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Emotion Regulation, Fast or Slow: A Computational Model of Strategy Choice

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Different emotion regulation strategies have very different consequences. This observation has inspired a growing body of work seeking to identify the factors that predict emotion regulation strategy choice. To explain these findings, several explanatory theories have been proposed. As with most theories in the field of affective science, they are formulated in natural language. Translating these theories into the language of mathematics may bring more clarity to the field and help generate new, testable hypotheses. The present article aimed to formulate more precise theoretical predictions by translating verbal theories about the emotion regulation selection process into formal mathematical language. Specifically, we focused on formally defining a theory that might help to explain the robust finding that people prefer distraction over reappraisal at high emotional intensities but prefer reappraisal over distraction at low emotional intensities. Through the process of theory formalization, we identified hidden assumptions and unanswered research questions, which resulted in a computational model that predicts results that match empirical work. This work demonstrates how theory formalization can accelerate theoretical and empirical progress in affective science. Better explanatory theories can then inform interventions designed to enhance the selection of adaptive regulation strategies.

Keywords: emotion regulation, strategy choice, computational model, formal theory, affective science

Sometimes things do not go as planned. A project at work may not yield the desired results, or a romantic interest may cancel a date at the last minute. These experiences often result in negative emotions. To feel better, one might binge-watch a Netflix show or try to look for the silver lining in the situation. Both actions are instances of emotion regulation, defined as the "processes by which individuals influence which emotions they have, when they have them, and how they experience and express these emotions" (Gross, 1998, p. 275). Failures to successfully regulate undesired emotions are a defining feature of most affective disorders, such as depression or anxiety disorders (Amstadter, 2008; Joormann & Stanton, 2016). Unsuccessful emotion regulation can also cause suffering in healthy people. Facilitating adaptive emotion regulation choices is consequently the aim of many interventions for well-being in healthy individuals as well as those with clinical conditions (Berking & Lukas, 2015; Cohen & Ochsner, 2018). A key to such interventions is understanding which factors drive the selection of adaptive and maladaptive strategies.

One popular framework for studying emotion regulation strategy selection is the extended process model of emotion regulation (Gross, 2015). It describes emotion regulation as a process consisting of multiple stages, including *identifying* the need to regulate, *selecting* a regulatory strategy, and *implementing* it. According to the process model, the selection stage itself then consists of three key phases: (a) a person *perceives* their available emotion regulation strategies, (b) they then *evaluate* the expected effectiveness of the strategies

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considering contextual factors, such as the availability of cognitive resources and the difficulty of implementing the strategy, and (c) this valuation process leads up to the *action* stage, which entails choosing a strategy. This framework has proven useful in guiding research about emotion regulation (McRae & Gross, 2020).

When studying the emotion regulation process, previous research has focused on two broad categories of regulatory strategies: *disengagement* and *engagement* (Campbell-Sills & Barlow, 2007; Gross, 2015). A typical example of disengagement is distraction from an emotional stimulus, and a typical example of engagement is reappraisal, where the meaning one assigns to the experienced emotion or stimulus is changed (McRae et al., 2010). A large body of work demonstrates that engagement strategies are generally associated with more positive emotions than disengagement strategies (e.g., Gross & John, 2003), although an alignment of situational demands and strategy choice is also important (Aldao et al., 2015; Rogier et al., 2019). Framed through the lens of the process model, questions about the effectiveness of different strategies relate to the implementation stage.

There has also been research that relates to the selection stage of the process model, which determines the strategy to implement. This research has focused on investigating what the circumstances are that influence strategy choice. Matthews et al. (2021) gave an overview of the findings for different choice determinants. Well-supported factors are individual differences, emotional valence, and mental health status. Another factor—and one that stands out due to its large effect size and robustness—is the intensity of an emotion. Sheppes et al. (2011) were the first to show that people prefer distraction over reappraisal for stimuli with high emotional intensity but prefer reappraisal over distraction for lower intensity stimuli. This finding has since been replicated many times in the lab, and the effect of emotional intensity on strategy choice has become one of the most robust findings in the field of affective science (Matthews et al., 2021).

Explaining Emotion Regulation Strategy Selection

Different theories have been offered to explain the effect of emotion intensity on emotion regulation choice. One prominent theory was offered by Sheppes, Scheibe, et al. (2014), who proposed that when selecting a strategy, people try to balance the perceived cost of implementing the given strategy with its anticipated benefits. The theory considers three cost–benefit dimensions of the available strategies, the *motivational*, *emotional*, and *cognitive* characteristics. To illustrate the trade-off between reappraisal and distraction, according to this theory, reappraisal has advantages when adapting to a stimulus that is expected to reoccur, thus concerning the motivational characteristics (Kross & Ayduk, 2008; Thiruchselvam et al., 2011). However, regarding the emotional characteristics, distraction reliably and quickly reduces emotional intensity (e.g., Sheppes & Meiran, 2007), whereas reappraisal can take a very long time to implement or fail altogether if one does not find a satisfactory alternative interpretation—especially if emotional intensity is high. Further, concerning the cognitive characteristics, reappraisal requires more cognitive resources than distraction, which are limited during periods of intense negative emotion (Sheppes, Brady, & Samson, 2014). Together, these proposed trade-offs could help explain the finding that people prefer distraction for emotionally intense stimuli but reappraisal for low-intensity stimuli.

