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Tracking self-regulated learning in action: How individual differences shape positive and negative regulation across three types of tasks ☆

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A B S T R A C T

Self-regulated learning (SRL) is essential for academic success yet few studies have explored how individual-level variables (e.g., prior academic achievement, self-reported SRL skills) relate to both adaptive (positive) and maladaptive (negative) SRL behaviors across different types of tasks. This study investigated the extent to which self-reported SRL skills and prior academic achievement predict both positive and negative SRL behaviors captured through think-aloud protocols, as well as task performance, across three cognitively distinct academic tasks (reading, oral analysis, and written analysis) within a repeated-measures design. Results showed that higher self-reported positive SRL and prior academic achievement predicted greater use of positive SRL strategies and better performance, whereas negative SRL behaviors appeared more sensitive to task demands than to individual traits. These findings highlight the value of distinguishing between positive and negative SRL and of integrating self-report and process data to better understand the dynamics of SRL and inform targeted educational interventions.

Educational relevance statement: This paper is educationally relevant because it shows that learning strategies should adapt to different tasks and stages providing evidence that self-regulated learning is context-dependent and dynamic, varying across tasks and individuals. Its findings inform the design of more responsive pedagogical interventions and valid assessment tools that capture students' regulation processes in real learning contexts, emphasizing the role of prior achievement and strategy use in adaptive regulation.

1. Introduction

Self-regulated learning (SRL) is a multidimensional process through which learners proactively plan, monitor, and evaluate their cognitive, motivational, and behavioral engagement with academic tasks (Greene, 2018). Over the past decades, several theoretical models have helped conceptualize SRL, including the cyclical model by Zimmerman (2000), the model by Butler and Winne (1995), or Pintrich's framework of regulation domains and phases (2000). These mentioned models share a core assumption: effective learners are those who actively regulate their thoughts, emotions, motivation, and actions to achieve their goals (Panadero, 2017).

A key challenge in understanding SRL lies in its multifaceted nature: learners differ in how they regulate their learning depending on key variables such as individual characteristics or the task characteristics, among others (Ben-Eliyahu & Bernacki, 2015; Donoghue & Hattie, 2021; Greene et al., 2015). Individual-level factors such as prior academic achievement, self-perceived regulatory ability, and motivational beliefs have been shown to influence how students plan, monitor, and adapt their strategies (Efklides, 2011; Musso et al., 2019; Usher & Schunk, 2018). These personal dispositions not only shape students' immediate engagement but also interact with contextual demands, reinforcing the need to examine SRL as the product of both individual-level factors and situational conditions.

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In addition, the characteristics of the tasks themselves also shape how students regulate their learning. Different academic activities (e.g., reading, oral analysis, written analysis) vary in their cognitive demands and temporal structure, potentially eliciting distinct self-regulatory responses. Therefore, understanding how SRL strategies adapt to the specific requirements of each task type is essential to capture the situational nature of regulation and to design more effective learning environments (De Bruin & van Merriënboer, 2017; Winne, 2018).

A further challenge in SRL research concerns its measurement. Traditional self-report questionnaires have provided valuable insights into learners' perceptions of their regulation but are limited by issues such as social desirability and their weak alignment with actual behaviors (Boekaerts & Corno, 2005; Winne, 2010). To overcome these limitations, more recent work has turned to online measures that capture regulation in action, such as think-aloud protocols, eye-tracking, or log data (Azevedo et al., 2018). These methods make it possible to observe both adaptive and maladaptive strategies, thereby offering a more nuanced understanding of how students regulate learning in real time. Combining these complementary approaches strengthens validity and allows researchers to address how SRL varies across learners and tasks (Panadero, 2023).

Building on these perspectives, the present study investigates how individual characteristics and task demands jointly shape students' self-regulation. By integrating self-report questionnaires with think-aloud protocols across three cognitively distinct tasks, we aim to clarify the interplay between stable learner dispositions and context-sensitive regulatory behaviors.

1.1. Individual characteristics and SRL: achievement, self-perceptions and task performance

Students' ability to self-regulate their learning is shaped by relatively stable learner characteristics[1] (e.g., Musso et al., 2019). Among these, prior academic achievement and self-perceived SRL skills are particularly relevant, as they reflect both past performance and learners' confidence in their regulatory abilities (e.g., Hirt et al., 2021). In turn, these characteristics also influence students' task performance, which is not only an outcome of SRL, but can itself shape future self-perceptions and regulatory engagement (Usher & Schunk, 2018). From this perspective, prior achievement becomes a key variable to consider when studying the interplay between individual traits and self-regulation. In what follows, we first discuss evidence on prior academic achievement as a predictor of SRL processes and outcomes, before turning to students' self-perceived regulatory abilities.

First, prior achievement has been found to predict more frequent and effective use of regulatory strategies such as planning, monitoring, and adaptation (Zhu & Mok, 2018). Students with higher academic achievement are also more likely to approach academic activities with a stronger sense of competence and goal orientation, which enhances motivation to regulate effort and strategy use (Dignath et al., 2020; Efklides, 2011). Moreover, achievement history often reinforces students' beliefs about their learning capacity, creating feedback loops that influence both actual behavior and its verbalization during tasks (Schunk & Zimmerman, 2006).

Second, self-perceptions of SRL ability, typically assessed through self-report questionnaires, represent students' beliefs about their typical regulatory behavior. These self-beliefs are important predictors of motivation, persistence, and adaptive help-seeking (Wolters & Brady, 2021). However, whether such self-perceptions translate into actual strategy deployment during task execution remains an open question. Some studies find modest alignment between perceived and enacted SRL, while others reveal substantial discrepancies, particularly among low-performing students (e.g., DiFrancesca et al., 2016).

Our study addresses this gap by examining how self-reported SRL skills and prior academic achievement predict regulatory behaviors observed through think-aloud protocols. This design allows us to test whether enacted SRL is more closely aligned with students' academic history or with their self-perceptions, and to identify potential mismatches between reported and observed regulation. Such discrepancies have important implications for both SRL theory and educational practice.

1.2. The role of task characteristics in SRL deployment

Increasingly, scholars argue that SRL is not uniformly deployed across contexts but is strongly modulated by the nature of the task and the cognitive operations it elicits (Li et al., 2022; Winne, 2018). Therefore, different tasks require different forms of cognitive engagement and regulation. For instance, reading tasks may invite monitoring and re-reading as dominant strategies, while oral analysis tasks may demand verbal elaboration and real-time planning (e.g., Risemberg, 1996). Writing tasks, in turn, often involve recursive planning, drafting, and revision processes (Graham & Harris, 2018). These variations influence the extent to which students deploy specific SRL strategies and the ease with which they can verbalize their regulatory actions during task engagement.

Recent empirical work supports the idea that the contextual features of tasks, such as complexity, modality, and temporal constraints, modulate SRL behaviors in nuanced ways (e.g., De Bruin & van Merriënboer, 2017). Thus, when studying SRL with real-time methods like think-aloud protocols, it becomes essential to account for task characteristics as potential sources of within-subject variability. Rather than treating SRL as a stable trait or a generalizable skill set, it should be understood as an adaptive system responsive to situational affordances and constraints.

Given this, we compare SRL behaviors across three authentic academic tasks that differ meaningfully in modality and cognitive structure: reading a text, oral analysis, and written analysis. By doing so, we aim to examine whether and how regulatory strategies vary not only between students but also within students across different task types.

1.3. Beyond effective regulation: the relevance of avoidance and maladaptive strategies

Self-regulated learning is often conceptualized as a set of constructive strategies that support learning. However, a growing body of research highlights the importance of also identifying and understanding maladaptive or avoidance-oriented regulatory behaviors, which may be equally revealing of students' cognitive and motivational engagement (e.g., Alonso-Tapia et al., 2014; Boekaerts & Niemivirta, 2000; De la Fuente et al., 2020; Wolters, 2003).

Avoidance strategies are typically deployed when learners perceive a task as threatening or excessively demanding (Alonso-Tapia et al., 2014; Boekaerts & Niemivirta, 2000). These behaviors may include superficial reading, deflecting attention, making irrelevant comments, or rushing to complete a task without adequate monitoring (Wolters et al., 2011).

[1] In the present study, we use the term individual-level predictors to refer to variables that reflect relatively stable -but not immutable- learner characteristics, such as prior academic achievement or self-reported SRL strategies. While these constructs vary in their degree of malleability and contextual sensitivity, we follow previous authors who adopt a broad definition of individual differences to include both enduring dispositions and recurring behavioral tendencies that influence learning processes (Efklides, 2011; Winne, 2018). It is important to note that our operationalization does not assume trait-like invariance, but rather acknowledges that these predictors may capture habitual patterns shaped by students' past experiences and educational trajectories. For this reason, they are used here to examine how pre-existing learner characteristics relate to real-time regulatory behaviors as captured through think-aloud protocols. Throughout the article, we use the term "individual-level predictors" to emphasize this functional, context-sensitive use of the constructs rather than to imply psychological fixedness.

