Supplementary Materials

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

Supplementary Materials A

Thorough Description of the Hypothesized and Alternate Models of Goal Setting, Performance, and Emotions and their Implementation

In the following subsections, we will discuss each equation of our hypothesized model of goal setting, performance, and emotions. We will also present our hypotheses in terms of the parameters that we will be estimating based on the theory presented in the earlier sections. Supplementary Table S1 presents a summary of all the parameters of the model that are presented in the subsections. Supplementary Table S2 provides a summary of the Hypothesized and Alternate Models.

Supplementary Table S1

Conceptualization of All Model Parameters

Parameter	Interpretation
Goal Setting	
γ^G	Implicit baseline goal level
α^G	Stability of goal (carry-over effect)
$\beta^{GP \to G}$	The effect of GPD ($P_t - G_t$) on goal setting in the next block
$\beta^{GP \to G \mid S}$ [a]	The effect of GPD in goal setting in the next block after success
$\beta^{GP \to G \mid F}$ [a]	The effect of GPD in goal setting in the next block after failure
$\beta^{E \to G}$	The effect of emotions on goal setting in the next block
ε^G	Random errors in goal setting
Performance	
γ^P	Implicit baseline performance level
α^P	Stability of the performance (carry-over effect)
$\beta^{GP \to P}$	The effect of GPD ($G_{t+1} - P_t$) on performance in the next block
$\beta^{E \to P}$	The effect of emotions on performance in the next block
ε^P	Random errors in performance
Emotions	
γ^E	Implicit baseline emotions level
α^E	Stability of the emotions (carry-over effect)
$\beta^{GP \to E}$	The effect of the GPD ($P_{t+1} - G_{t+1}$) on emotions in the next block
ε^E	Random errors in emotions

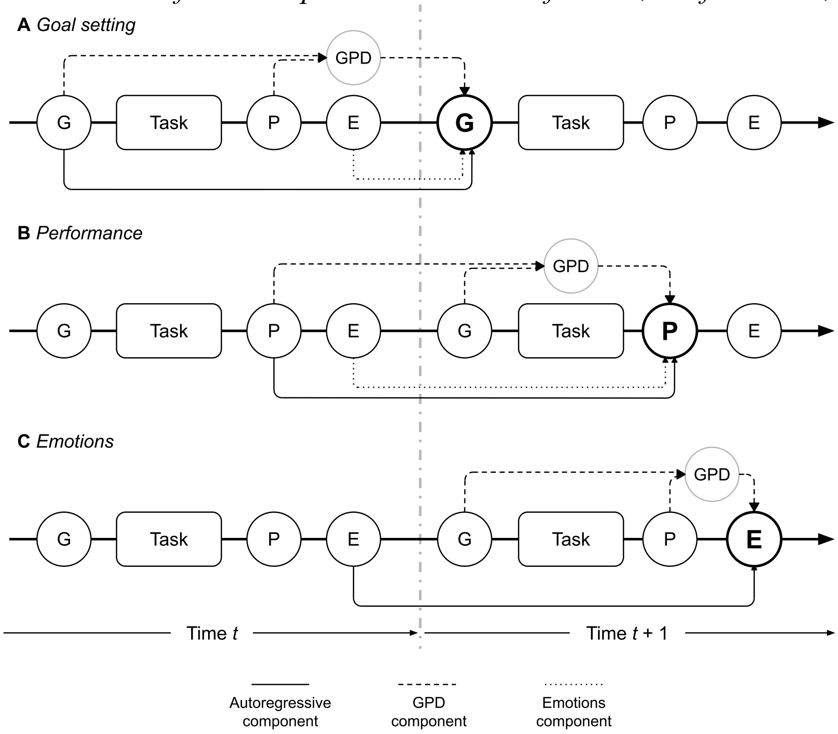
[a] Estimated only in Alternate Model 1, which accounts for goal success and failure.

Hypothesized Model

Our model of goals, performance, and emotions relies on having tasks that allow participants to specify goals (G), complete a task and obtain performance (P), and indicate the valence (i.e., positivity) of their state emotions (E) at time point t. Note that, in both studies, emotions were examined both at the level of aggregated valence (i.e., positive or negative affect) and as discrete emotions. This pattern then repeats in a dynamic manner such that multiple instances of goals, performances, and emotions over the course of several goal-striving episodes are observed. More positive values of G represent higher levels of goals, P represent better performance, and E represent stronger emotions (when different emotions are aggregated, higher values represent more positive emotions). Supplementary Figure S1 provides a visualization of the structure of such tasks as well as a graphical representation of each formula of the model. In the following subsections, we provide a detailed explanation of each of the three equations of the hypothesized model. We also created a Shiny App[1]to simulate data and performed parameter recovery (see Supplementary Materials B).

Supplementary Figure S1

Graphical Representation of the Computational Model of Goals, Performance, and Emotions



Note. We assume a temporal order of events in a typical goal-striving episode, starting with A) goal setting, B) performance on a task, and C) emotional reactions. Each variable is

[1] The Shiny App along with information on how to simulate data can be assessed at https://gpemodel.shinyapps.io/gpe-model/.

computed as a sum of the intercept representing the baseline value (not shown), an autoregressive component, a GPD component, an emotions component (only goal setting and performance), and random errors (not shown).

Goal Setting

The first equation in our model captures the goal at time $t + 1$ (G_{t+1}), which represents the goal that individuals want to achieve in the next goal-striving episode. The goal at $t + 1$ is assumed to be a function of several different components as follows:

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

First, we set an intercept term γ^G, which defines the baseline goal level. Second, the goal at $t + 1$ is dependent on the goal of the previous time point G_t multiplied by the weight α^G. This is a typical autoregressive or Markov process assumption, which is commonly supposed for many time series data, and captures the relative stability of the goals over time (i.e., carry-over effect).

Third, we suppose that the goal at $t + 1$ is influenced by the GPD. Theories regarding discrepancies suggest that the goal is adjusted based on previous experience with the task (Bandura, 1991), which, for example, could be the performance students have previously achieved in a study session. The model assumes that the past performance is compared with the previous goal ($P_t - G_t$) multiplied by a weight $\beta^{GP \to G}$. When $\beta^{GP \to G}$ is positive, individuals would set a high goal when their performance has met or exceeded their goal (i.e., goal success, $P_t \geq G_t$) and set a low goal when their performance has not met their goal (i.e. goal failure, $P_t < G_t$). When $\beta^{GP \to G}$ is negative, individuals would set a low goal when their past performance exceeds their previous goal and set a high goal when past performance has not met their previous goal.

