	1	2.4	Roman et al. (2026)
Educational Process: International Journal	1	2.4	Melisa et al. (2025)
Educational Psychology	1	2.4	Joo et al. (2026)
Educational Psychology Review	1	2.4	Huang et al. (2026)
Educational Research Review	1	2.4	Liu & Zhong (2025)
European Journal of Education	1	2.4	Hu & Zhang (2025)
Innovations in Education and Teaching International	1	2.4	Karaoglan Yilmaz & Yilmaz (2025)
International Journal of Applied Linguistics	1	2.4	Barış Horzum et al. (2026)
International Journal of Education and Practice	1	2.4	Li & Samah (2026)
International Journal of Engineering Pedagogy	1	2.4	Sardi et al. (2025)
International Journal of Learning, Teaching and Educational Research	1	2.4	Burger et al. (2026)
International Review of Research in Open and Distributed Learning	1	2.4	Faza & Lestari (2025)
Journal of Computing in Higher Education	1	2.4	Ballantyne et al. (2025)
Journal of Culture and Values in Education	1	2.4	Salido et al. (2025)
Journal of Educational Data Mining	1	2.4	Borchers et al. (2025)
Journal of Learning Analytics	1	2.4	Hilliger et al. (2026)
LEARN Journal: Language Education and Acquisition Research Network	1	2.4	Kalra et al. (2026)
Learning and Motivation	1	2.4	He (2025)
npj Science of Learning	1	2.4	Lan & Zhou (2025)
Periodicals of Engineering and Natural Sciences	1	2.4	Alshaketheep et al. (2025)
SAGE Open	1	2.4	Liu (2026)
Sustainability	1	2.4	Chang et al. (2023)
TOTAL (34 journals)	**42**	**100.0**	

Note. Percentages are calculated on n = 42 and rounded to one decimal place. Because of rounding, the displayed row values sum to 100.6%; the unrounded total is 100.0%.

Study designs were classified from the design field of the extraction records (Appendix A): quantitative survey, structural, network, or computational studies (17; 40.5%); systematic, scoping, or bibliometric reviews (7; 16.7%); experimental or intervention studies (5; 11.9%); conceptual, opinion, or design-principle articles (5; 11.9%); design-based or development studies (3; 7.1%); mixed-methods studies (2; 4.8%); qualitative studies (2; 4.8%); and one meta-analysis (2.4%). This heterogeneity supports conceptual mapping but limits causal aggregation; associations, moderation, and mediation are therefore distinguished wherever the primary evidence permits.

Table 2. Distribution of Included Studies by Research Design (n = 42)

Research Design	Number of Studies	Percentage (%)	Included Studies
Quantitative (survey, SEM, network, or computational analysis)	17	40.5	AlMuhaysh (2026); Alshaketheep et al. (2025); Barış Horzum et al. (2026); Bećirović et al. (2026); Borchers et al. (2025); Chen & Alibakhshi (2026); Cheng & Cheung (2026); Fan & Gao (2026); He (2025); Hu & Zhang (2025); Jin et al. (2025); Kalra et al. (2026); Karaoglan Yilmaz & Yilmaz (2025); Li & Samah (2026); Liu (2026); Liu et al. (2025); Roman et al. (2026)
Systematic, scoping, or bibliometric review	7	16.7	Faza & Lestari (2025); Lan & Zhou (2025); Liu & Zhong (2025); Melisa et al. (2025); Salido et al. (2025); Sardi et al. (2025); Schorr et al. (2026)
Experimental or intervention study	5	11.9	Du et al. (2025); Ingkavara et al. (2022); Joo et al. (2026); Lim et al. (2024); Lu & Zeng (2026)
Conceptual, opinion, or design-principle article	5	11.9	Anders & Dux Speltz (2025); Ballantyne et al. (2025); Chang et al. (2023); Chiu (2025); Jamil (2026)
Design-based or development study	3	7.1	Hilliger et al. (2026); Luo et al. (2026); Neshaei et al. (2025)
Mixed methods	2	4.8	Fan et al. (2025); Galindo-Domínguez et al. (2026)
Qualitative (interview or case study)	2	4.8	Burger et al. (2026); EL Hosayny et al. (2026)
Meta-analysis	1	2.4	Huang et al. (2026)
TOTAL	**42**	**100.0**	

Note. Categories follow the design field in Appendix A. Percentages are rounded to one decimal place; the unrounded total is 100.0%.

