

# AI-Supported Learning and the Development of Student Self-Regulation

Haiyun Shi

Al-Farabi Kazakh National University, Kazakhstan.

Doctoral Candidate, Farabi International Business School, DBA in Business Administration  
(Major Code: 8D04104).

shihaiyun997@163.com

## Abstract

Artificial intelligence has become an increasingly influential force in education, offering personalized learning experiences and adaptive feedback that can transform how students engage with knowledge. Beyond enhancing learning efficiency, AI-supported environments have the potential to foster self-regulated learning (SRL), a critical skill for lifelong education. This study examines how AI tools such as intelligent tutoring systems, learning analytics dashboards, and adaptive recommendation mechanisms contribute to the development of students' self-regulation skills, including goal setting, self-monitoring, and reflection. By drawing upon self-regulated learning theory and technology-enhanced pedagogy, the research explores how AI promotes motivation, autonomy, and metacognitive awareness, and how continuous feedback loops help learners sustain engagement over time. The analysis also considers challenges such as overreliance on automation and reduced learner agency, highlighting the importance of balancing technological assistance with human-centered teaching strategies. The findings aim to provide insights for educators and policymakers to design AI-supported learning systems that not only improve academic outcomes but also cultivate students' capacity for independent learning, adaptability, and sustained personal growth in an evolving digital landscape.

## Keywords

Artificial Intelligence, Self-Regulated Learning, AI-Supported Learning, Student Autonomy, Adaptive Feedback, Learning Analytics, Higher Education, Motivation, Lifelong Learning, Educational Technology.

## 1. Introduction

Artificial intelligence is increasingly integrated into educational environments, offering real-time adaptation and personalized learning experiences that aim to support students' academic development. Beyond simply delivering content, AI applications can provide scaffolding for learners' cognitive processes and adaptive feedback that aligns instruction with individual progress. A growing body of research suggests that AI technologies have the potential to support self-regulated learning (SRL), defined as the process through which learners plan, monitor, and evaluate their own learning goals and strategies 错误!未找到引用源。 . In online and blended learning contexts, where student autonomy is higher and instructor presence is often reduced, supporting SRL has become a central pedagogical concern.

Self-regulated learning is recognized as a key determinant of academic success because it encompasses learners' abilities to set meaningful goals, select appropriate strategies, monitor performance, and reflect on outcomes. However, SRL is a complex interplay of cognitive, metacognitive, behavioral, and motivational processes that many students struggle to develop

independently. Recent systematic reviews have highlighted that AI systems can make meaningful contributions to SRL by dynamically adjusting learning pathways and providing learners with timely insights, yet the integration of AI in fostering SRL is still at an early stage of empirical development. These reviews call for further research to clarify how AI applications can be designed to support self-regulation across the full cycle of learning activities.

Despite this promise, important questions remain about the mechanisms through which AI supports sustained SRL. For example, learners' perceptions of AI's role in their own regulation, the extent to which AI feedback aligns with students' strategic goals, and the ability of AI tools to foster motivation and self-monitoring practices are not fully understood. Understanding these issues is essential because SRL not only affects academic performance but also underpins learners' ability to adapt to complex, technology-enhanced learning environments. This study addresses these gaps by investigating how AI-supported learning influences the development of self-regulation skills in higher education contexts.

## 2. Literature Review

The integration of artificial intelligence into education has generated an expanding body of research on its potential to enhance self-regulated learning (SRL). Self-regulation refers to the process by which learners set goals, plan, monitor, and evaluate their learning, integrating cognitive, motivational, and behavioral elements [4]. In the digital age, SRL has become increasingly vital, as online and AI-mediated learning environments require students to take greater ownership of their progress. Existing studies indicate that AI technologies can foster SRL by providing adaptive feedback, personalized guidance, and learning analytics that heighten learners' awareness of their learning processes [2].

A systematic mapping review by Banihashem et al. (2025) offered one of the most comprehensive analyses of AI-supported SRL to date. Reviewing 187 publications, the authors identified three main mechanisms through which AI contributes to SRL: adaptive scaffolding, personalized feedback, and predictive analytics. These systems track learners' behaviors in real time, delivering recommendations that align with their goals and cognitive development [3]. However, Banihashem and colleagues also observed that most AI-SRL interventions tend to emphasize the "monitoring" and "evaluation" phases of self-regulation, while paying less attention to "goal setting" and "planning." This points to a research gap regarding how AI can support learners' proactive regulation rather than merely reacting to performance outcomes.