The fourth component of the equation accounts for the effect of emotions by adding the emotions reported after the previous goal-striving episode directly into the equation (E_t) weighted by $\beta^{E \to G}$. As described earlier, we analyzed the effect of emotions using emotions aggregated along the valence dimension as well as each of the discrete emotions themselves. To compute the aggregated emotions variable, we derived an index by combining all discrete emotions into one score representing general positivity of emotional states (e.g., higher values represent stronger positive emotions while lower values represent stronger negative emotions). When we use this aggregated index, positive $\beta^{E\rightarrow G}$ values mean that positive emotions after the goal-striving episode would add to the next goal while negative emotions would subtract from it; when $\beta^{E\rightarrow G}$ is negative, positive emotions would subtract from the next goal while negative emotions would add to it. When we separately analyzed each discrete emotion, we used ratings provided by participants; positive $\beta^{E\rightarrow G}$ values mean that the stronger the emotion was, the higher the next goal was.

Finally, ε_t^G represents the random error in goal setting at time t. Computationally, we assume a normal distribution of random errors with a mean of 0 and a standard deviation σ^G, which is estimated along with the other parameters in the model.

In the goal equation, we are particularly interested in the $\beta^{GP\rightarrow G}$ and $\beta^{E\rightarrow G}$ parameters. Based on the discussion above on the interplay between goal setting and performance, we align our hypothesis for the $\beta^{GP\rightarrow G}$ with social cognitive theory (Bandura, 1986, 1991) and suggest that positive GPDs (i.e., goal success) lead to higher level of goals whereas negative GPDs (i.e., goal failure) lead to lower level of goals. In education (and achievement) settings, this trend may be observed since reaching or surpassing goals would increase individuals' self-efficacy and promote a sense of challenge; not reaching goals may lower self-efficacy, thereby lowering goal levels (Bandura, 1991). To account for this trend, we expect $\beta^{GP\rightarrow G}$ to be positive. If $\beta^{GP\rightarrow G}$ is non-significant (i.e., $\beta^{GP\rightarrow G}$ is estimated to be 0), then there would be no effect of the previous performance on goal setting. This could indicate that individuals believe that their current goal setting strategy is adequate.

In terms of the effects of emotions, two possibilities may emerge. First, positive emotions are interpreted as a signal to indicate goal success, leading to stronger perceived control and higher levels of subsequent goals, whereas negative emotions are considered to lead to lower levels of perceived control and lower levels of subsequent goals (e.g., Ilies et al., 2010). If the effect of emotions reflects this process, we would expect $\beta^{E \to G}$ to be positive for the models with the aggregated emotion index. However, different emotions within the same valence may show different impacts on subsequent goal setting. For example, boredom, a negative activity emotion, is considered to signal the lack of value, whereas anxiety, a negative outcome emotion, is considered to signal strong achievement value with lower perceived control (Pekrun, 2006, 2018); thus, these two emotions may affect subsequent goal setting differently. In this case, we would expect $\beta^{E \to G}$ to vary across different emotions in the same valence category.

Performance

The second equation in our model accounts for the performance on the task at time t+1 (P_{t+1}). The structure of the formula resembles that of goal revision and conceptually contains the same five components expressed as follows:

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

First, we assumed that there is a baseline performance γ^P, and an autoregressive effect of performance (i.e. carry-over effect), which is denoted by the previous performance P_t multiplied by the weight α^P. Second, we assume that the performance at time $t+1$ is also influenced by the GPD and is weighted by $\beta^{GP \to P}$. This GPD, however, is the difference between the goal that was set in the current goal-striving episode and the performance of the previous goal-striving episode ($G_{t+1} - P_t$). We define the GPD in this way to account for the motivational effects that goals have on performance (Locke & Latham, 1990). If $\beta^{GP \to P}$ is positive, then goals set higher than the previous performance (i.e., $G_{t+1} \geq P_t$) would encourage high performance while goals that are set lower than the previous performance (i.e., $G_{t+1} < P_t$) would encourage a low performance. If $\beta^{GP \to P}$ is negative, then goals set higher than the previous performance would encourage low performance and goals set lower than the previous performance would encourage high performance. If $\beta^{GP\rightarrow P}$ is non-significant (i.e., if $\beta^{GP\rightarrow P}$ is estimated to be 0), then goals would have no effect on performance. This could indicate that individuals believe that adequate progress has been made or enough effort is being exerted while working toward their goals.

The fourth component accounts for the effects of emotions from the previous goal-striving episode E_t, weighted by $\beta^{E\rightarrow P}$. When we use aggregated emotions based on the valence dimension, positive $\beta^{E\rightarrow P}$ values mean that positive emotions after the goal-striving episode would add to the next performance while negative emotions would subtract from it. When $\beta^{E\rightarrow P}$ is negative, positive emotions would subtract from the next performance while negative emotions would add to it. When modeling using the discrete emotions, positive $\beta^{E\rightarrow P}$ values mean that more of the emotion would increase the next performance. Likewise, negative $\beta^{E\rightarrow P}$ values would mean that less of the emotion would increase the next performance.

The term ε_t^P represents the random error in performance at time t. As in the goal setting equation, we assume a normal distribution of random errors with a mean of 0 and a standard deviation σ^P, which is estimated with the other parameters in the model.

We are particularly interested in the parameters $\beta^{GP\rightarrow P}$ and $\beta^{E\rightarrow P}$. The GPD in the performance equation accounts for the effect that the current goal has on the performance by comparing the goal set with the performance of the previous goal-striving episode. Given the motivational effects of goals (Locke & Latham, 1990), discrepancy production could be used as a strategy to motivate more goal-directed behavior. Goals set higher than the previous performance would encourage high performance (e.g., Donovan & Hafsteinsson, 2006; Donovan & Williams, 2003; Williams et al., 2000) and goals set lower than the previous performance would encourage lower performance. To account for this trend, we expect the $\beta^{GP\rightarrow P}$ parameter to be positive.

