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The Dynamic Interplay Between Goal Setting, Performance, and Emotions in Self-Regulated Learning: A Computational Modeling Approach

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In self-regulated learning (SRL), students often set goals that influence how they subsequently perform on tasks. Furthermore, emotions have been considered to play a key role in this process; yet, the exact dynamic relationship between goals, performance, and emotions has not been specified. In the present study, we employed computational modeling to delineate the specific dynamic interplay of goals, performance, and emotions in multiple goal-striving episodes. We developed and applied our computational model of SRL to data collected from an online math task (Study 1) and from an online learning app used to study for a high-stakes state exam in Germany (Study 2). Across both studies, we found that students who set higher goals (compared with their previous performance) had higher subsequent performance, highlighting the importance of setting high goals for learning. Furthermore, emotions are not only influenced by previous goals and performance, but they also influence subsequent goal setting and performance. We found that stronger positive emotions (particularly enjoyment) predicted higher levels of goals, whereas predicting lower performance in the online math task and higher performance when studying for the high-stakes exam. Our work highlights computational modeling as a valuable tool to theorize and empirically analyze the processes of SRL in education research.

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Educational Impact and Implications Statement

Self-regulated learning is essential for academic success, and a growing body of evidence highlights the critical role that emotions play in how students set goals and manage their performance. The current work proposed and validated a mathematical model that describes how these variables—goals, performance, and emotions—interact with each other during the process of self-regulated learning. The proposed model can help us understand when people set high (or low) goals, how different goals lead to various types of emotions during learning, and how the goals and emotions predict performance. Our empirically validated model showed that goals motivate students to study, and emotions, such as enjoyment, play facilitative roles in setting higher goals and modulate efforts to reach these goals in real-world learning contexts.

Keywords: self-regulated learning, goals, emotions, computational modeling, Bayesian inference

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Imagine studying for a final exam by answering review questions on a series of topics to be tested. On each day you study, you set a goal of how many questions you want to answer. On some days, you may reach your goal, whereas on others you might fall short. At the end of each study session, you will probably reflect on how well you did while studying that day relative to the goal and respond emotionally to it. Now, how do these emotions then influence your next study session? If you are proud that you exceeded your goal, will you set higher goals to challenge yourself, or lower your goal to save on effort? Will pride help you work harder next time or stop you from exerting effort? How would your next goal and performance interact to form your next emotional experience?

The example above highlights the dynamic nature of self-regulated learning (SRL), which describes effective learning behavior as a cyclical process (Pintrich, 2000; Winne, 1996; Winne & Hadwin, 1998; Zimmerman, 2000; Zimmerman & Moylan, 2009). In most of these interpretations of SRL, planning, performance monitoring, and reflection are key subprocesses that repeat over time. To observe these phases, previous studies typically assessed variables including the goals set, the performance on a task, and subsequent emotional responses (DiBenedetto & Zimmerman, 2010; Ilies et al., 2010). Much research has demonstrated that the difference between the goal and the performance (goal–performance discrepancy [GPD] plays a role in how future goals are set and in the performance on a task (Donovan & Hafsteinsson, 2006; Donovan & Williams, 2003). In addition, emotions, another crucial part of SRL, have been posited to influence goal setting and performance, with research in achievement settings showing that specific emotions may have nuanced effects on these processes (Pekrun, 2006; Pekrun et al., 2017, 2023). However, little research has formulated *specifically how* goals, emotions, and performance dynamically influence each other.

In the present study, we introduce a new framework to address the limitation: a computational model of goals, performance, and emotions with the aim of understanding how these three variables work in conjunction with each other in SRL in a more specific manner (see Murayama & von Keyserlingk, 2025 for arguments for and Schuetze, 2024 for a use case of computational modeling in educational psychology). In particular, we are interested in the effects of the GPD on goal setting, performance, and emotions, as well as the reciprocal effects of emotions back on goal setting and performance in future goal-striving episodes. We chose to follow a computational modeling approach because it allows us to formally and precisely specify intricate dynamic processes of how the three variables interact. After formulating a ground model, we empirically validated it by applying the model to two data sets: (a) data collected in a gamified online experiment with a math task and (b) data collected from students studying for a high-stakes medical exam in Germany.

Mechanisms Behind SRL

Interplay Between Goals and Performance

In educational psychology, the cognitive and motivational mechanisms underlying goal setting have often been described by social–cognitive theory (Bandura, 1986, 1991). According to this theory, learners are motivated to achieve goals, with the idea that high but realistic goals encourage greater effort, leading to improved performance (Carver & Scheier, 1990). A substantial body of research has demonstrated that goals indeed serve important motivational functions (for a review, see Locke & Latham, 1990). For example, students who set personal best goals and demonstrated adaptability in their goal setting showed sustained academic engagement and achievement over time (Burns et al., 2018). In another example, goal setting has led to greater performance improvements in physical activity, likely due to a commitment to self-set goals (Smith et al., 1996).

Social–cognitive theory also posits that the degree to which performance exceeds or falls short of a goal (i.e., GPD) influences the goal-setting process. Specifically, the theory predicts that learners tend to set higher goals after successfully attaining a goal (i.e., when GPD is positive) because goal success enhances their sense of self-efficacy (Converse et al., 2010; David et al., 2007; Donovan & Hafsteinsson, 2006). Conversely, failing to attain a goal (i.e., when GPD is negative) tends to lead learners to set lower goals, as failure decreases their self-confidence to achieve the same goal. Of course, other possibilities exist. For example, goals and effort may remain relatively stable over time when individuals judge themselves fully capable of reaching their goals and, therefore, feel no need to adjust either their goals or effort (Bandura, 1991). Alternatively, quickly meeting a goal may even prompt learners to lower their goals, as they may feel they expended unnecessary effort to achieve the initial target (Carver & Scheier, 1990).

Much of the empirical evidence on the relation between goal setting and performance in achievement contexts supports the predictions from social–cognitive theory: Positive GPDs (i.e., when performance exceeds goals) predict higher subsequent goals, whereas negative GPDs (i.e., when performance falls short of goals) predict lower goals, both in laboratory tasks (Ilies & Judge, 2005; Tolli & Schmidt, 2008) and in learning contexts (Ilies et al., 2010; Theobald et al., 2021). Similar results were also reported in sports psychology. A program of research investigated goal setting in athletes, whereby initial goals were observed to be set higher than previous performance (Donovan & Williams, 2003; Williams et al., 2000). Critically, subsequent goal setting followed the predicted pattern: Positive GPDs led to higher goals, whereas negative GPDs led to lower goals. Corroborating these individual findings, a recent systematic review suggested that most evidence supports the social–cognitive perspective on goal-setting behavior in achievement settings (Theobald et al., 2025).

Role of Emotions in Goal Setting and Performance

Self-regulation is also closely related to emotions. For example, control theory (Carver, 2003; Carver & Scheier, 1990) posits that goal progress that is faster than expected is considered to lead to stronger positive emotions, which signal adequate progress toward the goal, and that performance can be reduced. In contrast, when progress is slower than expected, negative emotions are considered to arise, resulting in learners' motivation to increase their performance. Thus, control theory focuses on the valence dimension of emotions and suggests that positive versus negative emotions have different impacts on subsequent performance and goal-setting behavior.

However, there has been an increasing recognition that the role of emotions is more complex in achievement settings (Ben-Eliyahu, 2019; Efklides, 2011; Pekrun et al., 2017; Pekrun & Linnenbrink-Garcia, 2014; Tamir, 2016). One framework that puts emotions at the forefront is the metacognitive and affective model of SRL (MASRL; Efklides, 2011; Efklides & Schwartz, 2024). According to MASRL, emotions affect SRL at both macro- and microlevels. The macrolevel predicts that learners' stable characteristics (beliefs, abilities, and metacognition) interact when they form general/abstract perceptions about tasks. When learners are engaged in a specific task at the microlevel, emotions are further considered to affect representations of tasks, task performance, and metacognitive monitoring. In addition, the MASRL model emphasizes the importance of learners' awareness of their emotional states and emotion regulation; when learners realize that they experience strong negative emotions (e.g., anxiety), they may implement emotion regulation to overcome these emotions and help them reach their long-term learning goals. Recently, Ben-Eliyahu (2019) further developed the notion that emotions and emotion regulation are a fundamentally important aspect of SRL and proposed that learners actively engage in regulating their emotions while at the same time regulating their motivation, cognition, and learning behavior.

Research in educational psychology also highlights the importance of discrete emotions beyond the positive versus negative dichotomy. For example, the control-value theory (Pekrun, 2006, 2018) posits that emotions arise from appraisals of perceived control and subjective value. Control appraisals refer to perceptions of competence, whereas value appraisals refer to perceived importance. The theory particularly focuses on two facets of value: How important individuals perceive the task (intrinsic value) and the perceived importance of achievement outcomes (achievement value). Control-value theory focuses not only on the valence of emotion (positive/pleasant vs. negative/unpleasant) but also on object focus (activity vs. outcome). For the object focus dimension, activity emotions concern a learning task, whereas outcome emotions concern the result of the performance on the task. Examples of positive activity emotions include enjoyment while solving challenging math problems; examples of positive outcome emotions include pride after success; examples of negative activity emotions include boredom with a repetitive task and anger about the large volume of assignments; and examples of negative outcome emotions include anxiety about upcoming examinations.

According to control-value theory, achievement emotions reciprocally influence achievement via their interactions with learners' motivation, the use of learning strategies, self-regulation, and available cognitive resources (Pekrun, 2006, 2018; Pekrun et al., 2017, 2023). Given the importance of goal setting in SRL described earlier, it seems plausible that emotions shape goal setting as well as performance. For example, positive activity emotions, such as enjoyment, are associated with high perceived control and high intrinsic value; these emotions are considered to encourage students to challenge themselves and engage deeply in the task. Consequently, enjoyment may promote higher goal setting and facilitate performance to sustain goal-directed behavior. Negative activity emotions, such as anger or boredom, are associated with the lack of value; thus, they may lead to reduced motivation, increasing the likelihood that students set lower levels of goals and disengage from tasks. Positive outcome emotions, such as gratitude, signal that prior goals and performance were successful, reinforcing perceived control and promoting more ambitious subsequent goals. Finally, negative outcome emotions, such as anxiety and sadness, are associated with high achievement value and lack of perceived control; these emotions thus potentially lead students to set more conservative, attainable goals while increasing performance to avoid failure.

