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Fostering self-regulated learning through adaptive learning technology: A differentiated perspective on the role of feedback

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ABSTRACT

Background: Adaptive learning technology (ALT) has the potential to foster self-regulated learning (SRL) by providing personalized feedback. However, limited research has examined how differentiated feedback types—directive, informative, and transformative—delivered through ALT and taken up by learners relate to SRL components across its phases.
Aims: This study investigates the effects of differentiated feedback on SRL during pre-actional, actional, and post-actional phases. It examines how engagement with adaptive feedback moderates relationships among (meta-)cognitive, motivational, emotional, and behavioral aspects across these phases.
Sample and method: The study was conducted with 194 students enrolled in a stochastics course who used an ALT to work on course content and access personalized feedback opportunities over eight weeks. Data were collected through self-report measures and trace data and analyzed using hierarchical linear modeling to assess within- and between-subject effects across SRL phases.
Results: Findings revealed that task value, self-efficacy, goal orientation, and positive emotions in the pre-actional phase positively influenced regulatory behavior in the actional phase, while negative emotions hindered it. Post-actional satisfaction was positively associated with motivation, metacognitive activity, and positive emotions in the subsequent pre-actional phase. However, adaptive feedback's moderating effects were limited and, in some cases, negatively affected regulatory outcomes, suggesting that transformative feedback may contribute to cognitive overload.
Conclusion: This study highlights the importance of designing feedback through educational technology. While ALT feedback can promote SRL, its effectiveness is context-dependent, requiring tailoring to learners' needs. Future research should examine how to optimize feedback design and address individual differences in SRL development.

1. Introduction

The integration of digital technologies into education has grown significantly over the past 30 years (Morel & Spector, 2022). In the field of self-regulated learning (SRL), these advances have transformed the way SRL processes are collected, analyzed, and facilitated (Azevedo & Gašević, 2019; Järvelä & Bannert, 2021). The COVID-19 pandemic further accelerated the adoption of educational technologies, linking them more closely to SRL research (Winne, 2022; Ye & Pennisi, 2022). Because of this rapid development, further research is needed to understand how educational technologies, particularly adaptive learning technologies (ALT), can provide personalized and timely support for SRL (Broadbent & Poon, 2015; Tsai et al., 2020).

This study investigates the role of feedback through ALT in different phases of SRL, exploring variations in feedback forms. To this end, we implemented an ALT over eight weeks in a university course to investigate how students' SRL processes unfold across the different phases of SRL and how the feedback provided by the ALT is associated with these processes.

1.1. The dynamic and cyclical nature of self-regulated learning

Theoretical models have illustrated the multifaceted, dynamic process of SRL (Panadero, 2017). While these models emphasize different

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aspects of SRL, they agree on the central role learners play in purposefully guiding and controlling their learning processes (Boekaerts, 1996; Pintrich, 2004; Winne & Hadwin, 1998; Zimmerman, 2008).

Zimmerman's (2000) social-cognitive model outlines SRL as a cyclical process with three phases: forethought, performance, and self-reflection. In the forethought phase, learners analyze tasks, set goals, and plan strategies based on motivational beliefs. During the performance phase, they execute tasks, monitor progress, and employ self-monitoring strategies. The self-reflection phase involves evaluating outcomes and adjusting future actions. Feedback loops connect these phases, facilitating adaptations to environmental changes, learning outcomes, as well as internal thoughts and feelings (Zimmerman, 2008). This paper adopts the self-regulation process model (Schmitz, 2001; Schmitz & Wiese, 2006), which builds on Zimmerman's framework by dividing SRL into pre-actional, actional, and post-actional phases. These correspond to Zimmerman's phases, emphasizing the application of SRL strategies during each stage (Schmitz, 2001).

In the pre-actional phase, motivation plays a pivotal role, comprising three key components: task value, goal setting, and self-efficacy (Martin et al., 2015). Task value has been shown to positively influence learners' effort levels, regardless of the learning context, content, or individual learner characteristics (Dietrich et al., 2017). Similarly, goal setting is critical in this phase. When learners autonomously set goals for upcoming tasks, they are more likely to engage in metacognitive activities, as evidenced by several empirical studies (Pintrich, 2004; Sitzmann & Ely, 2011). The third component, self-efficacy, is essential for planning and executing SRL strategies. Research indicates that students with higher self-efficacy are more likely to effectively employ these strategies (Schunk & DiBenedetto, 2016). Conversely, underachieving students often exhibit significantly lower self-efficacy, which leads to reduced use of SRL strategies, as highlighted in a review by Fong and colleagues (2023). While motivational factors are crucial in the pre-actional phase, emotional states also exert a significant influence on subsequent phases (Boekaerts, 2011). In their meta-analysis, Zheng et al. (2023) revealed that enjoyment and pride are positively correlated with the use of metacognitive strategies, while indicating that anxiety and frustration have primarily negative impacts on metacognitive activity.

In the actional phase, learners engage in regulatory behavior by implementing and adjusting their cognitive, metacognitive, affective, and resource-management strategies while working on the learning task (Schmitz & Wiese, 2006). The effective use of such strategies supports productive task engagement (Winne & Hadwin, 1998; Zare et al., 2024) and is positively associated with academic achievement (Xu et al., 2023). Learners may, for instance, apply resource-management strategies to maintain focus in the presence of potential distractions (Deng et al., 2024; Pintrich, 1999). Moreover, the adaptive adjustment of strategies during task engagement is a central mechanism of effective SRL (Molenaar et al., 2021; Raković et al., 2022).

The post-actional phase involves reflection and evaluation, where learners compare their set goals with their actual achievements and assess how satisfied they are with their learning and its outcomes. Effective SRL requires adjusting or maintaining strategies based on these outcomes (Schmitz, 2001). Liborius et al. (2019) explored the role of satisfaction during SRL among university students and found that satisfaction is not only a significant predictor of time investment but is also strongly linked to other SRL components, such as planning, effort, and procrastination. Additionally, satisfaction or dissatisfaction is closely tied to emotions, emphasizing their critical role in metacognitive regulation (Boekaerts, 1997; Pekrun et al., 2002; Zheng et al., 2023).

1.2. Improving self-regulated learning through adaptive feedback and technology

Feedback is a process through which learners collect information from various sources (e.g., teachers) and adjust their learning behaviors accordingly (Boud & Molloy, 2013). In models of SRL, feedback is considered integral to the SRL process. Effective SRL requires learners to use internal feedback loops to continuously monitor and control their learning, adapting strategies for future learning sessions (Butler & Winne, 1995; Panadero, 2017; Theobald et al., 2023).

However, research indicates that many higher education students struggle to implement such internal feedback loops effectively. For example, students may face challenges in monitoring their learning progress (Miller & Geraci, 2011) or in selecting and applying appropriate SRL strategies for specific situations (Foerst et al., 2017). As a result, externally provided feedback has been identified as a valuable tool to support SRL (Butler & Winne, 1995; Theobald & Bellhäuser, 2022). High-information feedback, which addresses task, process, and self-regulation levels, has proven particularly effective in enhancing student learning (Wisniewski et al., 2020). This form of feedback helps students identify not only the mistakes they made but also the underlying reasons for these errors and strategies to avoid them in the future.