The theory of Sheppes, Scheibe, et al. (2014) provides a useful conceptualization of which factors may impact the selection of emotion regulation strategies. To maximize the predictive value of this theory, one crucial task is more precisely specifying the ways these factors interact. As it is very difficult to exactly specify such a complex process verbally, we employed a formal modeling approach that utilizes mathematical equations to express relationships among the different factors (Meehl, 1978). Unlike in statistical models, the relationships between the factors in this approach are not directly derived from data but are based on theoretical considerations. The resulting model allows us to simulate data to make unambiguous predictions, across the complete range of all included factors. Typically, it is very difficult to make such clear-cut predictions with verbal theories, especially when the subject of study are systems such as humans which consist of many variables that interact in complex ways at different time scales (Robinaugh et al., 2021; Smaldino, 2016). Relatedly, formal theories prevent researchers from interpreting the same theory differently and deriving conflicting predictions—as might happen with verbal theories (Farrell & Lewandowsky, 2018). In addition to making predictions more precise, the process of formalizing theories itself can be very fruitful for theory development. To formalize a theory, every aspect must be specified with utmost precision. This process uncovers hidden assumptions and forces the researcher to be concrete about all aspects of the theory—including those that concern relationships that are not yet well-established empirically. Forcing such concrete specifications about every aspect of a theory might lead to several false hypotheses. However, to develop a theory further, uncovering and testing all its aspects are crucial.

In this article, we apply a formal modeling approach to explain the relationship between stimulus intensity and emotion regulation strategy choice. As a starting point, we build on the existing verbal theory by Sheppes, Scheibe, et al. (2014). The process of formal modeling forces us to be concrete, which leads us to identify new open questions. We then discuss our preliminary answers to those questions and how they may motivate future research. After introducing our computational model, we simulate numerical predictions about the outcomes of a hypothetical experiment in which the phenomenon is typically established, demonstrating that our computational model indeed accounts for the phenomenon in question. We end by discussing how our model can be extended and how computational models can generally contribute to emotion research.

Formalizing Emotion Regulation Strategy Selection

Deriving a formal theory from a verbal theory is a complex process that requires a structured approach. Over the past years, methodologists have proposed various procedures, with multiple frameworks emerging more recently (Borsboom et al., 2021; Haslbeck et al., 2022; van Rooij & Baggio, 2021). In the present study, we follow the theory construction methodology framework, consisting of five steps (Borsboom et al., 2021).

First, the modeler selects one or more phenomena that the theory should explain. In the present study, this is people's preference for distraction over reappraisal at high emotion intensities and for reappraisal over distraction at low emotion intensities (see the Identify Empirical Phenomenon and Scope of the Theory section). Next, what Borsboom et al. (2021) term a *proto theory*, that is, any nonformal theory, is set up. As we are building on the existing verbal theory by Sheppes, Scheibe, et al. (2014), this step is already partially addressed. Still, we modified the verbal theory at certain points to present one that is more optimally suited for computational modeling (see the Develop Verbal Theory section). Third, equations or other formal expressions are set up that correspond to the relationships specified in our verbal theory (see the Formalize Theory section). The fourth step entails assessing the adequacy of the formal theory by simulating data from a computational implementation and comparing these data to the empirically established data pattern. This involves comparing the data output of the computational model implementation with the data patterns we have empirically observed in studies of people's preferences for distraction and reappraisal at differing emotional intensities (see the Check Explanatory Adequacy via Simulation section). Last, the researchers should assess the overall value of the theory, for instance, based on its predictive abilities, explanatory breadth, analogy, and simplicity (Thagard, 1993). We present an initial assessment of the formal theory along with the general discussion (see the Discussion section). These five steps of the theory construction methodology framework correspond to the structure of the remainder of this article and are visualized in Figure 1.

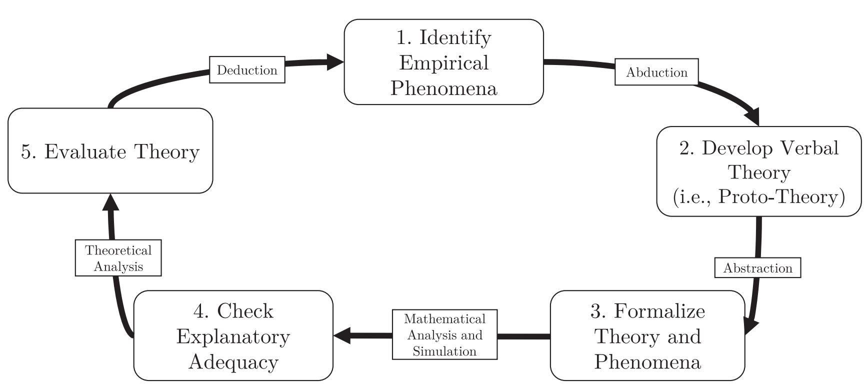
Identify Empirical Phenomenon and Scope of the Theory

One of the most consistent findings in affective science is that individuals tend to opt for distraction when confronted with high-intensity stimuli, whereas they opt for reappraisal in response to low-intensity stimuli (Matthews et al., 2021). The most common way of studying this is with an experimental task developed by Sheppes et al. (2011), in which participants are trained in the use of distraction and reappraisal and subsequently face stimuli of differing intensities and choose the strategy they would like to use for each one.

For the outcome of this and similar paradigms, a systematic review by Matthews et al. (2021) counts 51 replications and a large sample-weighted average effect size of $r = 0.61$. It is noteworthy, however, that all of these replications concern laboratory tasks. The translation of the findings to a less controlled setting—where people are not limited to only two regulation strategies—yields less clear results (e.g., De France & Hollenstein, 2022). Still, given the large number of replications, we believe this finding has reached the status of a robust *phenomenon* (Bogen & Woodward, 1988; Woodward, 2011). The construction of formal theories necessitates robust phenomena as a first step, because, without a stable phenomenon, there is nothing against which to evaluate the explanatory adequacy of the theory (Borsboom et al., 2021). The present study focuses on this relationship, between emotional intensity and the selection of regulation strategies.