There are several studies that examined the moment-to-moment fluctuations of achievement emotions and their dynamic interactions with goal setting and performance at a fine-grained level of SRL (Theobald et al., 2021). However, these have found somewhat complex and nuanced relationships between emotions and goal setting and performance. For example, Seo and Patall (2021) examined the reciprocal effects between achievement emotions and effort to reach students' achievement goals; they found that stronger pride (but not enjoyment) was predictive of reduced levels of effort on the following day. Chong and Park (2017) found that anger (but not sadness) led to higher goal setting in an academic setting. These results thus suggest the importance of considering the role of discrete emotions beyond the valence dichotomy.

The Need for Computational Models of Self-Regulation

We have shown piecemeal evidence that goals, performance, and emotions influence one another. However, these findings illustrate only part of the overall picture of how learners regulate these factors collectively over time. One exception is a study by Ilies et al. (2010), who applied a path model to investigate how both the GPD as well as positive and negative emotions influence goal revision in students studying for midterm exams throughout the semester. However, they used only a nonrecursive standard path model and were thus unable to capture the dynamics that develop over time. Addressing this gap requires more appropriate methodological approaches. One way to comprehensively examine the intricate interactions across all three variables is to use a formal model (Adner et al., 2009). Computational modeling is a suitable tool to achieve this goal (Farrell & Lewandowsky, 2010), especially when multiple variables are tracked over time and with each variable affecting other variables at future time points. In such contexts, traditional statistical approaches, such as multilevel and structural equation modeling, become increasingly difficult to specify (DeShon, 2012). In contrast, computational modeling offers greater flexibility to build models grounded in substantive theoretical knowledge. Despite its potential to illuminate the complex interplay of variables in learning contexts (Guastello & Liebovitch, 2009), however, computational modeling has rarely been applied in educational psychology (Kaplan & Garner, 2020; Koopmans, 2020). To address this gap, Murayama and von Keyserlingk (2025; see also Murayama & Jach, 2024; Schuetze, 2024) have recently called for a more serious adoption of computational modeling to advance motivation theories in educational psychology.

Research in adjacent disciplines within psychology offers insights into how one can build a computational model of goal setting, task performance, and emotions. In organizational psychology, for example, several models of self-regulation that revolve around goal setting exist. Using a computational model that accounts for goal biases, Gee et al. (2018) showed that individuals were sensitive to framing (i.e., approach versus avoidance contexts). In another work, Scherbaum and Vancouver (2010) derived a computational model of positive discrepancy production that used control theory principles. Although these models have provided important insights in goal setting processes, they did not include other important phases of dynamic self-regulation, namely an avenue for incorporating emotions as a manifestation of self-reflection processes (Panadero, 2017).

Present Study

The primary goal of the present study is to develop a computational model that captures the dynamic interactions between goal setting, performance, and emotions, grounded in the theoretical framework presented above. To examine its applicability across different learning situations, we empirically tested our computational model using data from two distinct studies: in a controlled experiment with a math task (Study 1) and in a more naturalistic learning setting where students studied daily for a high-stakes medical exam for a period of up to 40 days (Study 2).

It is important to note that the learning settings differ substantially across the two studies. As a result, participants in the two studies may have had different motivations for completing the tasks. Participants in Study 1 were likely motivated to solve as many problems as possible, as the reward was contingent on reaching the goal. However, the task itself may have held little intrinsic importance for them. In contrast, students in Study 2, who studied using an online learning tool, likely placed high importance on the task because of its strong personal relevance to their future careers. In addition, the studies differed in terms of the temporal distance between goal-striving episodes (a few minutes vs. several days).

What are the implications of these different settings for our computational model? Although we expect that such differences will likely influence our model's parameter estimates, we believe that the *functional* relationship between goals, performance, and emotions specified in the model is relatively robust across contexts. For example, our model (discussed in the next section) assumes that the GPD in one situation influences goal setting in the next. Although we expect that different contexts may alter the magnitude—or even the direction—of these effects, the model's core assumption, that the GPD drives goal setting, is expected to generalize across situations. As discussed later, we can gain insights into this aspect through the model's overall fit to the data. Our aim is to develop a computational model that is broadly applicable across contexts while also capturing situational differences through the estimated parameters. To evaluate our model across these two contexts, we assess both situation-general aspects reflected in model fit (i.e., model fit indices and visual inspection of simulated data) as well as situation-specific aspects (i.e., interpretation of the parameter estimates with regard to the context of the tasks).

A Computational Model of Goals, Performance, and Emotions

We employ a computational model of goal setting, performance, and emotions to ascertain the effects of the GPD and emotions in dynamic SRL (see Supplemental Materials A for a comprehensive explanation of the model and Supplemental Materials B for a discussion of the parameter recovery procedures).

Hypothesized Model

Our computational model captures the dynamic interplay between goal setting, task performance, and emotions across repeated goal-striving episodes (e.g., study sessions in which individuals set goals as to how many questions to answer). At each time point, individuals set quantitative and tractable goals, complete a task, see their performance, and report their emotional experiences. Each of these phases is also influenced by prior experiences with the task. These steps—goal setting, performance, and emotions—are expressed as three interdependent equations below.

$$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{GP\rightarrow G}(P_t - G_t) + \beta^{E\rightarrow G} E_t + \varepsilon_t^G \tag{1}$$

$$P_{t+1} = \gamma^P + \alpha^P P_t + \beta^{GP\rightarrow P}(G_{t+1} - P_t) + \beta^{E\rightarrow P} E_t + \varepsilon_t^P \tag{2}$$

$$E_{t+1} = \gamma^E + \alpha^E E_t + \beta^{GP\rightarrow E}(P_{t+1} - G_{t+1}) + \varepsilon_t^E \tag{3}$$

These equations define what the next goal, performance, and emotions would be at time $t + 1$ based on the interactions between the goal, performance, and emotions in the immediately preceding time point t. More specifically, each equation is defined as the summation of five components: (a) the baseline component for each equation represented by γ, (b) the autoregressive component (i.e., accounting for the influence of the previous value on the current value) represented as the product of the parameter α and the value of each variable at the preceding time point t, (c) the GPD component represented as the product of the parameter β^{GP}, and the GPD (the arrow in the equations points to the variable that the GPD affects), (d) the emotions component in the goal setting and performance equations expressed as the product between the parameter β^{E} and the value of the emotions at time point t, and finally (e) the residual ε. For the purposes of the main text, only the GPD and emotions components will be discussed; a more comprehensive discussion of the model can be found in Supplemental Materials A.

A key feature of the model is the inclusion of a GPD component, which captures the distance between an individual's performance and their self-set goals. Due to the timing of the three variables within a goal-striving episode, we operationalize the GPD differently. In the goal-setting equation, the GPD is operationalized as the difference between the previous performance and the previous goal (both at time point t) and is thought to shape how individuals adjust subsequent goals. Exceeding a goal (positive GPD) may lead to higher aspirations and therefore higher goals, whereas falling short (negative GPD) may be associated with more cautious goals, consistent with social–cognitive theory (Bandura, 1986, 1991). The GPD also affects subsequent performance. In the performance equation, it is defined as the new goal minus the previous performance. Goals set higher than the previous performance (positive GPD) can boost motivation and effort, thereby encouraging higher performance; goals set lower than the previous performance may therefore weaken subsequent performance.

Emotions are modeled as both outcomes and inputs in the computational model. As outcomes, they are shaped by the GPD from the current goal-striving episode. Exceeding the goal that was just set elicits positive emotions (e.g., enjoyment), whereas falling short of the goal triggers negative emotions (e.g., anger). This reflects the notion that emotional reactions serve as immediate affective evaluations of goal attainment (Lebeau et al., 2018; Nummenmaa & Niemi, 2004). As predictors, emotions shape subsequent goal setting and performance. Positive emotions can boost perceived control and value, potentially leading to higher goals and better performance. Alternatively, they may signal sufficient progress toward a goal, resulting in reduced effort (pushing/coasting; Carver, 2003; Thürmer et al., 2020). Negative emotions may undermine engagement, or in the case of outcome-focused emotions (e.g., anxiety), enhance performance by signaling the importance of the goal. To get at the nuances of valence as well as discrete emotions, the model accommodates both aggregated and individual emotions to better understand how specific affective states guide behavior.

Alternate Models

Alternate models are also important for model comparison by either testing the necessity of certain components of the model or testing whether explanations for the relationships between variables fit better. Alternate Model 1 tests the idea that goal success and failure have different effects on future goal setting (Wang & Mukhopadhyay, 2012) by estimating separate GPD parameters depending on goal attainment (i.e., estimating $\beta^{GP\rightarrow G|S}$ for goal success and $\beta^{GP\rightarrow G|F}$ for failure instead of $\beta^{GP\rightarrow G}$). Models 2–4 test the necessity of individual components by fixing parameters to 0, including the effect of the GPD on goal setting (Alternate Model 2; $\beta^{GP\rightarrow G} = 0$), the effect of the GPD on performance (Alternate Model 3; $\beta^{GP\rightarrow P} = 0$), and the effect of emotions on goal setting and performance (Alternate Model 4; $\beta^{E\rightarrow G} = 0$ and $\beta^{E\rightarrow P} = 0$).

To determine the best-fitting model, we used the widely applicable information criterion (WAIC; Watanabe, 2010) for model comparison, which measures the predictive accuracy of a model while providing a correction that averages over the posterior distribution (Gelman et al., 2014).

Study 1

Method

Participants

In total, 367 participants took part in the study. We used the online platform Prolific to invite participants from the United Kingdom to the study. To be eligible, participants needed to be over the age of 18 and speak English fluently. After data collection, we excluded participants based on the following criteria: First, we excluded data from participants who indicated in the postexperiment survey that they used a calculator at any point during the task ($n = 5$). Second, we also excluded data from participants who, in any block, indicated an unrealistic goal (i.e., a goal higher than 60, meaning that they intended to answer each question in 2 s or less; see *Math task* below for details on the task; $n = 4$). We also excluded data from one participant who could not provide all state emotion ratings. This resulted in a final sample size of 357 participants ($n_{\text{female}} = 212$, $n_{\text{male}} = 145$, $M_{\text{age}} = 38.83 \pm 12.40$ years).