From a motivational standpoint, such strategies are often linked to low self-efficacy, fear of failure, or goal orientations focused on task avoidance rather than mastery (Elliot & Church, 1997; Hirt et al., 2021). While these behaviors may temporarily reduce anxiety or cognitive load, they hinder deep learning and long-term academic success. These patterns can also be framed within Boekaerts and Niemivirta's (2000) dual processing model, which distinguishes between learning- and well-being-oriented regulation.

Recent observational studies show that these manifestations of maladaptive regulation were particularly present among low-achieving students or in tasks with higher cognitive demands (Dignath & Veenman, 2021; Kim et al., 2023). This includes SRL actions that were counterproductive or revealed a strategic disengagement from the learning task, not only off-task comments and skipping important information, but also making affirmations of success without justification or prematurely ending a task.

Including maladaptive strategies in SRL analysis allows researchers to capture a broader spectrum of student behavior, moving beyond idealized models and acknowledging the complex interplay between cognitive, emotional, and motivational factors. This perspective is particularly valuable when working with verbal protocol data, where the quality and function of students' utterances can reveal not only effective engagement but also subtle forms of disengagement or avoidance. Thus, our analytical model incorporated negative SRL as a construct, both through self-report (via the EMSRQ avoidance scale; Alonso-Tapia et al., 2014) and through coding negative regulatory actions in the think-aloud protocols.

1.4. Observing SRL in action: from self-reports to think-aloud protocols

Understanding how students regulate their learning processes requires not only theoretical clarity but also robust methodological strategies. Historically, self-report questionnaires have dominated SRL research, providing valuable insights into learners' self-perceptions and general regulatory tendencies (e.g., Boekaerts & Corno, 2005; Fryer & Dinsmore, 2020; Winne & Perry, 2000). These instruments are practical and easy to administer, yet they face well-known limitations: they tend to be retrospective, rely on declarative rather than procedural knowledge, and may be affected by memory inaccuracies, social desirability, or students' limited awareness of their own regulation (Bannert & Reimann, 2012; Winne, 2010, 2020). Moreover, unless specifically designed to do so, questionnaires often fail to capture the situational and adaptive nature of SRL; that is, how learners adjust their strategies in response to specific task demands and evolving conditions. This gap between perceived and enacted regulation has led to growing interest in more process-oriented approaches (Azevedo et al., 2018; Panadero, 2023).

To better capture SRL as it unfolds in real time, researchers have increasingly turned to process-oriented methods such as think-aloud protocols (TAP) as one of the most informative approaches to capturing SRL in action. In TAP, participants verbalize their thoughts while completing a task, allowing researchers to observe regulatory behaviors as they unfold (Greene et al., 2018). This method has been used to identify metacognitive monitoring, planning, strategy use, and motivational regulation in real time, revealing nuances of SRL that are often inaccessible through questionnaires. As Boekaerts and Corno (2005) pointed out, these methods can complement questionnaires by capturing "online" processes. However, despite their potential, relatively few studies have examined the degree of alignment between self-perceptions and enacted behaviors, leaving an important gap in our understanding of how these two types of measures converge or diverge (Dignath-van Ewijk et al., 2013).

Beyond their standalone value, think-aloud protocols gain additional strength when combined with self-report questionnaires, as this triangulation allows researchers to examine how learners' perceived SRL relates to their enacted behaviors during tasks (Azevedo et al., 2018; Panadero, 2023). While some studies have begun to explore these relations (e.g., Dignath & Veenman, 2021), further work is needed to clarify how self-perceptions align or misalign with real-time regulatory activity under different task conditions. Building on this methodological foundation, the present study integrates both approaches to investigate SRL across three cognitively distinct tasks, enabling the analysis of interindividual differences (e.g., prior achievement, SRL self-concept) and intraindividual variability in regulatory behaviors.

1.5. Aim, research questions and hypotheses

This study investigates how individual-level characteristics and the demands of different academic tasks shape the deployment of positive and negative SRL actions as well as task performance. To capture this structure, we distinguish between task types and task phases. Task types refer to the three cognitively distinct activities under study (reading, oral analysis, and written analysis), whereas task phases denote the five concrete steps in which these activities were implemented across the experiment (Phase 1: reading; Phases 2 and 4: oral analysis; Phases 3 and 5: written analysis). Furthermore, we consider both positive and negative SRL behaviors as dependent variables in our repeated measures design.

The study draws on a multi-method design that combines self-report questionnaires and think-aloud protocols. Students completed two validated instruments -Deep Learning Strategies Questionnaire (DLSQ) and the Emotion and Motivation Self-Regulation Questionnaire (EMSRQ)- to capture their self-perceptions of SRL skills, along with providing their prior academic achievement scores. In addition, concurrent think-aloud protocols were collected to observe enacted regulatory behaviors in real time. This design enables the analysis of how individual level predictors (self-perceived SRL abilities and prior academic achievement) relate to regulatory actions displayed during task execution. The following research questions and hypotheses guide the empirical analysis:

RQ1. To what extent do individual-level predictors and task phase explain variation in the use of positive SRL actions?

H1. We hypothesize that higher levels of positively oriented self-regulation as measured by the DLSQ and the EMSRQ learning subscale, as well as higher prior academic achievement, will be associated with an increased use of positive self-regulated learning actions observed in think-aloud protocols. Conversely, higher scores on the EMSRQ avoidance subscale are expected to be associated with a reduced use of positive SRL actions. We also expect that the task phases will influence the use of positive SRL actions, with cognitively demanding phases (e.g., written analysis) eliciting more regulatory activity than less demanding phases (e.g., oral description).

RQ2. To what extent do individual-level predictors and task phase explain variation in the use of negative SRL actions?

H2. We hypothesize that higher scores on the EMSRQ avoidance subscale will be associated with an increased use of negative self-regulated learning actions observed in think-aloud protocols. In contrast, higher levels of positively oriented self-regulation as measured by the DLSQ and the EMSRQ learning subscale, as well as higher prior academic achievement, are expected to be associated with a reduced use of negative SRL actions. Additionally, we expect the task phase to impact the expression of negative SRL actions, with earlier phases or more novel tasks (e.g., initial rubric reading) generating more maladaptive responses.

RQ3. To what extent do individual-level predictors explain variation in students' task performance?

H3. We hypothesize that higher scores on the DLSQ, the EMSRQ learning subscale, and prior academic achievement will be positively associated with students' task performance. Conversely, higher scores on the EMSRQ avoidance subscale are expected to be negatively associated with task performance.

2. Method

2.1. Participants and study design decisions

2.1.1. Inclusion and exclusion criteria

Our sample were students enrolled in six different undergraduate programs at the same university. The only exclusion criterion was the presence of vision impairments or recent eye surgeries. As a result, only one student was excluded, ensuring that all participants had normal or corrected-to-normal vision.

2.1.2. Participants characteristics

Our initial sample included 138 first-year university students. To ensure data quality, only the 120 students with complete and reliable think-aloud data were retained for analysis. Of these, 85 were female. The group included students majoring in Psychology (45.83 %), Medicine (17.50 %), Education (14.17 %), Sport Sciences (10.83 %), Social Work (5.83 %), and Social Education (5.83 %). The average academic achievement of the participants prior to university entry was 7.3 out of 10, reflecting an average level of prior academic performance in comparison to national statistics.

This study was approved by the Universidad de Deusto ethics committee, and all procedures were conducted in accordance with the ethical standards of the institutional research committee. All participants provided informed consent prior to participation.

2.1.3. Sampling procedure

Our sample was a convenience sample, as the participants were readily accessible first-year students from Universidad de Deusto (Spain). Initially, we visited the students in their classrooms to present the study and invited all of them to participate. Those who were interested were asked to provide their email addresses on a sheet of paper. We reached out to seven classroom groups, with 174 students providing their contact information, and 138 eventually participating. Out of these, only 120 were included in the study due to think-aloud data loss. Participants who fully completed the experiment received a 5€ economic incentive.