The sign of $\beta^{E \to P}$ would give us insights into the effects of emotions on performance. For example, coasting/pushing mechanisms have been hypothesized to take place, especially regarding progress towards a goal (Carver, 2003; Carver & Scheier, 1998; Thürmer et al., 2019). According to this view, positive emotions may signal that adequate progress is being made and that performance can be lowered; conversely, negative emotions would signal that progress is poor and that more effort is needed to raise performance. To account for this trend, $\beta^{E \to P}$ is expected to be negative when the aggregated emotion is used. On the other hand, different emotions in the same valence can be associated with different control-value appraisals. Positive emotions may add to the performance equation through positive influences on perceived intrinsic value and perceived control, leading to higher performance. A positive value of $\beta^{E \to P}$ would make this trend true. In contrast, negative outcome emotions, such as sadness and anxiety, are considered to reflect high achievement value which may consequently lead to higher performance. Lastly, anger and boredom (i.e., negative activity emotions) are considered to signal lack of value, leading to lower performance. Thus, the sign of $\beta^{E \to P}$ can be different between negative activity emotions vs. negative outcome emotions; such that $\beta^{E \to P}$ values are positive for negative outcome emotions but negative for negative activity emotions.

Emotions

The final equation of our model captures the emotions experienced after the current goal-striving episode. Again, the structure of this formula resembles that of the formulas for goal revision and performance as follows:

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

Like the other equations, the model includes the baseline emotion parameter γ^E, which could also be thought of as representing a trait-like/habitual experience of the emotions. This is followed by the autoregressive effect of previous emotion E_t weighted by α^E. Stronger autoregressive effects (i.e., higher α^E values) can be considered to reflect higher stability of the emotion, whereas weaker autoregressive effects reflect larger instabilities in the specific emotion. Individuals with high emotion regulation skills can show lower stabilities in their emotions (Houben et al., 2015; Houben & Kuppens, 2020; Kuppens et al., 2010; Wang et al., 2012), indicating that they may be in better control of their emotions (e.g., better regulation of anxiety). Thus, the α^E parameter may reflect learners' emotion regulation skills. We also assume that the GPD is a predictor of emotions. In the emotions formula, the discrepancy is the difference between the performance and goal from the current goal-striving episode ($P_{t+1} - G_{t+1}$), weighted by $\beta^{GP \to E}$. This operationalization of the GPD is used because the current performance on the task relative to the goal should have the most immediate influence on the emotions experienced. Reaching or surpassing goals should lead to more positive emotions (i.e., $P_{t+1} \geq G_{t+1}$) while failing to reach goals should lead to more negative emotions (i.e., $P_{t+1} < G_{t+1}$).

We again represent the random errors in the emotions equation at time t with ε_t^E, assumed to be drawn from a normal distribution of random errors with a mean of 0 and a standard deviation σ^E, which is estimated with the other parameters in the model.

The $\beta^{GP \to E}$ parameter is the particularly interesting parameter in the emotions equation. Here, we expect that the GPD of the current goal-striving episode would have clear effects on the emotions felt right after an achievement task. Goal success would lead to positive emotions while goal failure would lead to negative emotions. Thus, we expect that the $\beta^{GP \to E}$ parameter is positive when we use the aggregated emotion index or positive discrete emotions. We also expect that the $\beta^{GP \to E}$ parameter is negative when we use negative discrete emotions. The effects may be stronger for outcome emotions (e.g., anxiety) than for activity emotions (e.g., boredom).

Alternate Models

The following sections provide more details about the Alternate Models that were described in the main text. Table A1 provides an overview of the equations that are used in each Alternate Model.

Alternate Model 1

The first alternate model accounts for the differing effects that goal success (reaching or surpassing the goal) and goal failure (not reaching the goal) may have on goal setting. This model is based on work by Wang & Mukhopadhyay (2012), who showed that the effect of the GPD is different based on whether participants managed to reach their goals. To account for success and failure, our first alternate model estimates two separate $\beta^{GP \to G}$ parameters. The first equation is estimated only in the case of goal success with the parameter $\beta^{GP \to G|S}$ in place of $\beta^{GP \to G}$:

$$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{GP \to G|S}(P_t - G_t) + \beta^{E \to G} E_t + \varepsilon_t^G \quad \text{(A1)}$$

In this case, the parameter $\beta^{GP \to G|S}$ is the effect of the GPD after goal success. It is important to note here that the GPD can only take on positive values or zero since goal success is defined as reaching or surpassing the goal. A positive value of $\beta^{GP \to G|S}$ will therefore add to the baseline goal while a negative value will subtract from the baseline goal. The next equation is estimated only in the case of goal failure with the parameter $\beta^{GP \to G|F}$ in place of $\beta^{GP \to G}$:

$$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{GP \to G|F}(P_t - G_t) + \beta^{E \to G} E_t + \varepsilon_t^G \quad \text{(A2)}$$

Likewise, the parameter $\beta^{GP \to G|F}$ scales the effect of the GPD after goal failure. In this case, the GPD will always take on negative values since this equation will only be estimated if goals are lower than performance. Therefore, a negative value of $\beta^{GP \to G|F}$ will add to the baseline goal and a positive value would subtract from the baseline goal.

