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# Learner Agency in AI-Supported Self-Regulated Learning: Distributed and Delegated Regulation

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## Abstract

Self-regulated learning involves the coordination of cognitive, metacognitive, motivational, and behavioral processes through which students interpret task demands, set goals, select strategies, and adapt their actions. However, these processes are often examined as distinct components, leaving insufficiently integrated the relationships through which regulatory information informs decisions and subsequent action. This article develops an integrative theoretical-conceptual analysis of self-regulated learning, focusing on the coordination among metacognitive judgements, motivational beliefs, strategic planning, and adaptive decision-making. Particular attention is given to the conditions under which students translate intentions into effective action, with consideration of the roles of self-efficacy, volitional control, and procrastination. The analysis also examines how artificial intelligence and digital learning technologies may redistribute specific cognitive-regulatory functions by providing feedback, structuring information, supporting planning, and shaping strategic choices. Such support may expand students' regulatory resources, but it may also promote cognitive offloading and reduce active monitoring when AI-generated outputs are accepted without adequate evaluation. Drawing on these relationships, the article proposes a conceptual framework in which regulatory effectiveness refers to the capacity to coordinate task appraisal, metacognitive judgement, motivational commitment, decision-making, and adaptive action in ways that support learning goals and preserve learners' regulatory agency. The framework distinguishes distributed from delegated regulation and sets out theoretical propositions for future empirical research on how responsibility for regulation is shared between learners and artificial intelligence.

## Keywords

Self-Regulated Learning, Metacognition, Motivational Beliefs, Adaptive

Decision-Making, Artificial Intelligence

## 1. Introduction

Self-regulated learning (SRL) can be conceptualized as a form of cognitive coordination involving a complex set of cognitive and regulatory processes through which learners interpret task demands, establish goals, monitor their progress, and adapt their actions. Understanding this complexity requires moving beyond the examination of individual regulatory components to consider how these processes interact and are coordinated over time. From this perspective, metacognition, planning, beliefs, and decision-making are not isolated regulatory operations but functionally interconnected processes within a broader regulatory system. The introduction first examines the cognitive complexity of SRL, then considers the coordination among its principal regulatory components, and finally sets out the aims, guiding questions, and conceptual contribution of the article.

### 1.1. The Cognitive Complexity of Self-Regulated Learning

SRL is commonly understood as a dynamic process through which learners actively monitor and regulate their cognition, motivation, behaviour, and engagement in pursuit of learning goals (Pintrich, 2000; Zimmerman, 2000). Although this multidimensional character is well established, the cognitive architecture underlying SRL remains insufficiently captured when its regulatory processes are examined primarily as separate components. Metacognitive monitoring, planning, competence beliefs, strategic action, and decision-making are not independent mechanisms operating in parallel. Rather, they are functionally interdependent processes whose influence on learning depends, in part, on how information generated by one process is interpreted and used within other regulatory processes (Azevedo & Aleven, 2013; Panadero, 2017).

From this perspective, the cognitive complexity of SRL derives not simply from the number of processes involved, but from how they are coordinated over time. Learners must establish goals, assess their current knowledge and performance, anticipate task demands, select strategies, interpret feedback, and decide whether the approaches being used should be maintained, modified, or abandoned (Winne & Hadwin, 1998; Zimmerman, 2000). These processes involve continuous interplay between monitoring and control, through which metacognitive information can inform subsequent regulatory decisions (Efklides, 2008; Nelson & Narens, 1990). Regulation therefore involves not only knowing what to do or possessing appropriate strategies, but also determining when and why particular responses are warranted.

This view also highlights the temporal and recursive nature of SRL. Regulatory decisions are made on the basis of information available at a particular moment, but the consequences of those decisions can generate new information that mod-

ifies subsequent monitoring, planning, and action (Winne & Hadwin, 1998; Zimmerman, 2000). A learner who evaluates a strategy as ineffective may revise the plan, while a learner who interprets an unexpected task difficulty as evidence of insufficient preparation may mobilize additional effort. The same experience, however, may be interpreted in light of existing self-efficacy beliefs, thereby affecting persistence or disengagement (Bandura, 1997). Cognitive regulation thus involves successive adjustments based on information generated during learning, rather than the linear execution of a predetermined sequence.

### 1.2. From Individual Regulatory Components to Their Coordination

Recognition that SRL integrates multiple regulatory processes has led to influential models that distinguish different phases, areas, or dimensions of regulation. The models developed by Zimmerman (2000), Pintrich (2000), and Winne and Hadwin (1998), for example, have contributed to explaining how learners establish goals, monitor performance, mobilize strategies, and adapt their behaviour in response to learning demands. Although these perspectives organize the processes differently, they converge in conceptualizing SRL as a dynamic process in which regulatory components are functionally related.

Metacognition provides a particularly clear example of this interdependence. Monitoring generates information about perceived knowledge, understanding, or task performance, but such information does not, in itself, produce effective regulation. Its regulatory significance depends on how it is interpreted and used to guide subsequent action (Flavell, 1979; Nelson & Narens, 1990). Similarly, planning is not merely a preliminary activity that precedes learning. Plans may be revised in response to monitoring, task feedback, or changes in perceived demands (Winne & Hadwin, 1998). Competence and control beliefs may likewise influence the interpretation of regulatory information and the evaluation of possible or appropriate courses of action (Bandura, 1997; Pintrich, 2000).

Accordingly, this perspective shifts analytical attention from which regulatory components learners possess to how these components are coordinated during learning. Such coordination involves functional interdependence: monitoring may inform planning; planning may guide subsequent decisions; beliefs may influence the interpretation of monitored information; and decisions may modify the conditions under which subsequent monitoring occurs. Regulatory processes therefore operate not as isolated operations but as elements of a system in which information generated by one operation can alter the function of others throughout learning activity.

This perspective is particularly relevant in learning contexts in which learners interact with digital and AI-based systems. These technologies can provide information, generate feedback, support planning, or externalize particular cognitive processes. However, their regulatory value depends on learners' capacity to critically evaluate the outputs, decide how they should be used, and retain control over the decisions that guide learning. The central issue is therefore not technological

assistance in itself, but how external resources can be integrated into regulatory processes without displacing the learner's cognitive and decision-making activity.

### 1.3. Aims, Guiding Questions, and Conceptual Contribution

Against this background, this article analyses SRL from a cognitive-regulatory perspective centred on the interplay among metacognition, planning, beliefs, and decision-making. Rather than treating these processes as distinct determinants of learning, the article conceptualizes them as interdependent operations within a dynamic and recursive regulatory system. The analysis is guided by three questions: (1) how do the principal cognitive and regulatory processes interact during SRL? (2) how does information derived from monitoring, planning, and beliefs contribute to regulatory decision-making? and (3) how does AI redistribute regulatory responsibility between learners and AI systems, and under what conditions does this give rise to distributed rather than delegated regulation?

The conceptual contribution lies in proposing an integrated framework for understanding the functional relationships among these processes and examining how regulatory responsibility is redistributed in AI-supported learning. In particular, the article shifts the analysis from identifying individual regulatory components towards understanding how cognitive information is monitored, interpreted, and used to guide action. The coordination among metacognition, planning, beliefs, and decision-making is therefore conceptualized as a central mechanism of regulation, helping to explain how learners adjust their strategies under different learning conditions. The framework further distinguishes distributed regulation, in which cognitive functions are shared between learners and AI while learners retain responsibility for interpretation and consequential decisions, from delegated regulation, in which substantive regulatory functions are transferred to the AI system. This distinction provides a basis for examining when external resources can support learner agency and cognitive control and when they may displace them.

## 2. Methodological and Theoretical Foundations of the Integrative Analysis

This article adopts an integrative theoretical-conceptual review designed to bring together complementary perspectives on the cognitive and regulatory processes involved in SRL. Rather than estimating effects or systematically mapping the empirical literature, the review examines how established theoretical constructs can be related within a coherent account of cognitive coordination. This section therefore clarifies the rationale and scope of the review, explains how the literature was selected, organized, and interpreted, and identifies the analytical dimensions used to integrate theoretical contributions within the proposed conceptual framework.