2.1.4. Study design: analytical scope and exclusion of experimental factors

In methodological terms, the present study can be described as a repeated-measures, mixed design: task phases were treated as a within-subjects factor, individual characteristics as continuous covariates, and between-subjects manipulations were excluded from the analyses. Importantly, the original experimental design included two between-subjects factors (rubric type and feedback type), we intentionally chose not to include them in the current analyses. This decision was based on the structure of our broader research programme and the results of a companion study using the same dataset (Panadero et al., under review). That study tested the effects of rubric order (ascending vs. descending) and feedback type (control, product, process, rubric-based) on students' SRL behaviors, using the same coding scheme applied here. Results showed no significant effects of feedback type and only one significant interaction for rubric order, limited to negative SRL actions. Given the limited and context-specific nature of these effects, and considering our focus on modeling the contribution of continuous, learner-level predictors to SRL and performance, including the experimental factors would have added unnecessary complexity without advancing our central research questions. Therefore, we modelled only the individual predictors as covariates in a repeated-measures design, allowing us to examine intra-individual variation across tasks.

2.2. Materials and measures

2.2.1. Task materials

2.2.1.1. Landscape analysis. A landscape analysis typically involves a comprehensive examination and evaluation of the physical, environmental, and socio-economic aspects of a particular area or region, as illustrated in an image. For this study, we selected two landscapes with distinct characteristics: (a) a rural area with a Continental climate and (b) a rural area with a Mediterranean climate (see Appendix A). Participants first conducted an oral analysis of the landscapes, followed by a written analysis. Each landscape was thus presented twice: (1) with the rubric during the oral analysis and (2) again with the rubric, along with a text processor (i.e., Word file), where participants composed their final written landscape analysis (see Fig. 1).

2.2.1.2. Rubric. The rubric used in this study was developed in a previous investigation (Panadero et al., 2012), where experts in social science were observed analyzing a landscape. It consists of four performance levels and five assessment criteria (see Appendix B). The order of the performance levels and assessment criteria was counterbalanced, alternating between highest-to-lowest (PL4 - PL1) and lowest-to-highest (PL1 - PL4). The rubric, which was in Spanish, was first presented on its own, and participants were given time to read and analyze it (see Fig. 1). The rubric was employed to operationalize task performance by calculating scores from the two writing tasks completed in the study. The same rubric provided to the students was used for scoring (see Appendix B).

To ensure reliability, the second and sixth authors independently scored two rounds of 15 % of the written landscape analyses until they achieved excellent inter-rater reliability (ICC = 0.99; Intra-class Correlation Coefficient, Hallgren, 2012). Any discrepancies were resolved through discussions between the two coders. The remainder of the scores were calculated by the sixth author. The internal reliability of the five rubric assessment criteria was evaluated using the omega coefficient (McDonald, 1999), which is considered more appropriate than Cronbach's alpha for items with fewer than five possible values (Trizano-Hermosilla & Alvarado, 2016). The omega values for the five assessment criteria was 0.603 and 0.631 for the first and second written analyses of the landscape, respectively. These modest values reflect the rubric's multidimensional nature: the assessment criteria targets different components of writing quality and are not assumed to represent a single latent construct.

2.2.2. Think-aloud methodology

As presented earlier, to investigate students' SRL processes during task completion, we collected concurrent think-aloud protocols (TAP), a widely recognized method for capturing cognitive and motivational processes as they unfold in real time (Ericsson & Simon, 1993; Greene et al., 2018).

The study required students to read a rubric and analyze two visual landscapes first through oral analysis, and later through written production. This structure was identical for all participants, ensuring that differences in SRL behavior were not attributable to task content. The task was designed to elicit a moderate cognitive load: challenging enough to activate deliberate regulatory processes, but not so complex as to disrupt verbalization fluency. This design aligns with established recommendations in TAP methodology (Charters, 2003; Ericsson & Simon, 1993). Although unrelated to students' university curricula, the task was conceptually aligned with their secondary education in social sciences. More importantly, landscape analysis was selected because it inherently demands a combination of observational reasoning, inferential thinking, and written argumentation, which are cognitive activities that require planning, monitoring, and regulation. These characteristics make it suitable for eliciting self-regulated learning

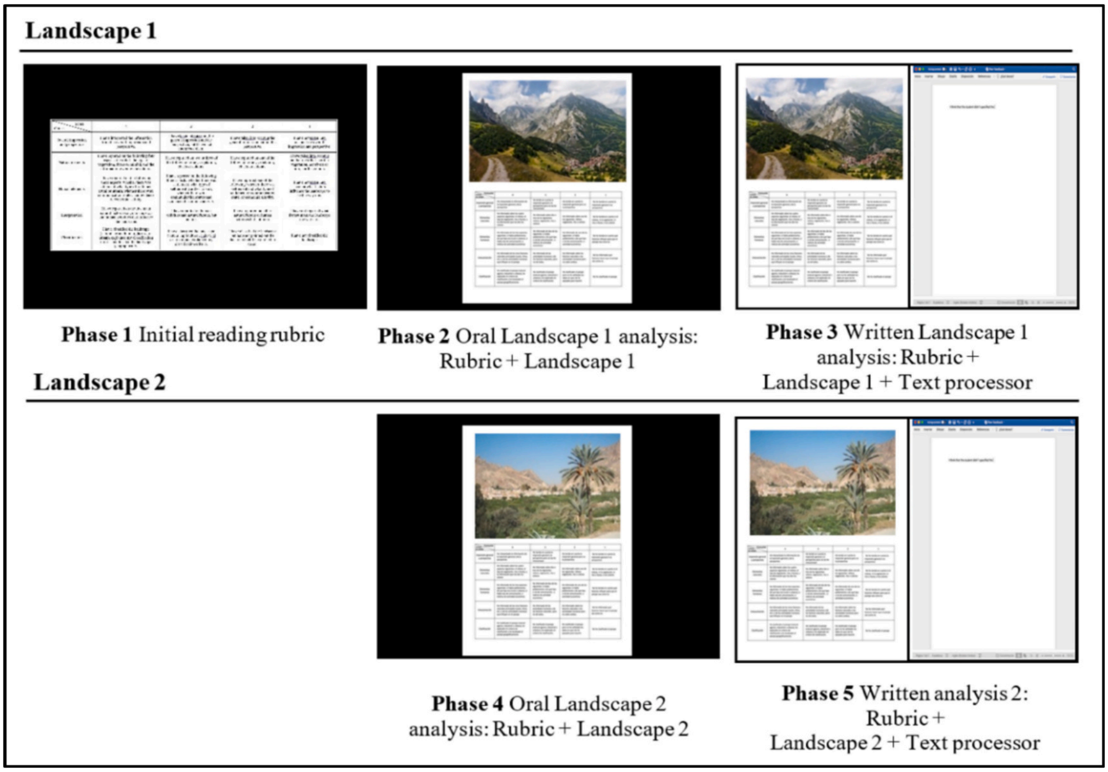

Fig. 1. Visualization of the process and materials shown to the participants.

behaviors, especially when the task is broken into phases (e.g., oral interpretation, written synthesis) and supported with rubrics and feedback. Prior work has also shown that SRL processes emerge clearly in open-ended tasks involving interpretation and justification, particularly when learners must transfer prior knowledge to a novel context.

2.2.2.1. Think-aloud level of verbalization. Before beginning the task, participants received a short standardized training in verbalization procedures, including a familiarization exercise ("describe your home as you walk through it") to practice articulating thoughts without justification or interpretation. During the task, participants were prompted to verbalize if they remained silent for 30 s, following standard TAP procedures (McDonald & Petrie, 2013).

Consistent with Ericsson and Simon's (1993) classification, our protocol was designed to elicit primarily Level 1 and Level 2 verbalizations. Level 1 verbalizations reflect direct verbal expression of thoughts already in short-term memory (e.g., reading a rubric element aloud or describing a visual feature). Level 2 verbalizations involve slight transformation of internal cognition into speech (e.g., brief explanations of decisions). We deliberately avoided eliciting Level 3 verbalizations, which require metacognitive justification and could introduce reactivity into the cognitive process.

2.2.2.2. Segmentation and unit of analysis. We defined each distinct idea expressed by participants as a unit of analysis. Distinct idea defined as a coherent expression of a single cognitive, emotional, or strategic action. In most cases, this corresponded to a complete sentence (e.g., *"Now I'm checking the last part of the rubric"*), but longer utterances could also be grouped into a single unit if they reflected a continuous and uninterrupted expression of the same idea (e.g., *"I think this landscape has more contrast because of the different climate. It makes it harder to decide how to rate it."*). In contrast, fragmented or unrelated utterances (e.g., *"This is hard… maybe I'll read again"*) were treated as separate units.