Participants were reimbursed £8.00 for their time, plus a bonus payment that was contingent on their performance on the task. Ethics approval was obtained from the Ethics Commission of the Faculty of Economics and Social Sciences at the University of Tübingen. Before starting the experiment, all participants gave informed consent.

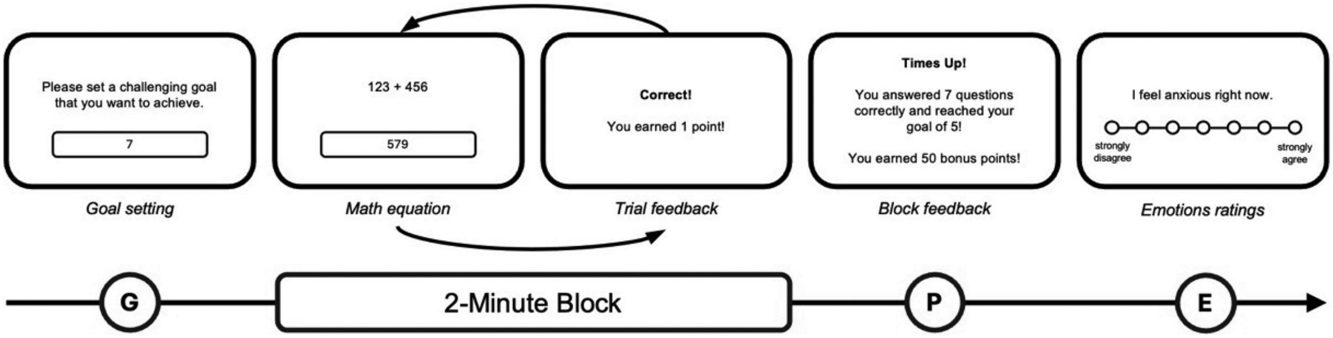
Math Task

Figure 1 shows one block of our online math task in which participants answered three-digit addition and subtraction problems (see Supplemental Materials D for the criteria used in generating the stimulus set). This stimulus set was randomized for each participant and was presented in that order during the task. Equations were presented horizontally in the middle of the screen. Participants typed their answer to the question into a response box directly under the equation and pressed the return key to submit their answer. Afterward, participants were informed whether they answered the question correctly.

The math task was divided into 20 two-min blocks of equations. Participants were instructed to answer as many of these questions as they could in the 2 min they were given for each block. Before each block, participants set a goal as to how many questions they wanted to answer correctly in the upcoming block. After the 2 min were over, participants saw how many questions they answered correctly, the number of points they earned during the block, and whether they reached the goal that they set at the beginning of the block. After the presentation of the feedback, participants rated how much enjoyment, sadness, anxiety, and boredom

Figure 1

Study 1 Experimental Design



Note. An online math task was used in which participants were prompted to set a goal as to the number of questions they wanted to answer correctly (*G*), answer as many math questions correctly as possible, after which their performance in the time allotted was shown (*P*), and rate their emotions on a 7-point Likert scale (*E*).

they felt at the current moment on a 7-point Likert scale (1 = *strongly disagree*, 7 = *strongly agree*). On average, participants answered about nine trials per block (*SD* = 4.0 trials) and about 197 trials during the whole experiment (*SD* = 77.1 trials).

To motivate participants to answer as many questions correctly as they can, we incentivized the task such that participants would collect points that would be exchanged for a bonus payment at the end of the experiment. One point was awarded for each correct answer, and one point was deducted for each incorrect answer. Subtracting points from incorrect responses was done to encourage participants to answer all questions and not skip hard questions. At the end of each block, participants received extra points if they reached their goal, which was equal to the product of their goal and 10 (e.g., 50 extra points were awarded if participants set a goal of five and managed to answer at least five questions correctly during the current block). On average, participants earned 1,381.65 ± 685.18 points.

Procedure

Eligible participants were given a link that led to a page with details about the study. Upon accepting the invitation, participants continued to a separate screen in which they read through a consent form. If participants gave their informed consent to participate in the study, they were prompted to complete a questionnaire package including several demographic questions. Once the survey package was completed, participants were given a new link to the task and were instructed to only open the link when they were able to dedicate between 40 and 50 min to the task without distraction.

Before the main math task, participants completed a 2-min practice block of the task. This block served as a way for participants to familiarize themselves with the task and to get an idea of what a reasonable goal was for their own abilities. Following the practice block, participants started the experiment. Afterward, participants were shown their overall performance on the task as well as how much bonus money they earned (awarded at a ratio of £1.00 per 500 points). Participants were then asked to answer questions about distractions, calculator use, and self-assessed reliability of their data. They were encouraged to answer honestly because their answers would not influence reimbursement.

Measures

Goal Level. The goal levels that participants set at the beginning of each block, which indicated the number of questions they wanted to answer correctly, were entered as the goal in our model.

Performance. After each block, the number of correct answers was shown to the participant and was also entered into the model as performance.

Emotions. Four discrete emotions (anxiety, boredom, enjoyment, and sadness) were assessed on a 7-point Likert scale. To compute the aggregated emotion index, we first reverse-coded the responses for the two negative emotions (sadness and anxiety) and then centered the responses of all emotions. We then used the average of the emotion ratings as the aggregated emotions variable, such that positive values would indicate positive emotions and negative values would indicate negative emotions. The average Cronbach's α for the emotions parameter in each block was α = .66 ± .03.

Trait Measures. Although not the main focus of the current study, we also collected self-reported ratings on trait depression, anxiety, and negative emotionality using the Center for Epidemiologic Studies Depression Scale (Radloff, 1977), the Trait Anxiety Inventory (Spielberger et al., 1983), and the negative emotionality scale of the Next Big-Five Inventory (Soto & John, 2017); respectively, as part of the questionnaire packet administered before the task (see Supplemental Materials C for how these trait measures are related to parameters of our model when estimating using emotions aggregated along the valence dimension).

Computational Modeling

Computational modeling was implemented using the open-source software Stan (Stan Development Team, 2022). The models were written using Stan syntax to predict the goal level, performance, and emotions at the reach time point using Equations 1 to 3 for the hypothesized model and the corresponding modifications to the equations as noted in Supplemental Materials A for the alternate models. A hierarchical Bayesian framework using Markov chain Monte Carlo (MCMC) methods was employed to estimate posterior distributions of each parameter on the population level and the participant level (with the exception of the

Table 1
Within-Person Descriptive Statistics for Study 1

Variable	*M*	*SD*	1	2	3	4	5	6	7
1. Goal	7.09	3.39	—						
2. Performance	8.41	3.96	.34**	—					
3. Positive emotions	0.94	1.34	.02	.30**	—				
4. Anxiety	3.37	1.88	−.02	−.16**	−.65**	—			
5. Boredom	2.98	1.96	.03*	.00	−.33**	−.06**	—		
6. Enjoyment	4.38	1.86	.00	.25**	.73**	−.10**	−.53**	—	
7. Sadness	2.20	1.49	−.03*	−.23**	−.75**	.30**	.17**	−.37**	—
8. Trial	10.50	5.77	.31**	.29**	−.08**	−.11**	.43**	−.24**	.00

Note. "Positive emotions" refers to the variable that is aggregated along the valence dimension. This is computed by reverse-coding the negative emotions and centering all emotions. Positive values indicate positive valence, and negative values indicate negative valence. For interpretability, all discrete emotions were left as the raw values such that low values indicate low levels of the emotion and high values indicate high levels of the emotion (i.e., 1 is the lowest and 7 is the highest). A total of 357 participants' data were used (7,140 observations).
* $p < .05$. ** $p < .001$.

residual standard deviations; Ballard et al., 2018). The median value of each posterior distribution was taken as the value of the estimated parameter; a 95% high density interval (95% HDI) is also provided, which allows us to determine significance (i.e., if 0 is not included in the interval). For this article, we will only discuss the results based on the population-level parameters. See Supplemental Materials A for full details on how we applied our computational modeling method.

To reduce the computational demand and for the purpose of simplicity, we decided to focus on the aggregated emotion index (positive–negative) for model selection and model fit evaluation. However, to examine potential differences in discrete emotions, we applied the final model not only to the aggregated emotion but also to discrete emotions (in separate models) to obtain parameter estimates. As you will see, the final model we selected was the most complex model (Alternate Model 1), including all possible parameters in the model; therefore, it is unlikely that our procedure masked some important effects specific to a certain type of emotion (i.e., if a certain effect does not exist for a specific type of emotion, the effect should be statistically nonsignificant in the full model).

Transparency and Openness

All data and analysis code to run the hypothesized and alternate models for Study 1 can be assessed at https://osf.io/qc6hm/. Data were analyzed using the open-source program Stan, CmdStan Version 2.31.0, via the CmdStanPy package, Version 1.8, on Python, Version 3.11.1 (Stan Development Team, 2022). Correlations were run using the SciPy package, Version 1.9.3 (Virtanen et al., 2020), and figures were made using the matplotlib package, Version 3.6.1 (Hunter, 2007). The study's design and analyses were not preregistered.

Table 2
WAIC Values for the Hypothesized and Alternate Models for Study 1

Model	WAIC
Hypothesized	52,934.65
Alternate 1: Goal success and failure	52,743.25
Alternate 2: No GPD in goal setting	54,236.72
Alternate 3: No GPD in performance	53,144.51
Alternate 4: No emotions in goal setting and performance	53,020.43

Note. The bolded model denotes the best-fitting model. GPD = goal–performance discrepancy; WAIC = widely applicable information criterion.

Results

Descriptive Statistics

Descriptive statistics and within-participant correlations between goals, performances, and emotions are shown in Table 1. A trial was included to show trends in the variables over the course of the task. Mean goals and performances suggest that participants were, for the most part, able to reach and surpass their goals. Participants also improved on the task over time, as suggested by the positive correlation between goals and trial, as well as performance and trial. Generally, there are weak to moderate correlations between the study variables.[1]

Model Comparison

Table 2 shows the WAIC values for the hypothesized and alternate models for Study 1. The model with the lowest WAIC value is the one in the group of models that has the highest predictive accuracy. The model that fits the data the best is Alternate Model 1, which separately considers goal success and failure when assessing the effect of the GPD on goal setting (see Supplemental Table S4 for all estimated parameter values of the best-fitting model for Study 1). This result suggests that goal success and failure influence goal setting differently, potentially in a way that maximizes the reward earned in the task.

