The Influence of Using AI Tools on Chinese Higher Education Students' Self-Regulated Learning: A Review of Literature

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Abstract

Artificial intelligence (AI) is increasingly integrated into diverse fields, including education, where it offers innovative approaches to enhance self-regulated learning (SRL). For many students in Chinese higher education, developing robust SRL skills remains a significant challenge. This review addresses the need for a clearer understanding of how AI tools influence these skills by synthesizing ten empirical studies published between 2021 and 2025. Following the PRISMA framework, the literature was identified from prominent academic databases, including Web of Science, Scopus, and ERIC. Drawing on Zimmerman's SRL Three-phase Model, this synthesis suggests that AI tools show potential to assist students with goal-setting and foster motivation within the forethought phase. During the performance phase, such tools may support learning-strategy deployment and progress monitoring via timely feedback. In the reflection phase, AI can facilitate outcome evaluation and subsequent strategy adjustment. However, the review also identifies potential risks, such as student over-reliance on AI, and notes a limited research focus on long-term SRL development and group regulation. Accordingly, future research should adopt longitudinal designs, investigate AI's role in co-regulated learning, and integrate AI literacy and emotional support into SRL development frameworks.

Keywords: ***AI; Self-Regulated Learning; Chinese Higher Education; College Students; Review***

1. Introduction

Chinese higher education, as an important supporting force for the national strategy of strengthening human resources, bears the core responsibility of cultivating innovative and complex talents (Xue & Li, 2022). With the in-depth promotion of

the national "double first-class" construction and the continuous implementation of the policy to increase the enrollment of colleges and universities, the scale and quality of China's college and university education system have continued to improve, and it has become one of the largest higher education systems in the world (Liang, 2024). In other words, higher education in China plays an increasingly important role and has become a major force for national development and social progress.

According to the 2022 National Education Development Statistics Bulletin released by China's Ministry of Education (2023), by the end of 2022, there were more than 23 million students enrolled in higher education nationwide. This large higher education student population emphasizes the importance of Chinese universities in the global higher education landscape. More individuals have access to higher education nowadays (Gao, 2018), while the students need to have high level of learning autonomy to enable them to adapt to various learning environment during their studies (Vy & Jinming, 2024). In this context, how to effectively improve college students' self-regulated learning (SRL) skills has become the key challenge for higher education professionals.

Yet, the lack of SRL ability has become a major bottleneck in improving the learning effectiveness of current college students. For instance, studies (Yang et al., 2025) noted that college students usually suffer from weak SRL skills in the learning process. It is found that more than 60% of college students had difficulty with the establishment of specific objectives during the opening phases of college, and nearly half lacked permanent processes of self-supervision and the ability to reflect upon their own learning (Li et al., 2025). Poor metacognitive awareness, difficulty with emotional regulation, and ineffective transfer of strategy have become the core obstacles to their long-term learning and transferability to complex tasks (Schuster et al., 2020; Wirth et al., 2025). Additionally, the pedagogical process of "passive listening - passive test-taking" is common to the contemporary college classroom, and students are mostly less involved with autonomous process management and task design (Wang et al., 2022). This problem is of particular significance in online pedagogical situations, in which the student is unable to effectively initiate and take advantage of independent materials for learning, and most often manifest in the form of "shallow learning" or "strategy loss" (Faza & Lestari, 2025).

AI tools, being an example of the evolution of educational technology, have gradually unveiled their probable strengths in supporting SRL among college undergraduates (Ng et al., 2024). In recent years, several AI tools have been introduced in higher educational settings, and the list is expanding, such as intelligent recommender systems, computer-based learning assistants, and ChatGPT-based generative feedback systems, which might help students conduct key tasks such as the setting of goals, tracking of progress, solicitation of strategy feedback, and reflection on learning (Lan & Zhou, 2025; Zawacki-Richter et al., 2019; Chiu, 2024). Recent research has shown that the degree of structure and the intensity of student-centered support of instruments of AI have significant impact on their effectiveness in developing SRL competencies (Lan & Zhou, 2025). The findings of one research carried out with the assistance of structural equation modeling demonstrated that there was statistically significant positive connection between AI literacy and SRL (Shi et al., 2025). According to the findings of another study, an AI platform that embeds metacognitive cues has the capacity to significantly increase the preparation, monitoring and reflection of the students in digital environments (Khotimah & Rusijono, 2024). Accordingly, AI tools with well-structured designs and clearly defined learning support mechanisms have the potential to effectively foster students' metacognitive development and SRL, thereby enhancing their autonomous learning abilities.

During the entire intelligent upgrading process of Chinese higher education, explaining the mechanism of the operation of the application of AI instruments in the cultivation of college students' SRL has become common interest among academicians and policymakers. Especially under the policy direction of "promoting AI-enabled teaching process and serving personalized learning" proposed by the Ministry of Education of China in 2022, to systematically explore this topic will provide practical significance and theoretical value. Therefore, the purpose of this paper is to review the current existing empirical studies on the relationship between AI tools and SRL of Chinese college students in the past five years. It explores how the use of AI tools will impact SRL, especially its three phases (i.e., Forethought, Performance, Reflection), of Chinese college students, as well as making recommendations for future research and practice.

The research questions that guide this study are:

RQ1: How do AI tools influence the development of Forethought phase of SRL among Chinese college students?

RQ2: How do AI tools influence the development of Performance phase of SRL among Chinese college students?

RQ3: How do AI tools influence the development of Reflection phase of SRL among Chinese college students?

RQ4: What gaps exist in current research on AI-supported SRL in Chinese higher education?

2. Literature Review

2.1 Self-Regulated Learning (SRL)

SRL refers to learners' active management of their own learning behaviors during the learning process, which includes setting learning goals, choosing learning strategies, monitoring learning progress, and adjusting based on feedback (Zimmerman, 2000). SRL is more than just a process, yet it is a recursive and ongoing process, wherein the student has to, during every phase of learning, adapt and reflect so that they might achieve the objectives of learning more effectively (Zimmerman, 2000). The essence of SRL lies in student self-regulation and agency that requires the student to have a high level of metacognitive awareness and the ability to effectively manage the processes in their learning (Zimmerman, 2000). SRL has, in the recent past, been recognized as one of the most important competencies in the attainment of lifelong learning and performance of complex thinking tasks, and it has been most influential, in specific terms, in higher education (Dhiasa et al., 2025).

Zimmerman has otherwise argued that SRL is divided into three phases, which are the Forethought Phase, the Performance Phase, and the Reflection Phase (Zimmerman, 2000). There is specific performance behavior and mental activity that is suggested under each phase, such as goal setting, self-evaluation and self-monitoring, which constitutes the overall process of the active involvement and self-regulation of learners (Schunk & Zimmerman, 2011). The model is the cyclical process that proceeds in sequential manner throughout the whole three phases (see Figure 1).