Effective feedback can be classified into three categories (Hattie & Timperley, 2007): feed-up, which provides information about learning goals; feed-back, which evaluates progress toward those goals; and feed-forward, which offers guidance on adjustments to improve future performance. Expanding on this framework, Theobald and Bellhäuser (2022) examined the effects of three feedback types on SRL: (1) directive feedback, emphasizing feed-forward; (2) informative feedback, focusing on feed-back; and (3) transformative feedback, combining feed-back and feed-forward. The authors hypothesized that transformative feedback would be the most effective; however, all three types were shown to positively impact SRL. Directive feedback reduced procrastination and improved self-monitoring, time management, and goal achievement. Informative and transformative feedback enhanced planning strategies, self-control, and concentration.

From a process perspective, these feedback functions introduced by Theobald and Bellhäuser (2022) can be linked to different points in the SRL cycle. Informative feedback primarily provides information about goal progress and can therefore support monitoring and calibration processes during reflection, which may subsequently inform planning and affective adjustment for the next learning episode. Directive feedback emphasizes strategy suggestions and may be particularly relevant when learners struggle to select or implement suitable strategies, thereby supporting the translation of forethought into regulatory behavior during task engagement. Transformative feedback combines both elements and may therefore be especially relevant for connecting post-actional reflection to subsequent forethought. Because SRL is cyclical, these alignments are not meant to imply that particular feedback types are only useful in one phase. Rather, they describe where the respective feedback function may be especially salient given typical regulatory demands.

Despite the enduring significance of comprehensive and tailored feedback, its practical integration into educational settings faces persistent challenges. Instructors often lack the time and resources to provide individualized feedback, leading to inaccurate or insufficient guidance on applying and modifying SRL strategies (Pardo et al., 2019; Tempelaar, 2020). For feedback to be meaningful and actionable—allowing learners to actively adapt their learning behaviors (Lim et al., 2020)—the traditional "one-size-fits-all approach" is inadequate (Khalil et al., 2024, p. 1281).

A promising solution lies in the adoption of adaptive learning technology (ALT) to facilitate personalized and timely feedback processes (Xie et al., 2019). ALT refers to digital learning environments that continuously analyze learner data to interactively support learning processes in a personalized and tailored manner (Aleven et al., 2017). By triggering iterative cycles of self-monitoring, performance, and assessment, ALT can provide feedback to both learners and instructors, aiding in the evaluation and adjustment of learning processes (Schmid et al., 2022). For example, rather than delivering generic feedback to all learners, ALT can identify specific areas (e.g., planning, self-reflection) and phases in the SRL process (e.g., pre-actional, post-actional) where a learner requires support, delivering feedback tailored to these needs (Edisherashvili et al., 2022). ALT has shown substantial potential in promoting SRL (Aleven et al., 2017; Khalil et al., 2024; Molenaar & Van Campen, 2016), contributing positively to students' adaptation of learning behaviors (Molenaar et al., 2021) as well as their academic performance and motivation (Faber et al., 2017).

However, despite these advances, there remains a gap in understanding how differentiated feedback (i.e., directive, informative, and transformative feedback) through ALT influences components of the SRL process across its different phases. While numerous studies have explored the relationships between SRL and academic performance (e.g., Cheng et al., 2025), as well as between feedback and academic performance (e.g., Wisniewski et al., 2020), it remains unclear how metacognitive, motivational, and emotional aspects of SRL evolve over time and how they interact with different types of adaptive feedback in an ALT.

2. The present study

Understanding how SRL components evolve and interact across phases of the SRL process is critical to interpret learning processes and design meaningful learning experiences that are tailored to the learners' needs. Specifically, questions arise about how SRL components change and influence one another during each phase of the SRL process (Mejeh et al., 2024; Liborius et al., 2019; Loeffler et al., 2019), and how adaptive feedback may influence the individual components of the SRL process (Theobald & Bellhäuser, 2022; Theobald et al., 2023).

This study aims to address two key objectives: first, to examine how the effects of feedback on the SRL process vary depending on the type of feedback provided (Theobald & Bellhäuser, 2022); and second, to connect learners' self-reported SRL processes with trace data on their use of adaptive feedback, thereby examining how different feedback types influence SRL dynamics across phases. In doing so, we respond to ongoing calls to examine SRL using multiple, complementary data sources, thereby enabling more validated and sustainable insights for its promotion and development (Azevedo & Gašević, 2019; Järvelä & Hadwin, 2024; Matcha et al., 2019). Importantly, in our setting, self-report appraisals did not only capture SRL development but also determined which feedback became available. By linking phase-specific SRL appraisals with trace-based indicators of feedback uptake, this integration enables us to move beyond examining whether feedback relates to SRL. In doing so, we examine when, and under which phase- and state-dependent conditions, different feedback functions are associated with strengthened or weakened SRL dynamics. This provides a basis for theorizing feedback as a phase-sensitive mechanism within SRL cycles, rather than as a uniform external input.

Building on these objectives, we extend prior research by operationalizing different forms of feedback as trace indicators of feedback use and examining their differentiated impacts on the SRL process, emphasizing the importance of combining self-reports and log data for a comprehensive understanding of students' SRL (Theobald et al., 2023). Grounded in the self-regulation process model of learning (Schmitz & Wiese, 2006), this study employs an ALT to integrate self-reports with trace data, offering a more nuanced understanding of SRL development. By combining these approaches, we aim to explore the following research questions and corresponding hypotheses:

RQ1: How are the components of the pre-actional, actional, and post-actional phases of SRL interrelated?
RQ2: How does engagement with different forms of feedback (directive, informative, and transformative) through an ALT relate to learners' SRL processes across these phases?

Because SRL unfolds across phases, we do not assume that feedback functions exert uniform effects across the cycle. Instead, we examine whether associations among SRL components are contingent on the timing of students' engagement with directive, informative, or transformative feedback. Accordingly, we focus on phase-to-phase relations and on the extent to which these relations differ as a function of feedback engagement. Based on these research questions, we formulate the following hypotheses:

1. H1: In the pre-actional phase, learners' metacognitive activity, motivation, and positive emotions are positively related to regulatory behavior during the subsequent actional phase, whereas negative emotions are negatively related to regulatory behavior.
2. H2: These relationships between the pre-actional phase and actional phase are moderated by engagement with adaptive feedback, such that adaptive feedback strengthens positive relationships and attenuates negative relationships.
3. H3: In the post-actional phase, satisfaction is positively related to metacognitive activity, motivation, and positive emotions, and negatively related to negative emotions in the subsequent pre-actional phase.
4. H4: These relationships in the post-actional phase are also moderated by engagement with adaptive feedback, with adaptive feedback enhancing positive relationships and mitigating negative ones.

The hypotheses are visualized in Fig. 1.

3. Method

3.1. Participants

The sample consisted of 194 students ($M = 23.5$ years, $SD = 5.6$) from a German university, including both graduate and undergraduate pre-service teachers enrolled in a stochastics course. Among the participants, 144 were female (74.2%), 46 were male (23.7%), and 4 (2.1%) did not specify their gender. Ethics approval for the study was granted by the first author's university (Approval number: 2023-03-03). All participants were informed about the study's purpose and provided their informed consent.