Another stream of research has explored specific AI technologies that actively engage learners in self-regulated practices. For instance, Guan et al. (2025) conducted a systematic review of educational chatbots and reported that conversational agents can effectively scaffold SRL components such as self-monitoring, self-explanation, and metacognitive reflection. Chatbots can provide immediate feedback and reminders that improve learner engagement and strategy use. However, Guan and colleagues noted that while these tools assist with surface-level regulation—such as reminding students to complete tasks—they are less effective in supporting deeper motivational and reflective processes. This underscores the need for AI systems that are not only responsive but also capable of nurturing learners' intrinsic motivation and sense of control [5].

Building upon these findings, more recent studies have examined how AI literacy—students' knowledge of and ability to use AI tools—relates to their self-regulation. Shi (2025) found that learners with higher levels of AI literacy exhibit stronger self-monitoring and goal-directed behaviors when engaging with AI-supported learning environments. This suggests that AI's effectiveness in promoting SRL depends not only on system design but also on learners' capacity to use the technology purposefully. Likewise, Lan et al. (2025), in a qualitative systematic review published in *npj Science of Learning*, emphasized that effective AI-SRL

integration requires aligning AI feedback mechanisms with learners' self-regulatory cycles. They argued that AI should act as a "co-regulator," complementing human instruction by offering personalized, data-driven insights while preserving learner autonomy and motivation [2].

Beyond theoretical and empirical contributions, several studies have also explored the pedagogical implications of AI-supported SRL. Research conducted in open and distance learning environments suggests that digital tools—especially when combined with reflective prompts and metacognitive scaffolding—can enhance learners' capacity for self-regulation [6]. These results are consistent with earlier SRL theories that highlight feedback loops and self-reflection as essential elements of effective learning [4]. However, as Banihashem et al. (2025) caution, overreliance on technology remains a concern: when AI systems make too many decisions on behalf of students, they may inadvertently weaken rather than strengthen SRL skills [3].

Taken together, the literature suggests that AI technologies hold significant potential to enhance SRL through adaptive feedback, data analytics, and personalized learning pathways. Yet this potential depends critically on thoughtful system design and implementation. Effective AI-supported SRL requires balancing automation with learner agency, ensuring that feedback mechanisms promote self-reflection rather than dependence. As Guan et al. (2025) observe, the ultimate goal is not for AI to regulate learning on behalf of students, but to help them become more capable and independent self-regulators. Collectively, existing studies point to the need for future research that integrates educational psychology with AI design to create systems that genuinely cultivate autonomy, reflection, and sustained motivation in learners [5].

### 3. Theoretical Foundations

The theoretical understanding of self-regulated learning (SRL) is deeply grounded in motivational and cognitive psychology, emphasizing the learner's active role in directing their own learning processes. SRL involves goal setting, self-monitoring, strategy use, and reflective evaluation, forming a cyclical process of self-improvement and control. Within this process, motivation and self-efficacy serve as the driving forces that sustain engagement and persistence. The emergence of artificial intelligence in education has created new opportunities to enhance these psychological mechanisms through adaptive support, immediate feedback, and data-driven insights. To understand how AI contributes to the development of SRL, it is essential to examine its theoretical foundation through the lenses of Self-Determination Theory (SDT), Social Cognitive Theory (SCT), and the traditional SRL model.

Self-Determination Theory (SDT) provides a foundational framework for understanding intrinsic motivation in learning. Deci and Ryan (2000) assert that learners are naturally motivated to grow when their psychological needs for autonomy, competence, and relatedness are fulfilled. In AI-supported environments, this theory helps explain how intelligent systems can either enhance or undermine learners' motivation. When AI technologies provide personalized learning paths and adaptive feedback, they can increase perceived competence and engagement by helping learners experience progress that is directly relevant to their goals. For example, intelligent tutoring systems and adaptive learning platforms that respond to students' individual needs support autonomy by allowing flexible pacing and personalized control. Conversely, if AI systems are overly prescriptive or impose rigid pathways, they risk diminishing learners' sense of agency. Therefore, from the perspective of SDT, the design of AI-based learning environments must balance guidance with freedom of choice to foster genuine self-regulation.