### 2.1. Rationale and Scope of the Integrative Theoretical-Conceptual Review

An integrative theoretical-conceptual review is particularly appropriate when the

aim is to relate theoretical perspectives that have often been examined separately and to develop a more comprehensive understanding of a phenomenon. In the context of SRL, this approach is relevant because research on self-regulation has generated extensive work on metacognition, planning, motivational beliefs, strategy use, monitoring, and decision-making, yet these processes are not always examined as components of a common cognitive-regulatory system (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000). An integrative approach makes it possible to examine conceptual relationships across these domains while preserving the distinctive contributions of the theoretical traditions from which they originate.

The review is therefore not intended either to provide an exhaustive inventory of SRL studies or to determine the relative effectiveness of specific regulatory processes. Instead, it seeks to identify, compare, and articulate theoretical propositions that help explain how learners generate, interpret, and use regulatory information during learning. This orientation is consistent with the broader function of theoretical-conceptual reviews, which can contribute to theory development by synthesizing existing conceptual knowledge, identifying relationships among constructs, and formulating integrative explanations (Snyder, 2019; Torraco, 2005, 2016).

The analysis deliberately focuses on four interrelated dimensions: metacognition, planning, beliefs, and decision-making. These dimensions were selected because they capture complementary aspects of cognitive regulation. Metacognition provides mechanisms for monitoring and evaluating cognitive states and performance (Efklides, 2008; Flavell, 1979; Nelson & Narens, 1990); planning establishes anticipated courses of action in relation to goals and task demands (Winne & Hadwin, 1998; Zimmerman, 2000); beliefs influence how learners interpret situations and evaluate their capacity to act (Bandura, 1997; Pintrich, 2000); and decision-making links regulatory information to the selection, maintenance, or modification of actions. These dimensions are therefore treated not as exhaustive components of SRL, but as a theoretically meaningful set through which cognitive coordination can be examined.

The review also recognizes that SRL is embedded within broader motivational, behavioral, and contextual processes (Pintrich, 2000; Zimmerman, 2000). These dimensions are considered when they contribute directly to understanding the central cognitive-regulatory relationships, but remain secondary to the analytical purpose of the article. This delimitation preserves conceptual coherence and prevents the analysis from becoming an undifferentiated account of all factors associated with self-regulated learning.

### 2.2. Literature Search and Selection Criteria

The literature search was conducted in the Scopus, Web of Science and ERIC databases between September and October 2026. The search strategy combined terms relating to the article's main thematic domains, including self-regulated

learning, metacognition, self-regulation, motivational beliefs, planning, monitoring, strategic action, decision-making, student agency, generative artificial intelligence, academic guidance and academic counselling. Equivalent expressions and combinations of these terms were also considered to identify publications addressing the individual domains and, where relevant, their intersections. The search was supplemented by examining the reference lists of relevant publications to identify additional theoretical and empirical contributions. Publications in English, Portuguese and Spanish were considered, with particular attention to research published between 2018 and 2025. Earlier seminal works were also included where necessary to establish the theoretical foundations of the analysis, together with selected publications from 2026 considered relevant to the development of the conceptual framework.

The literature was selected according to its conceptual relevance to the processes examined. Priority was given to influential theoretical and conceptual contributions that have shaped understanding of SRL, metacognition, self-regulation, motivational beliefs, planning, monitoring, strategic action, and decision-making. Foundational works were considered alongside subsequent theoretical developments and more recent empirical contributions where these extended, refined, or problematized established assumptions, including research on volitional and self-regulatory factors associated with academic performance (Lourenço et al., 2025). This combination was necessary because the proposed framework draws both on the historical foundations of SRL research and on subsequent discussions of the conditions under which cognitive regulation occurs. The selection was guided by three main criteria: (1) thematic relevance to one or more of the article's core domains; (2) conceptual or empirical contribution to understanding the constructs, processes and relationships under examination; and (3) alignment with the article's objectives, particularly its focus on regulatory processes, student agency and the implications of GenAI for academic guidance and counselling.

Within this process, 22 articles published between 2018 and 2025 were identified and selected for the conceptual synthesis. These were considered alongside foundational theoretical contributions and selected publications from 2026. The reference list comprises 46 publications, including the works examined in the conceptual synthesis and additional sources cited to support specific arguments.

The literature was organized thematically rather than solely chronologically. This organization made it possible to identify convergences, complementarities, and conceptual tensions across theoretical traditions. Contributions were therefore considered in terms of the regulatory function attributed to particular processes and, especially, the relationships established among them. Particular attention was given to models of metacognitive monitoring and control, goal setting and planning, self-efficacy and other motivational beliefs, strategic adaptation, and the role of decisions in regulating subsequent action (Bandura, 1997; Efklides, 2008; Flavell, 1979; Nelson & Narens, 1990; Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000).

The selected literature was analyzed through iterative reading, thematic comparison, and conceptual mapping, with attention to the definitions, regulatory functions, and relationships among the central constructs. This procedure made it possible to examine not only the meanings attributed to different constructs, but also how they could be related within a common cognitive-regulatory architecture. The analysis therefore moved from identifying relevant concepts towards understanding the functional relationships that support their integration.

Interpretation relied on conceptual comparison and synthesis rather than quantitative aggregation. The analysis examined how similar constructs were defined across different perspectives, when apparently distinct constructs performed related regulatory functions, and how processes described separately could be understood as functionally connected. Particular attention was given to the direction and nature of these relationships. For example, monitoring may provide information for planning, while planning may establish the standards against which subsequent monitoring occurs; beliefs may influence the interpretation of regulatory information, while regulatory experiences may in turn modify those beliefs. These reciprocal relationships were considered analytically relevant because they help explain the dynamic character of self-regulation (Bandura, 1997; Nelson & Narens, 1990; Winne & Hadwin, 1998).

The literature was therefore not treated as a collection of independent theoretical propositions; rather, each contribution was interpreted in relation to the broader regulatory architecture emerging from the analysis. This approach reduces the risk of simply juxtaposing established concepts and supports the development of a framework in which their functional relationships can be examined explicitly. The process of conceptual integration thus moved from the identification and comparison of theoretical contributions towards the formulation of the dimensions and principles that structure the conceptual model presented in the following sections.

### 2.3. Analytical Dimensions and Principles of Conceptual Integration

The conceptual integration is guided by three analytical principles: functional interdependence, temporal recursiveness, and regulatory decision-making. Functional interdependence refers to the premise that metacognition, planning, beliefs, and decisions influence one another rather than operating as isolated mechanisms. Temporal recursiveness emphasizes that regulatory processes unfold over time, with the outcomes of previous regulatory operations potentially becoming information for subsequent monitoring, interpretation, and action (Nelson & Narens, 1990; Winne & Hadwin, 1998; Zimmerman, 2000). Regulatory decision-making identifies the point at which information and evaluations are mobilized for choices concerning strategy use, effort, persistence, or adaptation (Bandura, 1997; Pintrich, 2000; Zimmerman, 2000).

Within this framework, four analytical dimensions organize the conceptual

analysis. The first is monitoring, concerned with generating and evaluating information about knowledge, comprehension, performance, and task conditions (Flavell, 1979; Nelson & Narens, 1990; Efklides, 2008). The second is planning, concerned with formulating and revising goals, strategies, and anticipated courses of action (Winne & Hadwin, 1998; Zimmerman, 2000). The third is belief-based interpretation, concerned with the role of self-efficacy and other beliefs in interpreting regulatory information and evaluating possible actions (Bandura, 1997; Pintrich, 2000). The fourth is decision-making, concerned with the selection, maintenance, modification, or abandonment of regulatory responses (Winne & Hadwin, 1998; Zimmerman, 2000).

These dimensions are analytically distinct but functionally interconnected. Their integration does not imply that they should be reduced to a single process. Rather, preserving their conceptual distinction makes it possible to examine how information circulates among them and how each contributes to the regulation of subsequent activity. The proposed framework consequently treats cognitive coordination as an emergent property of their functional relationships rather than as an additional regulatory component. This formulation represents an analytical synthesis developed through the integration of the perspectives considered, rather than the attribution of a single mechanism to any particular theoretical tradition.