3.2. Context

The course lasted 12 weeks, during which students were required to complete and submit at least six out of eight weekly online homework assignments. To facilitate this process, the ALT "studybuddy was implemented as a digital learning environment through which students accessed the weekly homework assignments and engaged with its SRL-support features. A video demonstration of studybuddy is provided in the appendix (Appendix A). studybuddy comprises four components aiming to assist students' SRL: an automated feedback system, a digital dashboard, personalized SRL strategies, and a planning tool (for a comprehensive description, see Mejeh et al., 2024). In the present study, we focus specifically on two of these components: the personalized SRL strategy recommendations and the digital dashboard. At the beginning of the course, students were introduced to the ALT and its main functions, including the personalized SRL strategies and the dashboard, and were encouraged to use these features to monitor and adapt their learning over the semester.

The eight homework assignments were delivered over a period of eight weeks and followed a consistent format. Each week, studybuddy notified students of new homework assignments available for completion. Studybuddy provided personalized support for SRL based on students' answers in brief pre- and post-task surveys. Before and after each weekly homework assignment, studybuddy prompted students to complete single-item measures assessing their motivation, emotions, and metacognitive activity. In this way, students' weekly homework completion process was divided into a pre-actional, an actional, and a post-actional phase, according to Schmitz and Wiese (2006). Upon

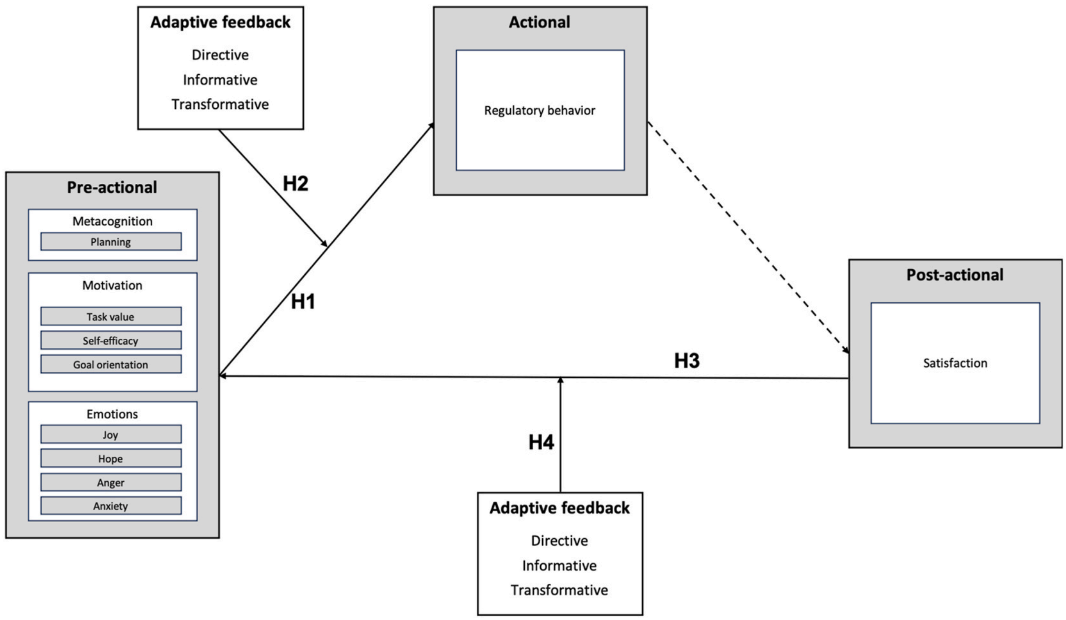

Fig. 1. Research hypotheses.

accessing the homework, learners entered the pre-actional phase, where they reviewed task instructions. At this stage, studybuddy prompted them to reflect on their motivational and emotional states, as well as their metacognitive activity, in relation to the task (see Section 3.3.2). Next, students proceeded to the actional phase, where they worked on their homework. Upon completing the task, they entered the post-actional phase, during which they were prompted to reflect on their cognitive and metacognitive activities, as well as their emotional and motivational states related to the completed assignment (see Section 3.3.2). Based on students' responses in these pre- and post-task surveys, studybuddy identified areas in which SRL support might be helpful (e.g., low task value) and provided support in the form of personalized SRL strategies and the dashboard. Thus, the system adapted the availability of strategy prompts based on self-report thresholds, while engagement with these prompts remained voluntary.

3.2.1. *Personalized SRL strategies*

Studybuddy provided SRL strategy videos offering concrete suggestions for adjusting learners' learning behavior. Fig. 2 (upper panel) presents an example strategy recommendation. If a student's response in the pre- or post-task survey fell below a specific threshold, the tool automatically recommended an appropriate SRL strategy. For instance, when assessing task value, learners were asked, "Do you believe that understanding today's task is important and useful?" If a student selected one of the four lowest values ("Partly True," "Somewhat Not True," "Mostly Not True," or "Not True") on the 7-point Likert scale, studybuddy suggested a relevant SRL strategy as a short video, which students could choose to view. An overview of all SRL strategies of studybuddy is presented in Appendix B.

3.2.2. *Dashboard*

The dashboard visualized learners' responses over time through individualized progress curves, enabling them to reflect on patterns in their metacognitive activity as well as their motivational and emotional states. Fig. 2 (lower panel) represents an example dashboard view. In the present study, the dashboard compiled learners' weekly responses from the short surveys, calculated average values for each variable, and presented them as individualized time-series graphs for each SRL component (e.g., self-efficacy, anxiety). These visualizations allowed learners to observe trends across weeks – such as decreases in motivation or increases in negative emotions – that could prompt them to reconsider and adapt their learning behavior. Because the dashboard did not provide prescriptive feedback, it functioned as an indirect informational feedback source by encouraging learners to interpret their SRL patterns, reflect on possible causes, and make autonomous adjustments to their learning behavior. Learners could access the dashboard at any time during the course and use it to support planning of upcoming tasks or reflection on completed ones.

3.3. *Measurement instruments*

3.3.1. *Feedback*

Students' interactions with the strategy videos and dashboard were recorded weekly. Their engagement with the videos was considered directive feedback, whereas engagement with the dashboard was considered informative feedback. If students engaged with both the videos and the dashboard, this was considered transformative feedback. For the pre-actional and post-actional phases of each week, four different dummy variables for feedback were created:

- Directive feedback: 1 = the student interacted at least once with the prompted video(s) but not with the dashboard, 0 = the student was not prompted with a video or did not interact with the prompted video(s).
- Informative feedback: 1 = the student interacted at least once with the dashboard but not with the video(s) (if the student was prompted with a video), 0 = the student did not interact with the dashboard.
- Transformative feedback: 1 = the student interacted at least once with the prompted video(s) and at least once with the dashboard, 0 = the student did not interact with either the prompted video(s) or the dashboard, or with only one of the two.
- No feedback: 1 = the student did not interact with either the prompted video(s) or the dashboard, 0 = the student interacted at least once with either the prompted video(s) or the dashboard.

The ALT's log files served as trace data, capturing whether students accessed the strategy videos and/or the dashboard at least once in a given week. We operationalized these interactions as weekly dummy-coded indicators of the four feedback variants (directive, informative, transformative, and no feedback) described above. These indicators

Fig. 2. Example strategy recommendation and dashboard views from studybuddy

Note. The upper panel shows a personalized SRL strategy recommendation, presented as a short video when a learner's response on a pre- or post-task self-report fell below a predefined threshold. The lower panel shows the dashboard with individualized progress curves for motivational, emotional, and metacognitive dimensions.

therefore captured whether a learner engaged with a given feedback affordance at least once during the week, but not the frequency, intensity, or depth of processing. The category "no feedback" indicates that no interaction with any available feedback option was recorded in the log files during that week. Accordingly, we interpret these indicators as proxies for feedback uptake rather than as direct measures of feedback received.