This model also performed better than the models in which $\beta^{GP\rightarrow G}$ was set to zero and $\beta^{GP\rightarrow P}$ was set to zero, suggesting that incorporating information from the GPD is necessary for the goal revision and performance step. Importantly, this model performed better than the alternate model without the emotions parameters $\beta^{E\rightarrow G}$ and $\beta^{E\rightarrow P}$, suggesting that emotions also play a role in goal revision and performance and can be teased apart from the effects of the GPD in goal setting and performance. In summary, the best-fitting model for Study 1 confirms the importance of the

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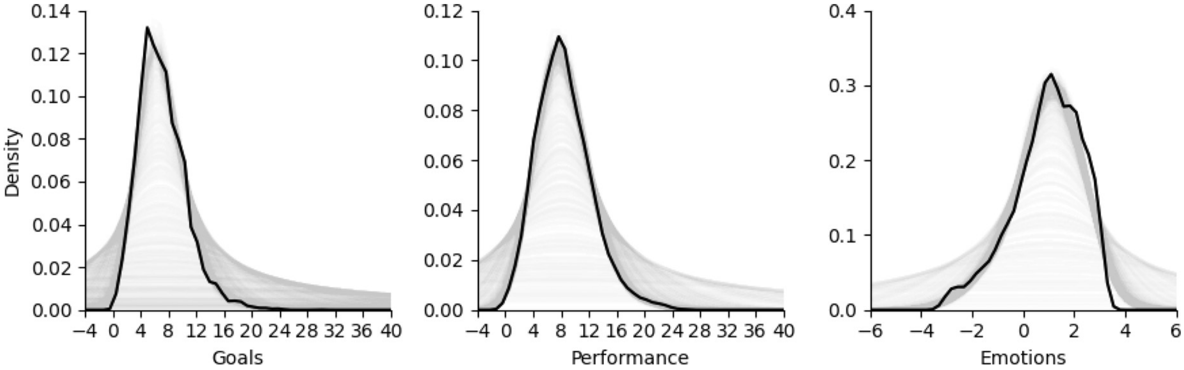
[1] This level of correlation is typical in within-person designs. For example, Goetz et al. (2016) found that the between-person correlation between mastery goals and enjoyment was .49 whereas the within-person correlation between the same variables was reduced to .24.

Figure 2

Visual Inspection of Estimated Goals, Performance, and Emotions for Study 1



Note. The densities of the observed and sampled goals, performance, and emotions for Study 1. The black line represents the density of the observed goals, performance, and emotions in their respective plots. The light gray lines represent the estimated goals, performance, and emotions from 500 randomly chosen iterations from the Markov chain Monte Carlo chains. The parameters in each iteration were used to estimate the goals, performance, and emotions of every participant to generate values. A visual inspection showed that the majority of the densities of estimated values mirrored the observed density (although they were more dispersed), indicating that the model was able to sufficiently reproduce the observed goals, performance, and emotions.

GPD in goal setting, performance, and—crucially—that emotions can play a direct role as well. This finding is in line with recent research showing that emotions may influence goal setting and performance more than just through success/failure outcomes (Theobald et al., 2021).

Model Fit

Although model comparison was done to determine the relative fit of the winning model, the next step is to ensure that this model can actually be able to produce similar goals, performances, and emotions that resemble those of the observed data. To this end, we had our Stan code generate goals, performances, and emotions after estimating a set of parameters in each iteration of the MCMC. We then plotted densities of the estimated goals, performances, and emotions from 500 randomly chosen iterations. Figure 2 shows these plots with the densities of the observed goals, performances, and emotions. A visual inspection confirmed that the majority of the estimated goals, performance, and emotions sufficiently reproduced similar densities as the observed data.

Role of the GPD on Goal Setting, Performance, and Emotions

The parameter values accounting for the effect of the GPD on goal setting, performance, and (aggregated) emotions were all nonzero (Table 3). For goal setting, the model estimated a positive value of $\beta^{GP\rightarrow G}$ for both goal success and goal failure ($\beta^{GP\rightarrow G|S}$ = 0.273, 95% HDI = [0.249, 0.296]; $\beta^{GP\rightarrow G|F}$ = 0.483, 95% HDI = [0.427, 0.539]). Crucially, the 95% HDI did not overlap, indicating that the parameters are indeed different from each other and that the effects of failure on goal setting were larger than those of success (see the *performance satisficing* proposition proposed by

Table 3

Median Estimates of the Parameters of Interest for Study 1

	Median [95% HDI]				
Parameter	Aggregate	Anxiety	Boredom	Enjoyment	Sadness
Effects of the GPD					
$\beta^{GP\rightarrow G\|S}$	0.273[a] [0.249, 0.296]	0.277[a] [0.254, 0.301]	0.278[a] [0.255, 0.302]	0.272[a] [0.248, 0.295]	0.278[a] [0.254, 0.301]
$\beta^{GP\rightarrow G\|F}$	0.483[a] [0.427, 0.539]	0.499[a] [0.444, 0.554]	0.502[a] [0.446, 0.558]	0.484[a] [0.428, 0.539]	0.496[a] [0.439, 0.553]
$\beta^{GP\rightarrow P}$	0.429[a] [0.383, 0.476]	0.430[a] [0.383, 0.477]	0.427[a] [0.380, 0.474]	0.426[a] [0.380, 0.473]	0.428[a] [0.381, 0.475]
$\beta^{GP\rightarrow E}$	0.128[a] [0.112, 0.145]	−0.086[a] [−0.103, −0.070]	−0.035[a] [−0.047, −0.022]	0.183[a] [0.161, 0.205]	−0.110[a] [−0.131, −0.090]
Effects of emotions					
$\beta^{E\rightarrow G}$	0.067[a] [0.038, 0.096]	−0.027[a] [−0.047, −0.007]	−0.020[a] [−0.039, −0.002]	0.050[a] [0.031, 00.070]	−0.019 [−0.044, 0.006]
$\beta^{E\rightarrow P}$	−0.103[a] [−0.172, −0.036]	0.009 [−0.033, 0.052]	0.063[a] [0.026, 0.100]	−0.089[a] [−0.132, −0.047]	0.031 [−0.021, 0.084]

Note. The parameter estimates in the aggregate column stem from the model using emotions aggregated along the valence dimension. Positive values of the aggregate emotions indicate positive valence, and negative values indicate negative valence. Although the computational modeling for the negative discrete emotions also used the reverse-coded emotions, we multiplied the emotions-related parameter estimates (i.e., $\beta^{GP\rightarrow E}$, $\beta^{E\rightarrow G}$, and $\beta^{E\rightarrow P}$) by −1 to allow for easier interpretability (e.g., a positive $\beta^{E\rightarrow G}$ value would mean that higher levels of anger would lead to higher goals). GPD = goal–performance discrepancy; HDI = high density interval.

[a] A median parameter estimate whose 95% HDI does not include 0 and is therefore significant.

Wang & Mukhopadhyay, 2012). This result suggests that participants set high goals after goal success and low goals after goal failure (positive parameter value in both cases multiplied by the difference $P_t - G_t$). For performance, the model also estimated a positive value of the $\beta^{GP \to P}$ parameter ($\beta^{GP \to P} = 0.429$, 95% HDI = [0.383, 0.476]). This result is in line with our hypothesis that a goal set higher than the previous performance would encourage higher performance, whereas a goal set lower than the previous performance would encourage lower performance (positive parameter value multiplied by the difference $G_{t+1} - P_t$). This finding aligns well with goal-setting theory (Locke & Latham, 1990), which suggests that setting challenging goals motivates goal-directed behavior and enhances performance through supporting effort regulation, which could help individuals persist in difficult tasks (Richardson et al., 2012). When using aggregated emotions, the model also estimated a positive value of the $\beta^{GP \to E}$ parameter ($\beta^{GP \to E} = 0.128$, 95% HDI = [0.112, 0.145]). As expected, this result reflects the fact that goal success leads to more positive emotions and goal failure to more negative emotions (positive parameter value multiplied by the difference $P_{t+1} - G_{t+1}$).

To further investigate whether the effects of the GPD on the emotions are different between discrete emotions, we ran the best-fitting model using the individual emotions rather than the aggregated emotion as the emotion variable. As expected, the parameter estimates that are not related to emotions (e.g., $\beta^{GP \to G}$) were very similar across all models. In addition, although all effects are statistically significant, the GPD effects on emotions are different in terms of their magnitudes (Table 3; also see Supplemental Table S4 for all parameter values). The positive GPD led to stronger enjoyment ($\beta^{GP \to E} = 0.183$, 95% HDI = 0.161, 0.205]), weaker sadness ($\beta^{GP \to E} = -0.110$, 95% HDI = [−0.131, −0.090]), weaker anxiety ($\beta^{GP \to E} = -0.086$, 95% HDI = [−0.103, −0.070]), and weaker boredom ($\beta^{GP \to E} = -0.035$, 95% HDI = [−0.047, −0.022]); although the magnitude of the effects differed across the three negative emotions and was particularly small for boredom. These results suggest heterogeneity in the effects of GPD on subsequent reactions across different emotions.

Role of Emotions on Goal Setting and Performance

The effects of emotions on both goal revision and performance were significant when considering the aggregated emotions variable (Table 3). The $\beta^{E \to G}$ parameter was positive, indicating that positive emotions were associated with setting high goals, whereas negative emotions were associated with setting low goals ($\beta^{E \to G} = 0.067$, 95% HDI = [0.038, 0.096]). The $\beta^{E \to P}$ parameter was negative, indicating that positive emotions led to low performance, whereas negative emotions led to high performance ($\beta^{E \to P} = -0.103$, 95% HDI = [−0.172, −0.036]). This finding can be indicative of coasting in that positive emotions would indicate that the current performance is adequate, whereas negative emotions would indicate that a higher performance is needed to reach goals in subsequent blocks.