Taking this phenomenon as a reference, we would like to clarify the explanatory scope of the theory further. First, the theory is, for now, concerned with the downregulation of negative emotions only, not the upregulation of positive emotions. Hence, we will only consider situations where people use reappraisal and distraction to feel less negative. The theory, thus, mainly applies to cases where people act out of a *hedonic motive*—although in principle other motives could lead to the goal of feeling less negative (Tamir, 2016). Second, the phenomenon that people prefer distraction over reappraisal at high intensities, and reappraisal over distraction at low intensities, has mostly been established by investigating the intensity of the respective stimuli. We assume for now that this stimulus intensity is equal to the subjective emotional intensity of the person perceiving the stimulus. Third, the theory does not aim to account for the fact that people might engage in polyregulation, that is, simultaneously selecting and implementing more than one strategy (Ford et al., 2019). Fourth, we will not consider any affective changes unrelated to the respective strategies and stimuli, for instance, habituation that might take place when repeatedly presenting similar stimuli. Last, the theory does not distinguish between conscious and unconscious strategy choices. We assume that people, on average, select the optimal strategy given the environment in which they learned to regulate, regardless of whether they have a cognitive representation of their motives. In this, our theory focuses on the resulting regulation strategy choices. It does not model the underlying cognitive mechanism. For instance, we do not explicitly model cognitive processes such as beliefs or working memory (cf. Dayan, 2012; Hitchcock & Frank, 2024).

Figure 1
The Five Steps of the TCM Framework



Note. Adapted from "Theory Construction Methodology: A Practical Framework for Building Theories in Psychology," by D. Borsboom, H. L. van der Maas, J. Dalege, R. A. Kievit, and B. D. Haig, 2021, *Perspectives on Psychological Science*, *16*(4), p. 762 (https://doi.org/10.1177/1745691620969647). Copyright 2021 by The Authors. TCM = theory construction methodology

Develop Verbal Theory

Our verbal theory to explain the effect of emotion intensity on strategy selection builds on the theory by Sheppes, Scheibe, et al. (2014) introduced above. They explain emotion regulation strategy selection by evaluating strategies—in particular distraction and reappraisal—across three dimensions:

- *Motivational characteristics* refer to the alignment of strategies with long-term goals. This is especially relevant for stimuli that one expects to reoccur. Distraction is often incongruent with long-term goals, as it disregards the meaning of a stimulus and hence does not aid emotion regulation in similar contexts in the future. Reappraisal, on the other hand, potentially changes the meaning of a stimulus in an enduring fashion—and therefore has a lasting impact on the emotional reaction to the stimulus. To make this more concrete, take the example of dealing with a difficult colleague. Between distraction and reappraisal, distraction might be more effective in the short-term to make you feel better. But your colleague will still be there the next day and likely evoke the same reaction. A good reappraisal of your colleague's behavior might help you much more interact with them in the long-term. It is noteworthy, however, that in some cases distraction might align better with one's long-term goals—for instance, when the stimulus is expected never to reoccur or when other goals than emotional long-term adaptation are primary.
- *Emotional characteristics* refer to the impact of a strategy on the emotional state. In the case of distraction, this emotional impact is said to take place at an early processing stage and to work reliably—even for emotionally intense stimuli. Reappraisal, on the other hand, is thought to work at a later processing stage and unreliably for emotionally intense stimuli (Fine et al., 2023; Shafir et al., 2015; Sheppes & Meiran, 2007; Thiruchselvam et al., 2011).
- *Cognitive characteristics* refer to the complexity of the underlying cognitive processes. For distraction, the theory states that these cognitive processes are relatively simple (Sheppes, Brady, & Samson, 2014; Strauss et al., 2016). The content of distracting thoughts is independent of the stimulus and hence creates no processing conflicts with the content of the affective stimulus. Reappraisal, in contrast, engages more complex processes: The content of a reappraisal semantically depends on the stimulus and creates thoughts in direct competition with the initial emotional information.

According to Sheppes, Scheibe, et al. (2014), the preference for distraction over reappraisal for high-intensity stimuli and for reappraisal over distraction for low-intensity stimuli results from a trade-off across the three dimensions. In any given emotional situation, individuals weigh the costs and benefits in one, two, or three of these categories to select their choice of strategy. While this explanation of the process appears intuitive, it is not yet clear how exactly individuals compare the value of a strategy across the different kinds of characteristics. For example, how does someone weigh the cost of using reappraisal now against the potential future benefit of reappraisal if the situation happens to reoccur? Or how does someone weigh a certain amount of cognitive effort against an amount of reduction in emotional intensity?

Highlighting and then filling in areas of ambiguity are the first contribution of the formal modeling process. More concretely specifying the theory allows for better evaluation with empirical data. As there is no previous research aimed at disentangling the contributions of the cognitive, emotional, and motivational factors on strategy choice, we cannot rely on that for orientation. Our guiding principle is, thus, to interpret and implement the trade-off in a simple and plausible manner that explains the preference for distraction over reappraisal for high-intensity stimuli and reappraisal at low-intensity stimuli. To achieve the most parsimonious implementation of the trade-off, we make several simplifications to the previously described theory.

Our first move is to simplify the motivational characteristics to concern only the reduction of the long-term emotional impact of a stimulus, whereas emotional characteristics refer to the immediate reduction in negative emotion. Accordingly, for our theory, we refer to the emotional and motivational characteristics as *short-term* and *long-term emotional characteristics*, respectively. Next, to simplify the trade-off between distraction and reappraisal, we aimed to implement it using the smallest necessary number of characteristics. The characteristics we focus on for this specific trade-off are the short-term and long-term emotional characteristics, as we now express both characteristics on the same dimension—in the form of emotional impact.

In line with the theory put forward by Sheppes, Scheibe, et al. (2014), we propose that reappraisal performs better concerning long-term emotional characteristics. The reason for this is that engaging with a stimulus and finding an alternative interpretation can pay off during all future encounters of the same stimulus. The previously articulated alternative interpretation might simply be reused. Distraction, on the other hand, does not involve meaningful processing of the emotional stimulus and thus has no advantages in implementation during future encounters of the same stimulus.