Within this framework, "alignment" refers to the functional coherence established among task appraisal, metacognitive judgement, motivational commitment, regulatory decision-making, and adaptive action. It does not imply a fixed sequence or complete correspondence among these processes, but rather their capacity to inform and guide one another in ways that remain consistent with learning goals and task demands. "Regulatory effectiveness", in turn, refers to the extent to which this coordination enables learners to make informed decisions, implement appropriate strategies, monitor their consequences, and adjust their actions in response to emerging information. Importantly, regulatory effectiveness should not be equated with successful task completion alone. A learner may achieve an immediate task outcome with substantial AI assistance without necessarily exercising or developing the capacity to regulate learning independently. Accordingly, the educational value of AI-supported regulation also depends on whether learners retain meaningful responsibility for interpreting information, evaluating alternatives, making decisions, and adapting their learning activity.

This analytical position also provides a basis for considering external cognitive resources, including AI-based tools, within the broader regulatory system. Such resources may participate in generating, organizing, or externalizing information, but their presence does not, in itself, constitute self-regulation. Their regulatory relevance depends on how learners monitor, interpret, and evaluate the information provided and how they incorporate it into subsequent decisions. This distinction is consistent with research on cognitive offloading, which indicates that external resources can support particular cognitive operations without eliminating the need for internal processes of evaluation and control (Dunn & Risko, 2016;

Risko & Gilbert, 2016). This distinction is particularly important for the conceptual model developed in the following sections.

## 3. The Cognitive Coordination of Self-Regulated Learning: From Appraisal to Adaptive Action

SRL involves the dynamic coordination of cognitive, metacognitive, motivational, and behavioral processes through which students orient their activity towards learning goals. Although these processes can be distinguished analytically, their functioning depends on the relationships established among them throughout task performance. Task appraisal informs planning; metacognitive judgements influence strategy selection; motivational beliefs contribute to decisions to initiate and sustain effort; and information generated during performance can lead to the revision of procedures initially adopted. This perspective is consistent with the models of Zimmerman (2000), Pintrich (2000) and Winne and Hadwin (1998), as well as with Panadero's (2017) comparative analysis of major SRL models. Within this framework, understanding how students coordinate initial appraisal, planning, personal resources and decision-making is particularly important when learning conditions require successive adjustments.

### 3.1. Task Appraisal, Metacognitive Judgements and Strategic Planning

Task appraisal is an important component of learning organization because it enables students to interpret what is required, identify the knowledge and resources needed, and establish working goals. This appraisal involves more than reading instructions or identifying the expected outcome. It also requires estimating task difficulty, recognizing gaps in prior knowledge and anticipating obstacles that may interfere with performance. From the perspective of Winne and Hadwin (1998), defining the task and constructing an interpretation of its requirements condition subsequent planning and monitoring operations. Similarly, Zimmerman (2000) places task analysis and goal setting within the preparatory phase of the self-regulatory cycle.

The quality of task appraisal depends partly on students' knowledge of themselves, the task, and the strategies available. Flavell (1979) highlighted the importance of metacognitive knowledge for understanding and regulating cognitive activity, while Nelson and Narens (1990) distinguished between processes of monitoring cognition and processes of control that can be guided by monitored information. This distinction helps explain why recognizing a difficulty does not necessarily mean knowing how to overcome it. Monitoring provides information about the perceived state of learning, whereas control involves decisions concerning the continuation, modification or interruption of ongoing activity.

Metacognitive judgements therefore play an important role in linking appraisal to action. During learning, students form estimates about what they have understood, remembered or will be able to perform. Such estimates do not necessarily

correspond to actual learning. Familiarity with a text, reading fluency or the apparent ease of a task may be interpreted as evidence of mastery even when understanding remains incomplete. Research on the accuracy of metacognitive monitoring highlights the importance of distinguishing subjective confidence from demonstrated performance and of considering interventions that help students calibrate their judgements (Gutierrez de Blume, 2022). Monitoring should consequently be understood not as an infallible assessment, but as a source of information that can be evaluated against evidence of performance.

These judgements have direct implications for strategic planning. When students overestimate their understanding, they may allocate less time to revision or select strategies that are insufficient for task demands. Conversely, more accurate appraisal may support time allocation, priority setting and the selection of procedures compatible with established goals. Monitoring may, for example, reveal difficulties in retrieving information, applying concepts or integrating arguments. Such information can prompt reconsideration of the initial plan and encourage activities such as retrieval practice, problem solving or explaining content in one's own words. The relationship between monitoring and strategic choice is also consistent with evidence synthesized by Guo (2022), according to which self-monitoring can contribute to strategy use and academic performance.

Planning should therefore not be conceived as a fixed initial commitment. Although the advance definition of goals and procedures provides direction, the usefulness of a plan depends on its capacity to respond to information generated during learning. Winne and Hadwin (1998) describe self-regulation as a process in which information concerning the task, performance conditions and partial outcomes can feed into subsequent decisions. Similarly, Pintrich (2000) and Zimmerman (2000) emphasize that regulation involves planning, monitoring and adjustment activities that operate throughout learning. Revising a plan does not necessarily indicate inadequate preparation; it may instead represent an adaptive response to task demands that become clearer during performance.

The effectiveness of this process also depends on the quality of the criteria used to evaluate progress. If students merely verify whether an activity has been completed, they may confuse task completion with attainment of the learning objective. Regulatory evaluation therefore requires outcomes to be compared with relevant criteria, such as conceptual understanding, the ability to apply knowledge, the quality of justification or autonomy in problem solving. This orientation situates monitoring within a functional evaluation of learning rather than reducing it to recording time spent or activities completed.

Overall, task appraisal, metacognitive judgements and planning form a recursive system. Initial interpretation informs strategic choices, while information generated during performance can refine the understanding of task demands and prompt changes to goals or procedures. The regulatory value of monitoring therefore depends on how its results are interpreted in relation to learning objectives and used to inform subsequent planning. This coordination helps maintain learn-

ing activity as both goal-directed and responsive to available evidence (Panadero, 2017; Winne & Hadwin, 1998).

### 3.2. Motivational Beliefs, Volitional Control and the Intention-Action Gap

The cognitive coordination of learning depends not only on understanding the task or having appropriate strategies available. It also depends on how students evaluate their capacity to achieve their goals, assign value to the activity and regulate persistence in the face of difficulties. Self-efficacy beliefs, success expectations and perceptions of control can influence goal setting, effort investment and responses to unfavorable outcomes (Bandura, 1997; Pintrich, 2000). From Zimmerman's (2000) sociocognitive perspective, these factors form part of the preparatory phase of self-regulation and relate to how students initiate and conduct activity.

Self-efficacy is particularly relevant because it refers to individuals' beliefs about their capacity to organize and execute the actions required to perform a task. Such beliefs do not correspond directly to objective levels of competence, although they can influence choices, effort and persistence. Very low perceived capability may favor withdrawal or the selection of less demanding tasks, whereas excessively high perceived capability may contribute to insufficient preparation. Effective learning regulation therefore requires an articulation between personal beliefs, perceived demands and performance information rather than reliance on subjective evaluations of competence alone (Bandura, 1997; Zimmerman, 2000).

Within this context, it is important to distinguish the intention to learn from the capacity to translate that intention into sustained action. A student may value a task, recognize its importance and establish an appropriate plan, yet postpone starting the work or interrupt it in response to distractions and difficulties. This gap between intention and action is central to understanding volitional control. Corno (1993) emphasized the importance of volitional strategies for protecting learning intentions, while Boekaerts and Corno (2005) conceptualized regulation as involving the management of cognitive, motivational and emotional conditions of activity. Translating intentions into sustained action therefore requires mechanisms that help preserve goal direction when competing demands arise.

In this sense, volitional control refers to efforts to sustain goal-directed action, manage distractions and persist when a task becomes difficult or less appealing. It may involve organizing the study environment, dividing complex activities into stages, establishing work periods and using procedures to recover concentration following interruptions. These strategies do not eliminate motivational difficulties, but they can reduce dependence on momentary disposition and facilitate continuity of activity. Their function becomes particularly relevant when a significant interval exists between the decision to study and the actual execution of planned actions.