2.2.2.3. Coding and inter-judges agreement. Think-aloud data were analyzed using an open coding process (Bazeley, 2020). The first author reviewed a large portion of the think-aloud data and created initial categories for self-regulatory actions. This initial stage was guided by a specific coding approach, aimed at recognizing detailed and concrete instances of self-regulatory behaviors. For example, early categories included *planification of rubric reading* or *planification based on rubric scoring*, which reflected strategic uses of assessment tools as part of self-regulation.

Building on these initial categories, both the first and fourth author independently analyzed the transcripts of 40 participants, identifying existing categories and adding new ones when necessary. During this phase, the two authors worked closely together, maintaining constant communication to ensure consistency in their application and interpretation of the categories, as well as in identifying descriptive think-aloud protocols. As a result of this in-depth analysis, a total of 37 specific SR actions were identified and clearly defined in the final coding scheme (see Appendix C). Importantly, these self-regulatory actions were also grouped into two broader meta-categories: positive self-regulation actions and negative self-regulation actions. This distinction was based on whether a given action contributed to or hindered effective self-regulation. For instance, strategies that promoted planning, monitoring, or reflection were categorized as positive (i.e., planification of rubric reading, positive emotion). In contrast, negative self-regulatory actions represented behaviors that potentially hindered learning or demonstrated unproductive approaches (i.e., task avoidance regulation, negative emotion).

To ensure the reliability of the coding framework, the two researchers then independently coded 25 transcripts from five cases, achieving a Cohen's Kappa of 0.84, indicating almost perfect inter-rater reliability (Landis & Koch, 1977). This coding scheme was subsequently applied to the rest of the cases.

2.2.3. Individual differences measures

2.2.3.1. Prior academic performance. The students provided their

University Entry Exam results. In Spain's education system, these scores range from 7-the minimum required to enter Bachelor's programs-to 14, which is the highest possible score.

2.2.3.2. Deep Learning Strategies Questionnaire (DLSQ). The DLSQ (Panadero et al., 2021) is a 30-item self-report instrument designed to assess students' use of deep learning and self-regulation strategies in academic contexts. Items are phrased around typical learning scenarios, using a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). The instrument is structured into four first-order subscales: (1) Basic learning self-regulation strategies (e.g., "While I perform a task I check if the steps I am taking are appropriate"), (2) Visual elaboration and summarizing strategies (e.g., "I often make diagrams or drawings to represent what I study"), (3) Deep information processing strategies (e.g., "When I study I relate the material I read to what I already know"), and (4) Social learning self-regulation strategies (e.g., "I often discuss with my classmates ideas or aspects of what I have been studying"). These four subscales can be summed to obtain a second-order composite score reflecting deep learning strategy use.

The DLSQ has been validated with higher education students in Spain, showing good internal structure and external validity (Panadero et al., 2021). For the current sample, internal consistency was calculated using Cronbach's alpha resulting in a value of 0.819 for the second-order total score, indicating appropriate reliability.

2.2.3.3. Emotion and motivation self-regulation questionnaire (EMSRQ). The EMSRQ (Alonso-Tapia et al., 2014) is a 20-item self-report instrument designed to assess students' habitual ways of regulating emotion and motivation in academic settings. It includes five first-order subscales that cluster into two second-order dimensions: Learning self-regulation (which captures strategies aimed at maintaining engagement and focus on learning goals) and Avoidance self-regulation (which reflects tendencies to reduce effort or disengage in the face of negative emotions or low motivation). Participants rated their agreement with each item on a 5-point Likert scale ranging from 1 (complete disagreement) to 5 (complete agreement). Example items include: Learning self-regulation: "I try to control my thoughts so they do not distract me from the task."; Avoidance self-regulation: "If I feel incapable, I try not to think about the task anymore."

In the present study, reliability was calculated using Cronbach's alpha specifically for our sample. The Avoidance scale showed appropriate internal consistency ($\alpha = 0.818$), while the Learning scale yielded a somewhat lower reliability ($\alpha = 0.673$). Although the latter falls slightly below conventional thresholds (e.g., 0.70), it remains within an acceptable range for research involving psychological constructs (Loewenthal & Lewis, 2021). Given its theoretical relevance and prior validation (Alonso-Tapia et al., 2014), we retained the scale in our analyses but acknowledge this limitation in interpreting results based on this subscale.

2.3. Additional measures not analyzed in the present study

This study is part of a larger project. In addition to the instruments and measures reported above, we collected eye-tracking and electrodermal activity data from participants, along with self-reported individual differences through several questionnaires. As these data fall outside the scope of the present study, they are not analyzed here. Fig. 2 provides a detailed illustration of the instruments used for this paper, and Appendix D figure includes a comprehensive overview of the project.

2.4. Procedure

Participants individually attended the experimental setting with one of the authors. Before starting the procedure, each student was provided with an informed consent form outlining the study's purpose and procedures, which they were asked to sign. Afterward, students were briefed on the experimental process and received training on how to engage in the think-aloud method. Following the briefing, they completed the pre-test questionnaires. Each participant then sat in isolation, separated by a room divider, in front of a screen with a built-in eye tracker, which was calibrated individually for each participant. Once calibration was completed, the experimental procedure progressed through five phases (i.e., including different types of tasks: reading, oral analysis, and written analysis) centered around the two landscape analyses (see Fig. 2), with these phases highlighted in red.

Initially, participants were presented with a rubric and instructed to read it without any additional guidance on its use (Task type: reading - Experimental phase 1). This intentional lack of instruction was designed to observe how participants would naturally interact with the rubric. It is important to note two things. First, participants received two types of rubrics (i.e., organized from the best performance level to the lowest, and viceversa) depending on the condition there were randomly assigned to.[2]

And second, all participants had prior experience using rubrics. While reading the rubric, participants were prompted to verbalize their thoughts, emotions, and actions. After reviewing the rubric, participants were shown the same rubric alongside the first landscape (a rural area with a Continental climate) and instructed to describe the landscape aloud while continuing to verbalize their thoughts, emotions, and actions (Task type: oral analysis - Experimental phase 2). When participants indicated they were ready to write their final analysis, a text processor (Word file) was opened, displaying the rubric and landscape 1, and participants wrote their landscape analysis while continuing the think-aloud process (Task type: written analysis - Experimental phase 3).

Upon completing their written analysis, participants received oral feedback from either the second, third, or fourth author. The feedback content varied depending on the participant's randomly assigned condition: no feedback, rubric feedback, process feedback, or product feedback.[3] Feedback content was derived from a standardized document to ensure consistency within each condition, and the researcher working with each participant provided feedback tailored to their performance. After this, the eye tracker recording was stopped, concluding the first landscape analysis phase. Participants then completed a cognitive load scale, though the data from this scale are not included in the current study due to space limitations.

The analysis of the second landscape began immediately after the cognitive load scale. The eye tracker was recalibrated, and the same process was repeated with two key changes. First, the rubric was not presented alone at any point, as participants were already familiar with it. Second, a different landscape (a rural area with a Mediterranean climate) was introduced. Participants viewed the rubric alongside the

[2] These two rubric conditions (ascending vs. descending order of performance levels) were analyzed in a separate article using the same dataset (Panadero et al., under review). That study found a significant interaction between rubric type and occasion only for the negative self-regulatory actions, with no significant effects on other self-regulatory behaviors. Given that result and the specific focus of the present paper on individual-level predictors and intra-individual change, we did not include rubric type as a between-subjects factor here to avoid unnecessary complexity.

[3] Although different feedback conditions were part of the experimental design, we did not include this as a between-subjects factor in the present study. This decision was based on prior analyses using the same dataset, which examined the effects of feedback type on students' self-regulated learning behaviors as captured by think-aloud protocols. That study found no significant differences across conditions, suggesting that feedback type did not substantially influence students' SRL behaviors (see Panadero et al., under review). Therefore, we did not consider it necessary to further analyze the role of feedback conditions in this article, as doing so would unnecessarily complicate the model without adding meaningful explanatory power.