Concerning the short-term emotional characteristics, we propose that distraction is superior to reappraisal. However, to explain the trade-off at low versus high intensities of the two strategies, we propose that the short-term emotional advantage of distraction plays out especially at high intensities. We think that the mechanism behind this could be an increase in the time it takes reappraisal to have a regulatory effect at high compared to low emotional intensities, whereas distraction remains comparatively fast. An intuitive explanation for this asymmetric effect of emotional intensity on implementation time could involve the cognitive characteristics of the strategies. Engaging with a stimulus and processing its meaning always has a higher cognitive demand than distracting oneself—and thus takes longer. However, the difference in cognitive cost might increase even further, when the stimulus evokes intense emotions that interfere with the search for a good reappraisal. Indeed, previous research has suggested that distraction reduces brain activity associated with emotional arousal earlier than reappraisal (Schonfelder et al., 2014; Thiruchselvam et al., 2011). Furthermore, Shafir et al. (2015) have shown that distraction has a stronger effect in reducing highly negative affect than reappraisal after 5 s, though a study by Sheppes, Brady, and Samson (2014) found no difference after 8 s using combined low and high negative affect trials. Taken together, these findings provide initial support for the idea that distraction may work faster, but that reappraisal is equally effective given enough time.

In sum, we propose that at low intensities reappraisal and distraction work almost equally fast in reducing the short-term emotional impact—and reappraisal is preferred due to its superior long-term emotional characteristics. At high intensities, however, we propose that reappraisal takes much longer to reduce the short-term emotional impact, whereas distraction still works rather fast. Reappraisal is hence not a cost-effective emotion regulation choice anymore at high intensities, despite its better long-term characteristics. We define the trade-off among strategy characteristics in terms of emotional impact, which allows a clear weighing of the costs and benefits of each strategy on the same dimension. Table 1 summarizes this simplified cost–benefit profile of distraction and reappraisal.

Thus, the cognitive characteristics are, for now, not explicitly weighed in our simplified cost–benefit trade-off. This does not mean that we disregard the role of cognitive demands of strategies in determining strategy choice—or exclude them from our theory. Rather, we propose that for the theory in its current form, it is not necessary to explicitly weigh them in the trade-off, but only implicitly through their impact on the short-term emotional characteristics. To explain more complex phenomena—such as trade-offs that involve more than two strategies—it might very well be necessary to explicitly include the cognitive characteristics in the cost–benefit trade-off. Also, to take the step of not explicitly including the cognitive characteristics in the trade-off, we made speculative assumptions about their effect on the short-term emotional impact of distraction and reappraisal under differing emotional intensities. Should future research fail to support these assumptions, a more complex implementation of the trade-off—likely explicitly including the cognitive characteristics in the cost–benefit profile—might be necessary. We will return to these points in the Discussion section. In the following subsection, we describe the formal implementation of the verbal theory concerning long-term emotional impact, short-term emotional impact, and the trade-off under differing emotional intensities.

Formalize Theory

This section describes the formalization of the previously described verbal theory. First, it describes the formal expression of the differences in long-term emotional impact between strategies. Next, it turns to the formalization of the differences in short-term emotional impact. Last, we describe the formalized trade-off between the short- and long-term emotional impact.

Before moving to the formal implementation of the verbal theory, we wish to clarify some properties of the stimuli in our formal model. First, we assume that emotional stimuli disappear after some time or become irrelevant. That is, in the formal model, we assume that the number of recurrent encounters of the same stimulus is finite. Second, it is important to consider the scale of measurement for calculating emotional intensities. In our model, emotion intensities range from 0 to 10, with 0 being a completely neutral stimulus and 10 a very intensely negative stimulus. This scale is of course arbitrary, and only the rank order of the values is relevant. Similarly, when calculating the effect of a regulation strategy, a fixed value is subtracted from the emotional intensity. The values of these reductions are also grounded only in their rank order relative to each other. Table 2 presents an overview of all variables of the formal theory, their definitions, and their value range or set.

Table 1
The Simplified Cost–Benefit Profile of Distraction and Reppraisal

Characteristic	Distraction	Reappraisal
Short-term emotional	Effective with low- and high-intensity stimuli	Effective only with low-intensity stimuli
Long-term emotional	No increased effectiveness with similar future stimuli	Increased effectiveness with similar future stimuli

Long-Term Emotional Impact

While distraction does not entail processing the meaning of a stimulus, reappraisal does. This difference has consequences for the emotional impact of a reoccurring stimulus. When not processing the meaning of a stimulus, the emotional impact on the following encounter is unchanged. On the other hand, processing the meaning of a stimulus and finding a new appraisal change the emotional impact on future encounters.

Figure 2 illustrates this idea of the emotional impact of repeatedly encountering the same stimulus while using either distraction (left panel) or reappraisal (right panel). Formally, we express the subjective emotional intensity, $\text{peak}_{s,t}$, that is, the peak of the negative affect of stimulus s in trial t, of repeatedly applying reappraisals with:

$$\text{peak}_{s,t} = \text{intensity}_s - \text{adapt}\sum_{t=0}^{t} I(h_{s,t} = \text{reappraisal}), \tag{1}$$

where intensity_s is the initial emotional intensity of stimulus s at the beginning of the simulation, adapt is the adaptation effect of reappraisal on negative intensity, $h_{s,t}$ denotes the history of previously used strategies on stimulus s up until trial t, and $I(\text{condition})$ is an indicator function defined as:

$$I(\text{condition}) = \begin{cases} 1 \text{ if condition} = \text{true} \\ 0 \text{ if condition} = \text{false} \end{cases}. \tag{2}$$

For reappraisal, the subjective intensity $\text{peak}_{s,t}$ of stimulus s at trial t is, thus, the initial subjective intensity of the stimulus before any adaptation, subtracting the product of the adaptive effect of reappraisal and the number of previous reappraisals of that stimulus. When repeatedly applying distractions, $\text{peak}_{s,t}$ is simply a constant. Hence, for distraction, it holds that $\text{peak}_{s,t} = \text{intensity}_s$, as distraction has no effect lasting beyond each trial. This becomes visible also through the uniform peaks of the curves in the left panel of Figure 2.