Modeling the discrete emotions using the same model revealed for goal setting that enjoyment had positive effects ($\beta^{E \to G} = 0.050$, 95% HDI = [0.031, 0.070]), whereas anxiety ($\beta^{E \to G} = -0.027$, 95% HDI = [−0.047, −0.007]) and boredom ($\beta^{E \to G} = -0.020$, 95% HDI = [−0.039, −0.002]) had negative effects, indicating effects comparable to those of the aggregated emotions. This is in line with previous findings that positive activity emotions, such as enjoyment, enhance motivation and perceived value (Forsblom et al., 2021; Mega et al., 2014; Pekrun, 2006, 2018), thereby promoting goal generation (Webster & Hadwin, 2015). Furthermore, high anxiety is typically associated with high achievement value and increased avoidance goals (Pekrun, 2006; Sakaki et al., 2024), which could be expressed as lower goals to ensure that they are reached in subsequent blocks. However, given that we found similar patterns even for boredom (which is typically not associated with high achievement value), the results may not reflect mechanisms specific to anxiety.

Turning to performance, we found that enjoyment had a negative effect ($\beta^{E \to P} = -0.089$, 95% HDI = [−0.132, −0.047]) and boredom had a positive effect ($\beta^{E \to P} = 0.063$, 95% HDI = [0.026, 0.100]). These results contrast with the aforementioned previous findings on the positive effects of enjoyment (Forsblom et al., 2021; Mega et al., 2014; Pekrun, 2006, 2018); however, as mentioned earlier, this may reflect coasting, such that higher performance may be perceived as unnecessary when goals are reached. The positive effect of boredom is surprising, especially given that it has been associated with *lower* performance (Tanaka & Murayama, 2014; see Tze et al., 2016 for a meta-analysis). We suspect here that the extrinsic monetary rewards motivated participants to persist in doing well with the task despite their boredom or lack of enjoyment.

Lastly, we found no effects of sadness on goal setting ($\beta^{E \to G} = -0.019$, 95% HDI = [−0.044, 0.006]) or on performance ($\beta^{E \to P} = 0.031$, 95% HDI = [−0.021, 0.084]). Although the empirical evidence would suggest that there should be effects of sadness on goal setting and performance (Chong & Park, 2017), our results show that there are low levels of average sadness ($\gamma^{\mathrm{E}} = -0.799$, 95% HDI = [−0.900, −0.701]), potentially masking effects of sadness.

Overall, Study 1 showed that goal setting, performance, and emotions can be captured by the best-fitting computational model. However, the study took place in a controlled laboratory setting. Although participants were able to earn a monetary reward based on their performance, they may not have viewed the task as personally meaningful. Emotional effects on goal setting and performance may differ in real educational contexts, where task importance is higher. As Bandura (1991) noted, greater importance can drive higher goals and aspirations. To examine this, we next apply the computational model to data from a more authentic educational setting.

Study 2

In Study 2, we aimed to extend Study 1 by applying the model to data collected in a real-life learning context. Data were obtained from German medical students who studied for a high-stakes exam (Breitwieser et al., 2022). Although not the main purpose of the present study, some participants were asked to internalize an implementation intention in an effort to stick to their goal for the day. Because the study was conducted as an intervention, the hypothesized model was used to estimate mixture weights to determine if noticeable differences between groups could be detected (Ballard et al., 2018; Bartlema et al., 2014). The results showed that both control and intervention groups could be combined (see Supplemental Materials F).

Method

The details of the procedure are outlined in Breitwieser et al. (2022). Only the methods relevant to the present study will be highlighted here.

Participants

German medical students using an online learning platform to study for their upcoming second state exam were given the opportunity to participate in the study. In total, 365 participants registered for the study, and 352 students used the learning platform. For our analyses, we dropped participants who provided less than 20 days of complete data. The data did not have to consist of consecutive days for the participant to be included, i.e., intervals of more than one day between learning days were allowed in the data. Participant exclusion led to a final sample size of 305 participants ($n_{\text{female}} = 213$, $n_{\text{male}} = 92$, $M_{\text{age}} = 25.96 \pm 3.56$ years).

Ethics approval was obtained from the Ethics Committee of the DIPF | Leibniz Institute for Research and Information in Education. Before testing, all participants were given informed written consent. Participants were instructed that the study would run for 40 days. They received 1€ for each day with complete data and 10€ for providing 30 days of complete data. On average, participants included in the study completed 30.2 ± 3.0 days of study.

Procedure

Figure 3 outlines a typical study session. At the beginning of each study session, participants were asked to complete a prelearning survey that assessed their learning goal for the day (i.e., the number of questions they intended to answer) and their ratings as to how much enjoyment, anger, tension, and boredom they currently felt. They were then instructed to begin their study session for that day. At the end of their study session, participants were given a postlearning survey that assessed the ratings as to how much enjoyment, pride, anger, anxiety, and boredom they currently felt. Importantly, students did not receive external feedback from the study platform; however, they had the option to view their performance at the end of the learning session if they chose to do so. For participants in the experimental group, a prompt was shown on some days that asked them to internalize the following sentence: "If I am thinking about stopping to answer questions today, I will tell myself that I will continue answering questions until I have reached my intended workload!"

Measures

Goal Level. Because participants were allowed to answer as many or as few questions as they saw fit, they were asked to type in the number of questions they wanted to answer on the current day's learning session into a free-response text field.

Performance. Performance was calculated from log file data as the number of questions answered (i.e., attempted) in each learning session.

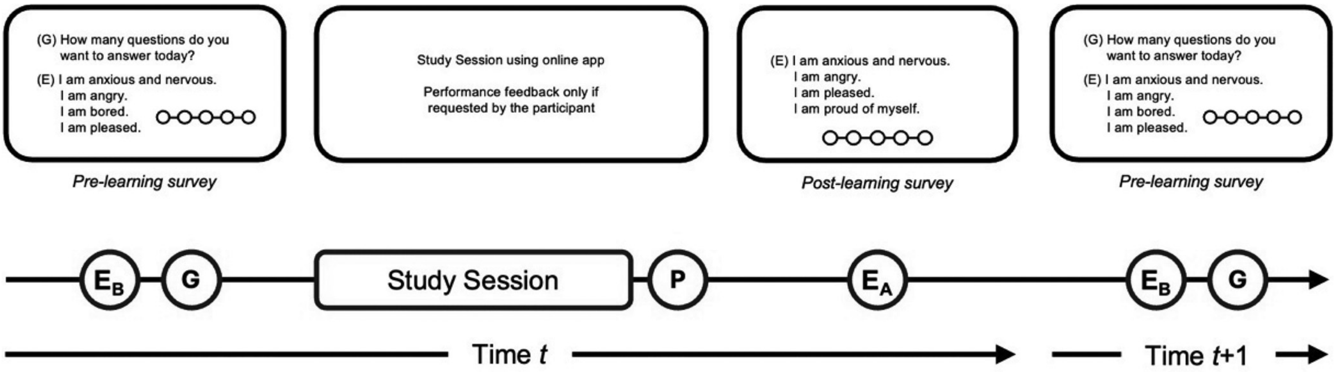
Emotions. Participants were asked to rate their current emotions (e.g., *I am proud of myself.*) on a 5-point Likert scale (1 = *strongly disagree*, 5 = *strongly agree*) both before and after the learning session. Emotions assessed in the prelearning session survey were enjoyment, anger, anxiety, and boredom; emotions assessed in the postlearning session survey were enjoyment, pride, anger, and tension. To compute the aggregated emotion, we negatively coded the negative emotions (anger and tension) and then centered all emotions. Then we computed the average value of the emotions. Cronbach's α was computed for each day using all nonmissing emotions responses. A between-subjects Cronbach's α reached an average value of $\alpha = .52 \pm .06$ for emotions from the prelearning survey and $\alpha = .78 \pm .04$ for emotions from the postlearning survey.

Computational Modeling

Because it was not clear what the effects of emotions are over an extended period, we ran our hypothesized and alternate models using emotions assessed in the pre- and postlearning surveys

Figure 3

Study 2 Experimental Design



Note. Students used an online learning platform to study for a high-stakes exam for up to 40 days. Before each study session, they completed a prelearning survey that asked for the number of questions they wanted to answer that day (G) and their state emotions (E_B). Afterwards, they studied for the exam by completing questions on the online platform. Performance, however, was not shown to participants after the study session, but participants were given the opportunity to see it after the learning session (P). Finally, they were given a postlearning survey that assessed state emotions (E_A). It is important to note that the emotions in Study 2 (E_B and E_A) were considered to be a "result" of the goal and performance directly preceding them. The bottom arrows below the figure represent the time point from which the variables are from (either time t to time $t + 1$).

separately. Although the goal set and the performance on the current day's learning session should have the largest effect on the emotions assessed in the postlearning session survey, the resulting emotions may not have such a large impact on the goals set and the performance in the following learning session. The emotions assessed in the prelearning session survey may still be influenced by the previous learning session, but time would have passed in which participants could have experienced other, unrelated emotions. These emotions may therefore only be weakly associated with the emotions that arose after the previous learning session. Nevertheless, the prelearning emotions may still have an impact on the goal setting and performance processes of the current session, possibly in a mood-as-information manner (Richard & Diefendorff, 2011). We compared the hypothesized and alternate models used in the model comparison for Study 2 once with the prelearning survey emotions models and again with the postlearning survey emotions models, leading to two groups of models. See Supplemental Materials A for more details on the computational modeling (especially the section "Additional Considerations for Study 2"). Other modeling procedures are the same as in Study 1.

Transparency and Openness

All analysis code to run the hypothesized and alternate models for Study 2 can be assessed at https://osf.io/qc6hm/. Data were analyzed using the open-source program Stan, CmdStan Version 2.31.0, via the CmdStanPy package, Version 1.0.8, on Python, Version 3.11.1 (Stan Development Team, 2022). Correlations were run using the SciPy package, Version 1.9.3 (Virtanen et al., 2020), and figures were made using the matplotlib package, Version 3.6.1 (Hunter, 2007). The study's design and analyses were not preregistered.