3.3.2. *Self-report questionnaires*

In this study, a time unit consisted of one week, during which students were free to decide when and how to work on the assigned tasks. The variables of interest were measured using single items. For efficiency, single items that best represented their respective overall scales were selected based on the criteria of face validity and convergent validity (Allen et al., 2022; Martin et al., 2015; Schmitz & Wiese, 2006). The reliability of each measurement item was assessed by calculating separate means for odd- and even-numbered weeks (split-half reliability) and correlating these means across participants (Liborius et al., 2019). Process measurements were conducted at the beginning of the pre-actional phase and at the end of the post-actional phase. An overview of all items used for the pre- and post-actional measures including the reliability measures, is provided in Appendix C.

In the pre-actional phase, metacognitive activity was assessed through measures of goal setting and planned strategy use (Schmitz & Wiese, 2006). Task value, self-efficacy, and goal orientation were evaluated using the Motivation and Engagement Scale (MES; Martin et al., 2015). The positive emotions "joy" and "hope" as well as the negative emotions "anger" and "anxiety" were measured using the Achievement Emotions Questionnaire (AEQ-S; Bieleke et al., 2021). In the actional phase, we measured regulatory behavior by asking learners to reflect on the extent to which they adapted their regulatory strategies. This was done using an item from the short version of the Learning Strategies of University Students (LIST-KS; Klingsieck, 2018). In the post-actional phase, we assessed satisfaction with one's learning using a validated single-item measure (Schmitz & Wiese, 2006).

To clarify how the various instruments and data types relate to the study's objectives and research questions, Table 1 provides an overview of the data sources, measures, and operationalized variables included in the analyses.

3.4. *Data analyses*

To assess the progression of various components of SRL, we employed hierarchical linear modeling (HLM). This method accommodates multiple observations per individual, varying numbers of observations across participants, and non-equidistant measurement intervals. Additionally, HLM provides model estimates for missing data and enables the differentiation between within-subject and between-subject effects (Snijders & Bosker, 2011).

In this study, a sample size of $n = 194$ students corresponded to 194 upper-level units in a multilevel design, which is comparable to those used in previous multilevel SRL studies (e.g., Liborius et al., 2019; Loeffler et al., 2019; Theobald et al., 2023). To test our hypotheses, we used two-sided tests and set significance levels at $\alpha = .05$ for all analyses.

All linear mixed-effects models were run using the nlme package (v3.1.164; Pinheiro et al., 2023). Missing data were handled using maximum likelihood estimation, which is superior to other methods (e.g., mean imputation) for accurately estimating missing values in longitudinal research (Velicer & Colby, 2005). The percentage of missing values on the dependent variables ranged from 0.67% to 1.13%, arising from voluntary non-participation and absences due to illness during the survey period. The data and analytical code supporting the findings of this study are available from the corresponding author upon reasonable request. The supplementary materials for this study, including appendices, can be accessed via OSF (Mejeh & Fromm, 2025).

4. Results

To explore the development and relationships among the variables, we fitted three hierarchical linear models. The baseline model (Model 1) included only the intercept. The random intercept model (Model 2) allowed for varying intercepts across students, and the random intercept and slopes model (Model 3) accounted for variation in both intercepts and slopes. Model fit was assessed using AIC, BIC, and likelihood ratio tests. For outcomes where Model 3 did not significantly improve fit or explained minimal additional variance, Model 2 was retained for parsimony. This reflects that intra-individual differences in change rates were not uniform across outcomes. Detailed model fit statistics are

Table 1
Summary of data sources and variables by research question.

Research Question/Objective	Data Source	Instrument/System Component	Data Type	Operationalization (Variables)
RQ1: How are the components of the pre-actional, actional, and post-actional phases of SRL interrelated?	SRL self-reports	Pre- and post-task single-item measures (metacognition, motivation, emotion)	Self-report	Weekly scores for: task value, self-efficacy, joy, anxiety, planning, reflection
RQ2: How does engagement with different forms of feedback (directive, informative, and transformative) through an ALT relate to learners' SRL processes across these phases?	ALT trace data (log files)	Strategy video views (SRL strategy recommendations), dashboard access	Trace/behavioral	Weekly dummy-coded indicators for: directive, informative, transformative, no feedback
General objective: Integrated modeling of weekly SRL measures and trace data	Combined dataset	SRL measures + trace data	Longitudinal multilevel dataset	Time (week), SRL variables, feedback dummies

provided in Appendix D.

4.1. Descriptive statistics

Table 2 presents the means, standard deviations, correlations, and reliabilities (shown in square brackets) for all variables. As expected, all variables showed significant correlations in the expected directions across measurement points.

Students reported their levels of planning (ICC = 0.44), task value (ICC = 0.46), self-efficacy (ICC = 0.43), goal orientation (ICC = 0.30), joy (ICC = 0.50), hope (ICC = 0.37), anger (ICC = 0.50), anxiety (ICC = 0.46), regulation (ICC = 0.38), and satisfaction (ICC = 0.33). While the explained variance varies across variables, the ICC values suggest that there is a significant proportion of variance attributed to differences between individuals.

4.2. Pre-actional to actional phase and adaptive feedback

Consistent with our first hypothesis (H1), the linear mixed-effects model revealed that planning, task value, self-efficacy, goal orientation, and joy were significantly positively associated with regulation. Conversely, anger and anxiety showed significant negative associations with regulation. However, contrary to H1, no significant relationship was found between hope and regulation. This relationship only reached marginal significance ($p < .10$; for detailed results, see Tables 3 and 4).

To test the second hypothesis (H2), several interaction effects were analyzed. Notably, the interaction between joy and transformative feedback was significant, albeit unexpectedly indicating that the positive association between joy and regulation was attenuated when students interacted with transformative feedback. No other significant interaction effects on regulation were identified, although the interaction between anger and directive feedback was marginally significant ($p < .10$). This finding suggests that the negative association between anger and regulation was slightly reduced when students interacted with directive feedback.

Overall, these findings do not support H2. The results indicate that the moderating effects of adaptive feedback in the pre-actional phase are minimal and, in some cases, may even weaken positive relationships between emotions and regulation. Fig. 3 summarizes the (marginal) significant effects describing the transition from the pre-actional to the actional phase (see Tables 3 and 4 for additional details on regression results).

4.3. Post-actional to pre-actional phase and adaptive feedback

Supporting our third hypothesis (H3), the linear mixed-effects models revealed significant associations between satisfaction in the post-actional phase and several aspects of the subsequent pre-actional phase. Specifically, satisfaction was positively related to task value, self-efficacy, joy, and hope, while negatively associated with anger and anxiety. However, contrary to H3, no significant relationships were found between satisfaction and planning as well as satisfaction and goal

Table 2
Means, standard deviations, correlations with confidence intervals, and reliabilities of the variables.