Academic procrastination illustrates some of the difficulties involved in this transition. It can be understood as the voluntary delay of an intended activity de-

spite anticipating that the delay may have negative consequences. It should not, however, be explained solely in terms of a lack of motivation or treated as a stable personal characteristic. Its occurrence may be associated with difficulties in time management, low confidence when facing demanding tasks, avoidance of unpleasant experiences and problems in sustaining effort. Research on procrastination has highlighted its relationship with self-regulatory difficulties and examined interventions directed towards factors that contribute to the maintenance of delay (Steel, 2007; Turner & Hodis, 2023).

This issue is particularly relevant to the relationship between procrastination, volitional control, and academic performance. Lourenço and Paiva (2025) examined these factors in relation to SRL and academic success, providing empirical evidence for understanding performance as dependent on the interaction of multiple regulatory processes rather than on a single factor. Their contribution is consistent with the view that the capacity to maintain goal-directed behaviour should be considered alongside the processes through which learning is organized and regulated. The evidence does not imply that procrastination, by itself, explains academic outcomes; rather, it supports examining the relationships among delay, action control, and self-regulation.

Turner and Hodis (2023) further emphasize the importance of addressing procrastination through the mechanisms associated with it rather than assuming that a single intervention will be effective for all students. Regulatory responses may include clarifying proximal goals, planning intermediate steps, reducing environmental obstacles and monitoring whether intentions are being enacted. The usefulness of each strategy depends on the specific difficulty and the conditions under which the task is performed. A student who delays because the task is poorly understood may require clarification and cognitive support, whereas one who understands the task but is frequently distracted may benefit more from environmental restructuring and time organization.

The relationship between motivational beliefs and volitional control may, in turn, be understood as reciprocal. Beliefs about capability and task value may influence willingness to initiate and persist, while experiences of progress or failure may also contribute to changes in those beliefs. Completing intermediate steps, for example, can provide evidence of progress and support a more calibrated perception of personal capability. Conversely, repeated delays may reduce available time, increase pressure and make task completion more difficult, potentially contributing to less favorable perceptions of competence. These relationships should therefore be understood as potentially reciprocal processes rather than as a single, invariant causal sequence.

The transition from intention to action is therefore an essential dimension of SRL. Goals and plans provide direction, but their enactment depends on the capacity to protect intentions, manage competing conditions and adjust behaviour over time. The articulation of motivational beliefs, volitional control and monitoring helps explain why students with similar goals may display different patterns

of engagement and persistence (Boekaerts & Corno, 2005; Lourenço & Paiva, 2025; Panadero, 2017).

### 3.3. Decision-Making, Strategy Implementation and Regulatory Adaptation

Decision-making occupies a central position in the coordination of self-regulatory processes because it transforms available information into choices about what to do, how to proceed, and when to modify activity. During learning, students decide whether to continue with a strategy, devote additional time to particular content, seek assistance, revise a plan or evaluate the outcomes obtained. Such decisions are not necessarily preceded by explicit and prolonged analysis; they may result from rapid judgements, established routines or the interpretation of signals of difficulty. Their quality nevertheless depends on the relationship between available information, goals, and the criteria used to evaluate progress.

In the model of Nelson and Narens (1990), monitoring and control represent distinct but interdependent functions: information about the state of cognition can guide control decisions, which in turn modify subsequent activity. This distinction allows regulatory decision-making to be understood as an operation that depends on the interpretation of information rather than as an automatic response to detected difficulty. A student may recognize that a concept has not been understood but decide to continue reading without changing strategy; alternatively, the student may interpret the problem and select a more appropriate activity, such as reconstructing an argument or applying the concept to an example.

Strategy implementation therefore requires a reasonable fit between task demands and the procedures selected. Strategies that are effective in one situation may be insufficient in another, and familiarity with a particular method does not guarantee its suitability for the objectives pursued. Panadero's (2017) review of SRL models shows that different theoretical perspectives emphasize interactions among cognitive, metacognitive, motivational and behavioral processes. This convergence supports an approach in which strategy selection and implementation are understood in relation to task characteristics, available resources and the conditions emerging during learning.

Regulatory adaptation occurs when information generated during activity warrants a modification of procedures. This may involve changing strategy, reorganizing time, reformulating an intermediate goal or seeking additional resources. Research on self-monitoring indicates that systematic observation of one's own activity can support strategy use and academic performance (Guo, 2022). Monitoring alone, however, does not guarantee adaptive change. Students need to interpret the information obtained, compare outcomes with relevant criteria and determine whether the current approach remains appropriate.

Help-seeking provides another example of this coordination. When difficulties arise, students may choose to persist independently, consult learning materials,

request clarification from a teacher or collaborate with peers. Such decisions depend on the nature of the problem, available resources and judgements about the usefulness of assistance. Self-regulated help-seeking involves recognizing when existing resources are insufficient and selecting assistance that supports rather than replaces productive engagement with the task (Newman, 2008). Help-seeking can therefore contribute to learning when it facilitates clarification and deeper understanding, but it may become less productive when it systematically substitutes for independent analysis or engagement with the task.

Adaptation also requires students to distinguish between temporary difficulties and indications that the procedure being used is inadequate. A demanding strategy may require time and effort before producing results; abandoning it at the first obstacle may prevent productive learning. Conversely, persisting with a procedure that does not support understanding or task completion may waste available resources. The decision to persist or change therefore involves interpreting performance trajectories, considering the costs of alternatives and evaluating the fit between procedures and learning objectives. Effective regulation does not involve constant strategy switching; rather, it requires the capacity to justify continuation or change on the basis of relevant information.

These processes are recursive. Decisions made during performance modify learning conditions and generate new outcomes that can subsequently be monitored and used to guide further decisions. In Winne and Hadwin's (1998) model, information generated during task performance contributes to updating the understanding of learning conditions and procedures. Similarly, Zimmerman's (2000) cyclical model connects preparation, performance and reflection on outcomes, emphasizing that evaluation of activity can influence subsequent cycles. Decision-making is therefore not an isolated stage but a cross-cutting function linking task interpretation, strategy implementation, and evaluation of outcomes.

The coordination of monitoring, decision-making and adaptation is particularly relevant in complex tasks whose demands cannot be fully anticipated in advance. In such situations, students need to update their judgements, reconsider priorities and mobilize different resources while maintaining their learning objectives. Regulatory autonomy does not consist in executing a plan without deviation, but in maintaining intentional direction while responding reasonably to information that emerges during activity.

Overall, SRL can be understood as a coordination system in which task appraisal informs planning, motivational beliefs and volitional processes sustain action, and monitoring provides information for decisions about strategy implementation and adaptation. These relationships are neither linear nor sufficient, in isolation, to guarantee positive academic outcomes; their relevance lies in the coordination established among them throughout learning. This perspective provides a conceptual basis for examining in subsequent chapters how external resources and artificial intelligence (AI) technologies may support monitoring, planning and decision-making operations without assuming that the availability of

such support, by itself, ensures more effective self-regulation.

## 4. Artificial Intelligence and the Redistribution of Cognitive-Regulatory Functions

The increasing integration of AI into learning environments is changing the conditions in which SRL takes place. While digital technologies have long supported information access, feedback, adaptive practice, and learning analytics, generative AI (GenAI) extends this support to activities traditionally performed by learners, including information search, explanation, planning, drafting, comparison, and evaluation. These developments are particularly relevant to SRL because planning, monitoring, strategy selection, and evaluation constitute interconnected regulatory processes (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2002). AI may therefore participate in cognitive-regulatory processes by providing information, generating alternatives, externalizing aspects of regulation, and supporting subsequent decisions (Banihashem et al., 2025; Lan & Zhou, 2025).

This development does not necessarily imply a replacement of human regulation. Rather, AI may redistribute regulatory functions between learners and technological systems, potentially reducing cognitive demands while also creating risks when essential monitoring, judgement, or strategic control is delegated (Risko & Dunn, 2015; Risko & Gilbert, 2016). The central question is therefore which regulatory functions are supported or externalized by AI and which remain dependent on learners' cognitive and metacognitive agency. The following sections examine this redistribution through AI-supported monitoring, planning and strategic choice, followed by cognitive offloading, epistemic trust, and learner agency.