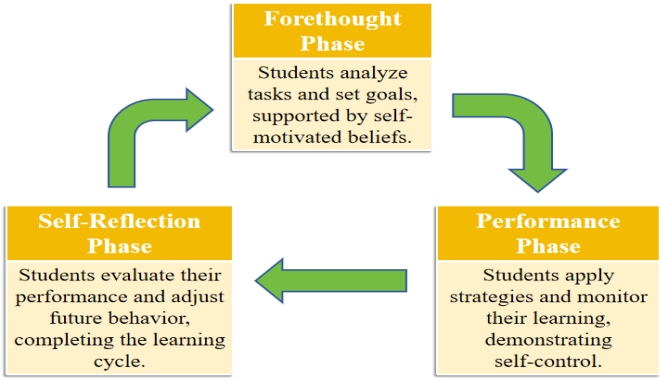


Figure 1. Three-Phase Model of Self-Regulated Learning (SRL) adapted from Zimmerman (2000)

Specifically, in the Forethought Phase, students start by analyzing tasks. They set clear goals and make strategic plans. These activities are supported by self-motivational beliefs. For example, students rely on their self-efficacy and outcome expectations to maintain effort. They also consider their interest in the task and focus on long-term learning goals (Woreta et al., 2025). These beliefs help prepare them for the next phase.

In the Performance Phase, students begin to take action. They apply specific strategies like imagery, self-instruction, and focusing attention. These are acts of self-control. Simultaneously, learners observe their knowledge through self-monitoring. They keep track of their progress and try their methods. Such actions keep them on course and allow them to make learning adjustments while performing the task.

Finally, in the Reflection Phase, students assess their performance. This is assessing outcomes in self-evaluation and grasping causality in attribution. These are self-judgments. Students also respond emotionally. They can be satisfied or dissatisfied. Depending on this, they either change their future behavior or justify their previous decisions. Such reactions determine their entry in the next learning cycle.

2.2 The Importance of SRL in Promoting Student Learning

SRL competence is widely recognized as a determinant of academic success and deep learning, which involves learners' core competencies such as goal-setting, self-monitoring, emotional regulation, and reflection on learning during the

learning process (Schunk & Zimmerman, 2011; Zimmerman, 2011). In the context of the current transition from teaching-centered to learning-centered higher education in China, students are required to possess stronger SRL skills, including learning planning, task execution monitoring and reflective adjustment (Wang et al., 2020). Therefore, the enhancement of SRL competencies has become one of the key objectives for developing students' core literacy in higher education.

SRL is also an important mechanism to enhance students' motivation and engagement in learning. Wei (2023) pointed out that when students are able to set their own goals, choose appropriate strategies, and flexibly adjust their learning styles, their motivation is significantly enhanced, which results in positive learning attitudes and contributes to long-term academic development.

SRL also plays an important role in motivational stability and learning persistence, and Zimmerman and Moylan (2009) pointed out that SRL not only helps to enhance learners' intrinsic motivation but also improves their persistence and self-efficacy in the face of complex tasks, which promotes the realization of long-term learning goals.

Further, students with high SRL ability usually have stronger attention control, time management awareness, and can effectively transfer mastered learning strategies to different learning situations (Broadbent & Poon, 2015). These abilities are precisely the goals that colleges and universities pay most attention to in developing students' independent and lifelong learning abilities. Therefore, the systematic development of SRL is increasingly becoming a central issue in higher education teaching and learning reform and student development support.

2.3 Facilitation of SRL by technological tools

With the rapid development of educational technology, Artificial Intelligence (AI) is gradually becoming a key tool to support SRL in higher education. AI can provide learners with real-time feedback, personalized recommendations and strategy guidance, which can help them with goal-setting, task-monitoring and learning reflection (Lan & Zhou, 2025). These are advantages that traditional teaching cannot provide.

For example, Ba et al. found that generative AI (e.g., ChatGPT) significantly promotes students' goal setting and cognitive engagement in online learning, which helps them to establish a clear learning direction in the early phases of learning (Brünner & Ebner, 2025); while Wu et al. pointed out that AI platforms, by fulfilling the students' psychological needs (e.g., autonomy and sense of competence) during the learning process, enhance their learning motivation and strategy use levels (Wu & Chiu, 2025), which in turn stimulates deeper learning behaviors. In addition, several studies have found that the instant feedback, bottleneck identification, and personalized path recommendations provided by AI tools not only help students better cope with difficulties in the learning process, but also significantly improve their learning efficiency and quality (Pohn et al., 2025).

It is worth noting that research has also shown that AI tools may induce metacognitive inertia, which refers to students' reliance on AI suggestions to the exclusion of independent judgment (Li & Fan, 2024). Therefore, AI intervention in SRL may become either an external support or a substitute for internal competence, and how to guide students to use AI appropriately has become a new issue of concern.

2.4 Structural model of SRL: Zimmerman's three-phase model and its technological adaptation

The three-phase model proposed by Zimmerman has been widely applied in educational research and is increasingly being applied to AI-supported learning environments (Zimmerman, 2000). For the Forethought Phase, goal setting is a key element. Research indicates that students who set clear and meaningful goals often demonstrate higher learning engagement and achievement (Schunk, 2003). In this context, AI tools can help personalize this process. For example, AI chatbots and learning analytics systems can assist students in what might be characterized as identifying appropriate goals based on learning histories and preferences (Zimmerman, 2008). Likewise, Chang et al. found that chatbot-driven scaffolding improved goal formulation among college students (Chang et al., 2023). Similarly, Wang et al. indicate that AI could suggest goal-setting strategies aligned with university students' prior achievements and needs (Wang et al., 2025). These interventions contribute to an increased likelihood that students enter learning tasks with ostensibly clearer direction and motivation.

During the Performance Phase, students monitor their actions and regulate learning strategies in real-time. AI applications, including feedback platforms, chatbots, and dashboards, play a significant role in enhancing this phase. Brünner and Ebner (2025) found that adaptive AI feedback improves students' use of monitoring strategies in writing tasks. To further explore these relationships, Lee et al. examined a guided ChatGPT model within blended courses. Their results demonstrate that this model helps learners track progress and respond to setbacks more flexibly (Lee et al.,

2024). The study further confirmed that AI guidance increases both cognitive engagement and the timely use of learning resources.