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10
1. Planning	4.98	1.57	[0.94]									
2. Task Value	6.07	1.10	0.26**	[0.98]								
3. Self-Efficacy	5.30	1.17	0.22**	0.39**	[0.93]							
4. Goal Orientation	5.67	1.54	0.30**	0.36**	0.25**	[0.99]						
5. Joy	3.96	1.52	0.28**	0.18**	0.34**	0.15**	[0.98]					
6. Hope	5.43	1.22	0.23**	0.34**	0.73**	0.23**	0.38**	[0.88]				
7. Anger	3.41	1.69	−0.19**	−0.22**	−0.37**	−0.17**	−0.56**	−0.40**	[0.99]			
8. Anxiety	3.00	1.58	−0.03*	−0.15**	−0.51**	−0.15**	−0.23**	−0.55**	0.41**	[0.92]		
9. Satisfaction	5.45	1.37	0.17**	0.22**	0.35**	0.11**	0.14**	0.33**	−0.18**	−0.26**	[0.83]	
10. Regulation	5.06	1.45	0.33**	0.25**	0.17**	0.19**	0.13**	0.18**	−0.11**	−0.07**	0.38**	[0.88]

Note. M and *SD* are used to represent mean and standard deviation, respectively. Split-half reliability is displayed in square brackets on the diagonal. * indicates $p < .05$. ** indicates $p < .01$.

Table 3
Effects of metacognition, motivation, and adaptive feedback on regulatory behavior in the actional phase.

Predictors	Regulation			Regulation			Regulation			Regulation		
	Estimates	CI	p	Estimates	CI	p	Estimates	CI	p	Estimates	CI	p
Intercept	5.08	4.92 – 5.25	**<0.001**	5.08	4.90 – 5.25	**<0.001**	5.07	4.90 – 5.25	**<0.001**	5.09	4.91 – 5.26	**<0.001**
Planning	0.20	0.13 – 0.29	**<0.001**									
Directive feedback	−0.05	−0.40 – 0.07	0.171	−0.05	−0.41 – 0.07	0.170	−0.06	−0.42 – 0.07	0.160	−0.06	−0.41 – 0.06	0.149
Informative feedback	0.02	−0.60 – 1.10	0.565	0.02	−0.51 – 0.86	0.619	0.01	−0.61 – 0.80	0.793	0.02	−0.55 – 0.90	0.639
Transformative feedback	0.00	−0.32 – 0.35	0.921	−0.01	−0.41 – 0.26	0.662	−0.01	−0.41 – 0.26	0.653	0.00	−0.35 – 0.31	0.894
Planning*directive feedback	−0.02	−0.18 – 0.09	0.520									
Planning*informative feedback	−0.03	−0.76 – 0.33	0.438									
Planning*transformative feedback	−0.03	−0.30 – 0.10	0.326									
Task value				0.13	0.01 – 0.25	**0.035**						
Task value*directive feedback				0.04	−0.10 – 0.30	0.314						
Task value*informative feedback				0.00	−0.76 – 0.76	0.997						
Task value*transformative feedback				0.03	−0.14 – 0.46	0.299						
Self-efficacy							0.10	0.01 – 0.24	**0.034**			
Self-efficacy*directive feedback							−0.01	−0.20 – 0.16	0.798			
Self-efficacy*informative feedback							0.01	−0.68 – 0.91	0.779			
Self-efficacy*transformative feedback							0.02	−0.20 – 0.39	0.531			
Goal orientation										0.12	0.03 – 0.18	**0.007**
Goal orientation*directive feedback										0.00	−0.12 – 0.14	0.893
Goal orientation*informative feedback										−0.01	−0.71 – 0.61	0.891
Goal orientation*transformative feedback										0.02	−0.16 – 0.27	0.606
Random Effects												
Residual variance	1.27			1.26			1.26			1.27		
Intercept variance	0.56			0.68			0.74			0.70		
Marginal R^2/Conditional R^2	0.049/0.338			0.026/0.368			0.015/0.380			0.019/0.368		

Note. Directive, informative, and transformative feedback were dummy coded with no feedback as reference category. CI = 95% confidence interval.

orientation (for detailed results, see Tables 5 and 6).

Not supporting our fourth hypothesis (H4), no statistically significant interaction effects were observed between satisfaction and adaptive feedback on the subsequent pre-actional phase. However, several marginally significant trends ($p < .10$) were identified. Specifically, a positive interaction between satisfaction and informative feedback on planning suggested that the association between satisfaction and planning was strengthened when students engaged with informative feedback. The analysis also indicated a marginally significant positive effect of transformative feedback on goal orientation as well as a marginally significant negative effect of informative feedback on anger.

At the same time, and contrary to our H4, a marginally negative interaction between satisfaction and directive feedback on hope revealed that the positive relationship between satisfaction and hope weakened when students interacted with directive feedback. Finally, a marginally significant interaction between satisfaction and transformative feedback on task value suggested that the positive association between satisfaction and task value was diminished when students engaged with transformative feedback.

Overall, these results suggest that the moderating effects of adaptive feedback in the post-actional phase are subtle and, in some instances, may even negatively influence various SRL components. Fig. 4 summarizes the (marginal) significant effects describing the transition from the post-actional to the subsequent pre-actional phase (see Tables 5 and 6 for additional details on regression results).

5. Discussion

Overall, our findings paint a differentiated picture of SRL and adaptive feedback. We found robust evidence that metacognitive, motivational, and emotional components in the pre-actional phase were linked to students' regulatory behavior, and that post-actional satisfaction shaped motivation and emotions in the following SRL cycle. In contrast, the moderating effects of adaptive feedback were limited and inconsistent. While several additional effects emerged, they did not converge into a clear pattern, underscoring the complexity of delivering adaptive feedback through educational technology.

5.1. SRL dynamics across phases

Consistent with H1 and H3, the results reveal a coherent pattern of SRL dynamics across phases. A key finding of our study is the link

Table 4
Effects of emotion and adaptive feedback on regulatory behavior in the actional phase.

Predictors	Regulation			Regulation			Regulation			Regulation		
	Estimates	CI	p	Estimates	CI	p	Estimates	CI	p	Estimates	CI	p
Intercept	5.06	4.88 – 5.24	**<0.001**	5.07	4.90 – 5.25	**<0.001**	5.07	4.89 – 5.25	**<0.001**	5.06	4.88 – 5.24	**<0.001**
Joy	0.09	0.07 – 0.23	**0.001**									
Directive feedback	−0.04	−0.37 – 0.11	0.290	−0.06	−0.41 – 0.07	0.163	−0.05	−0.39 – 0.09	0.226	−0.05	−0.39 – 0.09	0.231
Informative feedback	0.03	−0.53 – 1.15	0.467	0.02	−0.45 – 0.87	0.535	0.03	−0.57 – 1.11	0.527	0.03	−0.49 – 1.07	0.473
Transformative feedback	−0.01	−0.36 – 0.29	0.827	−0.02	−0.42 – 0.25	0.619	−0.01	−0.36 – 0.30	0.857	−0.01	−0.38 – 0.30	0.804
Joy*directive feedback	−0.06	−0.27 – 0.03	0.113									
Joy*informative feedback	−0.03	−0.66 – 0.26	0.392									
Joy*transformative feedback	−0.08	−0.50 to −0.03	**0.029**									
Hope				0.09	−0.01 – 0.20	**0.066**						
Hope*directive feedback				0.01	−0.13 – 0.20	0.673						
Hope*informative feedback				−0.02	−0.77 – 0.42	0.562						
Hope*transformative feedback				0.02	−0.24 – 0.41	0.618						
Anger							−0.07	−0.19 to −0.03	**0.007**			
Anger*directive feedback							0.06	−0.02 – 0.24	**0.090**			
Anger*informative feedback							0.02	−0.29 – 0.57	0.530			
Anger*transformative feedback							0.05	−0.06 – 0.35	0.155			
Anxiety										−0.11	−0.19 to −0.02	**0.015**
Anxiety*directive feedback										0.00	−0.13 – 0.13	0.976
Anxiety*informative feedback										0.02	−0.46 – 0.78	0.616
Anxiety*transformative feedback										0.00	−0.20 – 0.18	0.948
Random Effects												
Residual variance	1.25			1.26			1.26			1.24		
Intercept variance	0.73			0.73			0.75			0.79		
Marginal R^2/Conditional R^2	0.021/0.383			0.014/0.377			0.013/0.381			0.017/0.399		