The concentration of publications in 2024-2026 reflects rapid scholarly response to generative AI. It also means that many relationships have been examined in short-term, context-specific studies. The SR-AI Model is therefore presented as a provisional synthesis requiring prospective validation rather than as a consolidated theory.

Thematic Synthesis: Four Recurrent Patterns

The synthesis generated four recurrent patterns, not four equally strong themes. Table 3 reports all coded theme occurrences, recalculated directly from the study-level coding in Appendix A. Because a study could be coded to more than one theme, the counts are not mutually exclusive and their total exceeds 42: Theme 1 was coded in 30 studies, Theme 2 in 11, Theme 3 in 17, and the emerging-concern theme in 6, giving 64 theme assignments across the 42 studies. Twenty studies received more than one theme code (18 received two codes and 2 received three), and the most frequent overlap was between Theme 1 (SRL) and Theme 3 (metacognition and critical thinking), which co-occurred in 9 studies. Primary-theme counts are not reported because the extraction records did not designate a primary theme for each study, so such counts could not be reproduced from Appendix A. The relative size of each theme should therefore be read as breadth of coverage within the corpus, not as a ranking of evidential strength.

The coding framework linked first-order descriptive codes to analytical categories: planning, monitoring, and evaluation to SRL; adaptive feedback and learner calibration to personalization; AI critique and reflective prompts to metacognition and critical thinking; and overreliance, shallow processing, and reduced independent checking to the emerging risk category. Findings that personalization or AI support was ineffective without scaffolding were retained as boundary or contradictory evidence rather than discarded.

Table 3. Thematic Synthesis of 42 Included Studies (All Coded Occurrences; Totals Exceed 42)

Theme	n (Coded Occurrences)	Key Findings	Representative Studies
Theme 1: SRL as a proposed regulatory or mediating mechanism	30	Thirty studies link SRL with AI-engagement quality. Evidence includes associations, profiles, moderation, and mediated pathways in which SRL acts as a predictor; no included study tested SRL as the mediator between AI interaction and higher-order outcomes, and the evidence does not establish a universal causal mechanism.	He (2025); Cheng & Cheung (2026); Liu (2026); Galindo-Domínguez et al. (2026); Hu & Zhang (2025); Borchers et al. (2025)
Theme 2: Personalized and Adaptive AI Systems and Learning Outcomes	11	AI-driven personalized learning systems are associated with improved academic performance and self-regulation quality. However, purely algorithmic personalization without pedagogical scaffolding shows limited effect on higher-order outcomes. Human-centered design of personalization is consistently identified as a critical differentiator.	Kalra et al. (2026); Ballantyne et al. (2025); Lim et al. (2024); Jamil (2026); Chang et al. (2023)
Theme 3: Metacognition and Critical Thinking as Target Outcomes	17	Metacognitive capacity is associated with the quality of AI engagement; students with stronger metacognition tend to evaluate AI outputs more critically. Critical thinking development requires explicit instructional scaffolding and is not an automatic product of AI use frequency.	Fan et al. (2025); Schorr et al. (2026); Du et al. (2025); Neshaei et al. (2025); Joo et al. (2026); Salido et al. (2025)

Theme	n (Coded Occurrences)	Key Findings	Representative Studies
Emerging concern: AI overreliance and reduced independent cognitive engagement	6	Six studies report overreliance, shallow processing, reduced monitoring, or diminished independent checking under some conditions. The pattern is treated as an emerging concern and boundary condition.	Fan et al. (2025); Galindo-Domínguez et al. (2026); Liu (2026); EL Hosayny et al. (2026)

Note. Counts are all coded occurrences taken from the Theme column of Appendix A. Twenty studies were coded to more than one theme, so the column total (64) exceeds the number of included studies (42).

Theme 1: Proposed Regulatory and Mediating Role of Self-Regulated Learning

The most prominent theme across the corpus concerns the regulatory role of SRL in AI-based learning contexts. Thirty of the 42 included studies were coded to this theme because they investigate or report on the relationship between self-regulatory capacity and the quality of AI interaction outcomes. He (2025) demonstrated through a social cognitive theory framework that learner autonomy is reliably predicted by AI-supported SRL, with stronger self-regulatory behavior correlating with more productive and independent AI engagement. Cheng and Cheung (2026) extended this finding through ordered network analysis, showing that students with higher SRL engage in qualitatively different sequential interaction patterns with generative AI, characterized by greater cognitive elaboration and metacognitive checking.