However, while this formal implementation appears intuitive, the process of formalization suggested another possible mechanism behind the long-term effect of reappraisal: not as a change in the emotional reaction to a recurring stimulus ($\text{peak}_{s,t}$), but as having an increasing short-term effect ($r_{s,t}$) over time. Thus, the emotional response remains unchanged over multiple encounters, but the reappraisals become more effective in reducing negative affect. Figure 3 illustrates an example of this alternative mechanism. Formally, the

Table 2
Formal Model Variables

Symbol	Name	Description	Range/set
s	Stimulus	The index referring to a specific stimulus	$\{1, \ldots, n_s\}$
t	Trial	The index referring to a specific trial	$\{1, \ldots, n_t\}$
n_x	Maximum value	A positive, finite, discrete number defining the maximum value of variable x	$\mathbb{Z}_+$
intensity_s	Stimulus intensity	The initial emotional intensity of stimulus s at the beginning of the simulation (i.e., before any adaptation occurs)	[1, 10]
$\text{peak}_{s,t}$	Stimulus peak impact	The initial emotional intensity of stimulus s at trial t (i.e., before regulation occurs within trial t)	[0, 10]
$A_{s,t}$	Strategy/action	A single strategy selected for stimulus s at trial t	{distraction, reappraisal}
$h_{s,t}$	Strategy history	A vector containing all strategies used for stimulus s, up until trial t	$\{A_{s,1} \ldots, A_{s,t}\}$
$dTime$(intensity)	Time to distraction	A function defining the required time for distraction to have an effect	[0, 10]
$rTime$(intensity)	Time to reappraisal	A function defining the required time for reappraisal to have an effect	[0, 10]
l	Trial duration	The duration of a single trial	$[1, n_l]$
adapt	Reappraisal adaptation effect	The long-term adaptive effect of reappraisal	[0, 10]
$r_{s,t}$	Reappraisal immediate effect	The immediate regulation effect of reappraisal on stimulus s at trial t	[0, 10]
d	Distraction immediate effect	The immediate regulation effect of distraction	[0, 10]
m_s	Reappraisal affordances	The level of reappraisal affordances of stimulus s	{low, high}
$c_{s,t}$	Within-trial impact	The cumulative negative affect of stimulus s, within a single trial t	$[0, 10l]$
$v_{s,t}$	Across-trial impact	The cumulative negative affect of stimulus s, across all trials up until trial t	$[0, tc_{s,t}]$

Note. $\mathbb{Z}_+$ refers to the set of all positive integers.

initial emotional reaction $\text{peak}_{s,t}$ now remains constant for repeated reappraisals as well as repeated distractions. But unlike in the previous implementation, the short-term effect of the reappraisal $r_{s,t}$ now changes over multiple encounters. This we can formalize as:

$$r_{s,t} = r_{s,t=0} + \text{adapt} \sum_{t=0}^{t} I(h_{s,t} = \text{reappraisal}), \tag{3}$$

where $r_{s,t=0}$ is the short-term effect of reappraisal before any adaptation took place, adapt is the adaptation effect of the reappraisal, and $h_{s,t}$ denotes the history of previously used strategies on stimulus s up until trial t. The short-term effect of reappraisal on stimulus s at encounter t is, thus, defined as the short-term effect at the first encounter, adding the product of the number of previous reappraisals of stimulus s and the adaptation effect. Notice how in Figure 3 the peaks of the curves remain constant, but the effect of reappraisal increases over encounters, as becomes clear from the fact that the shaded area under the curve (AUC) gets smaller. The distinction between the two mechanisms is whether we view the adaptive effect of reappraisal, adapt, applying to the short-term effectiveness of reappraisal, $r_{s,t}$ (i.e., the reduction in negative affect), or to the initial subjective intensity, $\text{peak}_{s,t}$ (i.e., the peak of the curve).

To reconcile these distinct mechanisms, we propose that they relate to the concept of *reappraisal affordances* of a stimulus, that is, how easy it is to find a good reappraisal for a certain stimulus (Suri et al., 2018; Young & Suri, 2019). An example of a stimulus with high reappraisal affordances is a graphic image of medical procedures. While such images are high in negative valence, they allow for believable reappraisals—for instance, that the procedure is safe and necessary and will likely have a positive outcome. An example of a stimulus with low reappraisal affordance, on the other hand, might be an image of an injured child in a war zone. While the image of a medical procedure might be similarly graphic and high in negative valence, the latter stimulus allows for very few believable reappraisals of the situation that move it into a more positive light. Thus, people can reappraise stimuli with high reappraisal affordances with believable, situation-specific reappraisals. We propose that such reappraisal might permanently change the meaning of a stimulus, and then, reappraisal will have a long-lasting influence on the initial emotional impact of the stimulus, that is, the peak of the curve (as depicted in Figure 2). However, people might only be able to find generic, less believable reappraisals (e.g., "It's all for the good") for stimuli that offer low reappraisal affordances. In such cases, reappraisal will not alter the peak emotional impact of the stimulus. However, it might still become more effective in reducing the emotional impact (as depicted in Figure 3), as the generic appraisal might be more readily available and more convincingly articulated. While reappraisal affordances are a continuum, and a mixture of the two mechanisms is conceivable, for the sake of simplicity, we characterize the two possible working mechanisms, thus, as applicable to high and low reappraisal affordance stimuli, respectively. Formally, taking different levels of reappraisal affordances, m, into account, the adaptive long-term effect of reappraisal is, thus, defined as:

$$\text{peak}_{s,t} = \begin{cases} \text{intensity}_s - \text{adapt} \sum_{t=0}^{t} I(h_{s,t} = \text{reappraisal}) & \text{if } m_s = \text{high} \\ \text{intensity}_s & \text{if } m_s = \text{low} \end{cases}, \tag{4}$$