Social Cognitive Theory (SCT) complements this perspective by focusing on how self-efficacy and social modeling influence learning behavior. According to Bandura (1986), human

behavior results from reciprocal interactions among personal factors, environmental conditions, and behavioral outcomes. Learners develop self-regulatory competence when they believe in their ability to control learning outcomes, a belief strengthened through successful experiences and feedback. AI technologies operationalize this theory by providing learners with continuous data on their progress and adaptive challenges that encourage persistence. Research shows that when feedback is specific, timely, and framed constructively, it enhances self-efficacy and supports greater self-monitoring. AI-driven dashboards, virtual tutors, and intelligent analytics embody these principles by giving learners a clearer picture of their performance and encouraging reflection on strategies. By doing so, they reinforce the SCT principle of self-efficacy as the foundation for sustained self-regulated behavior.

Bringing these theories together, the SRL framework described by Zimmerman (2002) offers a structural model for understanding how AI supports each phase of the self-regulation cycle: planning, monitoring, and reflection. In the planning phase, AI systems assist learners in setting goals by using predictive analytics and performance data to recommend learning strategies. During the monitoring phase, adaptive algorithms provide real-time feedback that helps learners adjust their actions, maintain focus, and manage effort. In the reflection phase, AI-generated summaries and insights enable learners to assess their performance, evaluate strategy effectiveness, and refine their approaches for future learning. Banihashem et al. (2025) found that AI can serve as a co-regulator by facilitating feedback loops and metacognitive reflection across these phases. However, they also caution that excessive dependence on algorithmic guidance may weaken self-directed learning behaviors over time. AI's role, therefore, should not be to replace human judgment but to augment it, helping learners develop greater autonomy and awareness of their learning processes.

Integrating SDT, SCT, and SRL theory provides a comprehensive foundation for understanding how AI influences self-regulation. SDT explains the motivational conditions under which AI fosters autonomy and engagement, SCT clarifies how feedback and self-efficacy drive persistence, and SRL theory situates these psychological processes within a structured learning cycle. Together, these frameworks suggest that effective AI-supported learning environments promote both external guidance and internal control, leading to deeper reflection, stronger motivation, and more sustainable learning behaviors. Theoretical integration also underscores a crucial balance: AI must serve as a supportive partner in the learning process, empowering students to become autonomous, motivated, and self-aware learners rather than passive recipients of technological direction.

#### **4. Case Study Analysis**

At the National University of Singapore (NUS), artificial intelligence has become an integral element of teaching and learning innovation, especially in supporting personalized and self-regulated learning. The university's digital learning ecosystem integrates adaptive analytics that collect and process student data from lectures, assessments, and collaborative activities. Through AI-driven dashboards, students can visualize their progress in real time, identify performance trends, and receive predictive feedback about potential academic risks. The system generates personalized recommendations, such as topics to review, study pacing adjustments, and suggestions for supplementary materials. These features are designed to make the learning process more transparent and to encourage students to take an active role in their academic progress.

In practice, the use of AI at NUS reflects the key phases of self-regulated learning: planning, monitoring, and reflection. At the planning stage, students analyze the learning analytics reports to set specific goals and timelines based on their current progress. During the monitoring phase, adaptive notifications alert them to incomplete modules or knowledge gaps,

encouraging timely intervention. The reflection phase is supported through automated summaries that help learners evaluate their strategies and performance outcomes over time. The system thereby reinforces metacognitive awareness, helping learners not only track their behavior but also understand the impact of their study habits. Importantly, the design maintains a balance between technological support and learner autonomy. Instructors use the AI-generated data to guide discussions with students, encouraging reflection on learning strategies rather than passive acceptance of recommendations. This combination of machine intelligence and human mentorship cultivates both motivation and accountability, key elements of sustained self-regulated learning.