For the Reflection Phase, learners evaluate performance and outcomes. AI systems are distinguished by their capacity to support deeper reflection through data visualization and performance analytics. Hingle and Johri (2024) provided evidence that students using AI-generated learning logs engaged more frequently in reflective journaling. Furthermore, a systematic review by Lan and Zhou identified AI-enabled reflection environments that facilitate metacognitive awareness by prompting students to identify mistakes and plan revisions (Lan & Zhou, 2025). These findings collectively indicate that the Reflection Phase benefits from AI tools which provide feedback on the entire learning process, not merely the final results.

Furthermore, Panadero and Alonso-Tapia emphasized that AI-supported SRL systems should go beyond delivering content or tracking progress (Panadero & Alonso-Tapia, 2014). They should actively scaffold metacognition at all three phases. This includes prompting learners to think about their goals, analyze the effectiveness of their strategies, and make informed adjustments. This shift—from passive tool use to active metacognitive engagement—represents a key direction in current AI-SRL integration research.

3. Methods

This paper conducts a systematic integrative review to explore how artificial intelligence applications shape self-regulated learning behaviours among undergraduate populations within Chinese tertiary institutions. The whole review follows well-defined, theory-informed workflows for document retrieval, eligibility filtering and thematic evidence synthesis. Concrete procedures for literature handling and data processing are laid out in the following sub-sections.

3.1 Literature Search and Selection

To maintain transparency and reproducibility for this review project, the PRISMA 2020 reporting guideline was adopted to govern database retrieval, record filtering and final study inclusion decisions (Page et al., 2021). Three authoritative educational databases were selected for source retrieval: ERIC, Web of Science, as well as Scopus. Search operations targeted article titles, abstract segments and keyword fields. Publication windows were confined to works released between 2021 and 2025. Combined search terms covered artificial intelligence-related vocabulary, self-regulated learning constructs and population descriptors for Chinese university learners. Full search syntax applied to each database can be found within Table 1.

Table 1. Search String for Papers in Databases.

Database	Keywords
ERIC	("artificial intelligence" OR AI OR "generative AI" OR ChatGPT) AND ("self-regulated learning" OR SRL OR "self-regulation") AND (China OR Chinese OR "higher education" OR "university student" OR "college student")
Web of Science	("artificial intelligence" OR AI OR "generative AI" OR ChatGPT) AND ("self-regulated learning" OR SRL OR "self-regulation") AND (China OR Chinese OR "higher education" OR "university student" OR "college student")
Scopus	("artificial intelligence" OR AI OR "generative AI" OR ChatGPT) AND ("self-regulated learning" OR SRL OR "self-regulation") AND (China OR Chinese OR "higher education" OR "university student" OR "college student")

Initial database queries returned more than 5000 bibliographic entries in total. After automated de-duplication supplemented by manual checks, 5279 unique records remained for title-abstract level screening. At this preliminary screening round, 4853 entries were discarded. Major grounds for elimination included mismatched thematic focus, inappropriate educational settings, non-target participant groups and non-empirical manuscript formats. Full-text acquisition attempts were carried out for the remaining 426 publications. Among these candidates, 43 documents could not be obtained for complete content evaluation. This left 383 full-text papers ready for detailed eligibility assessment.
Pre-defined eligibility benchmarks were set in advance as follows:

(a) peer-reviewed journal publications;
(b) publication time falling within 2021-2025;
(c) original empirical research adopting quantitative, qualitative or mixed-method research designs;
(d) research participants comprised college-level students from Chinese higher-education establishments;

(e) manuscripts needed to report empirical associations between AI-tool usage and observable self-regulated learning constructs.

Pure policy commentary, theoretical conceptual papers and existing literature reviews were excluded from further analytical work. After full-text evaluation, 373 papers failed to satisfy one or multiple inclusion criteria. Specific exclusion triggers included publication outside the predefined time frame (n = 39), and absence of original empirical data situated within Chinese university contexts (n = 334). No manuscripts were removed for lacking peer-review status. Ultimately, ten empirical investigations satisfied all screening requirements and entered the final synthesis dataset.

The substantial drop from thousands of initial search outputs to ten included studies arises from strict eligibility constraints. A large share of retrieved records represent conceptual discussions, opinion pieces, or empirical projects focusing on K-12 participants or student groups outside mainland China. Such filtering outcomes reflect the comparatively limited volume of original empirical studies specifically targeting this niche research topic.

3.2 Screening Criteria

Two sequential judging dimensions guided full-text filtering steps to secure adequate study relevance.

First, each candidate manuscript was verified to confirm its empirical nature. Only works collecting primary data from Chinese university student samples proceeded to subsequent assessment. Pure theoretical arguments or secondary analytical documents were discarded.

Second, manuscripts had to deliver direct empirical observations linking AI-tool adoption to self-regulated learning behaviours. Texts discussing AI-related educational policies without measuring actual SRL-related learner performance were ruled out.

The complete article selection workflow is visualised within the PRISMA flow diagram (Figure 2). All numerical values presented inside the flow chart are strictly aligned with count information described within this textual section to guarantee reproducibility. Note: Shortened labels for exclusion categories are presented in Figure 2 for layout purposes; full descriptions of exclusion rationales are provided in Section 3.1.

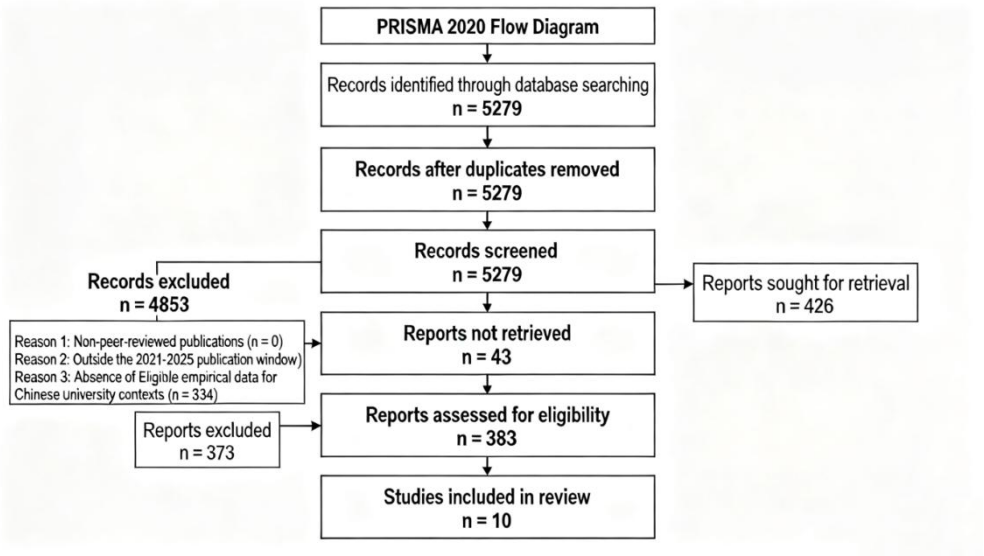


Figure 2. Articles Selection Procedure using PRISMA 2020

3.3 Data Analysis

This review applied a hybrid analytical scheme combining deductive theoretical guidance alongside inductive thematic coding work. Deductively, Zimmerman's three-phase cyclical framework for self-regulated learning served as the

high-level organising structure (Zimmerman, 2000). This theoretical foundation pre-identified six core analytical domains: goal formulation, motivational activation, learning strategy deployment, in-task progress monitoring, outcome evaluation, plus adaptive adjustment of learning tactics. These domains offered a stable structural backbone for arranging extracted empirical findings.