### 4.1. AI-Supported Monitoring, Planning and Strategic Choice

The cognitive architecture of SRL depends on the continuous coordination of goals, task representations, metacognitive judgements, strategic actions, and evaluations of progress. In Zimmerman's (2002, 2013) cyclical model, forethought prepares and directs action, performance involves strategic execution and self-monitoring, and self-reflection evaluates outcomes and informs subsequent regulation. Similarly, Winne and Hadwin (1998) conceptualize SRL as a recursive process in which learners construct task conditions, formulate goals and plans, enact tactics, and monitor the effects of their actions. Pintrich (2000) likewise places planning, monitoring, control, and reflection within an interconnected regulatory sequence. From these perspectives, AI can intervene at several points in the regulatory cycle, although its contribution depends on the regulatory function being supported and the information available to the system.

An important distinction is necessary, however, between AI systems that have access to evidence of students' learning activity and performance and general-purpose generative AI chatbots that do not normally have such access. Learning analytics platforms, adaptive learning environments, and intelligent tutoring systems

may, depending on their configuration and integration with learning environments, use interaction records, students' responses, error patterns, assessment results, and other performance-related data to identify progress and provide feedback. Their capacity to support monitoring is therefore potentially grounded in evidence generated during learning activity. By contrast, general-purpose GenAI chatbots do not ordinarily have direct access to students' learning histories, platform activity, or assessment records. Their responses depend primarily on the information included in the interaction, such as questions, descriptions of difficulties, or materials and performance data explicitly supplied by the learner. Consequently, these chatbots may help students reflect on their progress or interpret feedback, but they cannot be assumed to monitor their actual learning performance independently.

In environments supported by learning analytics and intelligent tutoring systems, monitoring can be facilitated by making performance-related information more visible and interpretable. Where appropriate data are available, these systems may identify patterns of errors, summarize progress, generate feedback, or draw attention to discrepancies between current performance and intended goals. Such affordances can strengthen the informational basis for metacognitive monitoring by providing learners with additional evidence against which to evaluate their performance. This corresponds to the distinction between monitoring and control proposed by Nelson and Narens (1990), whereby monitoring provides information about a cognitive state, whereas control involves decisions concerning subsequent action.

General-purpose GenAI chatbots support monitoring in a different and more conditional manner. They may invite learners to assess their understanding, formulate reflective questions, examine the quality of their work, or interpret performance information that they provide. They may also generate feedback on submitted texts, answers, or descriptions of learning difficulties. However, this feedback should not be equated with continuous monitoring based on direct access to the learner's actual performance. Its usefulness depends on the accuracy, completeness, and relevance of the information supplied, as well as on the learner's capacity to evaluate the response. Receiving information about performance, however, does not in itself constitute effective metacognitive monitoring. Flavell (1979) conceptualized metacognition in terms of knowledge and regulation of cognition, while Efklides (2008) emphasized the role of metacognitive experiences and judgements in guiding regulatory processes. Accordingly, whether feedback originates from a data-informed learning environment or from a GenAI chatbot responding to learner-provided information, it becomes educationally meaningful only when learners interpret it, evaluate its relevance, and incorporate it into subsequent action. Research on AI-supported learning environments suggests that such support may facilitate monitoring and self-evaluation, although its contribution depends on the type of system, the information available, and the way learners engage with the feedback provided (Banihashem et al., 2025; de Mooij et al., 2025; Lan & Zhou,

2025).

AI's contribution to planning is more complex. Planning requires learners to represent the task, establish goals and priorities, anticipate difficulties, and select strategies appropriate to contextual demands. Zimmerman (2002) and Pintrich (2000) locate these processes within the forethought phase of SRL, whereas Winne and Hadwin (1998) emphasize task definition as a basis for subsequent goal setting and strategic action. Both learning-oriented AI systems and general-purpose GenAI chatbots may support planning, although the information on which their suggestions are based differs. Systems integrated into learning environments may use available information about students' previous activity or performance to inform adaptive recommendations. General-purpose chatbots, by contrast, can help learners decompose complex tasks, identify resources, generate possible sequences of action, compare strategies, or formulate provisional study plans, but these suggestions are generally based on the context and constraints described by the learner rather than on independently verified records of learning progress. In this respect, AI can function as a planning scaffold that broadens the range of alternatives available to learners.

Yet generating a plan is not equivalent to developing the capacity to plan. When an AI system produces a complete strategy without necessarily requiring learners to articulate their goals, constraints, or reasons for selecting a particular course of action, learners may receive an externally generated regulatory product without fully engaging in the regulatory process. This distinction is important because educational chatbots have mainly supported learners in identifying learning resources, enacting appropriate learning strategies, and metacognitively monitoring their studying, while providing more limited support for goal setting, planning, reflection, and adaptation of future learning (Guan et al., 2025). AI-supported planning should therefore be understood as potentially regulatory rather than inherently so.

The third function, strategic choice, concerns the selection, coordination, and modification of strategies according to task demands and emerging feedback. Azevedo and Aleven (2013) emphasized the importance of adaptive regulation in complex learning environments, while Panadero (2017) showed that major SRL models converge on the cyclical adaptation of cognition, motivation, and behaviour. AI systems may contribute to strategic choice in different ways. Learning analytics and intelligent tutoring systems can, where supported by relevant performance data, identify difficulties or patterns that inform recommendations about subsequent learning activities. General-purpose GenAI chatbots can present alternative strategies, discuss their possible consequences, or generate recommendations in response to the task-related information provided by the learner. In the latter case, however, recommendations should not be interpreted as evidence-based diagnoses of the learner's actual progress unless they are grounded in relevant performance information. Such support may broaden the informational basis for decision-making, but the recommendation itself should not be equated with

the regulatory decision.

This distinction is particularly important when AI recommendations appear authoritative. A recommendation may be plausible while remaining inappropriate for a particular learner, task, or goal. Strategic regulation therefore requires learners to evaluate not only whether a recommendation is feasible but also whether it is relevant and justified. Recent reviews of AI-supported SRL indicate that AI applications increasingly address cognitive and metacognitive processes, including planning, monitoring, evaluation, and strategy support, while also identifying concerns related to accuracy, adaptability, AI literacy, and inappropriate reliance on AI-generated outputs (Banihashem et al., 2025; Lan & Zhou, 2025).

AI can therefore be conceptualized as an external regulatory resource rather than an autonomous regulator. Its educational value depends on whether it expands learners' capacity to consider alternatives and make informed strategic decisions. A system that simply supplies regulatory outputs may reduce immediate effort without necessarily strengthening regulatory competence; by contrast, a system that prompts learners to examine alternatives, justify choices, and evaluate consequences may contribute to the development of adaptive self-regulation. This distinction provides the basis for examining, in the next section, the implications of cognitive offloading, epistemic trust, and learner agency.

### 4.2. Cognitive Offloading, Epistemic Trust and Learner Agency

The possibility that AI may externalize cognitive-regulatory operations can be examined through the concept of cognitive offloading. Cognitive offloading refers broadly to the use of external resources to reduce the cognitive demands associated with a task. Research by Risko and Dunn (2015) and Risko and Gilbert (2016) demonstrates that people routinely distribute cognitive activity between internal processes and external representations or tools. From this perspective, cognitive offloading is not necessarily incompatible with effective learning; its consequences depend on the nature of the operation externalized and the extent to which learners remain cognitively engaged with the task.

Using AI to organize information, generate alternatives, formulate reminders, or provide intermediate explanations may therefore reduce unnecessary cognitive demands and allow learners to allocate resources to more demanding activities. However, the distinction between reducing extraneous demands and externalizing core learning processes is critical. Recent evidence suggests that generative AI use can be associated with cognitive offloading and shared metacognition, indicating that AI-supported externalization may contribute to learning when embedded within appropriate regulatory processes (Iqbal et al., 2025). The educational question is therefore not whether cognitive offloading occurs, but what is offloaded and what remains cognitively active.