Liu (2026) found that SRL ability was negatively associated with AI dependence among frequent users of AIGC tools, both directly and indirectly through lower AIGC usage frequency; in this model, SRL was the predictor and usage frequency was the tested mediator. Galindo-Domínguez et al. (2026) identified a related paradox wherein perceived usefulness of AI correlates positively with both engagement and dependency, with self-regulation capacity conditioning whether AI use becomes generative or consumptive. Hu and Zhang (2025) further demonstrated through latent profile analysis that students exhibit distinct AI-assisted SRL profiles, with high-regulation profiles consistently demonstrating superior critical engagement with AI outputs.

Taken together, the evidence indicates that SRL is associated with the quality of AI engagement and may moderate selected relationships. Liu (2026) tested a mediated pathway from SRL to AI dependence, while other studies reported associations, profiles, or sequential patterns; no included study tested SRL itself as the mediator between AI interaction and higher-order outcomes. The corpus therefore does not establish SRL as a universal causal mechanism. Positioning SRL as the regulatory layer of the SR-AI Model is a synthesis-derived proposition requiring empirical validation.

Theme 2: Personalized and Adaptive AI Systems

The second dominant theme concerns the design and effects of personalized AI-based learning systems. Eleven studies were coded to this theme, with consistent evidence that personalization enhances both learning outcomes and self-regulatory quality when implemented with adequate pedagogical grounding. Kalra et al. (2026) demonstrated significant improvements in academic outcomes in Thai higher education through AI-driven personalized instruction, while Ballantyne et al. (2025) showed that personalized generative AI chatbots in higher education enhance equity and learning access when designed with explicit attention to learner diversity. Lim et al. (2024) found that real-time personalized scaffolds improved learning regulation, particularly for students with lower baseline self-regulatory capacity.

However, a consistent qualification emerges across this theme: purely algorithmic personalization without embedded pedagogical scaffolding demonstrates limited impact on higher-order cognitive outcomes. Chang et al. (2023) identified goal setting, feedback, and personalization as the three critical design principles for AI chatbots that effectively support SRL, emphasizing that personalization must be integrated within a broader instructional architecture rather than implemented as an isolated feature. Jamil (2026), in an opinion article on adaptive and personalized lecture design, similarly argues that human–AI co-orchestration of personalization is pedagogically preferable to algorithmic personalization alone, a position that remains to be tested empirically. These findings underscore that personalization is necessary but insufficient as a standalone instructional mechanism, requiring integration with SRL support to generate meaningful cognitive outcomes.

Theme 3: Metacognition and Critical Thinking as Cognitive Outcomes

The third pattern concerns metacognition and critical thinking as proposed higher-order targets. Seventeen studies were coded to this theme, but designs and outcomes vary. Fan et al. (2025) reported reduced monitoring and shallower processing under unstructured AI use; this identifies a context-dependent risk rather than establishing a universal effect.

Schorr et al. (2026) framed generative-AI learning-to-learn as metacognitive adaptation. Du et al. (2025) found task-design-dependent facilitation and inhibition, while Neshaei et al. (2025) associated reflective LLM use with metacognitive awareness under explicit scaffolding. These findings support including metacognition as a target but do not establish a single causal sequence.

Salido et al. (2025) and Sardi et al. (2025) reported limited integration of critical thinking, SRL, and AI in their review corpora. Within the present corpus, this supports specifying metacognition and critical thinking as explicit design targets; it does not demonstrate that the proposed architecture will improve them.

Emerging Concern: AI Overreliance and Reduced Independent Cognitive Engagement

The fourth pattern, represented by six studies, is an emerging concern rather than a dominant theme. It concerns overreliance and reduced independent cognitive engagement, defined here as lower monitoring, shorter reflection cycles, and diminished independent checking during unscaffolded AI use. This label describes reported behaviors and is not introduced as a validated latent construct. Fan et al. (2025), Galindo-Domínguez et al. (2026), and Liu (2026) indicate that these risks vary with task design and self-regulatory capacity.