Results

Descriptive Statistics

Descriptive statistics and correlations between goals, performance, and emotions (both from the pre- and postlearning surveys) are presented in Table 4. Day was also included to show trends over the course of the study period (with a maximum of 40 days). The mean goal and performance suggests that participants were able to reach their goals. Over time, participants showed a slight tendency to decrease their goals, whereas performance increased over time, suggesting that goals were potentially set very high at the beginning of the study period and were gradually lowered. As with Study 1, we found weak-to-moderate within-person correlations between goals, performance, prelearning emotions, and postlearning emotions.

Table 5

WAIC Values for the Hypothesized and Alternate Models for Study 2

Model	WAIC	
	Prelearning emotions	Postlearning emotions
Hypothesized	34,540.99	28,623.50
Alternate 1: Goal success and failure	34,453.70	28,558.29
Alternate 2: No GPD on goal setting	34,713.43	28,788.17
Alternate 3: No GPD on performance	36,943.26	31,048.50
Alternate 4: No emotions in goal setting and performance	34,875.52	28,651.75

Note. The bolded model denotes the best-fitting model for both groups. GPD = goal–performance discrepancy; WAIC = widely applicable information criterion.

Table 4

Within-Person Descriptive Statistics for Study 2

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11
1. Goal	93.35	46.34	—										
2. Performance	95.09	56.01	.46***	—									
3. Positive emotions (pre)	0.66	0.77	.02	.03**	—								
4. Positive emotions (post)	0.43	0.95	.02	.16***	.20***	—							
5. Anger (pre)	1.44	0.85	−.01	−.01	−.09***	−.12***	—						
6. Enjoyment (pre)	2.47	1.10	.03**	.06***	.12***	.20***	−.18***	—					
7. Tension (pre)	2.02	1.22	.01	.02*	−.12***	−.15***	.36***	−.21***	—				
8. Anger (post)	1.99	1.23	.01	−.11***	−.14***	−.80***	.11***	−.08***	.10***	—			
9. Enjoyment (post)	2.86	1.24	.02	.13***	.15***	.80***	−.07***	.23***	−.06***	−.46***	—		
10. Pride (post)	2.78	1.23	.04***	.20***	.12***	.80***	−.05***	.19***	−.06***	−.49***	.66***	—	
11. Tension (post)	1.92	1.22	.00	−.05***	−.20***	−.66***	.14***	−.10***	.26***	.50***	−.32***	−.29***	—
12. Day	15.74	8.94	.04***	.04***	−.12***	−.04***	.03**	−.13***	.09***	−.04***	−.07***	−.06***	.04***

Note. "Positive emotions" refers to the emotions variable that is aggregated along the valence dimension. This is computed by reverse-coding the negative emotions and centering all emotions. Positive values indicate positive valence, and negative values indicate negative valence. For interpretability, all discrete emotions were left as the raw values such that low values indicate low levels of the emotion and high values indicate high levels of the emotion (i.e., 1 is the lowest and 5 is the highest). A total of 305 participants' data were used (9,209 observations).

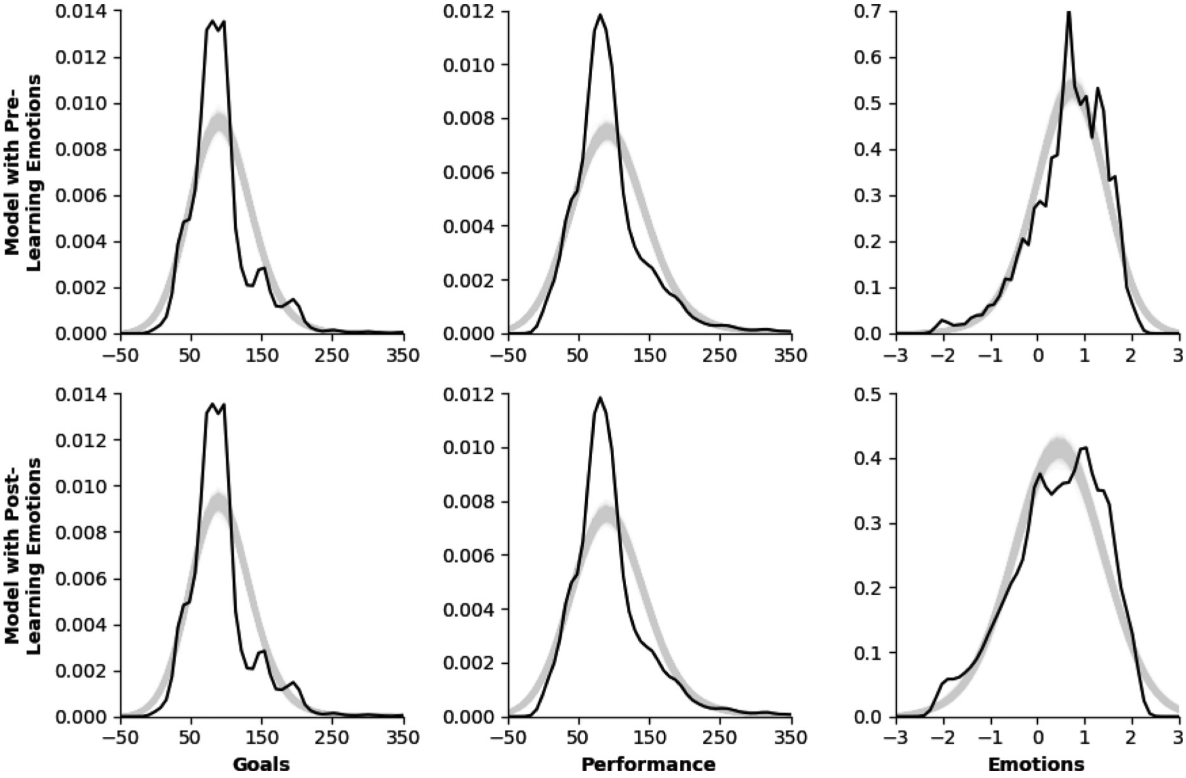
* $p < .05$. ** $p < .01$. *** $p < .001$.

Model Comparison

Table 5 shows WAIC values of the two groups of models. In both cases, model comparison revealed that the alternate model using a separate $\beta^{GP\rightarrow G}$ parameter for goal success and goal failure had the lowest WAIC value and was the best-fitting model in each group of models (see Supplemental Materials E for all estimated parameter values). As in Study 1, this model outperformed the hypothesized model, the model in which $\beta^{GP\rightarrow G}$ was set to zero, the model in which $\beta^{GP\rightarrow P}$ was set to zero, and the model in which $\beta^{E\rightarrow G}$ and $\beta^{E\rightarrow P}$ were set to zero. These results suggest that even in more ecologically valid settings in which participants are studying for an exam, the effects of GPD are still observed in goal revision, performance, and the experiencing of emotions, and emotions are observed to play a role in goal setting and performance.

Figure 4

Visual Inspection of Model Fit in Study 2



Note. The densities of the observed and sampled goals, performance, and emotions for Study 2 modeling with prelearning emotions (top row) and postlearning emotions (bottom row). The black line represents the density of the observed goals, performance, and emotions in their respective plots. The light gray lines represent the estimated goals, performance, and emotions from 500 randomly chosen iterations from the Markov chain Monte Carlo chains. The parameters in each iteration were used to estimate goals, performance, and emotions of every participant to generate values. A visual inspection showed that the majority of the estimated densities adequately mirror the observed densities, albeit with a higher density for goals and performance between 50 and 100.

Model Fit

To ensure that the best-fitting model could reasonably produce goals, performances, and emotions, we again had the model generate estimate these values for each participant using estimated parameter values from 500 randomly chosen iterations of the MCMC chains. These were then converted into densities and plotted against the observed goals, performances, and emotions. Figure 4 shows these densities for the best-fitting models using pre- and postlearning emotions. The overlapping densities confirm that there is a decent fit of the sampled data to the observed data, albeit with a slightly higher density for the observed goals and performance between 50 and 100.

Role of the GPD on Goal Setting, Performance, and Emotions

Table 6 shows the parameter estimates of the best-fitting model using the prelearning, and Table 7 shows the parameter estimates of the best-fitting model using the postlearning emotions. In the model with the aggregated emotions, the effect of the GPD on goal setting was positive after success (model with prelearning emotions: $\beta^{GP\rightarrow G|S} = 0.063$, 95% HDI = [0.028, 0.097]; model with postlearning emotions: $\beta^{GP\rightarrow G|S} = 0.059$, 95% HDI = [0.026, 0.093]) *and negative after failure* (model with prelearning emotions: $\beta^{GP\rightarrow G|F} = -0.128$, 95% HDI = [−0.178, −0.077]; model with postlearning emotions: $\beta^{GP\rightarrow G|F} = -0.119$, 95% HDI = [−0.171, −0.068]). Contrary to Study 1, this finding suggests that students also set high goals in subsequent study sessions (negative GPD multiplied by a negative weight), which we believe is due to the high-stakes nature of the exam, because students would want to set high goals—even after failure—to ensure they did not fall behind while studying. Indeed, this phenomenon was also observed in other achievement settings (Campion & Lord, 1982; Donovan, 2009). For performance, both models estimated a positive $\beta^{GP\rightarrow P}$ (model with prelearning emotions: $\beta^{GP\rightarrow P} = 0.631$, 95% HDI = [0.599, 0.663]; model with postlearning emotions: $\beta^{GP\rightarrow P} = 0.632$, 95% HDI = [0.600, 0.664]). This finding mirrors that of Study 1, suggesting that students also use goals to motivate goal-directed behavior to study for their high-stakes exam.