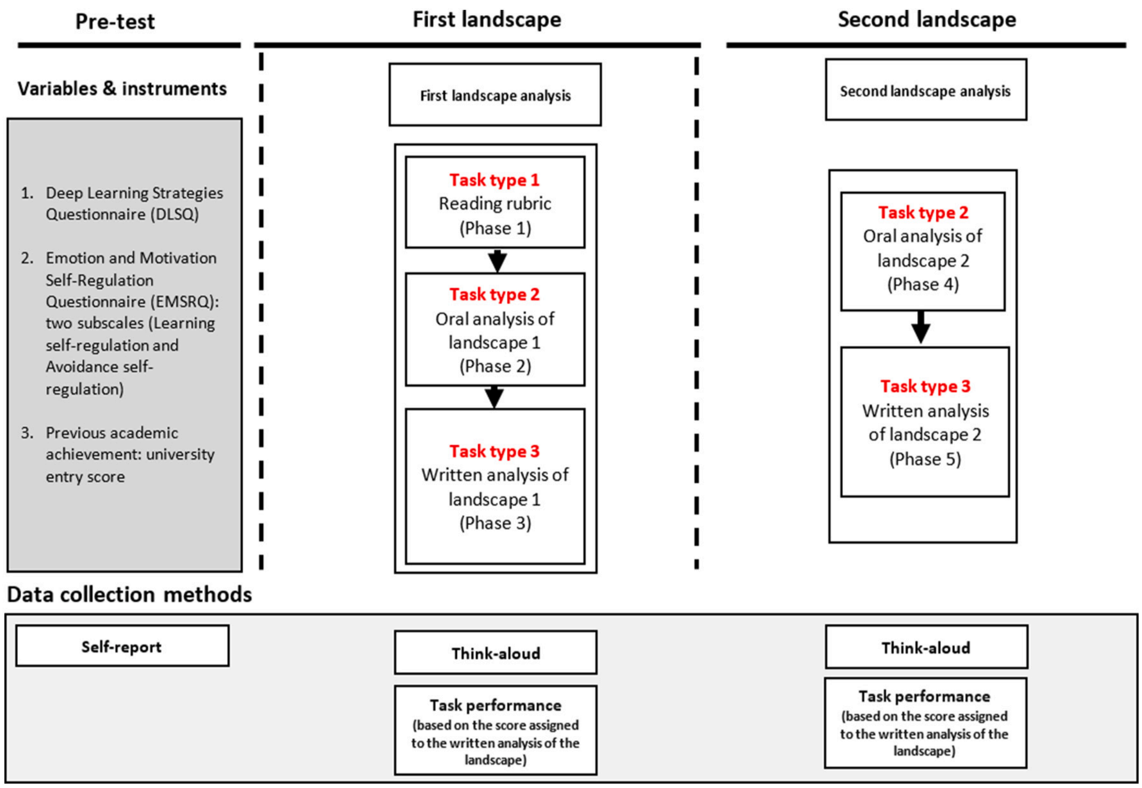

Fig. 2. A Detailed illustration of the procedure showing the information relevant for this publication.

second landscape and were once again prompted to engage in the think-aloud process (Task type: oral analysis - Experimental phase 4). When they indicated readiness to write their final analysis, a text processor (Word file) was opened, displaying the rubric and landscape 2, and participants wrote their second landscape analysis while continuing to verbalize their thoughts (Task type: written analysis - Experimental phase 5). Upon completion, participants received feedback from one of the authors based on their assigned condition. Finally, participants completed a new set of questionnaires during the post-test phase.

2.5. Data analysis

Prior to conducting the main analysis, descriptive statistics were calculated for all relevant variables. This included the means, standard deviations, and ranges for positive self-regulated learning (SRL) and negative SRL, each measured across the five distinct phases, as well as for task performance (measured twice). Descriptive statistics were also computed for the continuous predictors: prior academic achievement, DLSQ scores, EMSRQ avoidance scores, and EMSRQ learning scores.

A repeated measures General Linear Model (GLM) with covariates was conducted to examine the effects of the continuous predictors (prior academic achievement, DLSQ scores, EMSRQ avoidance scores, and EMSRQ learning scores) on the three dependent variables (DVs) across the different phases. Each DV, measured at multiple time points, was treated as a within-subjects factor, while the continuous independent variables were included as covariates in the model.

Prior to testing the model, the continuous predictors were centered on their grand mean. Centering the covariates improves the interpretability of the model by making the intercept reflect the expected value of the dependent variable when covariates are at their average. Additionally, centering reduces potential multicollinearity between covariates and interaction terms, ensuring more stable estimates in the analysis.

The analysis was carried out using SPSS Statistics 28, specifying a full factorial model to assess main effects of phase, covariates, and their interactions. *Post-hoc* comparisons with Bonferroni adjustments were applied where appropriate. Sphericity was evaluated, and when violated, the Greenhouse-Geisser correction was used to adjust degrees of freedom.

The primary focus was on identifying the main effects of each covariate, as well as their interaction with phase, to determine how these variables influenced changes in the DVs across the different phases. Estimates of effect size (partial eta squared) were reported alongside F-tests to assess the strength of relationships. Significance levels were set at $p < .05$ for all tests.

3. Results

3.1. Descriptive statistics for dependent and independent variables

The descriptive statistics of the dependent and independent variables of the study can be found in Tables 1 and 2, respectively.

Table 1
Descriptive statistics for the dependent variables, by phase.

Variable	Phase	*Min*	*Max*	*M*	*SD*
Positive SRL	1	0	28	3.7	3.8
	2	0	11	1.6	1.9
	3	0	33	4.1	5.4
	4	0	12	1.8	2.1
	5	0	16	2.7	3.1
Negative SRL	1	0	6	0.7	1.2
	2	0	5	0.2	0.8
	3	0	9	0.7	1.6
	4	0	4	0.2	0.6
	5	0	3	0.4	0.8
Task performance	1	3.0	9.3	5.6	1.2
	2	3.3	9.8	5.8	1.3

Note. $N = 120$.

Table 2
Descriptive statistics for the independent variables.

Variable	*N*	*Min*	*Max*	*M*	*SD*
DLSQ	120	70	144	112.1	11.9
EMRSQ avoidance	120	16	58	40.2	7.5
EMRSQ learning	120	28	59	46.4	5.2
Prior academic achievement	119	5	13	10.3	2.0

3.2. RQ1. To what extent do individual-level predictors and type of task explain variation in the use of positive SRL actions?

Table 3 shows the main effects of the within-subjects factor and the covariates, as well as the inter-intra interaction effects, on positive SRL.

We observed a significant effect of task phase. Post hoc comparisons showed significant differences (p < .050) between most task phase. The only non-significant differences were found between Task phase 1 (reading) and Task phase 3 (written analysis first landscape) ($p = 1.000$), Task phase 1 and Task phase 5 (written analysis second landscape) ($p = .104$), and Task phase 2 (oral analysis first landscape) and Task phase 4 (oral analysis second landscape) ($p = 1.000$). The graph of means to illustrate the main effect of task phase and these post hoc differences can be found in Fig. 3.

A significant interaction was found between DLSQ scores and task phase, suggesting that the effect of DLSQ on positive SRL varied across the tasks phases. Additionally, there was a main effect of DLSQ, where higher DLSQ scores were generally related to higher positive SRL scores across tasks phases. The parameter estimates were positive in all five tasks task phases (higher DLSQ scores were related to higher positive SRL scores) but were significant in the written analysis of the landscape 1 (Phase 3) only. In detail, the parameter estimates for each phase were as follows: Reading (Phase 1), $B = 0.066$, $p = .053$; Oral analysis landscape 1 (Phase 2), $B = 0.022$, $p = .213$; Written analysis landscape 1 (Phase 3), $B = 0.129$, $p = .006$, $\eta^2 = 0.065$; Oral analysis landscape 2 (Phase 4), $B = 0.006$, $p = .768$; Written analysis landscape 2 (Phase 5), $B = 0.050$, $p = .061$.

The analysis also revealed a significant main effect of EMSRQ learning on SRL scores across tasks phases, with negative parameter estimates in each task phase, indicating that higher EMSRQ learning scores were generally associated with lower SRL scores.

We found an interaction effect between prior academic achievement and task phase on positive SRL. The relationship between prior academic achievement and positive SRL was greater than 0 across all of task phases. However, statistical significance was only reached in the written analysis of landscape 1 (Phase 3). The parameter estimates were: Reading (Phase 1), $B = 0.090$, $p = .619$; Oral analysis landscape 1 (Phase 2), $B = 0.109$, $p = .242$; Written analysis landscape 1 (Phase 3), $B = 0.622$, $p = .012$, $\eta^2 = 0.054$; Oral analysis landscape 2 (Phase 4), $B = 0.051$, $p = .616$; Written analysis landscape 2 (Phase 5), $B = 0.183$, $p = .197$.