Other studies show that metacognitive prompts and explicit monitoring can reduce overreliance and improve output evaluation (EL Hosayny et al., 2026). Because the evidence base is small and heterogeneous, the pattern is treated as a boundary condition for model design: the proposed architecture should be tested against unscaffolded AI use rather than assumed to prevent overreliance.

Conceptual Gaps Identified Through Synthesis

Beyond the identification of dominant themes, the thematic synthesis revealed three persistent conceptual gaps that recur across the literature regardless of thematic focus. Table 4 presents these gaps alongside their evidential basis and the SR-AI Model's response to each.

Table 4. Conceptual Gaps Identified Through Thematic Synthesis

Gap	Description	Evidence from Literature	SR-AI Model Response
Gap 1	Fragmentation between technology integration and cognitive mechanism: most AI-based learning models address technological features without modeling how AI interaction connects to student cognitive processes.	Liu & Zhong (2025); Faza & Lestari (2025); Melisa et al. (2025)	The SR-AI Model explicitly integrates a Self-Regulation Mechanism layer that connects Core Process Layer (AI interaction) directly to Cognitive Outcome Layer, bridging the technology-cognition divide.
Gap 2	Absence of an integrated framework connecting personalized learning and SRL as a coherent instructional system. Studies examine these constructs separately without operationalizing their interaction.	Alshaketheep et al. (2025); Ballantyne et al. (2025); Kalra et al. (2026)	The SR-AI Model positions personalized learning as the Input Layer that directly conditions the Self-Regulation Mechanism, formalizing their integration within a single operational framework.
Gap 3	Underspecification of cognitive targets in AI-based instructional design. Most frameworks orient toward engagement and task efficiency rather than metacognition and critical thinking as explicit learning outcomes.	Salido et al. (2025); Schorr et al. (2026); Du et al. (2025)	The SR-AI Model designates metacognition and critical thinking as the primary Cognitive Outcome Layer, making them explicit targets of instructional design rather than incidental byproducts.

The three gaps provide a corpus-bounded rationale for model construction. They should not be read as proof that all prior literature is fragmented or that the SR-AI Model is uniquely effective. The model's contribution is the traceable organization of recurring functions into one provisional architecture.

The SR-AI Model: A Conceptual Framework

The proposed SR-AI Model comprises four dynamically connected layers: Input, Core Process, Self-Regulation Mechanism, and Cognitive Outcome. Components were included only when supported by recurring codes and mapped to a defined gap. Table 5 reports function and evidential basis; arrows between layers represent propositions unless a cited study directly tested the relevant relationship.

Table 5. SR-AI Model Components: Specification, Function, and Evidential Basis

Layer	Component	Function	Evidential Basis from 42 Articles
Input Layer	Personalized Learning Environment	Tailors content, difficulty, and learning strategy to individual AI literacy level, prior knowledge, and self-regulatory capacity.	Kalra et al. (2026); Ballantyne et al. (2025); Lim et al. (2024); Chang et al. (2023)
Input Layer	AI-Based Learning System	Provides AI tools, recommender systems, and data-driven interaction platforms that form the technological substrate of learning.	Jamil (2026); Borchers et al. (2025); Huang et al. (2026)
Core Process Layer	AI Interaction Process	Structured engagement with AI tools oriented toward knowledge construction, not passive information retrieval.	Cheng & Cheung (2026); Liu (2026); EL Hosayny et al. (2026)
Core Process Layer	Prompt Scaffolding	Guides students in formulating queries that require evaluative rather than retrieval-based reasoning.	Hilliger et al. (2026); Barış Horzum et al. (2026); AlMuhaysh (2026)
Core Process Layer	Reflection Tools	Structured prompts and journaling mechanisms that encourage students to evaluate the quality and implications of AI outputs.	Neshaei et al. (2025); Li & Samah (2026); Fan & Gao (2026)
Core Process Layer	AI Critique	Explicit evaluation activities in which students assess AI outputs for accuracy, bias, and epistemic limitations.	Du et al. (2025); Melisa et al. (2025); Salido et al. (2025)
Self-Regulation Mechanism	Planning	Goal setting, strategy selection, and pre-task calibration of AI use.	He (2025); Liu et al. (2025); Karaoglan Yilmaz & Yilmaz (2025)
Self-Regulation Mechanism	Monitoring	Real-time tracking of learning progress and evaluation of AI output quality during task execution.	Hu & Zhang (2025); Roman et al. (2026); Bećirović et al. (2026)
Self-Regulation Mechanism	Evaluation	Post-task reflection on the effectiveness of strategies used and the quality of cognitive outcomes achieved.	Galindo-Domínguez et al. (2026); Lu & Zeng (2026); Faza & Lestari (2025)
Cognitive Outcome Layer	Metacognition	Awareness and control of one's own thinking when processing AI-generated information.	Fan et al. (2025); Joo et al. (2026); Chen & Alibakhshi (2026); Fan & Gao (2026)
Cognitive Outcome Layer	Critical Thinking	Analytical capacity to evaluate, challenge, and construct evidence-based judgments from AI outputs.	Salido et al. (2025); Du et al. (2025); Schorr et al. (2026); Sardi et al. (2025)