Lastly, the model using the aggregated emotions from the postlearning survey estimated a positive $\beta^{GP\rightarrow E}$ whereas the model using the aggregated emotion from the prelearning survey of the next learning session estimated $\beta^{GP\rightarrow E}$ to be effectively zero (model using prelearning emotions: $\beta^{GP\rightarrow E} = 0.024$, 95% HDI =

Table 6

Median Estimates of the Parameters of Interest for Study 2, Prelearning Emotions

Parameter	Median [95% HDI]			
	Aggregate	Anger	Enjoyment	Tension
Effects of the GPD				
$\beta^{GP\rightarrow G\|S}$	0.063[a] [0.028, 0.097]	0.071[a] [0.034, 0.109]	0.069[a] [0.032, 0.107]	0.072[a] [0.034, 0.109]
$\beta^{GP\rightarrow G\|F}$	−0.128[a] [−0.178, −0.077]	−0.121[a] [−0.168, −0.074]	−0.122[a] [−0.169, −0.075]	−0.120[a] [−0.167, −0.073]
$\beta^{GP\rightarrow P}$	0.631[a] [0.599, 0.663]	0.657[a] [0.624, 0.69]	0.656[a] [0.623, 0.689]	0.656[a] [0.623, 0.69]
$\beta^{GP\rightarrow E}$	0.024 [−0.003, 0.052]	−0.040[a] [−0.072, −0.009]	0.042[a] [0.006, 0.078]	−0.022 [−0.058, 0.012]
Effects of emotions				
$\beta^{E\rightarrow G}$	0.005 [−0.010, 0.020]	−0.001 [−0.017, 0.015]	0.020[a] [0.003, 0.037]	0.006 [−0.007, 0.018]
$\beta^{E\rightarrow P}$	0.018[a] [0.002, 0.035]	−0.015[a] [−0.029, −0.002]	0.018[a] [0.006, 0.031]	−0.006 [−0.018, 0.005]

Note. The parameter estimates in the aggregate column stem from the model using emotions aggregated along the valence dimension. Positive values of the aggregate emotions indicate positive valence, and negative values indicate negative valence. Although the computational modeling for the negative discrete emotions also used the reverse-coded emotions, we multiplied the emotions-related parameter estimates (i.e., $\beta^{GP\rightarrow E}$, $\beta^{E\rightarrow G}$, and $\beta^{E\rightarrow P}$) by −1 to allow for easier interpretability (e.g., a positive $\beta^{E\rightarrow G}$ value would mean that higher levels of anger would lead to higher goals). GPD = goal–performance discrepancy; HDI = high density interval.

[a] A median parameter estimate whose 95% HDI does not include 0 and is therefore significant.

[−0.003, 0.052]; model using postlearning emotions: $\beta^{GP\rightarrow E}$ = 0.342, 95% HDI = [0.285, 0.401]). Although we did hypothesize that the GPD should influence subsequent emotional experiences, the lack of a significant finding using the aggregated prelearning emotions is not surprising. Emotions that were assessed directly after the learning session would have been more likely to be influenced by the performance of the learning session, whereas the emotions assessed right before the learning session could have been influenced by a plethora of emotional experiences occurring between sessions, thus lowering the impact of the GPD on these emotions (Schwarz & Clore, 1983).

Like Study 1, we also ran the model using the individual emotions rather than the aggregated emotions (see Table 6 for prelearning emotions and Table 7 for postlearning emotions; see also Supplemental Tables S5 and S6 for full results). Although the estimates stayed relatively stable across parameters not associated with emotions, we found differences in those that considered emotions. Importantly, the GPD has a significant effect on prelearning anger ($\beta^{GP\rightarrow E}$ = −0.040, 95% HDI = [−0.072, −0.009]) and enjoyment ($\beta^{GP\rightarrow E}$ = 0.042, 95% HDI = [0.006, 0.078]) but not on tension ($\beta^{GP\rightarrow E}$ = −0.022, 95% HDI = [−0.058, 0.012]). This would suggest that goal success from the previous learning session may have carried over to the next learning session and was associated with stronger feelings of enjoyment and weaker feelings of anger. Failure, on the other hand, was associated with weaker enjoyment and stronger anger. Regarding postlearning emotions, the GPD had a significant effect on all emotions, but the magnitudes were different, with pride being affected most strongly ($\beta^{GP\rightarrow E}$ = 0.589, 95% HDI = [0.509, 0.671]), then enjoyment ($\beta^{GP\rightarrow E}$ = 0.381, 95% HDI = [0.312, 0.451]) and anger ($\beta^{GP\rightarrow E}$ = −0.374, 95% HDI = [−0.451, −0.299]), and finally tension ($\beta^{GP\rightarrow E}$ = −0.157, 95% HDI = [−0.210, 0.104]). Conceptually, the results show that goal success leads to stronger positive emotions (stronger enjoyment and pride) and weaker negative emotions (weaker anger and tension), whereas failure leads to weaker positive emotions and stronger negative emotions. We interpret the findings from the postlearning emotions as a confirmation that participants monitored their performance, either by voluntarily

Table 7

Median Estimates of the Parameters of Interest for Study 2, Postlearning Emotions

Parameter	Median [95% HDI]				
	Aggregate	Anger	Enjoyment	Pride	Tension
Effects of the GPD					
$\beta^{GP\rightarrow G\|S}$	0.059[a] [0.026, 0.093]	0.074[a] [0.036, 0.111]	0.071[a] [0.034, 0.108]	0.067[a] [0.031, 0.104]	0.072[a] [0.034, 0.109]
$\beta^{GP\rightarrow G\|F}$	−0.119[a] [−0.171, −0.068]	−0.114[a] [−0.161, −0.068]	−0.114[a] [−0.16, −0.068]	−0.125[a] [−0.172, −0.079]	−0.118[a] [−0.164, −0.072]
$\beta^{GP\rightarrow P}$	0.632[a] [0.600, 0.664]	0.658[a] [0.626, 0.692]	0.656[a] [0.624, 0.689]	0.656[a] [0.623, 0.689]	0.657[a] [0.624, 0.69]
$\beta^{GP\rightarrow E}$	0.342[a] [0.285, 0.401]	−0.374[a] [−0.451, −0.299]	0.381[a] [0.312, 0.451]	0.589[a] [0.509, 0.671]	−0.157[a] [−0.210, −0.104]
Effects of emotions					
$\beta^{E\rightarrow G}$	−0.006 [−0.021, 0.009]	0.012 [−0.003, 0.028]	−0.007 [−0.025, 0.010]	0.008 [−0.007, 0.024]	0.013 [−0.003, 0.028]
$\beta^{E\rightarrow P}$	−0.004 [−0.015, 0.008]	−0.006 [−0.015, 0.003]	−0.003 [−0.013, 0.007]	−0.003 [−0.013, 0.006]	−0.002 [−0.012, 0.008]

Note. The parameter estimates in the aggregate column stem from the model using emotions aggregated along the valence dimension. Positive values of the aggregate emotions indicate positive valence, and negative values indicate negative valence. Although the computational modeling for the negative discrete emotions also used the reverse-coded emotions, we multiplied the emotions-related parameter estimates (i.e., $\beta^{GP\rightarrow E}$, $\beta^{E\rightarrow G}$, and $\beta^{E\rightarrow P}$) by −1 to allow for easier interpretability (e.g., a positive $\beta^{E\rightarrow G}$ value would mean that higher levels of anger would lead to higher goals). GPD = goal–performance discrepancy; HDI = high density interval.

[a] A median parameter estimate whose 95% HDI does not include 0 and is therefore significant.

checking it or through their metacognitive awareness of their progress, because each parameter estimate went in the expected directions, indicating appropriate reactions to goal achievement.

Role of Emotions on Goal Setting and Performance

We observed an effect of prelearning aggregated emotions on performance but not on goal setting ($\beta^{E\rightarrow G} = 0.005$, 95% HDI = [−0.010, 0.020]; $\beta^{E\rightarrow P} = 0.018$, 95% HDI = [0.002, 0.046]) but not effects of postlearning aggregated emotions ($\beta^{E\rightarrow G} = -0.006$, 95% HDI = [−0.021, 0.009]; $\beta^{E\rightarrow P} = -0.004$, 95% HDI = [−0.015, 0.008]). These findings suggest that the overall valence of the emotions experienced directly before a goal-striving episode may have a more influential impact on performance than those assessed at a point further in time. Nonetheless, pre- and postlearning emotions seemed to have no discernible influence on goal setting.

To investigate the role of discrete emotions, we applied the best-fitting model to each of the discrete pre- and postlearning emotions. These results are provided in Table 6 for prelearning and Table 7 for postlearning emotions. We found only a significant effect of prelearning enjoyment on goal setting ($\beta^{E\rightarrow G} = 0.020$, 95% HDI = 0.003, 0.037). Prelearning anger ($\beta^{E\rightarrow G} = -0.001$, 95% HDI = [−0.017, 0.015]) and tension ($\beta^{E\rightarrow G} = 0.006$, 95% HDI = [−0.007, 0.018]) had no significant effect. Prelearning enjoyment had facilitative effects ($\beta^{E\rightarrow P} = 0.018$, 95% HDI = [0.006, 0.031]), whereas anger (−0.015, 95% HDI = [−0.029, −0.002]) had impairing effects on performance. Prelearning tension ($\beta^{E\rightarrow P} = -0.006$, 95% HDI = [−0.018, 0.005]) did not show significant effects. No significant effects of the individual emotions on goal setting and performance were found for the postlearning emotions, which echoes the findings using the aggregate emotions.

General Discussion

The primary goal of the study was to develop a computational model that captured the dynamic interactions between goal setting, performance, and emotions in SRL. We grounded our model in a theoretical framework that largely focused on social–cognitive aspects of the relationship between the GPD and subsequent goal setting and performance (Bandura, 1986, 1991), while using theories of achievement emotions (Pekrun, 2006) and emotion regulation (Ben-Eliyahu, 2019; Efklides, 2011; Efklides & Schwartz, 2024) to better understand the role that emotions play. For our computational model, we devised three equations for goal setting, performance, and emotions that are composed of the same five components: (a) a baseline parameter, (b) an autoregressive component, (c) the effects of the GPD, (d) the effects of emotions (only in the goal setting and performance equations), and (e) residuals. We applied the model to data collected in a gamified online math task (Study 1) and real-world learning data where students studied for a high-stakes exam (Study 2). Importantly, our model remains robust even when applied to tasks and learners operating under different constraints (e.g., task demands, consequences of goal failure). As expected, we observed differences in parameter estimates between the two studies, reflecting how differences in goal-striving contexts may shape the ways individuals set and pursue goals while accounting for the differing effects of emotions. These parameter differences demonstrate the value of such an approach. In fact, despite the parameter differences, the same model was selected for both studies (among other alternate models). This means that they reveal how core SRL dynamics are preserved across contexts while also adapting to contextual affordances. This makes the model not only context-general (capturing stable processes) but also context-specific (reflected in the different parameter estimates across studies). We highlight that despite the context-specific differences, the model consistently yielded a good fit between observed and simulated data across both studies, suggesting that the model is both robust and informative for understanding SRL in varied learning settings.