This distinction becomes particularly consequential with GenAI because the technology can externalize not only memory or calculation but also increasingly complex linguistic and reasoning operations. Learners may ask AI systems to

summarize texts, formulate research questions, compare explanations, generate study plans, evaluate arguments, or propose solutions. Although each action can reduce immediate cognitive demands, their implications for learning differ substantially. Offloading the retrieval or organization of peripheral information may be relatively benign, whereas offloading interpretation, evaluation, or strategic decision-making may reduce opportunities to practice competencies that constitute important learning outcomes. The relationship between metacognition and cognitive offloading is therefore central: external support may facilitate regulation when learners monitor its use, but may become counterproductive when it substitutes for the regulatory activity that learning is intended to develop (Dunn & Risko, 2016; Iqbal et al., 2025).

This issue is closely connected to epistemic trust. Learners must determine whether AI-generated information is sufficiently accurate, relevant, and justified to warrant acceptance or further use. Such evaluation requires more than technological competence; it involves epistemic judgement about the quality of knowledge claims, evidence, reasoning, and sources. The fluent and coherent character of AI-generated responses makes this judgement particularly important because apparent clarity does not necessarily correspond to evidential reliability. Recent work on generative AI literacy similarly emphasizes the importance of critical engagement with AI outputs within SRL rather than simple operational competence (Anders & Dux Speltz, 2025).

Epistemic trust can therefore be understood as a regulatory condition of AI-supported learning rather than merely an attitudinal response to technology. Appropriate trust allows learners to use AI outputs as provisional resources for comparison, questioning, and further investigation. Excessive trust, by contrast, may encourage uncritical acceptance and reduce verification, whereas insufficient trust may prevent learners from benefiting from potentially useful assistance. Effective AI-supported learning therefore requires calibrated trust, whereby confidence in an AI output is proportionate to its evidential quality, contextual relevance, and verifiability. This calibration is consistent with broader research showing that learners' judgements about their own cognition and performance are consequential for subsequent regulatory decisions (David et al., 2024; Dunlosky & Thiede, 2013).

This issue is directly connected to metacognitive monitoring. A learner who evaluates an AI response against prior knowledge, task requirements, external sources, and alternative interpretations is engaging in active epistemic monitoring. Conversely, accepting a response primarily because it appears plausible reduces the need for independent evaluation. AI-supported learning may therefore strengthen or weaken metacognitive engagement depending on how responsibility for evaluating information is distributed between learner and system. Evidence from research on chatbot-supported self-regulation indicates that the effects of AI are particularly dependent on the presence of explicit metacognitive support rather than on AI assistance alone (Ng et al., 2024; Tsai et al., 2025; Xu et al., 2025).

Learner agency is likewise shaped by how AI is incorporated into learning.

Bandura's (1997, 2001) social-cognitive account of agency emphasizes intentionality, forethought, self-reactiveness, and self-reflectiveness, while contemporary work distinguishes learner agency from autonomy and related constructs by highlighting learners' capacity to exercise meaningful control over their learning processes (Gupta et al., 2024). These perspectives are particularly relevant to AI-mediated learning because agency involves more than making choices; it involves exercising intentional control over actions and evaluating their consequences.

When learners use AI to expand available options while retaining responsibility for goals, criteria, decisions, and evaluation, the technology may function as an agency-supportive resource. When learners allow AI to determine goals, strategies, interpretations, or conclusions, however, responsibility for regulation may progressively shift towards the technological system. Empirical evidence supports this distinction. Darvishi et al. (2024), for example, found that the effects of AI assistance on student agency depend on how assistance is structured, highlighting the importance of preserving active student involvement rather than treating AI as a substitute for learner participation.

Recent research therefore points to a dual possibility. AI can support reflection, metacognitive scaffolding, feedback, and self-regulation when learners remain actively involved in the regulatory process (Anders & Dux Speltz, 2025; Ng et al., 2024; Tsai et al., 2025; Xu et al., 2025). At the same time, excessive externalization may weaken independent monitoring and decision-making when learners increasingly rely on AI-generated outputs rather than evaluating them. The implications of cognitive offloading should consequently not be assessed simply according to the amount of effort removed, but according to which cognitive-regulatory responsibilities remain with the learner.

On this basis, a useful conceptual distinction can be drawn between augmentation-oriented and replacement-oriented uses of AI. In augmentation-oriented use, AI reduces unnecessary cognitive demands while preserving the learner's responsibility for interpretation, evaluation, and decision-making. In replacement-oriented use, AI performs functions that learners need to practice themselves, thereby reducing opportunities for cognitive engagement and regulatory development. This distinction should be understood as a conceptual framework rather than as an established dichotomy in the literature. The same technological system may operate in either mode depending on task design, prompts, learner expertise, and the degree of metacognitive support provided.

This distinction also clarifies why AI literacy cannot be reduced to knowing how to operate AI tools. Learners need to formulate purposeful requests, interpret generated outputs, identify uncertainty, verify claims, compare alternatives, and decide when AI assistance should be accepted, modified, or rejected. Generative AI literacy is consequently closely connected to SRL because effective use requires learners to coordinate technological interaction with metacognitive monitoring, evaluation, and decision-making (Anders & Dux Speltz, 2025). The central issue is therefore not the extent to which AI reduces cognitive effort, but whether its

use preserves and develops learners' capacity for metacognitive control, epistemic judgement, and autonomous regulatory action.

### 4.3. An Integrative Model of Cognitive Coordination in AI-Supported SRL

The preceding analysis suggests that AI should be incorporated into SRL theory neither as an independent regulatory agent nor as a neutral technological instrument. It is more appropriately conceptualized as a potentially active component of a distributed cognitive-regulatory system in which learners remain the primary locus of goals, evaluative criteria, and consequential decisions (Darvishi et al., 2024; Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2002).

The proposed model, shown in **Figure 1**, integrates four interconnected layers: learner regulation, AI-mediated cognitive support, epistemic evaluation, and adaptive control. The first layer comprises the learner's goals, task representation, prior knowledge, motivational beliefs, metacognitive knowledge, and strategic intentions. These processes correspond broadly to the forethought and task-analysis dimensions identified by Pintrich (2000), Winne and Hadwin (1998), and Zimmerman (2002).

The second layer concerns the AI-mediated support environment. Here, AI may provide information, explanations, feedback, alternative strategies, planning suggestions, simulations, or analytic representations of learner performance. Its function is not fixed. Depending on the task and interaction, AI may serve as a source of information, a feedback mechanism, a planning scaffold, a conversational partner, or an external cognitive resource. Research on AI-supported learning illustrates this differentiated role through applications involving conversational support, feedback, self-regulation scaffolding, and metacognitive support (Anders & Dux Speltz, 2025; Ng et al., 2024; Tsai et al., 2025; Xu et al., 2025).

The third layer concerns epistemic evaluation. AI-generated outputs enter the learner's cognitive system not as established knowledge, but as claims or recommendations requiring appraisal. The learner must compare them with task requirements, prior knowledge, available evidence, and alternative sources. This layer connects metacognitive monitoring with epistemic judgement and calibration, emphasizing that the usefulness of AI-supported feedback depends partly on the learner's capacity to assess its relevance, credibility, and adequacy (David et al., 2024; Dunlosky & Thiede, 2013; Efklides, 2008).

The fourth layer concerns adaptive control. After evaluating an AI-supported recommendation or feedback, the learner decides whether to maintain, modify, reject, or replace the current strategy. This corresponds to the control component of metacognitive regulation described by Nelson and Narens (1990) and to the adaptive dimensions of SRL emphasized by Efklides (2008), Winne and Hadwin (1998), and Zimmerman (2002). AI may therefore inform control without necessarily exercising it.

The transition from evaluative judgement and adaptive decision-making to ac-

tual learning activity also depends on motivational commitment and volitional control. Motivational commitment gives direction and personal significance to the learner's decisions, influencing willingness to invest effort and pursue established learning goals (Bandura, 1997; Pintrich, 2000). However, commitment alone does not guarantee that intentions will be translated into sustained action. Volitional control helps bridge this intention-action gap by supporting persistence, managing distractions, maintaining effort when tasks become difficult, and recovering concentration following interruptions (Corno, 1993; Boekaerts & Corno, 2005). In AI-supported SRL, an AI-generated plan or strategic recommendation therefore becomes educationally consequential only when learners are sufficiently committed to their learning goals and mobilize the volitional strategies needed to implement, monitor, and, where necessary, adjust their decisions. AI may facilitate this process by helping learners divide complex activities into manageable stages, organize study periods, or identify possible responses to difficulties. Nevertheless, such support does not replace the learner's motivational commitment or volitional control. These processes enable learners to move beyond evaluating and selecting AI-supported recommendations towards enacting them in a sustained and adaptive manner, while retaining responsibility for the direction and regulation of their learning.