The Input Layer establishes the personalized entry conditions for learning by combining a personalized learning environment with an AI-based learning system. The personalization operates not merely at the level of content recommendation but encompasses calibration of learning strategy, scaffolding intensity, and regulatory support to individual AI literacy levels and self-regulatory capacity. This design directly addresses Gap 2 by formalizing personalization as the input condition for SRL rather than an independent feature. The Core Process Layer positions AI interaction as the central activity of learning, supported by three categories of learning support tools: prompt scaffolding, reflection tools, and AI critique. These tools collectively ensure that student interaction with AI is oriented toward knowledge construction,

metacognitive monitoring, and critical evaluation rather than passive information consumption.

The Self-Regulation Mechanism comprises planning, monitoring, and evaluation. Evidence supports its association with productive AI engagement, and selected studies test moderation or mediation; the general cross-layer mediating role remains proposed. The Cognitive Outcome Layer specifies metacognition and critical thinking as design targets. A feedback path from outcomes to personalization represents an inferred recalibration process that must be tested longitudinally.

Bibliometric Evidence: Keyword Co-occurrence Analysis

The VOSviewer map was produced using full counting, association-strength normalization, a minimum keyword occurrence of two, and thesaurus cleaning that merged spelling variants and common synonyms such as AI/artificial intelligence and GenAI/generative AI. Both author and index keywords in the retained Scopus export were used. The retained project materials did not preserve a reliable item-and-link export from which node and edge counts could be reconstructed; those statistics are therefore not invented. The map is used only as descriptive corroboration of how terms co-occur in this corpus.