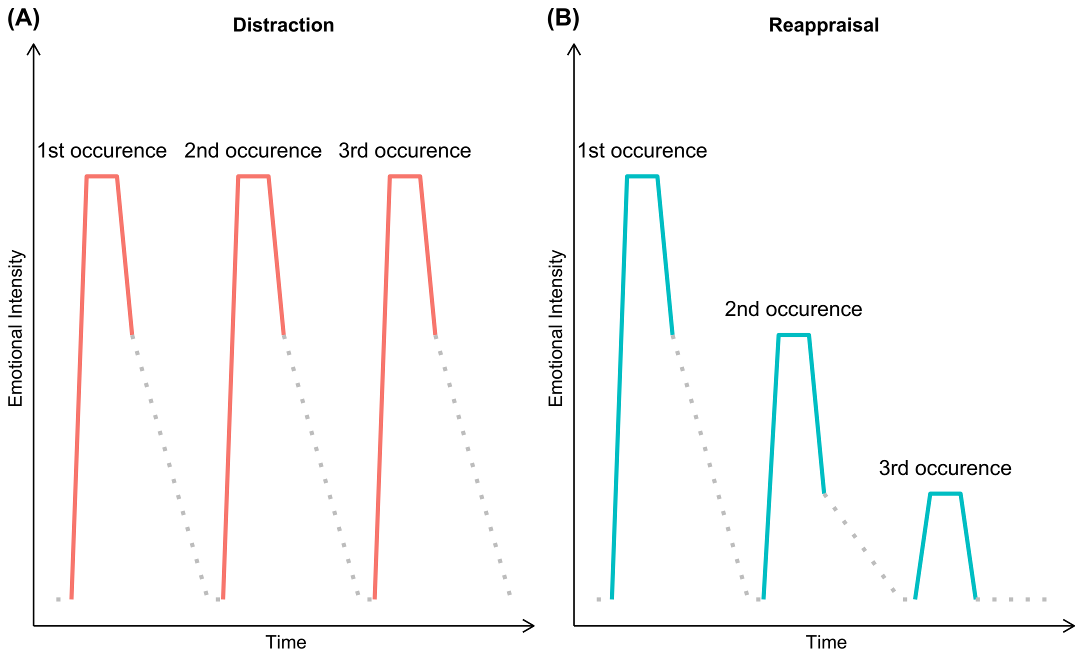
and

$$r_{s,t} = \begin{cases} r_{s,t=0} & \text{if } m_s = \text{high} \\ r_{s,t=0} + \text{adapt} \sum_{t=0}^{t} I(h_{s,t} = \text{reappraisal}) & \text{if } m_s = \text{low} \end{cases}. \tag{5}$$

Up to this point, we have formally described two ways in which reappraisal could have a superior long-term emotional impact over

Figure 2

The Effect of Distraction and Reappraisal When Reencountering a Stimulus



Note. Panel A shows the dynamics of negative affect during repeated distraction and Panel B during reappraisal. The *x*-axis shows the time. The *y*-axis shows the intensity of the negative affect. The solid lines indicate the development of the negative affect during the implementation of a regulation strategy. The dotted line indicates the development of the emotion as an effect of time passing and takes place on a larger timescale. See the online article for the color version of this figure.

distraction, either through altering the meaning of a stimulus in a long-lasting manner or through an increase in credibility and accessibility—and hence effectiveness—of a reappraisal after repeated use. But what kind of behavior would the current model imply? Note that for the illustrations in Figures 2 and 3, we assumed the magnitude of reduction in negative affect of reappraisal within each stimulus encounter, that is, the short-term emotional impact, to be at least equal to that of distraction—even before the adaptive effect of reappraisal plays out. However, this would lead to reappraisal always being the advantageous strategy, as it would perform equally well in the short-term but better in the long-term. Assuming people expect to reencounter a stimulus and think at least one step ahead, they should always select reappraisal—which is not what we observe empirically. Further, as described in the verbal theory, we have several theoretical reasons to assume that distraction and reappraisal have a distinct short-term emotional impact.

Hence, we must extend the theory and formalize the advantages that distraction holds over reappraisal in the short-term.