Alternate Model 2

The second alternate model eliminates the effect of the GPD on goal setting by fixing $\beta^{GP\rightarrow G}$ to 0. Doing so allows us to comprehensively check whether and how the GPD affects goal setting. Constraining the model in this way effectively changes the goal setting equation as follows:

$$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{E\rightarrow G} E_t + \varepsilon_t^G \tag{A3}$$

Alternate Model 3

The third alternate model checks the necessity of goals as a motivator of performance on the task. To do so, we fix $\beta^{GP\rightarrow P}$ to 0, essentially eliminating the effect of the GPD on performance and having the current performance rely solely on the baseline performance, previous performance, and emotions. Removing the effect of the GPD leads to a more constrained performance equation described as:

$$P_{t+1} = \gamma^P + \alpha^P P_t + \beta^{E\rightarrow P} E_t + \varepsilon_t^P \tag{A4}$$

Alternate Model 4

The final alternate model checks the necessity of emotions in goal setting and performance by constraining both $\beta^{E\rightarrow G}$ and $\beta^{E\rightarrow P}$ to 0. Eliminating the effect of emotions essentially makes the goal setting and performance equations rely on their baseline values, previous values, and the GPD. Both equations are then expressed as follows in this alternate model:

$$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{GP\rightarrow G}(P_t - G_t) + \varepsilon_t^G \tag{A5}$$

$$P_{t+1} = \gamma^P + \alpha^P P_t + \beta^{GP\rightarrow P}(G_{t+1} - P_t) + \varepsilon_t^P \tag{A6}$$

Supplementary Table S2

Summary of the Equations in the Hypothesized and Alternate Models

Model	Equation	Formula
Hypothesized	$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{GP\rightarrow G}(P_t - G_t) + \beta^{E\rightarrow G} E_t + \varepsilon_t^G$	1
	$P_{t+1} = \gamma^P + \alpha^P P_t + \beta^{GP\rightarrow P}(G_{t+1} - P_t) + \beta^{E\rightarrow P} E_t + \varepsilon_t^P$	2
	$E_{t+1} = \gamma^E + \alpha^E E_t + \beta^{GP\rightarrow E}(P_{t+1} - G_{t+1}) + \varepsilon_t^E$	3
Alternate 1: Goal success and failure	$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{GP\rightarrow G\mid S}(P_t - G_t) + \beta^{E\rightarrow G} E_t + \varepsilon_t^G$ [a]	A1
	$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{GP\rightarrow G\mid F}(P_t - G_t) + \beta^{E\rightarrow G} E_t + \varepsilon_t^G$ [b]	A2
	$P_{t+1} = \gamma^P + \alpha^P P_t + \beta^{GP\rightarrow P}(G_{t+1} - P_t) + \beta^{E\rightarrow P} E_t + \varepsilon_t^P$	2
		3

Model	Equation	Formula
	$E_{t+1} = \gamma^E + \alpha^E E_t + \beta^{GP\to E}(P_{t+1} - G_{t+1}) + \varepsilon_t^E$	
Alternate 2: No GPD effect in goal setting	$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{E\to G} E_t + \varepsilon_t^G$	A3
	$P_{t+1} = \gamma^P + \alpha^P P_t + \beta^{GP\to P}(G_{t+1} - P_t) + \beta^{E\to P} E_t + \varepsilon_t^P$	2
	$E_{t+1} = \gamma^E + \alpha^E E_t + \beta^{GP\to E}(P_{t+1} - G_{t+1}) + \varepsilon_t^E$	3
Alternate 3: No GPD effect in performance	$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{GP\to G}(P_t - G_t) + \beta^{E\to G} E_t + \varepsilon_t^G$	1
	$P_{t+1} = \gamma^P + \alpha^P P_t + \beta^{E\to P} E_t + \varepsilon_t^P$	A4
	$E_{t+1} = \gamma^E + \alpha^E E_t + \beta^{GP\to E}(P_{t+1} - G_{t+1}) + \varepsilon_t^E$	3
Alternate 4: No emotion effects	$G_{t+1} = \gamma^G + \alpha^G G_t + \beta^{GP\to G}(P_t - G_t) + \varepsilon_t^G$	A5
	$P_{t+1} = \gamma^P + \alpha^P P_t + \beta^{GP\to P}(G_{t+1} - P_t) + \varepsilon_t^P$	A6
	$E_{t+1} = \gamma^E + \alpha^E E_t + \beta^{GP\to E}(P_{t+1} - G_{t+1}) + \varepsilon_t^E$	3

[a] Used as the goal equation only in cases of success. [b] Used as the goal equation only in cases of failure.

Implementation of the Models in Studies 1 and 2

The hypothesized and alternate models for both Studies 1 and 2 were implemented 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). The models were written using Stan syntax to predict the goal level, performance, and emotions at reach time point using Equations 1 to 3 for the hypothesized model and the corresponding modifications to the equations as noted above for the alternate models. We did not predict the first block since there were no prior goal levels, performances, and emotions. Instead, the goal, performance, and emotion from the first block were loaded into Stan as constants and used as the starting values for each participant. No constraints on the values that the goal levels, performances, and emotions could take were set.

The equations used in our hypothesized and alternate models were coded using a hierarchical Bayesian framework to estimate the posterior distributions of each parameter. Each parameter was estimated on the population level and the participant level (with the exception of the residual standard deviations, which were estimated only on the population level), with the participant parameters drawn from a distribution defined by a population parameter mean and standard deviation. To code the hierarchical Bayesian framework in Stan, we followed the example provided by Ballard et al. (2018). We defined broad priors for population-level parameters (normal distributions with a mean of 0 and a standard deviation of 3), which were in turn entered as the priors for the participant-level parameters. Employing a hierarchical Bayesian framework allowed us to increase the statistical power of the model by pooling the information across participants and treating each participant as part of a group instead of as independent individuals (Katahira, 2016). We used four Monte Carlo Markov Chains (MCMC) using 1,000 burn-in iterations and 10,000 sampling iterations to ensure chain convergence. To assess the significance of each parameter on the population level, we computed 95% highest-density intervals (95% HDI) for each parameter. Significant parameters are regarded as those for which 0 is not included in the 95% HDI. For the purpose of calculating the model fit using the WAIC for the hypothetical and alternate models, our code also computed log likelihoods of every observation from the dataset given the set of estimated parameter values from each iteration of the MCMC chains.

Additional Considerations for Study 2

As mentioned in the main text, it is not clear what the effects of emotions are over an extended period of time. Therefore, we ran two groups of hypothesized and alternate models for Study 2, once using the emotions from the pre-learning survey and again using the emotions from the post-learning survey. In the group of models that used the emotions from the pre-learning survey, we coded the emotions at time $t + 1$ (as estimated using Equation 3) to be the emotions from the following time point. To visualize this using Figure 3, E_{t+1} would be E_B at time $t + 1$ and would be estimated as a result of the goal and performance at time t. Likewise for the group of models that use the emotions from the post-learning survey, E_{t+1} would be E_A at time t and would be estimated as a result of the goal and performance at time t.