Despite its benefits, NUS educators recognize that AI-supported learning also presents challenges. Some students report anxiety when confronted with constant performance data or algorithmic comparisons among peers. Others demonstrate a tendency to follow system-generated advice too rigidly, reducing their willingness to experiment or take initiative. In response, faculty incorporate reflective assignments and coaching sessions that emphasize personal goal setting and self-assessment. The NUS experience underscores the importance of integrating emotional and motivational support into AI-driven learning ecosystems. By combining intelligent analytics with pedagogical reflection, the university ensures that technology functions as an enabler of self-regulation rather than a mechanism of control.

Duolingo provides a contrasting example of AI-supported learning within an informal, global, and user-driven environment. The platform employs machine learning algorithms to adapt the difficulty, sequence, and pacing of lessons according to the learner's performance. Each user's experience is unique: those who excel are challenged with increasingly complex tasks, while those who struggle receive simplified reinforcement activities. Immediate feedback after each exercise provides continuous performance awareness, while the gamified structure—through streak counts, badges, and leaderboards—sustains user engagement and builds learning habits over time. The platform's mobile accessibility also promotes consistent micro-learning, making it easy for users to engage in short, frequent sessions that reinforce self-monitoring behavior.

From a self-regulation perspective, Duolingo excels at strengthening the monitoring and performance-control stages of SRL. Learners constantly receive information about their accuracy, speed, and consistency, enabling them to adjust practice intensity and frequency. The gamification elements effectively translate progress into visible, motivating indicators. However, these same features can sometimes narrow the learner's focus to short-term rewards rather than long-term reflection or strategy development. Many users concentrate on maintaining streaks or collecting virtual points rather than consciously analyzing their linguistic patterns or cognitive processes. This behavior highlights a critical distinction between behavioral regulation and metacognitive regulation. While Duolingo successfully promotes persistence and self-monitoring, it provides limited opportunities for deep reflection and autonomous goal adjustment, both of which are central to the development of higher-order self-regulated learning.

A comparison between the NUS and Duolingo cases reveals both convergence and contrast in the way AI supports SRL. Both systems successfully employ AI as a feedback mechanism that enhances learners' awareness of progress and encourages active engagement. In both contexts, data-driven insights function as external prompts for learners to plan, monitor, and adjust their learning processes. Yet, their pedagogical depth and motivational dynamics differ. At NUS, AI analytics operate within a structured academic context supported by educators who mediate feedback through discussion and reflection. This integration supports all three SRL phases and emphasizes the cultivation of autonomy and competence. In contrast, Duolingo relies on automated, behaviorally reinforced learning loops that sustain engagement but do not fully support metacognitive reflection.

These differences underline the complexity of aligning AI with self-regulated learning principles. AI is most effective when it acts as a co-regulator—facilitating self-awareness, providing timely feedback, and encouraging reflection without dictating behavior. Systems that overemphasize automation risk undermining learner independence, while those that integrate reflective prompts, goal setting, and mentorship create opportunities for sustainable SRL development. The key insight from both cases is that technology alone cannot ensure meaningful self-regulation. Rather, the effectiveness of AI in education depends on its capacity to nurture the cognitive, motivational, and emotional dimensions of learning. The balance between algorithmic precision and human insight ultimately determines whether AI becomes a scaffold for autonomy or a substitute for it.

## 5. Discussion

The results from both institutional and informal learning environments reveal that artificial intelligence has the potential to act as a co-regulator of self-regulated learning. Through adaptive feedback, data-driven personalization, and real-time analytics, AI enhances learners' capacity to plan, monitor, and reflect on their learning progress. However, the impact of AI on self-regulation depends greatly on whether its design and implementation support psychological needs such as autonomy, competence, and self-efficacy. When AI provides meaningful feedback that helps students understand their progress and maintain control over their goals, it promotes engagement and persistence. When it becomes overly directive, however, learners may lose agency and rely too heavily on algorithmic guidance.