Inductive thematic coding followed core principles for integrative review methodology outlined by Torraco (2016). Open coding was performed on raw result segments reported across the ten selected studies. Emerging observational patterns were extracted without forcing empirical evidence to fit rigid pre-established theoretical categories. Novel themes directly derived from primary study outputs, such as metacognitive inertia brought by over-reliance on generative AI tools, were captured during open-coding operations.

Upon completion of open-coding procedures, inductively generated themes were mapped back onto Zimmerman's three-phase SRL structure for result organisation and formal presentation. This hybrid analytical design balanced solid theoretical anchoring while preserving openness to unexpected patterns uncovered within recent empirical outputs.

A standardised coding matrix was built to organise information extracted from each included study (refer to Table 2). Extracted content covered study objectives, research designs, theoretical foundations, participant profiles, categories of AI tools deployed, data collection instruments, key empirical outcomes, documented study limitations and future research directions proposed by original authors. One extra column named "Quality rating" was added to this matrix to store methodological quality assessment outcomes. When conducting evidence synthesis, consistent findings recurring across multiple studies were aggregated as major thematic points. Contradictory or mixed empirical observations were retained and explicitly discussed rather than omitted. Where divergent results appeared, potential contributing factors including sample composition, learning task types and AI-system characteristics were noted for interpretation.

3.4 Quality Assessment of Included Studies

Methodological quality appraisal was conducted for all ten retained empirical works to gauge research rigor. A customised appraisal checklist adapted for educational empirical research covered five evaluation dimensions: clarity of stated research aims; transparent reporting of participant backgrounds and contextual settings; unambiguous description of AI-related interventions or measurement instruments; appropriateness of data collection and analytical procedures; and thorough disclosure of study limitations. Each paper was assigned either a "High" or "Moderate" quality grade. No study fell into the low-quality category that would trigger exclusion from synthesis. Quality ratings serve interpretive purposes rather than acting as additional exclusion criteria, since eligibility screening had already been completed prior to this appraisal step.

Nevertheless, several common methodological weaknesses could be identified across the dataset. Most notably, cross-sectional survey designs dominated the sample base, heavily relying on self-reported learner perceptions rather than objective behavioural logs. Many projects adopted short-term interventions without long-term follow-up measurements, and participant recruitment was frequently confined to single-institution samples. These inherent limitations of primary studies were weighted carefully during result interpretation to avoid over-generalised inference. Quality appraisal outcomes are documented within the summary matrix (Table 2).

Table 2. Summary of 10 Studies.

Author	Purpose	Sample	Methods	Results & Discussions	Limitations	Future study	Quality rating
Fan et al., 2025	This study examines how three different forms of learning scaffolds, namely generative AI (e.g., ChatGPT), human experts, and conventional writing tools, affect college students' SRL behaviors, motivation, and performance. It also focuses on the phenomenon of "metacognitive inertia", i.e., whether students reduce their thinking and monitoring behaviors after relying on AI.	117 Hong Kong university undergraduate students (English language learners)	**Design :** Quantitative experimental design **Grouping :** Randomly assigned to 4 groups (ChatGPT, Human Expert, Writing Tool, Control) **Data Collection :** Pre/post writing test scores, motivation questionnaire, SRL behavior logs, task outputs **Analysis :** ANOVA and regression analysis	a. AI feedback enhances short-term writing performance b.AI support promotes goal-setting behavior c.AI use inhibits monitoring and reflective strategies d. human scaffolding supports more balanced self-regulation strategies e. students are significantly dependent on AI f. AI failed to enhance knowledge transfer	a.Limited generalizability due to small sample and gender imbalance; b.Focused only on writing tasks; c.Metacognitive inertia inferred without direct measures.	Future research should expand samples, include varied tasks, and adopt mixed methods with cognitive tracking.	High