Parameter estimation using hierarchical Bayesian methods was implemented similar to Study 1. However, this study contained missing data because participants were allowed to complete each learning session as they wished. This led to several instances in which goals, performance, and emotions were not reported, which necessitated additional data cleaning and Stan code adjustments. First, we interpreted days with missing performance or a performance of zero as days on which no studying was done. These days were dropped from the dataset and the days before and after were treated as "consecutive" days for the purposes of running the model. Next, we re-coded missing goals and emotions as parameters to be estimated in the Stan model as suggested by the Stan Development Team (2022). In total, six participants did not report a goal on 1 day and one participant did not report a goal on 4 days. Furthermore, 163 participants did not report their post-learning emotions on at least 1 day. There was a median of 2 days of missing post-learning emotions across these participants, and the number of days ranged between 1 and 18. All participants reported emotions on the pre-learning survey on all days. If the goals and emotions were missing on the first day, we estimated it using a normal distribution with the mean and standard deviation describing the distribution of goals and emotions, respectively, from the participant that the missing variables are from. If goals and emotions were missing after the first day, we estimated them with the formulas provided in the hypothesized and alternate models.

Supplementary Materials B

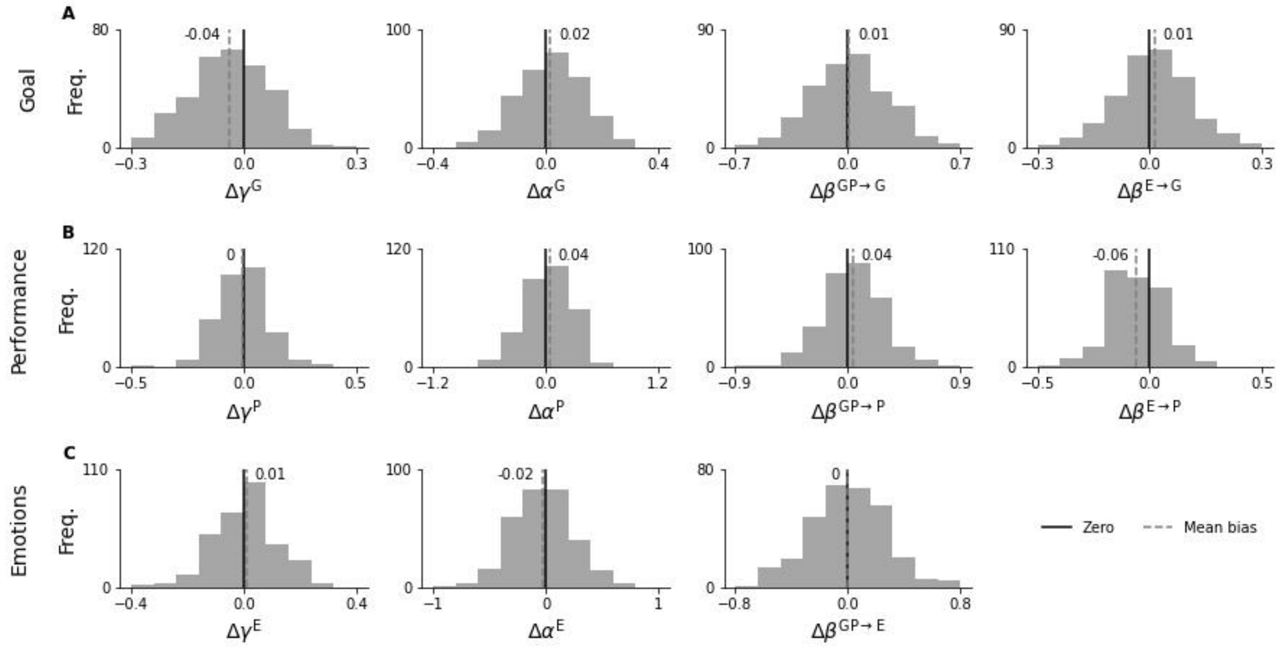
Parameter Recovery

We specified these models using a hierarchical Bayesian framework (Ballard et al., 2018; Lewandowsky & Farrell, 2011), which allows us to estimate a complex and dynamic model with a sophisticated estimation algorithm (i.e. Markov Chain Monte Carlo method; MCMC method). The model also allows us to estimate critical parameters while considering potential individual differences (e.g., the effect of emotions on goal setting $\beta^{E \to G}$ could be different between participants) by supposing hyperparameters. Here, to examine the robustness of our proposed computational model, we conducted a simple parameter recovery simulation.

Reasonable parameter values on the population level were simulated using a Shiny app coded in R, which allowed us to visualize how different parameter values would change the dynamics of goals, performance, and emotions. Using this simulation, we chose population-level parameter values which we used to draw individual parameter values for 300 fictitious participants based on the hypothesized model (Equations 1 to 3). Using these simulated data, we estimated the parameter values for each participant with Bayesian estimation to examine whether the true individual parameter values were recovered well. For each simulated participant, we computed the difference between the true and estimated parameter values for all parameters and each participant to assess the error of the estimation. Results show these differences centered around zero, indicating that the model and Bayesian estimation could recover parameters well (Supplementary Figure S2).

Figure S2

Distributions of the Difference Between True Parameter Values and Estimated Parameter Values for Each Participant



Note. Known parameter values were used to generate data, and parameters were recovered from this data. The histograms show the differences (i.e., observed minus estimated parameter values) for the hypothesized individuals. A visual inspection shows that there is no systematic deviation from zero. Row A depicts the parameters from the goal equation, Row B depicts the parameters from the performance equation, and Row C depicts the parameters from the emotions equation.

Supplementary Materials C

Correlations Between Self-Reported Trait Measures and Parameter Estimates from the Best-Fitting Model (Study 1)

We had the opportunity to assess the possible influence of trait emotions as the data collected in the online math task in Study 1 was part of a study that was originally interested in the individual differences in goal setting behavior in goal-setting behavior related to negative emotionality. To this end, we collected self-reported trait measures of depression, anxiety, and negative emotionality in the questionnaire packet administered before participants completed the math task. Participants responded to the Center of Epidemiologic Studies Depression Scale (CESD; Radloff, 1977), the Trait Anxiety Inventory (TAI; Spielberger et al., 1983), and the negative emotionality scale of the Next Big Five Inventory (BFI:NE; Soto & John, 2017).