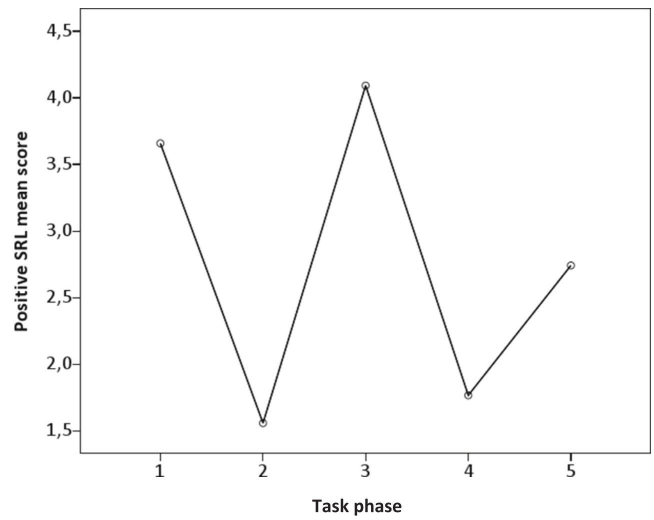

Fig. 3. Positive SRL think-aloud scores by task phase.
Note. 1: Readind the rubric; 2: Oral analysis landscape 1; 3: Written analysis landscape 1; 4: Oral analysis landscape 2; 5: Written analysis landscape 2.

Also, we observed significant a main effect for EMSRQ avoidance on positive SRL scores. The *B* parameters were positive, indicating that higher EMSRQ avoidance scores were related to higher positive SRL actions as measured via think-aloud protocols.

Taken together, these findings suggest that task phase played a relevant role in the frequency of positive self-regulated learning actions, with some task phases eliciting more of these behaviors than others. In particular, higher levels of positive SRL were observed during the written analysis of the first landscape, whereas reading and written analysis of the second landscape yielded comparable levels. Additionally, the oral analysis tasks showed lower SRL scores, especially in the second iteration. This pattern points to meaningful differences in how students engaged with each task, despite them being structurally related.

Regarding the individual-level predictors, three of the four covariates showed significant main effects: DLSQ scores, EMSRQ learning, and EMSRQ avoidance. Interestingly, while higher DLSQ scores aligned with more positive SRL actions -as expected- higher EMSRQ learning scores were associated with fewer positive SRL actions. This unexpected negative direction warrants further consideration in the discussion. Moreover, both DLSQ and prior academic achievement interacted with the task phase, suggesting that their influence was not uniform across the five activities. In summary, Hypothesis 1 is partially supported: we found the expected associations for DLSQ and prior academic achievement, a significant (but inverse) association for EMSRQ learning, and a positive association for EMSRQ avoidance that diverges from our prediction. Importantly, the hypothesis that the task phase would influence the frequency of positive SRL actions was confirmed, with task phase showing a robust main effect and modulating the impact of both DLSQ and prior achievement.

Table 3
Main and interaction effects on positive SRL measured via think-aloud protocols.

Within-subjects and interaction effects	*df*	*F*	*p*	η^2	1 - β
Task phase	2.7, 302.8	20.04	0.000	0.150	1.000
Task phase x Prior academic achievement	2.7, 302.8	3.16	0.030	0.027	0.691
Task phase x DLSQ	2.7, 302.8	3.75	0.015	0.032	0.772
Task phase x EMSRQ avoidance	2.7, 302.8	2.66	0.055	0.023	0.610
Task phase x EMSRQ learning	2.7, 302.8	0.96	0.405	0.008	0.246

Between-subject effects	*df*	*F*	*p*	η^2	1 - β
Intercept	1, 114	167.12	0.000	0.594	1.000
Prior academic achievement	1, 114	3.62	0.060	0.031	0.471
DLSQ	1, 114	6.89	0.010	0.057	0.740
EMSRQ avoidance	1, 114	4.21	0.042	0.036	0.530
EMSRQ learning	1, 114	6.25	0.014	0.052	0.698

Note. $N = 119$.

3.3. RQ2. To what extent do individual-level predictors and task phase explain variation in the use of negative SRL actions?

Table 4 shows the main effects of the within-subjects factor and the

Table 4
Main and interaction effects on negative SRL measured via think-aloud protocols.

Within-subjects and interaction effects	*df*	*F*	*p*	η^2	1 - β
Task phase	2.8, 322.6	10.51	0.000	0.084	0.998
Task phase x Prior academic achievement	2.8, 322.6	0.43	0.717	0.004	0.134
Task phase x DLSQ	2.8, 322.6	1.31	0.270	0.011	0.339
Task phase x EMSRQ avoidance	2.8, 322.6	1.61	0.189	0.014	0.409
Task phase x EMSRQ learning	2.8, 322.6	0.91	0.434	0.008	0.241

Between-subject effects	*df*	*F*	*p*	η^2	1 - β
Intercept	1, 114	43.65	0.000	0.277	1.000
Prior academic achievement	1, 114	3.77	0.055	0.032	0.487
DLSQ	1, 114	0.68	0.412	0.006	0.129
EMSRQ avoidance	1, 114	3.28	0.073	0.028	0.435
EMSRQ learning	1, 114	2.49	0.117	0.021	0.346

Note. $N = 119$.

covariates, as well as the interaction effects, on negative SRL.

In the case of negative SRL, we found a significant main effect of task phase, but no significant effects for any of the covariates or their interactions. Fig. 4 displays the mean scores of negative SRL actions across task phases. Post hoc comparisons revealed significant differences ($p <$ .050) between most task phases, with the exception of the following non-significant contrasts: Task phase 1 (reading) vs. Task phase 3 (first written analysis), $p = 1.000$; Task phase 1 vs. Task phase 5 (second written analysis), $p = .125$; Task phase 2 (first oral analysis) vs. Task phase 4 (second oral analysis), $p = 1.000$; Task phase 2 vs. Task phase 5, $p = .382$; and Task phase 3 vs. Task phase 5, $p = .069$.

Overall, the results indicate a significant effect of task phase on the frequency of negative SRL actions, as measured through think-aloud protocols. Specifically, students' engagement in maladaptive regulatory actions varied meaningfully depending on the task type. Post hoc comparisons showed that this effect was driven by a subset of pairwise differences between task phases, with non-significant contrasts primarily occurring between tasks that shared a similar structure or cognitive demand (e.g., the two oral analysis tasks, or the two written tasks).

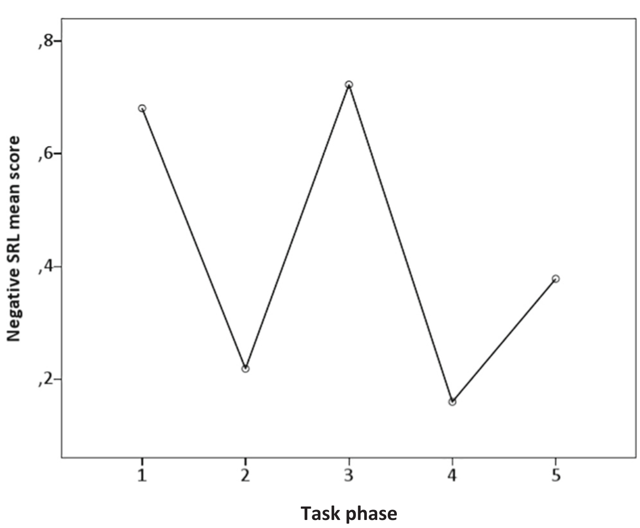

Fig. 4. Negative SRL think-aloud scores by task phase.
Note. 1: Readind the rubric; 2: Oral analysis landscape 1; 3: Written analysis landscape 1; 4: Oral analysis landscape 2; 5: Written analysis landscape 2.

In contrast, none of the individual-level predictors showed significant main or interaction effects on the use of negative SRL actions. Although some effects approached significance (e.g., prior academic achievement, $p = .055$; EMSRQ avoidance, $p = .073$), they did not reach conventional thresholds. Thus, variation in negative SRL behaviors across students appears to be more strongly shaped by task-specific features than by the baseline individual characteristics assessed in this study.

Taken together, these findings reject our second hypothesis: while we anticipated that individual-level predictors would be associated with the use of negative SRL actions, only task phases emerged as a significant factor in explaining variation. However, the hypothesis that the task phase would influence negative SRL actions was clearly supported, with task phase emerging as the only significant predictor. These findings highlight the central role of task types in shaping students' engagement in maladaptive regulatory behaviors, independently of their baseline self-regulatory profiles.

3.4. RQ3. To what extent do individual-level predictors explain variation in students' task performance?

In this analysis, the dependent variable was task performance, measured on two occasions corresponding to the participants' written analyses of Landscape 1 and Landscape 2. As both tasks involved the same type of activity (written analysis), this comparison reflects changes in performance over time rather than across qualitatively different task phases.

Table 5 presents the results of the repeated measures ANCOVA, showing the effects of the within-subjects factor (task repetition) and the between-subjects covariates.