Author	Purpose	Sample	Methods	Results & Discussions	Limitations	Future study	Quality rating
Zhou et al., 2024	This study investigates whether SRL with generative AI plays a mediating role between critical thinking and problem-solving skills among college students. The study aims to clarify whether AI self-regulation helps explain how students can improve their problem solving through thinking skills.	689 undergraduate students in generative AI-related courses	**Design:** Quantitative research design **Data Collection:** Structured questionnaire measuring critical thinking, SRL in generative AI context, and problem-solving ability **Analysis:** Structural Equation Modeling (SEM) to examine the mediating role of AI self-regulation	a. Students with strong critical thinking skills are more effective problem solvers b. students with strong AI self-regulation performed better in both thinking and problem solving c. AI self-regulation plays a mediating role between thinking and solving d. cognitive and metacognitive regulation of AI is particularly critical e. SRL competencies motivate students to use AI tools strategically	a. Self-assessment data may not reflect actual behavior b. Cross-sectional design limits causal inference c. Focused only on AI-assisted learning, excluding other teaching methods	Future research should incorporate behavioral tracking, adopt longitudinal designs, and consider contextual variables such as discipline and learning phase.	Moderate
Xu et al., 2025	This study examines how generative AI support can promote SRL and learning engagement among college students in an online learning environment. The study aims to reveal the mechanism of the relationship between AI use and SRL behavior and affective and cognitive engagement.	586 undergraduate students of professional fields	**Design:** Quantitative cross-sectional design **Data Collection:** Online structured questionnaire measuring AI usage frequency, SRL strategies (goal setting, strategy use, monitoring), and learning input (affective & cognitive) **Analysis:** Structural Equation Modeling (SEM) to examine direct and indirect relationships between variables	a. AI use is significantly and positively associated with self-regulatory behaviors b.AI-supported SRL enhances levels of affective and cognitive engagement c.AI indirectly affects SRL through learning inputs d. cognitive engagement is a key bridge between AI and SRL e. AI facilitates metacognitive monitoring mechanisms	a. Cross-sectional self-assessment data limits causal inference b. Focused on students' perceptions rather than actual interaction behavior c. Scenario restricted to online classroom setting	Future research should incorporate AI usage logs, adopt longitudinal or experimental designs, and explore diverse contexts such as disciplinary classrooms or blended learning environments.	Moderate
Ji et al., 2025	This study explores how AI literacy influences individual innovative behavior among college students, with a specific focus on the mediating roles of psychological need satisfaction, creative self-efficacy, and SRL. The aim is to uncover how students utilize AI knowledge to drive learning innovation.	415 undergraduate students of multiple academic disciplines	**Design:** Quantitative cross-sectional survey design **Data Collection:** Validated instruments measuring AI literacy, basic psychological needs (autonomy, competence, relatedness), creative self-efficacy, SRL strategies, and innovative behavior **Analysis:** Structural Equation Modeling (SEM) to assess model fit and examine direct and indirect path effects	a. AI literacy significantly predicts innovative behavior b. Psychological need satisfaction serves as a mediator c. Creative self-efficacy strengthens the AI–innovation link d. SRL acts as a bridging mechanism e. A multi-path mediation mechanism is formed	a. Cross-sectional self-reported data limits causal inference b. AI literacy measured via subjective perception, not objective tests c. Sample limited to Chinese higher education institutions	Future research should use objective AI competence measures, adopt longitudinal or experimental designs, and conduct intervention studies to enhance the role of SRL and psychological factors in innovation.	Moderate
Wang et al., 2025	This study investigates how the satisfaction of basic psychological needs—autonomy, competence, and relatedness—influences students' engagement, perceived learning outcomes, and SRL in AI-supported higher education environments. The goal is to reveal how intrinsic motivation fosters effective use of AI tools through enhanced SRL capabilities.	536 undergraduate students of diverse academic disciplines	**Design:** Quantitative cross-sectional design **Data Collection:** Structured questionnaires assessing psychological need satisfaction, AI learning engagement, perceived learning outcomes, and SRL abilities **Analysis:** Structural Equation Modeling (SEM) to examine path relationships and mediating mechanisms	a. Psychological need satisfaction significantly enhances AI learning performance and SRL abilities b. Learning engagement mediates the link between need satisfaction and learning outcomes c. Need satisfaction promotes goal setting and strategy use d. Competence emerges as the strongest predictor e. SRL supports effective AI learning experiences	a. Cross-sectional self-reported data limits objectivity b. AI learning outcomes based on perception, not behavioral tracking c. Gender and disciplinary differences not fully explored	Future research should integrate behavioral data, adopt experimental or longitudinal designs, and examine the differential effects of specific AI tools on SRL development.	Moderate
Shi et al., 2025	This study examines the relationship between AI literacy, self-regulated learning (SRL), writing performance, and student well-being in generative AI-supported higher education settings. It focuses on how AI-related competencies and SRL strategies contribute to academic writing outcomes and emotional well-being.	527 undergraduate students that completed a writing task supported by generative AI tools	**Design:** Quantitative cross-sectional survey design **Data Collection:** Structured instruments measuring AI literacy, SRL abilities, self-perceived writing performance, and	a. AI literacy significantly predicts SRL behaviors and writing performance b. SRL mediates the relationship between AI literacy and writing	a. Based on cross-sectional self-reported data b. Writing performance measured via self-perception, not objective scoring c. Specific AI platforms	Future research should use objective writing assessments, compare effects of different AI tools, and adopt experimental or longitudinal designs to track learning process changes.	Moderate

Author	Purpose	Sample	Methods	Results & Discussions	Limitations	Future study	Quality rating
			well-being (academic stress & positive emotion) **Analysis:** Structural Equation Modeling (SEM) to analyze relationships and mediating paths	outcomes c. SRL is positively associated with well-being d. AI literacy helps reduce academic anxiety e. Writing success enhances positive emotions	not detailed		
Pan et al., 2025	This study investigates how generative AI (GenAI)-empowered interactive support affects Chinese university EFL (English as a Foreign Language) students' use of self-regulated learning (SRL) strategies and their engagement in academic reading. The aim is to examine whether AI-generated prompts can enhance learners' metacognitive and cognitive regulation during the reading process.	128 undergraduate students of English majors	**Design:** Quasi-experimental quantitative design Grouping: Experimental group (GenAI tools) vs. Control group (traditional instruction) **Data Collection:** Pre/post-test scores, SRL strategy questionnaires, reading engagement scales **Analysis:** ANCOVA to control baseline differences and compare group outcomes	a. GenAI support significantly increased the frequency of SRL strategy use b. AI-generated prompts enhanced reading engagement c. AI-guided reflective behaviors were strengthened d. Cognitive strategies such as summarizing and inference were reinforced e. Learners developed greater autonomy	a. Small sample size from a single institution b. No long-term follow-up or assessment of final reading comprehension c. Lacked full randomization in design	Future research should increase sample size, adopt randomized controlled trials, and investigate how GenAI tools affect specific SRL components in reading.	High
Wei, 2023	This study examines the effects of AI-integrated language instruction on Chinese university students' English learning achievement, second language (L2) learning motivation, and self-regulated learning (SRL) abilities. The aim is to determine whether incorporating AI tools into English classrooms can enhance students' cognitive and motivational outcomes.	202 undergraduate students that enrolled in English courses incorporating AI-based instruction	**Design:** Quantitative quasi-experimental design Grouping: Experimental group (AI-integrated instruction) vs. Control group (traditional instruction) **Data Collection:** Pre/post-tests for English achievement; structured questionnaires for L2 motivation and SRL strategies **Analysis:** MANCOVA to control for baseline differences and assess between-group effects	a. AI-integrated instruction significantly improved English achievement b. AI use enhanced L2 learning motivation c. SRL strategies were reinforced in AI-supported settings d. AI promoted the development of metacognitive awareness e. Motivation and SRL mediated the relationship between AI and learning outcomes	a. Limited sample size and geographic coverage b. Did not differentiate among AI tool types c. Long-term learning effects not assessed	Future research should include follow-up studies, apply qualitative methods (e.g., interviews), and compare various AI platforms and task types in language learning contexts.	High
Pan et al., 2024	This study investigates how AI chatbots can support English-as-a-Foreign-Language (EFL) students in Chinese universities in developing self-regulated reading strategies. It focuses on the chatbot's specific role in facilitating planning, monitoring, and evaluation during reading tasks.	139 undergraduate EFL students that enrolled in an English reading course supported by AI chatbot tools	**Design:** Mixed-methods design (quantitative + qualitative) Quantitative Data: Pre/post questionnaires on SRL strategy use **Qualitative Data:** Chatbot-student interaction logs and semi-structured **interviews** **Analysis:** Integrated data analysis to evaluate AI support's impact on metacognitive SRL behaviors	a. AI chatbots enhanced students' awareness and use of SRL strategies b. Monitoring and reflection behaviors significantly increased c. AI provided real-time metacognitive prompts d. Students demonstrated greater learning autonomy e. Qualitative interviews revealed positive user attitudes	a. Small, homogeneous sample b. Chatbot support limited to reading tasks c. Long-term sustainability of SRL gains not assessed	Future research should incorporate diverse AI tools, expand to broader learning contexts, and adopt longitudinal designs to track SRL over time.	High
Wang et al., 2025	This study explores whether integrating ChatGPT-based feedback tools within a virtual reality (VR) learning environment can enhance university students' self-regulated learning (SRL) and higher-order thinking skills (HOTs). The focus is on the role of AI-driven real-time feedback in strengthening cognitive regulation and reflective thinking.	184 undergraduate students that participated in VR-based learning activities enhanced with ChatGPT feedback	**Design:** Quantitative quasi-experimental design **Grouping:** Experimental group (ChatGPT feedback) vs. Control group (standard VR instruction) **Data Collection:** Pre/post questionnaires measuring SRL and higher-order thinking skills (HOTs) **Analysis:** ANCOVA to control baseline differences and assess group effects	a. ChatGPT feedback significantly improved SRL behaviors b. Higher-order thinking skills were significantly enhanced in the experimental group c. Metacognitive awareness was strengthened through AI feedback d. Learners exhibited greater autonomy and strategic behavior e. The integration of AI and VR stimulated critical thinking	a. Single-institution sample b. Reliance on self-reported data c. Long-term retention of SRL and HOTs not assessed	Future research should include objective cognitive assessments, expand to multiple institutions, and apply delayed post-tests to evaluate long-term learning effects.	High