To explore whether the model is able to capture the trait-relevant influences on goal setting, performance behavior, and emotions, we examined how strongly the sum scores of these scales were correlated with the individual parameters estimated using the hierarchical Bayesian framework with the best-fitting model for the valence-based aggregated emotions (Supplementary Table S3).

We found significant correlations between the γ parameters of each equation and the self-reported questionnaire scores. Specifically, those who reported higher levels of depression, anxiety, and negative emotionality were less likely to report stronger positive states (*rs* = -.37, -.37, -.37, *ps* < 0.05). The results suggest that this parameter (γ^E) was particularly sensitive to individual differences in trait-like/habitual emotions. We also found that those who reported higher levels of depression, anxiety, and negative emotionality were more likely to set higher levels of goals (*rs* = .12, .13, .11, *ps* < 0.05). The results suggest that this parameter (γ^E) was particularly sensitive to individual differences in trait-like/habitual emotions. We also found that those who reported higher levels of depression, anxiety, and negative emotionality were more likely to have a higher average level of goals (*rs* = .12, .13, .11, *ps* < 0.05). Lastly, we also found that those with higher levels of depression and anxiety showed lower levels of performance. These results are in line with previous findings that depression and anxiety are associated with high average goal level (Ahrens, 1987) and are associated with achievement problems (Huang, 2015; von der Embse et al., 2018).

In contrast, none of the trait-like/habitual emotions measures were correlated with temporal changes in goals, performance, and emotions, nor with the effects between the two variables (e.g., the effects of goal on performance). These results suggest that our three trait-like emotional measures were not significantly associated with temporal changes in these measures at least in the context of Study 1.

Supplementary Table S3

Correlations Between Estimated Parameters and Trait Questionnaires from Study 1

Parameter	CESD	TAI	BFI: NE
γ^G	.12*	.13*	.11*
α^G	.09	.08	.09
$\beta^{GP\rightarrow G\|S}$	.05	.04	.01
$\beta^{GP\rightarrow G\|F}$	.01	-.05	-.02
$\beta^{E\rightarrow G}$	.08	.08	.09
γ^P	-.13*	-.15**	-.09
α^P	-.08	-.06	-.04
$\beta^{GP\rightarrow P}$	.01	.01	.04
$\beta^{E\rightarrow P}$	-.04	-.04	-.01
γ^E	-.37***	-.37***	-.37***
α^E	-.01	.00	.00
$\beta^{GP\rightarrow E}$	.05	.05	.10

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

Supplementary Materials D

Study 1 Math Task Stimulus Properties

We borrowed criteria from Artemenko et al. (2018) to create the addition problems in the stimulus set:

- Both operands needed to be a three-digit number and sum up to a three-digit number.
- Digits in each operand could not repeat within their respective operands as well as within their respective places across operands (e.g., 112 + 345 would not work because 1 is repeated in 112, and 123 + 453 would not work because 3 is repeated in the ones place).
- 0 could not appear in the operands or in the sum.

Subtraction problems were formed as the inverse of the addition problems (e.g. 123 + 456 = 579 becomes (579 – 456 = 123). We did not account for carrying in addition problems or borrowing in the subtraction problems to vary the difficulty of the trials throughout the task. All addition and subtraction equations were compiled together and randomized for each participant upon opening the link to the math task.

Supplementary Materials E

All Parameter Estimates for Studies 1 and 2

Supplementary Table S4

Parameter Estimates Using the Best-Fitting Model for Study 1

Parameter	Median [95% HDI]				
	Aggregate	Anxiety	Boredom	Enjoyment	Sadness
γ^G	0.622*	0.618*	0.620*	0.663*	0.604*
	[0.503, 0.747]	[0.503, 0.745]	[0.498, 0.748]	[0.545, 0.794]	[0.487, 0.731]
α^G	0.870*	0.877*	0.875*	0.870*	0.876*
	[0.851, 0.888]	[0.858, 0.894]	[0.856, 0.893]	[0.850, 0.887]	[0.858, 0.894]
$\beta^{GP\to G\|S}$	0.273*	0.277*	0.278*	0.272*	0.278*
	[0.249, 0.296]	[0.254, 0.301]	[0.255, 0.302]	[0.248, 0.295]	[0.254, 0.301]
$\beta^{GP\to G\|F}$	0.483*	0.499*	0.502*	0.484*	0.496*
	[0.427, 0.539]	[0.444, 0.554]	[0.446, 0.558]	[0.428, 0.539]	[0.439, 0.553]
$\beta^{E\to G}$	0.067*	-0.027*	-0.020*	0.050*	-0.019
	[0.038, 0.096]	[-0.047, -0.007]	[-0.039, -0.002]	[0.031, 0.070]	[-0.044, 0.006]
σ^G	0.859*	0.860*	0.858*	0.858*	0.861*
	[0.843, 0.875]	[0.845, 0.876]	[0.842, 0.874]	[0.842, 0.874]	[0.845, 0.877]
γ^P	3.991*	3.961*	4.074*	3.952*	4.004*
	[3.662, 4.321]	[3.645, 4.296]	[3.74, 4.411]	[3.627, 4.288]	[3.687, 4.337]
α^P	0.597*	0.588*	0.582*	0.594*	0.589*
	[0.556, 0.637]	[0.546, 0.628]	[0.541, 0.623]	[0.553, 0.635]	[0.547, 0.629]
$\beta^{GP\to P}$	0.429*	0.430*	0.427*	0.426*	0.428*
	[0.383, 0.476]	[0.383, 0.477]	[0.380, 0.474]	[0.380, 0.473]	[0.381, 0.475]
$\beta^{E\to P}$	-0.103*	0.009	0.063*	-0.089*	0.031
	[-0.172, -0.036]	[-0.033, 0.052]	[0.026, 0.100]	[-0.132, -0.047]	[-0.021, 0.084]
σ^P	1.533*	1.537*	1.533*	1.530*	1.536*
	[1.505, 1.561]	[1.509, 1.566]	[1.505, 1.561]	[1.503, 1.558]	[1.509, 1.564]
γ^E	0.313*	-0.100*	-0.075*	-0.026	-0.799*
	[0.245, 0.382]	[-0.186, -0.018]	[-0.136, -0.017]	[-0.108, 0.056]	[-0.900, -0.701]
α^E	0.515*	0.587*	0.794*	0.564*	0.489*
	[0.480, 0.550]	[0.548, 0.627]	[0.765, 0.824]	[0.527, 0.600]	[0.452, 0.527]
$\beta^{GP\to E}$	0.128*	-0.086*	-0.035*	0.183*	-0.110*
	[0.112, 0.145]	[-0.103, -0.070]	[-0.047, -0.022]	[0.161, 0.205]	[-0.131, -0.090]
σ^E	0.462*	0.712*	0.722*	0.726*	0.588*
	[0.454, 0.471]	[0.699, 0.725]	[0.708, 0.735]	[0.713, 0.740]	[0.577, 0.599]