Short-Term Emotional Impact

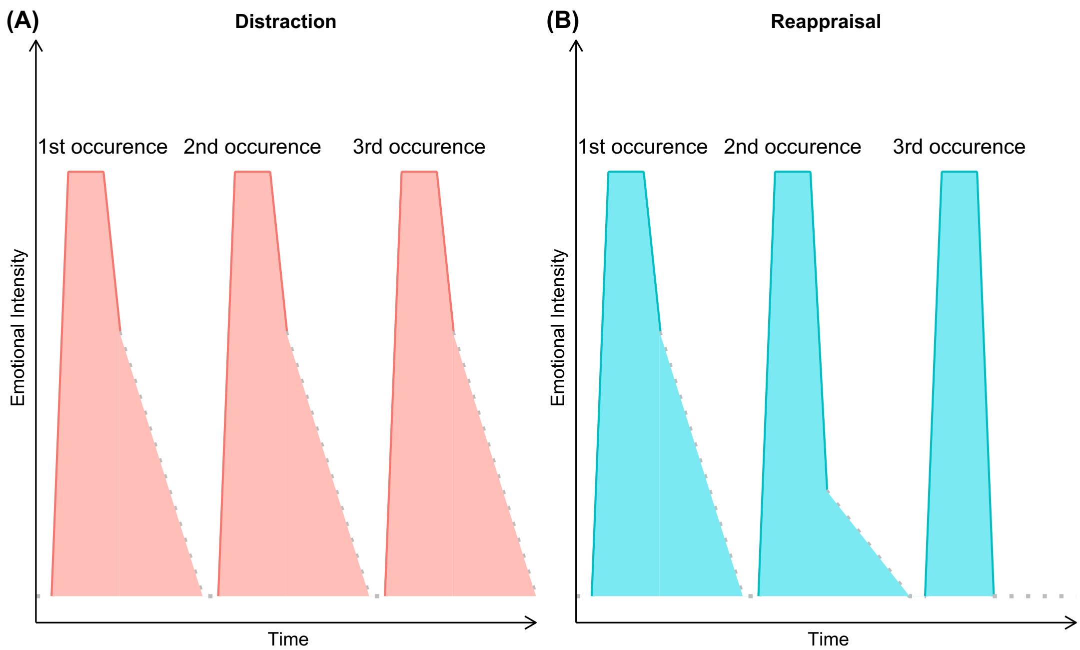
The proposed formalization of the long-term emotional impacts of distraction and reappraisal raises a question: Why would people ever prefer distraction, which does not have the same long-term emotional benefits as reappraisal? To answer this question, we propose that distraction conveys short-term emotional benefits that may outweigh those of reappraisal. Specifically, in line with the previously described verbal theory, we propose that distraction is more effective at reducing negative emotional intensity within a single stimulus encounter.

Furthermore, this short-term advantage must be most evident when dealing with high-intensity stimuli. As described in the previous section, the long-term emotional impact of reappraisal is constant across intensities—and hence, the short-term emotional impact must differ across intensities to drive the trade-off. For distraction to be the preferred option at high intensities but not at low intensities, its short-term impact must, therefore, be much better than that of reappraisal at high intensities, but less evidently better at low intensities.

In formalizing this idea, we propose that the time until the emotion regulation strategy starts taking effect is one factor that could explain how emotional intensity negatively affects the short-term emotional impact of reappraisal but not distraction. Specifically, it takes markedly longer to reappraise high-intensity stimuli than low-intensity stimuli, whereas the time it takes to distract oneself from a stimulus does not strongly depend on its intensity. This proposition is grounded in the idea that distraction—unlike reappraisal—stops the processing of a stimulus early on and abruptly; hence, there is less room for the emotional stimulus to continue interfering with the implementation of distraction. The proposed relationships between stimulus intensity and the time it takes to reappraise or distract are illustrated in Figure 4. Thus, we propose, that the time it takes to distract oneself from a stimulus grows only slowly in relation to the emotional intensity (e.g., linear growth), whereas for reappraisal, it grows rapidly (e.g., exponential growth).

Figure 3

Alternative Effect of Reappraisal When Reencountering a Stimulus



Note. Panel A shows the dynamics of negative affect during repeated distraction and Panel B during reappraisal. The *x*-axis shows the time. The *y*-axis shows the intensity of the negative affect. The solid lines indicate the development of the negative affect during the implementation of a regulation strategy. The dotted line indicates the development of the emotion as an effect of time passing and takes place on a larger timescale. See the online article for the color version of this figure.

Figure 5 illustrates how this hypothesized difference in time-to-effect between the strategies may result in markedly different short-term emotional impacts. It shows an example trajectory of a single encounter with a low- and high-intensity stimulus when employing either distraction or reappraisal. The short-term emotional impact corresponds to the AUC. The figure shows that at low intensities the AUC does not differ much between strategies, whereas for high intensities this difference is larger. This difference is a result of the time spent enduring the stimulus at full intensity. Specifically, if distraction always takes a comparatively short amount of time to work (e.g., 1.75 and 3 s in Figure 5), the time spent enduring an emotional stimulus at full intensity consequently also remains short (compare Panels A and B). The short-term emotional impact of a stimulus when using either strategy, hence, depends on the stimulus peak intensity and the trial duration. We formalize this as in Equation 6:

(see Equation 6 below)

where $c_{s,t}$ is the cumulative short-term emotional impact of using either distraction or reappraisal in response to a stimulus with initial intensity $\text{peak}_{s,t}$, and l is the duration of the trial, while d and $r_{s,t}$ denote the impact of distraction and reappraisal on the emotional intensity, respectively. *dTime*(intensity) and *rTime*(intensity) are functions that define the time it takes distraction or reappraisal to have an effect on a stimulus with peak intensity $\text{peak}_{s,t}$. The cumulative short-term emotional impact of the trial, thus, consists of two summed-up parts. First, the experienced emotional intensity is equal to the peak intensity of the stimulus, until the strategy starts to have an effect. Then, experienced emotional intensity is reduced by d or $r_{s,t}$ for the remaining trial duration. Mathematically, this is the product of the peak emotional intensity and the time it takes the strategy to have an effect, plus the product of the reduced emotional intensity and the remaining duration of the trial. We can express formally the relationship between the time it takes to employ distraction compared to reappraisal as *dTime*(intensity) ≤ *rTime*(intensity) for all values of intensity, as also depicted in Figure 4. Further, as intensity increases, the difference between *dTime*(intensity) and *rTime*(intensity) increases.