4. Results

Six themes were generated based on the Forethought Phase, Performance Phase, and Reflection Phase: 1) AI supports goal setting, 2) AI supports learning motivation and engagement, 3) AI facilitates the use of learning strategies, 4) AI facilities learning process monitoring, 5) AI facilitates learning evaluation, and 6) AI facilitates learning strategy adjustment.

Phase 1: Forethought Phase

Theme 1: AI Supports Goal Setting

The first theme shows that AI could facilitate Chinese college students' goal setting. Specifically, at the beginning of a task, students need to establish clear learning goals, which marks the starting point of the SRL process. Numerous studies have shown that AI tools can provide task-oriented suggestions at this phase to assist students in setting feasible goals. For example, Wang et al. found that students with high AI self-regulation abilities were more proactive in setting goals and planning action paths before engaging in critical tasks (Wang et al., 2025). Zhou et al. further pointed out that improved AI literacy enhances students' sense of competence and autonomy, guiding them to set more challenging learning goals (Zhou et al., 2024). Additionally, the studies by Wei and Fan et al. demonstrate that students with higher AI literacy or greater satisfaction of psychological needs demonstrated greater proficiency in formulating systematic learning plans and exhibited stronger goal-oriented behaviors in writing and English learning contexts (Wei, 2023; Fan et al., 2025). Within the scope of empirical cases examined in this review, these observed patterns indicate that AI-driven supports can offer practical guidance for goal formulation and may foster learners' goal-related awareness. It should be noted that such evidence is mostly derived from short-term task-based scenarios rather than long-term longitudinal observations. The evidence reveals a significant connection between technological literacy and self-directed learning behaviors.

Theme 2: AI Supports Learning Motivation and Engagement

As another key dimension of the forethought phase, learning motivation is positively influenced by AI tools, with variations observed across different contexts. Specifically, Yang et al. established that AI literacy boosts students' creative self-efficacy, thereby stimulating learning motivation through indirect pathways (Yang et al., 2025). Wang et al. emphasized that satisfying autonomy and relatedness needs activates intrinsic motivation, which enhances students' active engagement with AI platforms (Wang et al., 2025). Shi et al. found that students with strong AI skills were more likely to develop interest in writing tasks and maintain sustained focus (Shi et al., 2025). Furthermore, Wei reported that in AI-assisted language learning environments, students demonstrated stronger motivation and engagement, particularly in goal-directed behavior (Wei, 2023). Collectively, these findings suggest that AI may function not merely as a cognitive instrument but also as a potential motivational resource under certain contextual conditions. The reviewed studies indicate that AI tools can satisfy learners' psychological needs for competence, autonomy, and relatedness, which may build a favourable psychological foundation for initiating self-regulated learning, though such effects are not universally observed across all participants.

Phase 2: Performance Phase

Theme 3: AI Facilitates the Use of Learning Strategies

Theme 3 shows that during the execution phase of learning, students rely on various cognitive and metacognitive strategies to accomplish tasks. Research indicates that AI tools provide structured feedback and prompts that substantially enhance strategy use. For instance, Zhou et al. found that students using ChatGPT paid greater attention to planning and maintaining interim goals throughout the task, indicating heightened strategic awareness (Zhou et al., 2024). Similarly, Shi et al. reported a significant positive correlation between the frequency of AI use and students' strategic behavior in online learning environments (Shi et al., 2025). These findings challenge traditional interpretations of technology-enhanced learning. In the context of English learning, Pan et al. observed that AI-supported students were more likely to employ advanced cognitive strategies such as inference and summarization (Pan et al., 2025). Through interviews, Pan et al. further demonstrated that AI chatbots helped students flexibly select and adjust reading strategies (Pan et al., 2024). Taken together, these study outcomes suggest that AI can externalise parts of strategy-generating processes, enabling participating students to consciously deploy learning tactics to complete assigned tasks. The existing evidence points to increased frequency of strategy application and improved capacity for deliberate strategy choice among participants in sampled investigations; nevertheless, such effects cannot be generalised to all disciplinary or learning situations. Thus, AI increases both the frequency of strategy use and students' capacity for active choice, thereby helping them build strategic thinking during learning.

Theme 4: AI Facilitates Learning Process Monitoring

Ongoing monitoring and adjustment are central to high-level SRL during the learning process. Theme 4 demonstrates that AI plays a crucial role by offering real-time feedback and personalized prompts, which help students track progress, identify problems, and make self-adjustments. Specifically, Xu et al. found that automatic feedback from AI platforms helped students more clearly identify their learning status and adjust their behavior accordingly (Xu et al., 2025). Both Pan et al. and Shi et al. confirmed that AI effectively enhanced students' self-monitoring abilities in reading and writing tasks (Shi et al., 2025; Pan et al., 2024). In virtual reality environments, Wang et al. showed that ChatGPT-integrated feedback significantly improved students' cognitive monitoring and real-time adjustment behaviors (Wang et al., 2025).