Note. Directive, informative, and transformative feedback were dummy coded with no feedback as reference category. CI = 95% confidence interval.

between metacognitive activity, motivation, and emotions during the pre-actional phase and effective regulatory behavior in the actional phase (H1). Learners with higher task value, self-efficacy, goal orientation, and joy exhibited better regulatory behavior, whereas negative emotions like anxiety and anger undermined their regulatory efforts. Additionally, our results highlight the crucial role of post-actional satisfaction in future SRL cycles. Higher satisfaction levels were positively linked to task value, self-efficacy, joy, and hope, and negatively linked to anger and anxiety (H3). These findings support existing research on SRL as a cyclical, recursive process (Mejeh et al., 2024; Liborius et al., 2019; Schmitz & Wiese, 2006; Zimmerman, 2008) while offering new insights into the interplay between cognitive, motivational, emotional, and regulatory processes across SRL phases.

5.2. Effects of adaptive feedback on SRL

Our study further explored the moderating role of adaptive feedback in SRL, particularly its potential to strengthen positive relationships and mitigate negative effects between pre-actional and actional phases (H2) and between post-actional and subsequent pre-actional phases (H4). Overall, the findings provide limited support for these hypotheses, indicating that while adaptive feedback can enhance SRL, its effects are nuanced and context-dependent.

A key observation is that only a few interaction effects reached statistical significance. Although several associations approached significance ($p < .10$), the noteworthy significant interaction was that transformative feedback weakened the positive association between joy and regulatory behavior. This finding challenges the assumption that more comprehensive forms of feedback necessarily improve learning behavior (Wisniewski et al., 2020) and aligns with studies showing that transformative feedback does not consistently outperform directive or informative feedback when provided separately (Theobald & Bellhäuser, 2022).

One plausible explanation for this weakening effect is cognitive overload during the pre-actional phase, where learners must simultaneously process feedback, plan their strategy use, and prepare to engage with the upcoming task. This overload may have reduced learners' task-related enjoyment and subsequently hindered their regulatory efforts (de Bruin et al., 2025; Wang & Lajoie, 2023). However, this interpretation becomes more complex when considering the marginally significant effects of transformative feedback: it enhanced goal orientation but weakened the link between satisfaction and task value.

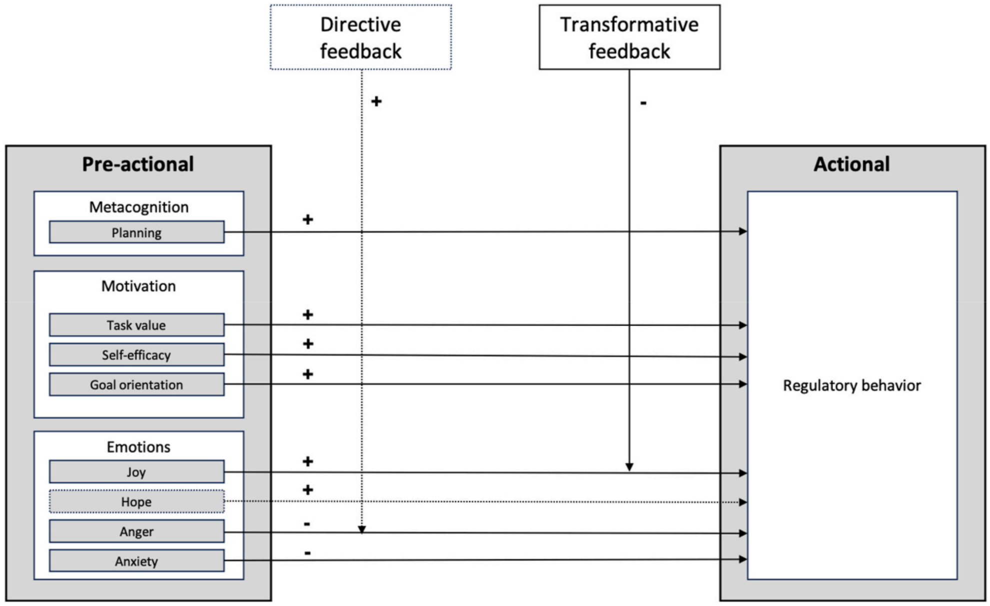

Fig. 3. SRL effects from the pre-actional to the actional phase (H1, H2)
Note. Statistically significant effects ($p < .05$) are indicated by solid arrows. Marginally significant effects ($p < .10$) are indicated by dotted arrows. Effects with $p >$ .10 are removed from the model.

Table 5
Effects of satisfaction and adaptive feedback on metacognition and motivation in the pre-actional phase.

Predictors	Planning			Task value			Self-efficacy			Goal orientation		
	Estimates	CI	p	Estimates	CI	p	Estimates	CI	p	Estimates	CI	p
Intercept	5.01	4.79 – 5.23	**<0.001**	6.03	5.87 – 6.18	**<0.001**	5.27	5.12 – 5.42	**<0.001**	5.55	5.35 – 5.75	**<0.001**
Satisfaction	0.09	−0.03 – 0.18	0.165	0.10	0.02 – 0.17	**0.012**	0.26	0.20 – 0.36	**<0.001**	0.09	−0.04 – 0.20	0.197
Directive feedback	0.00	−0.28 – 0.29	0.983	−0.04	−0.30 – 0.11	0.356	0.01	−0.20 – 0.23	0.903	0.05	−0.13 – 0.48	0.258
Informative feedback	0.01	−1.08 – 1.46	0.769	0.00	−0.98 – 0.87	0.908	0.01	−0.93 – 1.09	0.876	0.01	−1.31 – 1.76	0.775
Transformative feedback	−0.01	−0.37 – 0.32	0.886	0.00	−0.24 – 0.26	0.928	0.01	−0.22 – 0.31	0.721	0.08	−0.00 – 0.78	**0.053**
Satisfaction*directive feedback	0.00	−0.16 – 0.18	0.909	0.00	−0.13 – 0.11	0.932	−0.06	−0.24 – 0.02	0.104	0.02	−0.15 – 0.23	0.652
Satisfaction*informative feedback	0.09	−0.08 – 2.12	**0.071**	0.04	−0.50 – 1.09	0.464	−0.02	−1.00 – 0.73	0.758	0.02	−1.04 – 1.57	0.694
Satisfaction*transformative feedback	0.03	−0.17 – 0.39	0.440	−0.07	−0.38 – 0.02	**0.079**	−0.04	−0.32 – 0.11	0.348	0.03	−0.20 – 0.45	0.457
Random Effects												
Residual variance	1.16			0.62			0.76			1.86		
Intercept variance	1.23			0.57			0.44			0.54		
Marginal R^2/Conditional R^2	0.014/0.522			0.017/0.490			0.082/0.416			0.017/0.238		

Note. Directive, informative, and transformative feedback were dummy coded with no feedback as reference category. CI = 95% confidence interval.