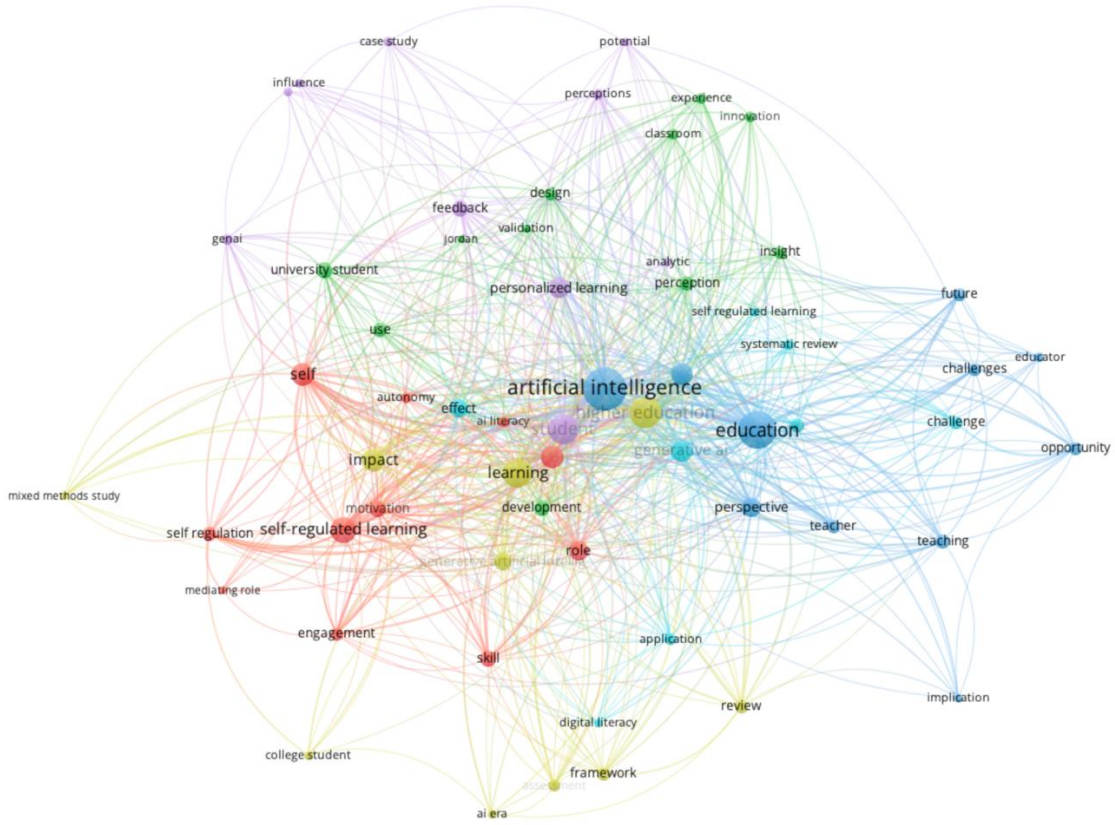

Figure 2. *Keyword Co-occurrence Network Map of 42 Included Articles (VOSviewer, minimum co-occurrence = 2)*

Artificial intelligence and education occupy central positions, while self-regulated learning, personalized learning, and critical thinking appear in differently connected regions. These spatial patterns may reflect author keyword choices, indexing practices, preprocessing decisions, and the occurrence threshold. They are consistent with the thematic observation that the constructs are not always discussed together, but they do not independently demonstrate a theoretical gap.

Accordingly, keyword co-occurrence is interpreted as a visualization of this corpus rather than confirmatory evidence of novelty, causality, or architectural integration. Sensitivity to preprocessing and threshold choices should be examined in future replications using preserved VOSviewer item and network exports.

Comparative Analysis: SR-AI Model Against Existing Frameworks

The comparison was bounded to frameworks that were cited in the included or framework-defining literature and represented the nearest alternatives across four functions: cyclical SRL, learning analytics and personalization, AI-chatbot instructional design, and generative-AI learning-to-learn. Dimensions were defined before rating. Ratings were based only on features explicitly documented in the cited framework and were checked by the second author, with the third author reviewing disagreements. Table 6 is therefore an illustrative conceptual comparison, not systematic proof of novelty.

Table 6. Comparative Analysis: SR-AI Model Versus Existing AI-Based Learning Frameworks

Dimension	Zimmerman (2000) SRL	Ifenthaler & Yau (2020)	Chang et al. (2023)	SR-AI Model
Primary scope	Cyclical learner self-regulation	Learning analytics for study success	AI chatbot design for SRL	Four-layer AI instructional architecture
Personalization	Not explicit	Data-informed support	Explicit design principle	Input condition calibrated to learner needs

Dimension	Zimmerman (2000) SRL	Ifenthaler & Yau (2020)	Chang et al. (2023)	SR-AI Model
AI interaction	Outside original scope	Analytics-enabled support	Chatbot interaction	Structured process with scaffolding, reflection, and critique
SRL function	Central cyclical process	Supported outcome/process	Goal setting, feedback, and regulation	Proposed cross-layer regulatory link
Cognitive targets	Performance and self-regulation	Study success	SRL and learning support	Metacognition and critical thinking
Evidence status	Established theoretical framework	Empirical learning-analytics framework	Design principles	Provisional synthesis-derived propositions

The comparison indicates that each framework contributes a relevant component. The SR-AI Model's proposed contribution is the explicit arrangement of personalized entry conditions, structured AI interaction, SRL processes, and higher-order outcomes in one architecture. The reviewed corpus did not identify the same arrangement, but this bounded finding does not exclude frameworks outside the search or establish empirical superiority.

The model adapts, rather than claims to extend, established SRL and instructional-design perspectives to AI-mediated learning. Its main inferential step is the proposed placement of planning, monitoring, and evaluation between structured AI interaction and higher-order outcomes, with personalization shaping entry conditions. The named framework comparison shows why this arrangement is worth testing but does not establish theoretical superiority.

Metacognition is treated as an outcome within a learning cycle and as information for subsequent recalibration. Evidence from Fan et al. (2025), Schorr et al. (2026), and Joo et al. (2026) supports the importance of metacognitive prompts and monitoring, but the direction and durability of effects vary by design. Longitudinal tests are required to determine whether repeated cycles strengthen transferable metacognitive capacity.