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. While the computational modeling for the negative discrete emotions also used the reverse-coded emotions, we multiplied the emotions-related parameter estimates (i.e., $\beta^{E\to G}$, $\beta^{E\to P}$, γ^E, and $\beta^{GP\to E}$) by -1 to allow for easier interpretability (e.g., a positive $\beta^{E\to G}$ value would mean that higher levels of anger would lead to higher goals).

* denotes a median parameter estimate whose 95% HDI does not include 0 and is therefore significant.

Supplementary Table S5

Parameter Estimates Using the Best-Fitting Model, Study 2 Pre-Learning Emotions

Parameter	Median [95% HDI]			
	Aggregate	Anger	Enjoyment	Tension
γ^G	0.608*	0.588*	0.609*	0.602*
	[0.579, 0.637]	[0.549, 0.628]	[0.574, 0.645]	[0.566, 0.637]
α^G	0.305*	0.316*	0.304*	0.312*
	[0.278, 0.333]	[0.28, 0.351]	[0.269, 0.339]	[0.277, 0.347]
$\beta^{GP\to G\|S}$	0.063*	0.071*	0.069*	0.072*
	[0.028, 0.097]	[0.034, 0.109]	[0.032, 0.107]	[0.034, 0.109]
$\beta^{GP\to G\|F}$	-0.128*	-0.121*	-0.122*	-0.120*
	[-0.178, -0.077]	[-0.168, -0.074]	[-0.169, -0.075]	[-0.167, -0.073]
$\beta^{E\to G}$	0.005	-0.001	0.020*	0.006
	[-0.010, 0.020]	[-0.017, 0.015]	[0.003, 0.037]	[-0.007, 0.018]
σ^G	0.343*	0.394*	0.385*	0.393*
	[0.337, 0.348]	[0.387, 0.402]	[0.378, 0.393]	[0.386, 0.401]
γ^P	0.269*	0.200*	0.235*	0.216*
	[0.238, 0.301]	[0.163, 0.237]	[0.203, 0.268]	[0.184, 0.25]
α^P	0.697*	0.726*	0.724*	0.726*
	[0.664, 0.729]	[0.693, 0.758]	[0.691, 0.757]	[0.693, 0.758]
$\beta^{GP\to P}$	0.631*	0.657*	0.656*	0.656*
	[0.599, 0.663]	[0.624, 0.69]	[0.623, 0.689]	[0.623, 0.69]
$\beta^{E\to P}$	0.018*	-0.015*	0.018*	-0.006
	[0.002, 0.035]	[-0.029, -0.002]	[0.006, 0.031]	[-0.018, 0.005]
σ^P	0.388*	0.417*	0.416*	0.417*
	[0.382, 0.394]	[0.411, 0.424]	[0.410, 0.422]	[0.410, 0.423]
γ^E	0.516*	-1.301*	-0.419*	-0.740*
	[0.461, 0.571]	[-1.374, -1.231]	[-0.491, -0.345]	[-0.833, -0.650]
α^E	0.208*	0.165*	0.234*	0.239*
	[0.179, 0.237]	[0.137, 0.193]	[0.205, 0.263]	[0.208, 0.271]
$\beta^{GP\to E}$	0.024	-0.040*	0.042*	-0.022
	[-0.003, 0.052]	[-0.072, -0.009]	[0.006, 0.078]	[-0.058, 0.012]
σ^E	0.485*	0.611*	0.704*	0.730*
	[0.477, 0.492]	[0.602, 0.620]	[0.693, 0.714]	[0.719, 0.741]

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. While the computational modeling for the negative discrete emotions also used the reverse-coded emotions, we multiplied the emotions-related parameter estimates (i.e., $\beta^{E\to G}$, $\beta^{E\to P}$, γ^E, and $\beta^{GP\to E}$) by -1 to allow for easier interpretability (e.g., a positive $\beta^{E\to G}$ value would mean that higher levels of anger would lead to higher goals).

* denotes a median parameter estimate whose 95% HDI does not include 0 and is therefore significant.