However, Fan et al. reported a phenomenon of metacognitive inertia among some students who relied too heavily on AI feedback—manifested as a lack of self-validation and reflection (Fan et al., 2025). This finding highlights that while AI offers powerful support, it requires complementary guidance from teachers to prevent passive dependence. In summary, within the contexts of reviewed experiments, AI has shown potential to strengthen learners' monitoring and in-task adjustment behaviours. Optimal benefits appear to occur when technological support is paired with appropriate instructor scaffolding to mitigate risks of over-reliance on artificial-intelligence outputs.

Phase 3: Reflection Phase

Theme 5: AI Facilitates Learning Evaluation

After completing a learning task, students need to evaluate their outcomes and assess the effectiveness of their strategy use. Theme 5 demonstrates that AI's feedback mechanisms and interaction logs make this process more concrete and data-driven. Specifically, Shi et al. found that students using AI for writing tasks demonstrated stronger self-evaluation and emotional regulation abilities (Shi et al., 2025). Similarly, Pan et al. and Xu et al. established that AI dialogue systems encouraged students to reflect on their learning paths and develop clear mechanisms for strategy evaluation (Xu et al., 2025; Pan et al., 2025). In a virtual reality learning experiment, Wang et al. further confirmed that AI feedback guided students to conduct systematic self-assessments after completing tasks, attribute errors appropriately, and plan for the next phase (Wang et al., 2025). Based on evidence gathered from this set of primary studies, these results suggest that AI-generated feedback may promote learners' self-evaluation practices and post-task reflective summarisation. Readers should bear in mind that most supporting data are obtained from short-term task interventions.

Theme 6: AI Facilitates Learning Strategy Adjustment

Reflection extends beyond outcome evaluation to form the foundation for constructing future learning approaches. The final theme, drawing on evidence from Pan et al., reveals that AI supports students in revising, maintaining, and transferring learning strategies after task completion (Pan et al., 2025). The findings demonstrate that during performance reflection, AI tools help students identify effective strategies and determine how to apply them in future learning. This support establishes a critical link between immediate feedback and long-term learning development. Specifically, Pan et al. demonstrated that AI feedback helped students develop more enduring strategy preferences and transfer them to subsequent tasks (Pan et al., 2025). This body of evidence implies that AI is not merely a task-oriented auxiliary tool; it may serve as a bridge turning situational learning experiences into internalised learner resources for participants in the sampled research. Evidence for long-term strategy transfer remains limited within current empirical datasets.

5. Discussions

It should be highlighted that all synthesised observations draw from ten eligible empirical investigations included in this review. A majority of these works adopt cross-sectional or brief quasi-experimental interventions, with research contexts concentrated on academic writing and English-as-foreign-language learning. Many primary studies depend heavily on self-reported learner perceptions rather than objective behavioural logs. Caution is required when extending these interpretations to broader disciplines, prolonged learning trajectories or other higher-education circumstances.

Overall, results from the included studies indicate AI may offer support for selected dimensions of Chinese college students' SRL behaviours, covering goal-setting, motivational activation, strategy deployment and reflective evaluation. Such patterns are mostly observed within short-term writing and EFL-oriented learning contexts.

For RQ1, the findings demonstrate that AI could support for planning goals and motivation for learning during the Forethought Phase. Specifically, the prompt systems for learning and AI comments can significantly enhance students' abilities to articulate learning goals. More AI-literate students, for instance, are more likely to establish more structured and clearer learning goals on their own (Wang et al., 2025; Zhou et al., 2024). Such a contribution is more evident for exercises on writing and language learning where structured guidance is the norm. More significantly, AI instruments are not only cognition tools but also motivators. Studies such as Ji et al. and Shi et al. indicate that AI instruments meet

learners' emotional needs for autonomy and competence and consequently foster intrinsic motivation (Shi et al., 2025; Ji et al., 2025). Accordingly, students are more self-assured and motivated when using AI instruments. It is worth noting that such motivational benefits do not apply uniformly to every learner. Individual differences such as prior learning experience and personal AI acceptance may mediate how learners respond to AI-provided scaffolding.

For RQ2, the findings show that AI tools show clear benefits in facilitating strategy use and learning process monitoring during the Performance Phase. Studies consistently indicate that structured prompts and intelligent feedback help students apply cognitive and metacognitive strategies more efficiently. For example, students using ChatGPT reported more frequent use of planning and summarizing strategies (Zhou et al., 2024; Pan et al., 2025). Similarly, AI-supported feedback systems allow learners to track progress, detect learning bottlenecks, and make real-time adjustments. However, one potential issue is metacognitive inertia. Fan et al. (2025) observed that some students tended to rely too heavily on AI feedback, showing reduced critical reflection. This finding suggests that while AI is effective, it should be integrated with teacher guidance to preserve learner autonomy. Even though positive effects on strategy deployment and monitoring emerge from the reviewed samples, these gains may diminish without appropriate pedagogical oversight. The risk of metacognitive inertia reminds educators that AI support cannot fully substitute learners' internal metacognitive efforts.

For RQ3, the findings indicate that AI could facilitate learning evaluation and strategy adjustment during the Reflection Phase. Particularly, AI-supported platforms provide concrete, data-driven feedback that encourages students to self-assess performance. Studies (Shi et al., 2025; Lee et al., 2024) report that students exposed to AI feedback were more likely to reflect on task outcomes and identify improvement areas. In addition, AI tools helped students develop transferable learning strategies. Pan et al. (2025) found that students used AI-generated insights not only to review past performance but also to adjust future approaches, showing signs of deeper metacognitive awareness. Nevertheless, evidence for stable long-term transfer of these reflective strategies remains thin among existing primary studies. Most measurements capture short-term changes immediately after AI-aided tasks rather than sustained metacognitive growth.

To answer RQ4 regarding the limitations in current research on AI-supported SRL, the findings show several research gaps remain. First, while many studies confirmed the effectiveness of AI-powered tools in enhancing students' SRL and higher-order thinking (Wang et al., 2025; Zhou et al., 2024), most of them were based on short-term interventions. For example, Wang et al. (2025) used a one-time randomized controlled trial in a virtual reality environment, and Pan et al. (2024) investigated a single-semester chatbot intervention. These designs lack long-term data to understand whether students can maintain their SRL gains and cognitive strategies over time. Longitudinal studies are crucial because SRL is not a fixed trait. It evolves with learning experiences, and without long-term tracking, it may be difficult to assess whether AI truly fosters sustainable reflective learning.