The marginally significant positive effect on goal orientation suggests that transformative feedback helps learners independently set or refine learning goals by stimulating monitoring and planning (Bellhäuser et al., 2023; Hattie & Timperley, 2007). This stands out given that students frequently generate vague or mediocre goals without targeted support (Martins van Jaarsveld et al., 2025). In contrast, the marginally significant negative interaction effect between transformative feedback and satisfaction on task value suggests that the complexity of transformative feedback imposes additional cognitive and emotional processing demands. This interpretation aligns with accounts of feedback as a potentially double-edged intervention that can either support or hinder learning, depending on how its complexity interacts with learners' available cognitive resources and affective states (Plass & Kalyuga, 2019; Wirth et al., 2020). Thus, transformative feedback may exhibit a dual nature: while it can promote strategic processes such as goal setting, its complexity may also challenge learners' affective processing or task perceptions. Overall, this pattern helps explain why adaptive feedback effects may appear inconsistent, as their impact depends on both feedback type and the cognitive and emotional resources available when it is processed.

5.3. *Complexity of adaptive feedback in ALT-based SRL support*

Another important aspect of our findings concerns the marginal trends observed across phases, which shed light on the complexity of adaptive feedback for SRL when it is implemented in ALTs. These trends suggest that feedback does not influence SRL uniformly but rather interacts with its dimensions in phase-specific ways.

Table 6
Effects of satisfaction and adaptive feedback on emotion in the pre-actional phase.

Predictors	Joy			Hope			Anger			Anxiety		
	Estimates	CI	p	Estimates	CI	p	Estimates	CI	p	Estimates	CI	p
Intercept	3.92	3.70 – 4.14	**<0.001**	5.39	5.23 – 5.54	**<0.001**	3.53	3.29 – 3.78	**<0.001**	3.02	2.80 – 3.23	**<0.001**
Satisfaction	0.07	0.02 – 0.23	**0.019**	0.27	0.20 – 0.38	**<0.001**	−0.09	−0.25 to −0.02	**0.024**	−0.14	−0.31 to −0.08	**0.001**
Directive feedback	0.00	−0.27 – 0.29	0.962	0.02	−0.18 – 0.28	0.667	−0.01	−0.34 – 0.28	0.866	−0.02	−0.38 – 0.21	0.580
Informative feedback	0.01	−1.07 – 1.46	0.763	−0.02	−1.35 – 0.82	0.633	−0.08	−2.81 – 0.07	**0.064**	−0.02	−1.75 – 1.09	0.649
Transformative feedback	−0.05	−0.58 – 0.10	0.172	0.03	−0.15 – 0.42	0.361	−0.02	−0.47 – 0.28	0.617	−0.01	−0.40 – 0.34	0.866
Satisfaction*directive feedback	−0.04	−0.26 – 0.07	0.266	−0.06	−0.26 – 0.01	**0.080**	0.02	−0.12 – 0.24	0.499	0.03	−0.11 – 0.25	0.433
Satisfaction*informative feedback	−0.01	−1.17 – 0.99	0.872	0.02	−0.73 – 1.13	0.673	−0.02	−1.46 – 0.96	0.691	0.01	−1.13 – 1.26	0.916
Satisfaction*transformative feedback	−0.04	−0.43 – 0.12	0.260	−0.02	−0.28 – 0.19	0.710	−0.01	−0.33 – 0.27	0.822	0.01	−0.25 – 0.35	0.722
Random Effects												
Residual variance	1.14			0.89			1.49			1.49		
Intercept variance	1.19			0.42			1.40			0.88		
Marginal R^2/Conditional R^2	0.010/0.515			0.081/0.377			0.018/0.494			0.023/0.387		

Note. Directive, informative, and transformative feedback were dummy coded with no feedback as reference category. CI = 95% confidence interval.

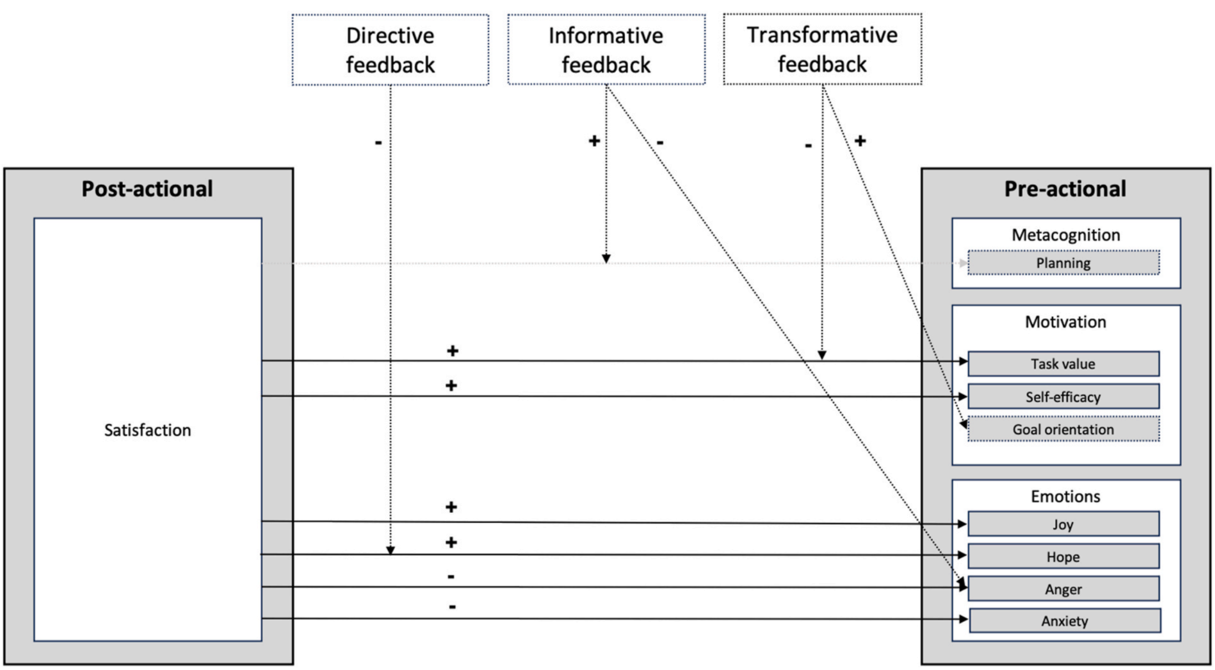

Fig. 4. SRL effects from the post-actional to the subsequent pre-actional phase (H3, H4)
Note. Statistically significant effects ($p < .05$) are indicated by solid arrows. Marginally significant effects ($p < .10$) are indicated by dotted arrows. Effects with $p >$ .10 are removed from the model.