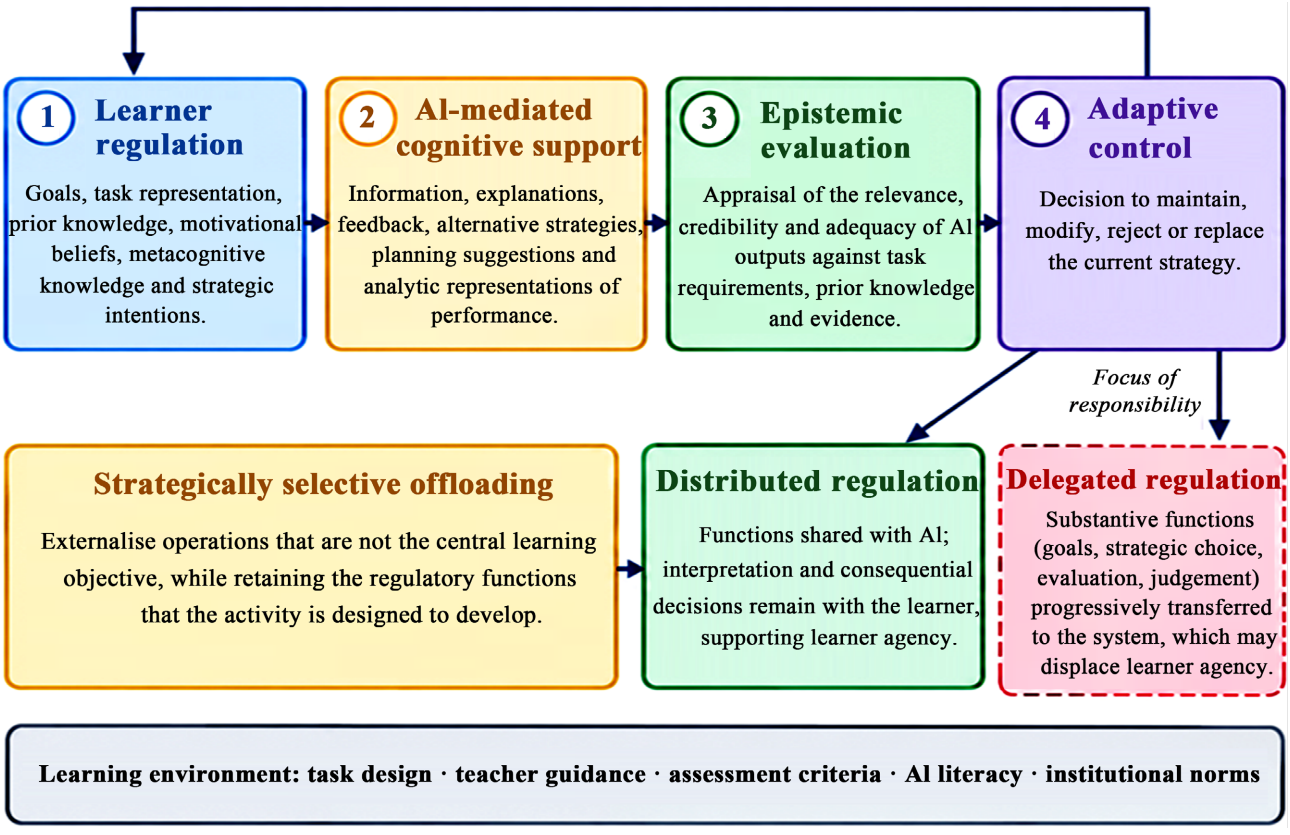


**Figure 1.** Integrative model of cognitive coordination in AI-supported self-regulated learning. Source: Author's own elaboration, based on Nelson and Narens (1990), Winne and Hadwin (1998), Pintrich (2000), Zimmerman (2002), Risko and Gilbert (2016) and Darvishi et al. (2024).

As **Figure 1** shows, these four layers form a recursive rather than linear system, in which outcomes modify subsequent task representations, metacognitive judgements, and strategic choices. This recursive organization is consistent with process-oriented accounts of SRL in which monitoring and control continuously interact with changing task conditions (Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2002). AI can participate repeatedly in this cycle, but the regulatory significance of each interaction depends on how responsibility is distributed across the system.

The model therefore distinguishes between distributed regulation and delegated regulation. Distributed regulation occurs when cognitive functions are shared between the learner and AI while responsibility for interpretation and decision-making remains with the learner. Delegated regulation occurs when the learner progressively transfers substantive regulatory functions to the system, including goal formulation, strategic choice, evaluation, or judgement. This distinction extends current discussions of learner agency in AI-supported learning, where technological assistance may either support or constrain learners' active participation in regulation (Darvishi et al., 2024; Gupta et al., 2024).

The distinction proposed here can also be situated in relation to existing approaches to co-regulation and hybrid human-AI regulation. Co-regulation accounts emphasize the ways in which regulatory processes are supported through interaction with external agents, while research on human-AI arrangements examines how regulatory functions may be shared between human users and artificial systems. These perspectives provide important foundations for understanding the social and technological mediation of regulation. The present model adds a more specific analytical distinction by examining not only whether regulatory functions are shared, but also how responsibility for their exercise is allocated. Distributed regulation describes arrangements in which learners and AI contribute complementary cognitive functions while learners retain responsibility for interpreting information, evaluating alternatives, and making consequential decisions. Delegated regulation, in contrast, refers to situations in which learners transfer substantive regulatory operations or decisions to AI systems, thereby reducing their direct involvement in the regulation of learning. The distinction thus makes it possible to examine a dimension that the identification of shared or hybrid regulatory activity does not, by itself, establish: whether the learner remains the principal agent of regulatory judgement and control. It consequently provides a conceptual basis for analyzing how different configurations of human-AI interaction may support learner agency or contribute to its displacement.

An important qualification concerns intentional and reversible delegation. The temporary transfer of a specific regulatory operation to an AI system should not, in itself, be classified as delegated regulation. When learners deliberately ask AI to perform a task, retain oversight of the process, evaluate the relevance of its contribution, and preserve the ability to revise or reject its output, regulatory control remains with the learner. For example, a learner may ask GenAI to generate a

study plan for an upcoming examination. If the learner examines the proposed schedule, considers whether it reflects their learning priorities and available time, justifies its acceptance or modifies particular elements, and subsequently monitors its suitability, this arrangement is more appropriately understood as distributed regulation. The same applies when the learner rejects the proposed plan and develops an alternative. Acceptance alone, however, does not demonstrate the maintenance of regulatory control: what matters is whether it results from an informed evaluation and remains open to revision. By contrast, regulation becomes delegated when the learner transfers substantive regulatory decisions to the AI system without meaningful evaluation or continuing oversight, thereby relinquishing responsibility for determining and adjusting the course of learning. Thus, the distinction depends not simply on whether a regulatory operation is temporarily entrusted to AI, but on whether the learner retains effective authority over its evaluation, use, and subsequent adjustment.

This distinction also provides a more nuanced interpretation of cognitive offloading. Offloading becomes problematic when the externalization of a process eliminates the learner's opportunity to perform or evaluate that process. Conversely, offloading routine operations can create cognitive space for higher-order activities. Research on cognitive offloading indicates that external representations and technological resources can reduce demands on internal cognition, while their educational value depends on how and why such externalization is used (Dunn & Risko, 2016; Risko & Gilbert, 2016). Recent evidence involving generative AI similarly connects cognitive offloading with shared metacognitive processes, suggesting that the consequences of AI-supported externalization depend on the regulatory functions that remain with the learner (Iqbal et al., 2025). The educational objective should therefore be selective, strategic offloading, whereby learners externalize operations that do not constitute the central learning objective while retaining those cognitive-regulatory functions that the learning activity is designed to develop.