Second, the current literature tends to focus mainly on individual SRL. Most studies view SRL as a personal process that students engage in alone when interacting with AI tools (Pan et al., 2024; Teng, 2024). However, in real-world classrooms, students often learn together. The concept of co-regulated learning (CoRL), where learners support and monitor each other's learning strategies (Yang et al., 2025), is rarely discussed in AI-supported settings. This topic needs to be paid attention to because AI tools are increasingly used in collaborative platforms, thus understanding how AI can facilitate not only personal but also socially shared regulation is essential for designing more effective group-based AI interventions.

Finally, although several papers mentioned challenges regarding AI education (AIED), metacognitive laziness and over-reliance on AI are still underexplored phenomena. Lee et al. (2024) clearly showed that students often reduce their effort in planning and monitoring when AI tools provide answers quickly. This behavior is called "metacognitive laziness," where students avoid reflective thinking and instead depend too much on AI-generated outputs. If such patterns are not addressed effectively, students may lose critical learning opportunities and become passive consumers of AI support rather than active learners.

These research gaps matter because they directly influence how students learn, adapt, and grow. Without long-term studies, it is difficult to know if AI-based interventions lead to lasting changes in learners' habits and thinking. Without attention to CoRL, we will miss the social dimension of learning that is vital in classroom settings. And without addressing metacognitive laziness, we will risk encouraging shallow learning, where students rely on AI without understanding or reflection. Ignoring these gaps may limit the educational value of AI in higher education and reduce its impact on students' SRL and CoRL development. It should also be noted that the research gaps summarised above are derived from the pool of ten included papers. Additional primary empirical work would be required to verify whether these gaps hold true across broader Chinese higher-education contexts. Future studies should consider multi-phase, behavior-tracking designs, and investigate how AI systems affect both individual and group-level SRL development in the long term.

6. Implications for Higher Education Stakeholders

Because AI is fast becoming an integral component of higher education, various stakeholders must embrace personalized strategies for facilitating AI-facilitated SRL. Firstly, educators must be guides and tutors. Although AI software can provide immediate feedback and strategy advice, research shows that reliance on AI develops metacognitive inertia and reduces learners' depth of reflection (Kasneci et al., 2023). Educators must, therefore, plan for scaffolding strategies in which AI-based feedback is supported with reflective prompts, self-analysis exercises, and late decision-making exercises (Kasneci et al., 2023). They must also assess learners' AI utilization practices at frequent intervals and encourage them to internalize thinking strategies rather than mechanical, uncritical reliance on AI outputs. Students must also be trained to develop AI literacy as well as critical use competencies. Experiments verified that learners high on AI literacy displayed higher motivation, effective strategy utilization, and adaptive behavior (Ji et al., 2025). It should be noted that these practical suggestions are inferred from the limited empirical evidence collected in this review. Local contextual factors such as subject characteristics, student cohorts, and institutional resources will shape how well these measures can be implemented on-site. Universities must incorporate AI literacy education in their planning for the curriculum so that learners not only understand how AI operates but even understand how to assess AI products in a critical manner, examine their thinking, and modify the course of study accordingly. Moreover, institutions must establish AI-based integration frameworks at the institutional level. That would entail organizing AI-based facilitated learning management systems in consonance with SRL frameworks, installing metacognitive tools for planning, tracking, and reflection (Azevedo & Aleven, 2013). There must also be policies in favor of interdisciplinary collaboration between instructional designers, data scientists, and educators for building AI-based systems that are ethically valid and pedagogically effective. Universities must also examine on a periodic basis the long-term consequences of AI on learners' study autonomy and institute protection mechanisms against dependence. Given that long-term empirical evidence remains insufficient in existing literature, institutional teams are advised to carry out continuous monitoring and iterative adjustment when rolling out such AI-enabled teaching frameworks, instead of directly adopting one-size-for-all solutions. Such a three-arm strategy would ensure that AI is not developed in isolation but is an integral component of a learner-centric education system. Educators, curriculum planners and university administrators need to cooperate closely. No single stakeholder can fully resolve risks such as metacognitive inertia or over-reliance on AI tools; coordinated efforts across multiple parties are required to foster healthy self-regulated learning under AI-enhanced environments.

7. Conclusions

This study aimed at exploring how AI tools support the SRL processes of Chinese college students, with particular focus on the Forethought, Performance, and Reflection phases of Zimmerman's three-phase model. By systematically reviewing 10 empirical studies published between 2021 and 2025, this research identified key pathways through which AI empowers SRL and revealed the potential role of AI in transforming learning in higher education.

Findings presented in this review are constrained by the quantity and methodological weaknesses of the included primary studies. Most source evidence comes from cross-sectional surveys and short-term interventions, which heavily rely on student self-reports. Broad generalisation covering all forms of Chinese higher-education contexts should be treated with prudence.

The results indicate that AI tools could help students become more aware of their goals and keep their learning motivation strong during the Forethought Phase. In the Performance Phase, AI could provide timely feedback and offer organized help, which would support students in using strategies and checking their progress. In the Reflection Phase, AI could help students better understand how they learn and manage their emotions, which would support students to turn short-term learning actions into lasting learning habits. Within the limits of available empirical evidence, AI tools show certain potential to raise learners' goal awareness and sustain motivational states in the forethought stage. During task execution, timely AI feedback and structured scaffolding may assist strategy application and progress checking. At the reflection stage, AI-generated inputs can promote metacognitive understanding and emotional regulation for participants in sampled investigations. Nevertheless, existing data cannot fully confirm that such short-term gains can automatically translate into stable, long-lasting learning routines. Our study further expands the field by introducing new research perspectives, particularly in emotional support, feedback internalization, and reflective mechanisms. At the same time, it clearly identifies current gaps in understanding the mechanisms of the Reflection Phase and AI's role in co-regulated learning, which merit deeper investigation in future studies. Therefore, based on these findings, future research should consider the following directions:

a. Examine the dynamic role and long-term impact of AI on SRL development through longitudinal tracking or mixed-method approaches.

b. Expand investigations into AI-supported reflection mechanisms, particularly regarding multi-task transfer, self-assessment, and strategy reconstruction.

c. Introduce a co-regulated learning perspective to explore how AI facilitates regulation in learning communities or group-based tasks.

d. Construct multivariate models that integrate AI literacy, emotional regulation, and SRL strategies to uncover complex mechanism interactions.

In conclusion, this study provides a foundation for understanding how AI can impact SRL among Chinese college students. It also offers practical recommendations for intelligent education practitioners and policymakers seeking to optimize AI integration in educational contexts. This work serves as an initial evidence base derived from a narrow set of recent empirical outputs. Further cumulative empirical efforts are still required to validate and extend the observations reported in this integrative review.

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