For example, in the transition from the pre-actional to the actional phase, directive feedback marginally tended to reduce the negative effects of anger by helping learners calibrate expectations prior to task engagement. In contrast, in the transition from post-actional to the subsequent pre-actional phase, directive feedback showed a marginal tendency to reduce the positive effects of satisfaction on hope. These differences suggest that the functions of feedback vary across phases. Whereas directive feedback may be effective before task engagement, it may not align with learners' emotional states after task engagement. Moreover, while informative feedback before task engagement did not impact regulation in the actional phase, informative feedback after task engagement showed a marginal tendency to reduce anger and to strengthen the positive relationship between satisfaction and planning in the subsequent pre-actional phase. At the same time, the marginally significant negative interaction between directive feedback and satisfaction on hope suggests that prescriptive feedback may not always align with learners' motivational states. Thus, our findings highlight that, even within a single ALT, different forms of feedback can play distinct, phase-specific roles in SRL. This is consistent with prior work contrasting feedback delivered via learning dashboards with feedback delivered through direct strategy prompts (Dignath & Veenman, 2021; Du et al., 2023; Matcha et al., 2020).

Taken together, these observations echo work indicating that high-information feedback supports learning most effectively when it is specific, timely, and actionable (Wisniewski et al., 2020) and when adaptive feedback in ALTs is personalized and aligned with learners' needs (Xie et al., 2019). In this context, it becomes evident that feedback delivered through ALTs can lose impact when it remains generic or insufficiently personalized (Khalil et al., 2024; Mejeh & Sarbach, 2024; Park et al., 2023), and that its effectiveness also depends on the extent to which it is integrated into course activities and supported by instructors (Molenaar & Van Campen, 2016; Pata et al., 2022).

6. Practical implications

Our findings provide implications for the design of adaptive feedback, although these should be interpreted with caution due to the marginal significance of several effects. First, while our findings highlight the dynamic interplay between cognitive, motivational, emotional, and regulatory processes across SRL phases, they also emphasize the need for holistic support mechanisms addressing not only cognitive and metacognitive aspects of learning but also motivational and affective dimensions—areas often underexplored in SRL research (Efklides & Schwartz, 2024; Zheng et al., 2023). Second, our study underscores that the role of adaptive feedback in SRL is best understood as context-dependent and conditional rather than uniform, and that comprehensive forms of feedback do not necessarily lead to better SRL (Theobald & Bellhäuser, 2022). In this regard, our findings provide a basis for conceptualizing feedback as a phase-sensitive element within SRL cycles, with timing and uptake representing key boundary conditions. Not only the provision of feedback across SRL phases but also the type of feedback provided should be adapted to students' (meta-) cognitive, motivational, and emotional resources.

For instructional implementation, this implies that ALTs should not be deployed as stand-alone feedback add-ons but should be embedded into instructional design through clear guidance on when and how students are expected to engage with feedback and how it connects to instructional goals. In addition, instructors may need to actively support students' interpretation and use of ALT feedback and to monitor whether feedback uptake occurs.

7. Limitations and future directions

Although our study provides valuable insights into the role of adaptive feedback in SRL, several limitations should be acknowledged. First, many observed effects were marginally significant, and the sample size of 194 participants, while acceptable, may have limited statistical power, particularly for detecting subtle interaction effects. Future research should therefore examine these patterns in larger and more diverse samples to test their robustness and generalizability. At the same time, subtle or unexpected tendencies in SRL data need not be dismissed as mere statistical noise. Recent methodological discussions in SRL research drawing on data from educational technologies argue that anomalies and unusual regulatory patterns can provide useful conceptual information that challenges prevailing assumptions and reveals alternative, yet valid, forms of self-regulation (Raković et al., 2024). From this perspective, the marginal effects observed here may help refine future hypotheses about when and for whom different forms of adaptive feedback delivered through ALTs are most supportive of students' SRL.

Second, while we combined self-reported SRL data with trace data on learners' use of the ALT, the reliance on self-reported data to prompt directive feedback introduces potential biases, including inaccuracies in learners' self-assessments. Furthermore, we did not measure students' real-time regulatory activities, as regulatory behaviors were assessed only after task completion. Relatedly, the degree of adaptivity implemented in the ALT should be interpreted carefully. Adaptation was primarily rule-based and relied on threshold-triggered strategy recommendations, while engagement with feedback resources was voluntary, and the dashboard functioned as an informational tool rather than as a prescriptive or model-driven adaptive component. While this enables timely and rich support, such rules are limited in capturing fine-grained temporal dynamics of SRL over cycles, highlighting the value of future work that integrates richer process indicators and more dynamic personalization. To address this, future research should incorporate richer, more objective process data (e.g., log traces such as time spent on task or multimodal indicators such as eye-tracking), which can both validate learning analytics and data science approaches to more dynamic personalization (Azevedo & Gašević, 2019; Järvelä & Hadwin, 2024).

Another limitation concerns the operationalization of feedback as a dummy variable, as it does not provide detailed insights into learners' engagement with the different feedback types. For instance, it is unclear whether and how learners applied the prompted strategies to their everyday learning or how exactly they used the dashboard visualizations to guide their learning processes. More differentiated measures may provide further insights into the complex and context-dependent effects of adaptive feedback.

A related concern involves the potential for cognitive overload caused by varying feedback types. This study, however, did not directly measure cognitive load, leaving room for interpretation. Since SRL relies heavily on learners' cognitive and affective resources, feedback interventions must balance the load by managing task demands, instructional structure, and the demands associated with planning and reflection (Seufert, 2018; Seufert et al., 2024). Although ALTs can help optimize feedback delivery, they must include mechanisms that minimize overload and reduce the risk of unintended negative effects. This is important because learners' perceptions of feedback shape its impact, such that positive feedback can lessen cognitive demands, while negative feedback can amplify them, hindering subsequent SRL processes (Redifer et al., 2021). Future research should include direct measures of cognitive load to determine whether feedback complexity induces cognitive strain.

We also did not fully investigate individual differences, such as prior knowledge or baseline motivation, which may influence how learners respond to feedback. Understanding these differences is essential, as feedback effectiveness may vary across individuals (Butler & Winne, 1995; Winne, 2022). Future studies should explore how learner-specific characteristics moderate feedback effects and design ALTs tailored to individual needs.

Finally, our study did not employ measures of learning performance. Since previous research has suggested that the design of effective ALTs requires a thorough investigation of the dynamic factors underlying learning processes (Gibson & Ifenthaler, 2026), the aim of our study was to investigate the dynamic interplay between different SRL phases and adaptive feedback rather than measuring learning performance (Lim et al., 2021). Nevertheless, future research should investigate the effects of adaptive feedback on learning performance to gain a broader understanding of the effectiveness of adaptive feedback in different SRL phases.

Even given these limitations, our findings contribute to the broader theoretical framework of SRL in highlighting the complex interplay between feedback types and SRL components across different phases of learning. While models such as those proposed by Zimmerman (2000) as well as Schmitz and Wiese (2006) emphasize the role of feedback loops in supporting SRL, our results indicate that feedback effectiveness depends on learners' emotional and motivational states during various learning phases. The findings also emphasize that feedback must be carefully tailored to meet learners' needs and delivered in a manner that complements their cognitive capacities, avoiding information overload. While ALTs have the potential to facilitate these processes, our findings suggest that their impact may vary depending on learners' individual needs and the timing of the feedback.

CRediT authorship contribution statement

Mathias Mejeh: Writing – original draft, Project administration, Formal analysis, Data curation, Conceptualization, Software, Writing – review & editing. **Yvonne M. Fromm:** Writing – review & editing, Formal analysis.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work the authors used ChatGPT-5 to assist with language review. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the final content of the publication.

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Appendices A-D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.learninstruc.2026.102394.

Data availability

Data will be made available on request.

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