The model also clarifies the role of teachers and learning environments. AI-supported SRL cannot be reduced to a private interaction between learner and technology. Task design, teacher guidance, assessment criteria, AI literacy, and institutional norms shape how learners interpret and use AI. Recent work on generative AI literacy and AI-supported self-regulation similarly emphasizes the importance of human-centred use, metacognitive support, and structured learning conditions rather than technological assistance alone (Anders & Dux Speltz, 2025; Miao & Holmes, 2023; Tsai et al., 2025; Xu et al., 2025).

Accordingly, the central educational principle is not to maximize AI assistance, but to optimize the distribution of cognitive-regulatory functions. AI should support learners where external assistance can improve access to information, feedback, comparison, or strategic alternatives, while preserving opportunities for goal formation, critical evaluation, epistemic judgement, and adaptive decision-making. This position is consistent with recent evidence that AI-supported interven-

tions can strengthen aspects of cognitive and metacognitive regulation, although their effects depend on the design of the support and the extent to which learners remain actively involved in the regulatory process (Ng et al., 2024; Tsai et al., 2025; Xu et al., 2025).

The resulting model places the learner at the center of a dynamic cognitive-regulatory ecology. AI expands the available regulatory resources without determining their educational value. That value emerges from the interaction between technological affordances and the learner's capacity to monitor, evaluate, decide, and adapt. In this sense, the future of AI-supported SRL should not be understood as a movement from human regulation towards automated regulation. It is better conceptualized as a transformation in the distribution and coordination of regulatory functions, in which effective learning depends increasingly on knowing what to delegate, what to verify, what to retain, and what must remain cognitively one's own.

## 5. Conclusions and Future Research

This integrative theoretical-conceptual analysis examined SRL from a cognitive-regulatory perspective, focusing on the interrelationships among metacognition, planning, beliefs, strategic choice, and decision-making, and considering how the increasing integration of AI may alter the distribution of these functions. Across the analysis, SRL was conceptualized not as a sequence of isolated cognitive operations but as a dynamic and recursive process in which learners construct task representations, formulate goals, monitor their cognition and performance, select and adapt strategies, and evaluate the consequences of their actions (Flavell, 1979; Pintrich, 2000; Winne & Hadwin, 1998; Zimmerman, 2000). AI introduces a significant new condition: some regulatory operations can increasingly be supported, externalized, or partially performed through interaction with technological systems.

The analysis suggests that the theoretical significance of AI for SRL lies less in its capacity to perform individual learning tasks than in its potential to redistribute cognitive-regulatory functions. AI can provide information, feedback, explanations, strategic alternatives, planning support, and representations of learner performance. These affordances may strengthen the informational conditions under which regulation occurs and reduce demands associated with routine cognitive operations. However, effective regulation cannot be inferred from such support. Monitoring requires interpretation, planning requires purposeful goal formation, and strategic choice requires evaluation of alternatives in relation to task demands and learner objectives. Consequently, AI assistance does not in itself establish that self-regulation has been strengthened.

A central conceptual implication is the need to distinguish between assistance that augments regulation and assistance that progressively replaces regulatory activity. Cognitive offloading can be beneficial when it reduces unnecessary demands while preserving opportunities for learners to practice and evaluate the

cognitive processes that constitute meaningful learning outcomes (Risko & Gilbert, 2016). Conversely, extensive externalization of interpretation, evaluation, strategic choice, or decision-making may reduce opportunities for developing these capacities. Epistemic trust therefore becomes an important regulatory condition: learners must assess the relevance, credibility, limitations, and evidential basis of AI-generated outputs rather than treating fluent responses as automatically reliable. AI literacy consequently extends beyond operational competence to include metacognitive and epistemic capacities required for calibrated use.

The proposed model integrates these considerations by conceptualizing AI-supported SRL as a distributed cognitive-regulatory system organized around learner regulation, AI-mediated cognitive support, epistemic evaluation, and adaptive control. Its central proposition is that cognitive functions may be distributed across learner and system without transferring ultimate responsibility for goals, evaluative criteria, interpretation, and consequential decisions. This distinction between distributed and delegated regulation provides a conceptual basis for analyzing when AI may support learner agency and when it may progressively displace it. The model therefore extends conventional accounts of SRL by treating technological systems as consequential components of the regulatory environment while retaining the learner as the primary locus of intentional regulation (Bandura, 2001; Zimmerman, 2000).

These considerations also have important pedagogical implications. Learning environments that incorporate AI should not be designed primarily to maximize efficiency or minimize learner effort. Instead, task design should make explicit which functions may appropriately be externalized and which learners need to perform themselves. Activities may use AI to generate alternatives or provide feedback while requiring learners to justify choices, verify claims, compare outputs, monitor progress, and explain subsequent adaptations. Teacher guidance, assessment criteria, and institutional expectations are consequently important in determining whether AI functions as a regulatory scaffold or as a substitute for learner engagement.

Several limitations should nevertheless be acknowledged. The analysis is theoretical and conceptual rather than empirical and therefore does not establish causal relationships between particular forms of AI use and SRL outcomes. The rapidly changing nature of generative AI also limits the stability of technology-specific conclusions. Moreover, the proposed distinctions between augmentation and replacement, and between distributed and delegated regulation, should be treated as conceptual frameworks requiring empirical validation rather than as fixed categories.

Future research should therefore examine how these regulatory configurations develop across different tasks, learner characteristics, levels of expertise, and forms of AI interaction. **Table 1** presents the theoretical propositions corresponding to the three guiding questions, together with suggested empirical tests. Testing these propositions would help determine not simply whether AI improves learning outcomes, but under what conditions it strengthens the cognitive-regulatory

capacities through which learners become increasingly capable of regulating their own learning.

**Table 1.** Theoretical propositions corresponding to the guiding questions and suggested empirical tests.

| Guiding question (Section 1.3) | Theoretical proposition | Suggested empirical test |
|---|---|---|
| Q1. How do the principal cognitive and regulatory processes interact during SRL? | P1. Regulatory effectiveness is expected to depend on the alignment among task appraisal, metacognitive judgement, motivational commitment, decision-making and adaptive action, rather than on the strength of any single component. | Process-oriented studies combining trace data or think-aloud protocols with measures of judgements, beliefs and strategy changes; tests of interactions among components. |
| Q2. How does information derived from monitoring, planning and beliefs contribute to regulatory decision-making? | P2. Monitoring and planning information is expected to guide decisions and action when supported by motivational commitment and volitional control; weak commitment, as in academic procrastination, is expected to disrupt the transition from intention to action. | Longitudinal and diary studies linking planned and enacted study behaviour with metacognitive judgements, self-efficacy, volitional control and procrastination. |
| Q3. How does AI redistribute regulatory responsibility between learners and AI systems, and under what conditions does this give rise to distributed rather than delegated regulation? | P3. In AI-supported SRL, regulation is expected to remain effective when cognitive functions are distributed between learner and AI while interpretation and consequential decisions stay with the learner; progressive delegation of substantive functions is expected to reduce active monitoring and strategic control. This relationship is expected to be conditioned by the learner's epistemic evaluation of AI outputs, by selective offloading of operations that are not the central learning objective, and by task design, teacher guidance and AI literacy. | Experimental and mixed-method studies comparing prompting and scaffolding conditions; trace indicators of acceptance, modification and rejection of AI outputs; measures of calibration and epistemic trust; longitudinal follow-up of monitoring and strategic choice; quasi-experimental classroom designs. |

Note. The propositions are conceptual and require empirical validation. Source: Author's own elaboration, based on the conceptual analysis developed in Sections 1.3 and 2-4.

In sum, the analysis shifts the question from whether AI supports self-regulated learning to how responsibility for regulation is distributed once it does. The distinction between distributed and delegated regulation offers a way of specifying that distribution, and the propositions in Table 1 translate it into testable expectations about cognitive coordination, the transition from intention to action, and the role of epistemic evaluation. Whether these expectations hold is an empirical matter that must be addressed by studies observing regulation as it unfolds during interaction with AI, rather than inferring it from learning outcomes alone.

## Author Contributions

Both authors contributed to the conception and design of the study. They were involved in the literature review, analysis and interpretation of the relevant information, and drafting and critical revision of the manuscript. Both authors read and approved the final version of the manuscript.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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