In terms of the parameter estimates, running our computational model on these two data sets generated several key results. Model comparison in both studies revealed that the alternate model that accounted for both goal success and failure in goal setting was the best-fitting model, indicating uneven effects of goal achievement in subsequent goal setting. Moreover, our model was able to detect effects of both aggregated and discrete emotions on goal setting and performance. For example, our results showed that (prelearning) enjoyment played a large role in both studies, showing that it predicted higher goal setting and lower performance (i.e., coasting behavior) in Study 1 while predicting higher performance (i.e., pushing behavior) in Study 2. Taken together, these results support the validity and generalizability of our computational model in capturing core mechanisms of SRL across different contexts. They also underscore the importance of integrating emotions in models of SRL, as they contribute extra information that enriches our understanding of how individuals regulate their behavior during learning tasks.

Theoretical Implications of the GPD

One central contribution of our work is to reveal that Alternate Model 1 showed the best fit for the data sets from both studies, providing evidence that the GPD exerts differential effects on goal setting depending on whether the previous goal was achieved. Although this asymmetric effect has been pointed out in prior studies (Wang & Mukhopadhyay, 2012), many of the theoretical frameworks of SRL did not account for the asymmetrical effects of goal success versus failure (Gee et al., 2018). Our results suggest the importance of considering this asymmetry as a general phenomenon across different contexts.

It is also important to note that although the same Alternative Model 1 was chosen across the two studies, the directions of the goal failure's effects were different across them. Goal failure led to subsequent lower levels of goals in Study 1. In Study 2, on the other hand, participants set high goals even after they failed to reach their self-set goals. These results are indeed reasonable if we consider distal goals. In Study 1, setting lower goals after goal failure would likely help participants achieve their overall/distal goal (i.e., to maximize the reward they would earn). In contrast, in Study 2, setting lower goals after goal failure would not help participants to achieve their distal goal (i.e., to pass an upcoming important examination). Instead, setting *higher* goals would help them compensate for their previous underperformance and help them achieve their distal goal. Thus, it appears that goal failure aids individuals in adjusting their goals to help achieve their distal goals.

Our findings also support a model of SRL in which individuals actively monitor their progress, interpret their discrepancies, and iteratively adjust their goals and performance in response to perceived successes and failures. Rather than maintaining a consistent level of goal and performance over time, our results show that both goals and performance are sensitive to fluctuations in the GPD, as evidenced by the significant effects of the GPD on goal setting (after goal success and failure) and on performance. These results add to the growing body of empirical evidence that students adaptively set goals (Theobald et al., 2025; Theobald & Brod, 2025). The dynamic feedback loop plays a central role in regulating these processes over goal-striving episodes, underscoring the importance of modeling how goals and performance interact over time.

Theoretical Implications of Emotions

Another core contribution of this work is the incorporation of emotions (aggregated and discrete) in our computational model of dynamic SRL. The control-value theory (Pekrun, 2006), for instance, suggests that emotions arise from appraisals of control and value, which in turn shape motivation and behavior in subsequent goal-striving episodes. Moreover, models of emotion regulation (Ben-Eliyahu, 2019; Efklides, 2011; Efklides & Schwartz, 2024) posit that emotions are responses to and help regulate subsequent behavior. These theories are reflected in our model by adding emotions as both a predictor to subsequent goal setting and performance, and as an outcome by providing a separate emotions equation that factors in the current goal-striving episode when predicting subsequent emotional reactions.

Our results are also consistent with these theories and suggest that emotions reciprocally interact with goal setting and performance. First, in line with previous findings (Lebeau et al., 2018; Nummenmaa & Niemi, 2004), Study 1 revealed that goal success was associated with more positive emotions and failure with more negative emotions. Furthermore, in Study 2, the GPD was predictive of not only emotions that were assessed right after the learning session (i.e., postlearning emotions), but also the anger and enjoyment participants felt before a *following* learning session (i.e., prelearning emotions). This finding suggests that postlearning emotions are an immediate reflection of the current performance (i.e., retrospective outcome emotions). In contrast, prelearning emotions may have been evoked based on students' metacognitive knowledge of past performance and task demands in the upcoming study session (see the MASRL model; Efklides, 2011; Efklides & Schwartz, 2024; see also Ben-Eliyahu, 2019).

These emotions were then found to predict subsequent behavior. Enjoyment, for example, showed effects on goal setting and performance. This finding reaffirms the role of enjoyment in the literature, which has been shown to make goal-directed behavior feel more intrinsically rewarding and reduce the perceived cost of effort (Ben-Eliyahu, 2019; Pekrun, 2006, 2018). From a control-value theory perspective, enjoyment may signal that the students perceive more control of the task and higher intrinsic value for the study material (Forsblom et al., 2022; Pekrun, 2006, 2018). This can explain why students who felt more prelearning enjoyment in Study 2 set higher goals and showed better performance. On the other hand, although participants in Study 1 set higher goals with higher enjoyment, enjoyment was observed to have a negative association with performance. This may reflect a different value appraisal of the math task (compared with the high-stakes exam), leading to the opposite effect of enjoyment on performance. Another interpretation would come from control theory (Carver, 2003; Carver & Scheier, 1990), which suggests that enjoyment may have fostered a coasting strategy to conserve effort on the task if goals were adequately attained. Overall, although the effects of enjoyment were consistent for goal setting across contexts, its effects on performance suggest that the same emotion may function differently depending on various factors such as the value of the task or context.

Our results also appear consistent with the MASRL model that students are not only influenced by their emotions but also actively regulate them (Efklides, 2011; Efklides & Schwartz, 2024). For example, in Study 1, we found that enjoyment had positive effects on subsequent goal setting but negative effects on subsequent performance. Likewise, boredom had negative effects on subsequent goal setting but facilitative effects on performance. These seemingly contradictory effects of emotions on goal setting versus performance may have been related to participants' emotion regulation efforts. By setting lower levels of goals and increasing performance, for example, participants were more likely to be able to achieve their goals in the next round, which then helped them to experience positive emotions. Thus, it is possible that individuals respond to negative emotions (or to the lack of enjoyment in Study 2) by adjusting goals and performance simultaneously to maximize their chance at feeling more positive emotions. Stronger boredom or other negative emotions may have encouraged participants to focus on the utility of the task (e.g., getting a monetary reward) and enabled them to reach higher levels of performance (Ben-Eliyahu, 2019). The MASRL model also posits that individuals regulate their effort in the cognitive processing step that their affect in the performance step of SRL (Efklides, 2011; Efklides & Schwartz, 2024), thereby leading to more credibility of this interpretation.

Limitations and Future Directions

Our study has several limitations. First, both studies assessed a limited set of emotions, with only enjoyment overlapping between them, making direct comparisons difficult. Although aggregated emotion ratings allowed us to compare the effects of positive and negative valence, discrete analyses provided more insight into the roles of specific emotions, even if not directly comparable across studies. Second, we relied on simplified goal-setting tasks that focused on single-level quantitative goals. Real-world goal pursuit often involves complex hierarchies and qualitative aspects of goal setting, such as achievement goals (Bernacki et al., 2014), which may also influence performance and emotions. Third, effort was not explicitly modeled, even though it is central in SRL frameworks (Ballard et al., 2018, 2021). Finally, our model was only tested in adult learners, who may have more developed SRL skills than younger students, limiting generalizability across developmental phases.

Our model was, however, intended as a foundation step toward using computational methods in self-regulation research (and more generally in educational research). We expect extensions to the model to be published, which could go further in developing and refining its assumptions. For example, we could consider nonlinear effects of the GPD on goal setting (Wang & Mukhopadhyay, 2012) or model temporal dynamics of goal hierarchies, as goal setting strategies often shift over time as distal goals near (Ilies & Judge, 2005). Such refinements would allow for a more fine-grained and time-sensitive account of how individuals adapt goals in response to changing contexts and motivational states.

Finally, we emphasize that this work represents one of the first applications of computational modeling to SRL research in educational psychology (Schuetze, 2024). Although not without limitations, this approach holds promise for complementing traditional statistical methods and advancing our understanding of self-regulation (Murayama & von Keyserlingk, 2025).

Implications for Research, Instruction, and Policy

Our findings offer important implications for SRL research and its application in educational practices and policies. From a research perspective, the computational modeling approach provides a generative framework for testing theory-driven hypotheses about SRL dynamics. By formalizing how goals, performance, and emotions interact over time, the model enables examination of both general trends and individual differences in SRL trajectories. For instance, we observed differences across studies in how the GPD predicted goal setting after failure and how enjoyment related to performance. Such differences are theoretically meaningful, as they may reflect underlying task representations, such as whether a task is perceived as intrinsically or extrinsically motivated. Differences in parameter estimates can therefore illuminate how task values moderate how individuals adjust their goals (Wang & Mukhopadhyay, 2012). Observing these differences in parameter estimates between the two tasks, therefore, opens new avenues for future research, and computational modeling can be used as a tool to further investigate them.

For instructional practice, our results underscore the importance of supporting students in monitoring and interpreting their own learning based on metrics such as goal setting and performance. Teachers and researchers might consider embedding scaffolds for reflecting on performance relative to goals, recognizing emotional responses, and adjusting strategies accordingly. For example, digital learning platforms could prompt users to evaluate their goal progress and emotional state after each learning session, then suggest regulation strategies based on their response relative to their performance in that session. Importantly, such tools should be sensitive to the task context, helping learners distinguish between signals that indicate sufficient progress versus those that warrant continued effort.

At the policy level, these findings support the integration of SRL training into educational programs, particularly in settings where learners are expected to study autonomously. Whether through formal curriculum components or embedded features in digital tools, policymakers and stakeholders can leverage SRL modeling insights to promote more personalized, emotionally aware learning environments. Given the increasing reliance on digital platforms and self-paced instruction, tools that account for the interaction between goals, performance, and emotions enhance both engagement and learning outcomes.

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