According to Self-Determination Theory, intrinsic motivation develops when the psychological needs of autonomy, competence, and relatedness are satisfied. AI-supported systems, as observed in the case analyses, can effectively fulfill the need for competence by giving learners immediate and personalized feedback. This responsiveness helps students recognize progress and maintain a sense of mastery, which strengthens motivation. At the same time, autonomy remains a critical condition. When learners can make independent decisions about pacing, strategy, and task selection, AI becomes a facilitator of intrinsic motivation rather than a controlling mechanism. In contrast, overly prescriptive AI feedback may reduce intrinsic motivation, leading to surface engagement rather than reflective self-regulation. The National University of Singapore example illustrates how integrating AI data with instructor mentoring preserves the learner's sense of ownership while improving performance. This dynamic supports Deci and Ryan's (2000) argument that true motivation arises from environments that support personal choice and perceived competence.

Social Cognitive Theory provides an additional lens for understanding how AI contributes to learning behavior. Bandura (1997) defines self-efficacy as the belief in one's capacity to organize and execute actions required to achieve goals. Learners with strong self-efficacy are more likely to persevere when facing challenges and to employ effective learning strategies. AI systems can enhance self-efficacy by making progress visible and by providing corrective feedback that focuses on growth rather than failure. As Schunk and DiBenedetto (2020) note, feedback is most effective when it promotes self-reflection and allows learners to see the connection between their efforts and achievements. When AI feedback follows this principle, it strengthens confidence and reinforces the cyclical process of planning, monitoring, and reflecting that defines self-regulated learning. However, when AI feedback emphasizes scores or rankings without explanation, learners may experience performance anxiety rather than motivation. The quality and interpretability of feedback are therefore central to how AI influences self-efficacy and engagement.

A comparative analysis of the institutional and informal cases further illustrates the tension between automation and autonomy. At the National University of Singapore, AI serves as a reflective scaffold that helps students identify learning patterns and evaluate their strategies. This combination of technological precision and human mentorship nurtures both competence and autonomy. In contrast, Duolingo's AI feedback primarily supports behavioral consistency through gamified reinforcement, fostering persistence but offering limited opportunities for deep reflection. These findings echo Bandura's (1997) emphasis on the importance of interpretive understanding in feedback. Learners must understand the rationale behind performance data to regulate their learning meaningfully. If AI systems present feedback as fixed judgments rather than developmental guidance, they risk undermining learners' confidence and reflective capacity.

The overall discussion suggests that effective AI-supported learning environments require balance. When AI acts as a co-regulator that assists but does not dominate, learners maintain agency and responsibility for their progress. Designing AI systems that allow learners to interpret data, set goals, and reflect critically aligns with both Self-Determination Theory and Social Cognitive Theory. As Deci and Ryan (2000) explain, motivation thrives in environments that respect autonomy and provide constructive feedback, while Bandura (1997) emphasizes that efficacy beliefs grow through mastery and reflection. Together, these principles highlight the dual role of AI as both a facilitator and a potential constraint. The challenge for educators and developers is to ensure that AI supports the cognitive, motivational, and emotional dimensions of learning, allowing students to become active agents in their own educational development.

## 6. Conclusion

Artificial intelligence has emerged as a transformative force in education, reshaping how learners engage with content and regulate their own learning processes. The findings of this study indicate that AI can significantly enhance self-regulated learning when its design supports motivation, autonomy, and reflection. By providing adaptive feedback, predictive insights, and opportunities for personalized learning, AI enables students to plan, monitor, and evaluate their progress more effectively. However, the benefits of AI depend on how it is integrated into pedagogical practice. When systems become overly directive or replace human judgment, they risk reducing learner autonomy and weakening intrinsic motivation.

The integration of psychological frameworks such as Self-Determination Theory and Social Cognitive Theory provides a deeper understanding of how AI influences learning behavior. Motivation and self-efficacy emerge as central factors in determining whether learners use AI tools to become more autonomous or more dependent. Effective AI-supported education therefore requires balance: the technology must assist learners without diminishing their agency. The institutional case of the National University of Singapore and the global example of Duolingo demonstrate that AI can either foster deep reflection and strategic control or encourage superficial engagement depending on its design and context.

In essence, sustainable learning in the era of artificial intelligence requires human-centered systems that combine technological precision with emotional and ethical awareness. AI should not dictate how students learn but rather empower them to take ownership of their educational journeys. When human guidance and intelligent systems operate in harmony, learners develop the motivation, confidence, and reflective capacity necessary for lifelong learning.

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