Pedagogically, the architecture shifts attention from tool adoption to scaffolding design. Instructors design prompt scaffolds, reflection tools, and AI-critique tasks; curriculum developers align these activities with explicit cognitive outcomes; and institutions provide faculty development, assessment standards, and data-governance support. These implications are design recommendations derived from the synthesis, not demonstrated implementation effects.

The discussion is organized around the three review questions and the four model layers. Relationships are labeled according to evidential status: evidence-based when directly examined in included studies, inferred when derived through thematic synthesis, and proposed when they represent an untested architectural relation. This distinction prevents a conceptual model from being described as an empirically validated theory.

For RQ1, the evidence indicates associations between SRL and productive AI engagement, with direct moderation or mediation tested in only part of the corpus. The Input and Core Process layers provide the conditions under which planning, monitoring, and evaluation may operate. Task complexity, prior AI literacy, disciplinary context, and baseline self-regulatory capacity are boundary conditions; the model should not assume equivalent effects across learners or tasks.

For RQ2, personalized and adaptive support appears most defensible when it calibrates scaffolding while preserving learner agency. System-driven adaptation can support goal setting and feedback, but excessive automation may reduce opportunities to practice regulation. The proposed relation from personalized input to SRL is therefore an inference that requires comparison with non-personalized and automation-heavy conditions.

For RQ3, metacognition and critical thinking are specified as target outcomes because the corpus repeatedly links reflective prompts, AI critique, and guided inquiry with deeper evaluation. Metacognition also informs later personalization through the proposed feedback path. This dual role is temporal rather than circular: metacognitive performance is an outcome of one learning cycle and an input for recalibration in the next.

Implementation implications are limited to AI-enhanced learning, SRL scaffolding, instructional design, faculty readiness, and institutional governance. Three propositions follow: P1, structured AI interaction with explicit SRL scaffolding will produce stronger metacognitive monitoring and critical evaluation than otherwise comparable unscaffolded AI use; P2, personalization will influence higher-order outcomes indirectly through planning, monitoring, and evaluation; and P3, these effects will vary with baseline SRL, AI literacy, task complexity, and disciplinary context. These propositions require prospective testing and should not be presented as corpus findings.

Conclusion

Summary and Contribution

The review identified three recurrent gaps within a 42-study Scopus and citation-search corpus: limited specification of regulatory processes in AI integration, inconsistent coordination of personalization and SRL, and underspecification of metacognition and critical thinking as design targets. The SR-AI Model organizes recurring functions into four layers and proposes testable relations among them. The SR-AI Model should therefore be treated as provisional: the corpus supports the relevance of its components, while the cross-layer architecture and general mediating role of SRL remain author-proposed relationships requiring empirical validation.

Limitations

This review has five limitations. First, the corpus is Scopus-centered and supplemented by 14 citation-search records that were screened under the same eligibility criteria; relevant work indexed only in Web of Science, ERIC, PsycINFO, IEEE Xplore, or regional databases may therefore be omitted. Second, English-language eligibility limits non-Western representation. Third, no formal design-specific risk-of-bias appraisal was conducted, so the synthesis is not quality weighted. Fourth, no formal inter-rater coefficient or record-level full-text exclusion list was retained. Fifth, VOSviewer node and edge statistics could not be reconstructed from the retained project materials. These limitations constrain claims of comprehensiveness, confidence, and novelty.

Validation Agenda

Validation should proceed in six stages: (1) expert content validation and construct specification for every layer and path;

(2) pilot usability testing of scaffolds, reflection tools, and AI-critique tasks; (3) development and validation of measurement instruments for SRL, metacognition, critical thinking, and overreliance; (4) experimental or quasi-experimental comparison of scaffolded and unscaffolded AI conditions; (5) mediation analysis of planning, monitoring, and evaluation with temporal ordering; and (6) replication across disciplines, institutions, learner profiles, and cultural contexts.

Declarations

Author's Contribution Statement

All authors contributed equally to this work. Cicilia Emita, Bayu Febriawan, Budi Wibawanta, Samuel Lukas, and Innocentius Bernanto contributed equally to the conceptualization, methodology, screening and data extraction, analysis, construction of the SR-AI Model, and writing and revision of the manuscript. All authors read and approved the final version.

Conflicts of Interest

The authors declare no conflicts of interest.

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