Supplementary Table S6

Parameter Estimates Using the Best-Fitting Model, Study 2 Post-Learning Emotions

Parameter	Median [95% HDI]				
	Aggregate	Anger	Enjoyment	Pride	Tension
γ^G	0.614*	0.599*	0.603*	0.600*	0.606*
	[0.587, 0.642]	[0.564, 0.635]	[0.566, 0.641]	[0.565, 0.635]	[0.571, 0.640]
α^G	0.308*	0.321*	0.306*	0.310*	0.315*
	[0.281, 0.335]	[0.287, 0.356]	[0.272, 0.341]	[0.275, 0.344]	[0.280, 0.349]
$\beta^{GP\rightarrow G\|S}$	0.059*	0.074*	0.071*	0.067*	0.072*
	[0.026, 0.093]	[0.036, 0.111]	[0.034, 0.108]	[0.031, 0.104]	[0.034, 0.109]
$\beta^{GP\rightarrow G\|F}$	-0.119*	-0.114*	-0.114*	-0.125*	-0.118*
	[-0.171, -0.068]	[-0.161, -0.068]	[-0.16, -0.068]	[-0.172, -0.079]	[-0.164, -0.072]
$\beta^{E\rightarrow G}$	-0.006	0.012	-0.007	0.008	0.013
	[-0.021, 0.009]	[-0.003, 0.028]	[-0.025, 0.010]	[-0.007, 0.024]	[-0.003, 0.028]
σ^G	0.330*	0.382*	0.370*	0.374*	0.382*
	[0.325, 0.335]	[0.374, 0.390]	[0.363, 0.378]	[0.366, 0.381]	[0.375, 0.390]
γ^P	0.282*	0.217*	0.224*	0.222*	0.222*
	[0.251, 0.313]	[0.185, 0.250]	[0.192, 0.255]	[0.191, 0.254]	[0.189, 0.255]
α^P	0.700*	0.726*	0.726*	0.728*	0.727*
	[0.667, 0.732]	[0.694, 0.760]	[0.693, 0.759]	[0.695, 0.760]	[0.693, 0.759]
$\beta^{GP\rightarrow P}$	0.632*	0.658*	0.656*	0.656*	0.657*
	[0.600, 0.664]	[0.626, 0.692]	[0.624, 0.689]	[0.623, 0.689]	[0.624, 0.69]
$\beta^{E\rightarrow P}$	-0.004	-0.006	-0.003	-0.003	-0.002
	[-0.015, 0.008]	[-0.015, 0.003]	[-0.013, 0.007]	[-0.013, 0.006]	[-0.012, 0.008]
σ^P	0.388*	0.417*	0.416*	0.417*	0.417*
	[0.382, 0.395]	[0.411, 0.424]	[0.410, 0.423]	[0.411, 0.423]	[0.411, 0.424]
γ^E	0.365*	-0.924*	-0.123*	-0.187*	-0.859*
	[0.306, 0.425]	[-1.006, -0.844]	[-0.195, -0.052]	[-0.264, -0.112]	[-0.951, -0.769]
α^E	0.155*	0.097*	0.190*	0.157*	0.198*
	[0.127, 0.184]	[0.074, 0.122]	[0.161, 0.220]	[0.130, 0.185]	[0.167, 0.228]
$\beta^{GP\rightarrow E}$	0.342*	-0.374*	0.381*	0.589*	-0.157*
	[0.285, 0.401]	[-0.451, -0.299]	[0.312, 0.451]	[0.509, 0.671]	[-0.210, -0.104]
σ^E	0.692*	0.973*	0.925*	0.909*	0.807*
	[0.681, 0.703]	[0.958, 0.988]	[0.911, 0.939]	[0.895, 0.923]	[0.795, 0.820]

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. While the computational modeling for the negative discrete emotions also used the reverse-coded emotions, we multiplied the emotions-related parameter estimates (i.e., $\beta^{E\rightarrow G}$, $\beta^{E\rightarrow P}$, γ^E, and $\beta^{GP\rightarrow E}$) 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).

* denotes a median parameter estimate whose 95% HDI does not include 0 and is therefore significant.

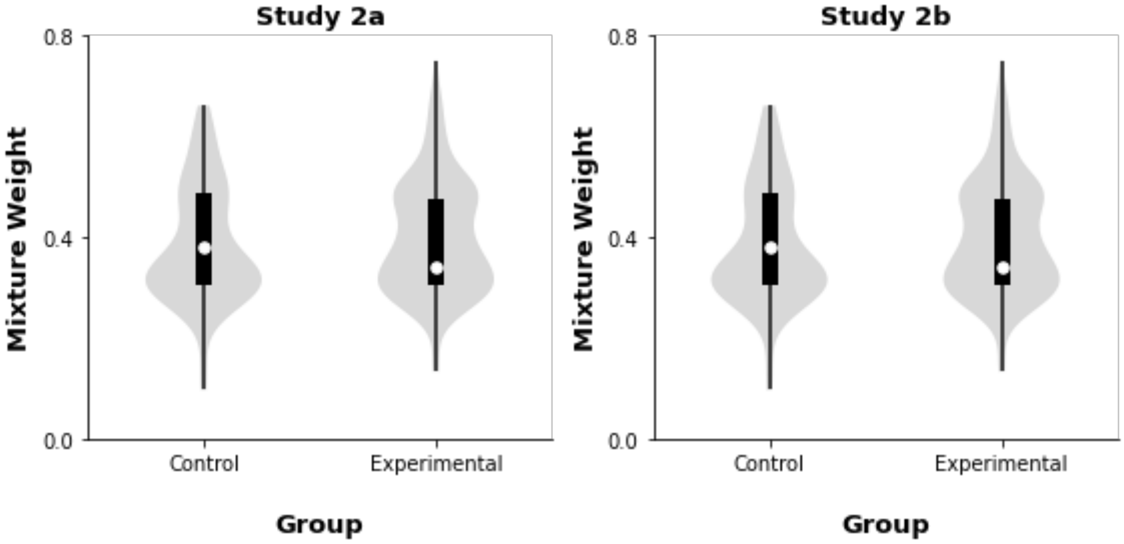
Supplementary Materials F

Comparison of the Control and Experimental Groups Reveals Undetectable Differences Between Groups (Study 2)

To check if we could combine the data from the experimental and control groups together, we used the hypothesized model to estimate mixture weights for each participant for both the pre-learning and post-learning emotions models (Ballard et al., 2018; Bartlema et al., 2014). The mixture weights represent the probability of each participant belonging to the control group. Supplementary Figure S3 shows the distribution of the mixture weights that were estimated for each participant, separated by the group. To compare the two groups statistically, we ran independent sample *t*-tests to compare the mixture weights of the control and experimental groups. For the pre-learning emotions model, there were also no differences in the estimated mixture weights between the control group (M = .38, SD = 0.12) and the experimental group (M = .40, SD = .11), $t(303) = 1.175$, $p = .241$. For the post-learning emotions model, there were no differences in the estimated mixture weights between the control group (M = .47, SD = .09) and the experimental group (M = .47, SD = .08), $t(303) = 0.208$, $p = .836$. These results showed that both groups' data could be combined into one dataset for further analysis.

Figure S3

No Difference in the Distributions of Mixture Weights



Note. Violin plots of the mixture weights for participants in the control and experimental groups. In both studies, the model was not able to detect whether participants belonged in one group or the other, confirming that the data could be combined into one dataset for analyses. The box in the middle of each violin plot represents the interquartile range and the white point the median value.

Supplementary Materials G

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