We found a significant main effect of task repetition ($F(1, 114) = 8.26$, $p = .005$, $\eta^2 = 0.068$), indicating an overall improvement in performance from the first to the second written task. Among the covariates, both prior academic achievement ($F(1, 114) = 6.83$, $p = .010$, $\eta^2 = 0.057$) and DLSQ scores ($F(1, 114) = 5.91$, $p = .017$, $\eta^2 = 0.049$) had significant main effects. In both cases, higher scores were associated with better task performance across both occasions. No significant interactions were found between task repetition and any of the individual-level predictors.

These findings suggest that students' prior academic achievement and their self-reported SRL strategies (as measured by the DLSQ) contributed meaningfully to their written task outcomes, regardless of the order in which the tasks were completed. The improvement in scores

Table 5
Main and interaction effects on task performance.

Within-subjects and interaction effects	*df*	*F*	*p*	η^2	1 - β
Task type	1, 114	8.26	0.005	0.068	0.813
Task type x Prior academic achievement	1, 114	3.48	0.065	0.030	0.457
Task type x DLSQ	1, 114	1.97	0.163	0.017	0.285
Task type x EMSRQ avoidance	1, 114	0.39	0.536	0.003	0.094
Task type x EMSRQ learning	1, 114	0.85	0.358	0.007	0.150

Between-subject effects	*df*	*F*	*p*	η^2	1 - β
Intercept	1, 114	3173.09	0.000	0.965	1.000
Prior academic achievement	1, 114	6.83	0.010	0.057	0.736
DLSQ	1, 114	5.91	0.017	0.049	0.674
EMSRQ avoidance	1, 114	0.00	0.950	0.000	0.050
EMSRQ learning	1, 114	3.37	0.069	0.029	0.445

Note. $N = 119$.

also indicates a learning or practice effect between the two written tasks.

Hypothesis 3 was partially supported, as both prior academic achievement and DLSQ scores significantly predicted task performance, while the EMSRQ variables did not show significant effects.

3.5. Summary of main findings

Across all three RQs, our analyses revealed that both the task phases and certain individual-level predictors significantly explained variation in students' SRL and task performance. Regarding individual-level predictors, DLSQ scores and prior academic achievement emerged as robust positive predictors of both SRL behaviors and task performance. Their effects were particularly evident in the written analysis tasks, where parameter estimates were higher and most often significant. EMSRQ learning scores, contrary to expectations, showed a consistent negative relation with positive SRL actions, while EMSRQ avoidance scores showed a small but significant positive effect. This pattern suggests that the meaning of these self-reports may differ when contrasted with real-time behavioral data, possibly capturing broader motivational tendencies rather than direct behavioral regulation.

Regarding the type of task consistently influenced both positive and negative SRL actions, suggesting that students adapt their regulation strategies depending on task demands. Notably, written analysis tasks elicited higher levels of positive SRL than the other tasks across the phases, and significant differences were observed in the frequency of negative SRL actions across tasks as well.

4. Discussion

The present study aimed to examine how individual-level predictors and task characteristics jointly influence students' SRL actions, as captured through think-aloud protocols, as well as their task performance. By considering both learner traits (e.g., prior academic achievement and self-perceived SRL abilities) and the cognitive demands of different task phases, the study provides a situated account of how regulation unfolds across diverse academic activities.

A distinctive methodological feature of this work lies in its multi-method design, which combines validated questionnaires with think-aloud protocols. Rather than assuming convergence across methods, we use them to capture complementary dimensions of SRL: students' trait-like beliefs and tendencies (via questionnaires) and their enacted regulatory behaviors during tasks (via think-aloud). Furthermore, our analyses differentiate between positive and negative SRL actions, an approach that extends beyond traditional focus on adaptive strategies and offers a more nuanced view of regulation in real time.

4.1. Differentiated predictive patterns for positive and negative SRL actions across tasks (RQ1 & RQ2)

For positive SRL actions (RQ1), the results indicate a significant effect of the task, with substantial variation across the five phases and three types of tasks. This supports the notion that SRL is dynamically modulated by task characteristics and evolving cognitive demands (Donoghue & Hattie, 2021; Winne, 2018). Such within-subject variability is consistent with theoretical models that conceptualize SRL as responsive to contextual cues and task affordances (Boekaerts, 1996; Panadero, 2017). One noteworthy finding was the particularly high level of positive SRL actions during the written analysis of the first landscape (Phase 3). This task required students to synthesize multiple criteria, generate a coherent written response, and self-monitor over an extended period, conditions known to foster metacognitive activity. Its placement after rubric reading and an oral task may also have increased familiarity with assessment criteria and facilitated goal internalization. Together, these features created a demanding yet structured context that likely stimulated more frequent regulation. Future research should examine how specific cognitive demands and sequencing effects elicit regulatory engagement in complex tasks.

Importantly, two individual-level predictors, namely prior academic achievement and deep learning strategies (DLSQ), showed significant positive associations with the use of positive SRL actions. Students with higher prior academic achievement were more likely to display adaptive regulation, a finding consistent with research linking prior achievement to more effective strategy use and sustained effort during demanding tasks (e.g., Schneider & Preckel, 2017). In parallel, students reporting a stronger deep learning orientation engaged more frequently in strategic regulation, suggesting a direct translation of learning dispositions into observable behavior. This aligns with prior evidence that learners using more advanced strategies tend to organize, monitor, and reflect more actively when facing complex tasks (Dignath et al., 2020; Greene et al., 2015). Together, these results reinforce the view that both prior achievement and deep learning strategies are not only motivationally desirable but also behaviorally consequential in shaping real-time SRL engagement.

In contrast, the EMSRQ learning subscale showed a negative relationship with positive SRL actions, a result that deviates from prior literature and warrants further discussion (Alonso-Tapia et al., 2014). While learning-oriented regulation is generally considered adaptive, it is possible that in cognitively demanding or evaluative settings, high endorsement of learning motives may not translate into overt regulatory actions, or may even lead to overcontrol or anxiety that dampens observable regulation (Boekaerts & Niemivirta, 2000). This interpretation is speculative but supported by work highlighting the tensions between goal orientation and self-efficacy under pressure (Hirt et al., 2021).

The role of avoidance tendencies (EMSRQ avoidance) is also intriguing. Contrary to our expectations, higher avoidance motivation was positively related to positive SRL actions. One possible interpretation is that some students may engage in SRL strategies not out of intrinsic engagement, but as a coping mechanism to manage perceived threat or task aversion. This echoes Boekaerts' (1996) dual-processing model, in which SRL can be activated through both learning-focused and well-being-focused pathways. In this case, observed regulatory actions may mask underlying motivational disengagement, a pattern previously noted by Hertel and Karlen (2021).

Regarding negative SRL actions (RQ2), the findings revealed a main effect of task phase but no significant effects of any covariates. This suggests that maladaptive or avoidance-oriented SRL behaviors are more sensitive to situational demands than to stable individual differences. This supports the contextualized view of maladaptive SRL proposed by Ben-Eliyahu and Bernacki (2015), who argue that negative SRL may arise from momentary appraisals of difficulty or control, rather than from dispositional traits alone. Our results are also consistent with findings from observational studies showing that task complexity and stressors -not general SRL tendencies- trigger disengagement behaviors such as skipping steps, surface processing, or premature closure (Kim et al., 2023; Wolters et al., 2011).

Importantly, none of the self-reported SRL measures significantly predicted negative SRL actions. This underscores the potential dissociation between declared and enacted regulation (Winne, 2010), particularly in the case of avoidance or stress-related responses. While students may acknowledge a tendency to avoid challenges in abstract terms, these beliefs do not necessarily predict how they behave during real-time task execution. This finding highlights the value of think-aloud protocols in capturing subtle forms of disengagement that may remain invisible in questionnaire data (Panadero et al., 2025).

The observed effects were small to medium in size ($\eta^2 = 0.068$–0.084; Cohen, 1988), which is meaningful given the complexity of SRL and the fine-grained nature of think-aloud data. However, these estimates should be interpreted cautiously, as task-specific features such as the dual demand of articulating outcomes and processes during oral analysis may have reduced the frequency of observed SRL actions. This highlights both the contextual sensitivity of SRL and the methodological constraints of think-aloud protocols (Donoghue & Hattie, 2021; Winne, 2018).

Taken together, the results of RQ1 and RQ2 support a differentiated view of SRL as a multi-faceted process influenced by both individual-level factors and task conditions. Whereas positive SRL seems to reflect both interindividual differences and within-subject adaptation, negative SRL appears to be primarily shaped by the situational characteristics of the task. This distinction has important implications for research and practice, suggesting that interventions aimed at enhancing SRL should distinguish between fostering adaptive strategies and mitigating context-induced maladaptive behaviors.

4.2. Task performance predicted by prior achievement and deep learning strategies (RQ3)

Our findings for RQ3 indicate that prior academic achievement and self-reported use of deep learning strategies (DLSQ) significantly predicted students' task performance across phases. These results support the idea that stable individual level factors play an important role in shaping learners' ability to succeed in cognitively demanding academic tasks. The positive association between prior academic achievement and task performance aligns with earlier findings showing that learners with stronger academic histories are more likely to engage in effective strategy use and to sustain their effort throughout a task (Donoghue & Hattie, 2021; Efklides, 2011; Zhu & Mok, 2018).

Similarly, the positive predictive effect of deep learning strategies reinforces the relevance of students' general approach to learning in determining performance outcomes. Students who report greater use of deep learning strategies tend to engage with content more elaboratively, organize their thinking, and apply metacognitive strategies, all of which likely contributed to better task performance in the writing activities analyzed in this study (Greene et al., 2015; Panadero, 2017). It is also notable that these individual differences predicted performance regardless of task phase, as indicated by the non-significant interaction effects. This stability suggests that these predictors function as general enablers of performance, offering students a consistent advantage across similar task phases.

In contrast, no significant effects were found for the two EMSRQ subscales: neither learning-oriented regulation nor avoidance-oriented regulation predicted task performance. This suggests that, while motivational and emotional self-regulation beliefs may explain students' strategy use (as shown in RQ1), they are less directly linked to performance outcomes in tasks requiring sustained written production. Recent studies similarly indicate that motivational regulation often plays an indirect role, shaping engagement with tasks rather than predicting outcomes directly (Dignath et al., 2020; Winne, 2018). These results therefore partially support H3: task performance was predicted by prior academic achievement and deep learning strategies, but not by motivational or avoidance regulation. This does not mean that motivational regulation is irrelevant; rather, its influence may be more indirect, more context-dependent, or less well captured by self-report measures. Caution is warranted in interpreting these null effects, particularly given the known limitations of self-reports for assessing dynamic processes (Dignath & Veenman, 2021; Winne, 2010).

In terms of magnitude, the effects observed for individual predictors of task performance also fell within the small to medium range. The partial eta squared values for prior academic achievement ($\eta^2 = 0.057$) and deep learning strategies ($\eta^2 = 0.049$) indicate modest but meaningful effects (Cohen, 1988). This suggests that while these variables contribute to explaining variation in students' performance, a large portion of variance remains influenced by other factors, including task-specific or situational elements not captured in our model. These findings are aligned with the broader literature on academic achievement, where individual differences typically account for part -but not the majority- of the variability in performance (Dignath et al., 2020; Zhu & Mok, 2018). Therefore, even small-to-medium effects are relevant in educational contexts where performance is shaped by multiple interacting influences.

4.3. Methodological implications: capturing SRL as a context-sensitive, multi-method construct

This study offers several methodological contributions to the assessment of self-regulated learning (SRL). First, by integrating validated questionnaires with think-aloud protocols (TAP), we contrasted students' stated beliefs with their enacted behaviors, showing the value of triangulating static and dynamic indicators to capture the multidimensional nature of SRL (Boekaerts & Corno, 2005; Panadero, 2023). The observed dissociation between self-reported skills and negative behaviors further cautions against relying exclusively on questionnaires to assess SRL in specific tasks or contexts. While questionnaires are valuable for capturing learners' general dispositions and beliefs, process-oriented measures such as think-aloud protocols are essential to observe how regulation unfolds in real time (Dignath & Veenman, 2021; Winne, 2010). Second, our design accounted for within-person variability across three task types and five task phases. The main effects of task phase on both positive and negative SRL demonstrate that regulatory actions are dynamically modulated by cognitive and structural task demands (Li et al., 2022; Winne, 2018), underscoring the need for repeated-measures designs rather than single-task approaches.

Third, we explicitly coded maladaptive behaviors such as avoidance or superficial engagement, which are often overlooked in SRL research. Including these negative forms of regulation revealed patterns independent of positive strategies or self-perceptions (Alonso-Tapia et al., 2014; Kim et al., 2023), contributing to a more ecologically valid model of SRL.

Taken together, these contributions highlight the importance of multi-method, context-sensitive designs that recognize both adaptive and maladaptive regulation. Such approaches are essential for advancing theory and for developing interventions that target the full range of learners' regulatory behaviors.

4.4. Limitations

This study has several limitations that should be considered when interpreting the findings. First, while the inclusion of interaction terms between predictors and task phases adds interpretive depth, the study may have lacked statistical power to detect smaller interaction effects. Some predictors showed effects in the expected direction but did not reach statistical significance, which suggests that larger sample sizes may be needed to fully capture the variability in these processes.

Second, although combining self-report questionnaires and think-aloud protocols strengthens methodological triangulation, these measures differ in their level of abstraction and temporal proximity to task performance. As such, the modest alignment between perceived and enacted SRL may reflect the inherent gap between trait-like beliefs and context-sensitive behaviors.

Third, the three tasks included in the study were all situated within an academic domain requiring analytical processing, which limits the generalizability of findings to tasks with different cognitive demands (e.g., creative or procedural tasks). Future work should examine whether similar SRL patterns emerge across more diverse disciplinary or instructional contexts.

Fourth, the use of think-aloud protocols, while well established, carries the risk of reactivity. Verbalizing thoughts during task performance may have affected participants' natural engagement, particularly in more demanding phases, potentially altering the frequency or nature of SRL behaviors.

Fifth, the reliability of the EMSRQ avoidance subscale yielded a Cronbach's alpha below the conventional 0.700 threshold. Although this scale has been validated in previous studies and measures a narrow construct with few items, the relatively low internal consistency may have reduced the precision of the scores and weakened potential associations with observed SRL behaviors.

Sixth, our analysis relied on frequency counts of SRL actions coded from think-aloud protocols, a common approach that facilitates interpretability and alignment with prior studies (e.g., Greene et al., 2018; Panadero, 2023; Panadero et al., 2025). However, this method does not capture the temporal dynamics or sequencing of regulatory behavior. More nuanced analytic techniques -such as those based on process mining or dynamic modeling- could reveal patterns and transitions in SRL that go beyond aggregate frequencies (Bernacki, 2018). We acknowledge this limitation and see it as a promising direction for future research. In particular, recent work by Bernacki (2025) illustrates how learning analytics grounded in SRL theory can yield richer insights from process data. Reanalyzing the current dataset using such approaches could further enhance our understanding of the regulatory trajectories activated across tasks.

Finally, despite the use of a structured coding scheme and inter-rater reliability procedures, the analysis of verbal data necessarily involves interpretive judgment. This affects replicability and may pose challenges for scaling the method to larger datasets or automated analysis frameworks. At the same time, acknowledging these interpretive elements highlights the value of methodological transparency and points to the need for continued innovation in SRL process analysis.

5. Conclusion

This study advances current understandings of SRL by demonstrating how individual-level and task characteristics jointly shape students' regulatory behaviors and task performance. Through the combined use of self-report instruments and think-aloud protocols, we have shown that both positive and negative SRL actions vary not only across learners but also within individuals depending on the cognitive nature of the task. By adopting a longitudinal, repeated-measures design, the study also captures intraindividual variability across multiple task phases, addressing a key gap in the field. Our results underscore the importance of modeling SRL as a situated and multidimensional process, one that cannot be fully captured through self-perceptions alone. Moreover, the findings highlight the predictive relevance of prior academic achievement and learning strategies, while also revealing the contextual and less trait-dependent nature of maladaptive regulation. As the field continues to seek more authentic and granular approaches to SRL assessment, this study contributes empirical evidence and methodological insights that can support the development of responsive pedagogical interventions and more valid tools for capturing regulation in action.

CRediT authorship contribution statement

Ernesto Panadero: Writing – original draft, Project administration, Funding acquisition, Conceptualization. **Alazne Fernández-Ortube:** Writing – review & editing, Methodology, Data curation, Conceptualization. **David Zamorano:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Leire Pinedo:** Writing – review & editing, Methodology, Data curation, Conceptualization. **Iván Sánchez-Iglesias:** Methodology. **Lucía Barrenetxea-Mínguez:** Writing – review & editing.

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Declaration of competing interest

The authors declare to not having any conflict of interest regarding this manuscript. This research has been approved by the ethics committee from Comité de ética de la investigación, Universidad de Deusto. Reference: ETK-5/21-22. PI: Ernesto Panadero.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.lindif.2025.102808.

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