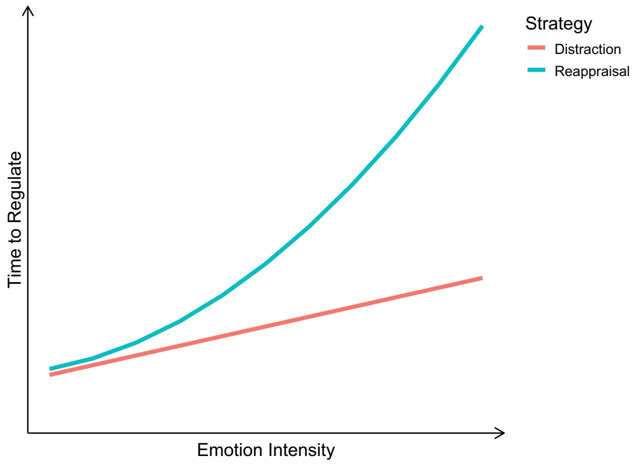
Combine Both Mechanisms to Model Trade-Off

After formalizing the short-term and long-term emotional impact of the strategies, we can turn to the trade-off that results in the relationship between emotion intensity and strategy selection. We propose that the trade-off is simply a calculation of the overall emotional impact of using the same strategy across multiple trials, thus, in the short-term and long-term. We assume that a strategy is preferred if it results in a lower overall emotional impact across multiple trials. Formally, we can express the emotional impact across trials as:

$$c_{s,t} = \begin{cases} dTime(\text{peak}_{s,t}) \times \text{peak}_{s,t} + (l - dTime(\text{peak}_{s,t})) \times (\text{peak}_{s,t} - d) & \text{if } A_{s,t} = \text{distraction} \\ rTime(\text{peak}_{s,t}) \times \text{peak}_{s,t} + (l - rTime(\text{peak}_{s,t})) \times (\text{peak}_{s,t} - r_{s,t}) & \text{if } A_{s,t} = \text{reappraisal} \end{cases}, \tag{6}$$

Figure 4

The Relationship Between Emotion Intensity and Time-to-Effect of Distraction and Reappraisal



Note. The x-axis shows the intensity of negative affect. The y-axis shows the time it takes a strategy to have an effect. See the online article for the color version of this figure.

$$v_{s,t} = \sum_{t=0}^{t} c_{s,t}, \tag{7}$$

where $v_{s,t}$ is the sum of the within-trial emotional impact $c_{s,t}$ for stimulus s across all previous trials up until trial t.

With low-intensity stimuli, reappraisal and distraction result in a similar emotional impact, $c_{s,t}$, at the first encounter. This is also reflected in the overall emotional impact, as $v_{s,t} = c_{s,t}$ for $t = 1$. However, over multiple trials t, the within-trial emotional impact resulting from reappraisal improves (i.e., decreases compared to the first trial)—and so does its overall emotional impact compared to distraction. Thus, at low intensities, it holds that for $t > 1$, $v_{s,t}$ increases less for repeated reappraisal than for repeated distractions, as t increases. At high intensities, we see a different picture: The within-trial emotional impact of reappraisal is much worse than that of distraction at the first encounter. Thus, already at $t = 1$, $v_{s,t}$ for reappraisal is much larger than for distraction. While reappraisal still improves over multiple encounters, this is not enough to make up for the high emotional impact of the early trials. So, while the increase of $v_{s,t}$ slows down for repeated reappraisals, this is not enough to catch up with distraction also for $t > 1$. Hence, distraction is the overall more valuable strategy for high-intensity stimuli. Here, it is important to recall that we assume the number of encounters to be finite as for very large values of t it would always hold that reappraisal eventually becomes advantageous, as reappraisal would simply continue to improve until it made up for the initial higher negative impact.

Summary of Theory Construction and Open Questions

To test this proposed trade-off and the other aspects of the formal model empirically, we implemented them as a computational model and conducted a simulation study, which is presented in the following section. But before turning to the simulation study, we briefly review important questions raised during the process of formalizing the verbal theory.

First, formalizing the long-term emotional impact of reappraisal has raised the question of whether a successful reappraisal permanently changes the emotional impact of a stimulus or if it instead becomes more effective in reducing this impact. Second, in both of these conceptualizations of the reappraisal mechanism, we assumed that reappraisal continues to become more effective with each use. This assumption raised the question of whether there is a limit to this improvement and which factors might determine the limit. Third, concerning the short-term emotional impact of distraction and reappraisal, we proposed that reappraisal takes longer than distraction, especially at high emotional intensities. Formalizing this relationship between emotional intensity and the time it takes the strategies to have an effect has raised two related questions. The first is the question of whether reappraisal ever works faster than distraction. This question is highly relevant to our theory: If reappraisal could be faster than distraction at low intensities, this could explain the advantage of distraction over reappraisal at high intensities and reappraisal at low intensities based only on short-term emotional impact. While it seems unlikely that engaging with a stimulus and finding an alternative interpretation for it, that is, a reappraisal, could ever be faster than coming up with an unrelated thought or distracting oneself in other ways, the implications of this question for the theory might warrant an empirical investigation. The formalization of the relationship between emotional intensity and the time it takes to effectively regulate the emotional response also raised the question of whether reappraisal not only takes longer but may even become impossible, that is, takes infinitely long to implement at very high intensities. These questions suggest new directions for future research and showcase the use of formal modeling as a tool for clarifying ambiguities that might have prevailed otherwise.

Check Explanatory Adequacy via Simulation

The purpose of simulating data based on our formal theory is twofold. First, we want to confirm that the formal model—including all mechanisms as presented above—does indeed account for reappraisal being a more valuable strategy compared to distraction at low intensities and for distraction being a more valuable strategy at high intensities. Second, we aimed to showcase the opportunities for simulating data from hypothetical experiments, which can serve as precise predictions for conducting such experiments in a real-life setting. This section first describes the technical details of implementing the computational model. Next, it presents the results of a simulation study aiming to answer the question under which conditions the computational model reproduces the data patterns established in previous research. Then, it presents an example of how the computational model can generate novel, empirically testable hypotheses.

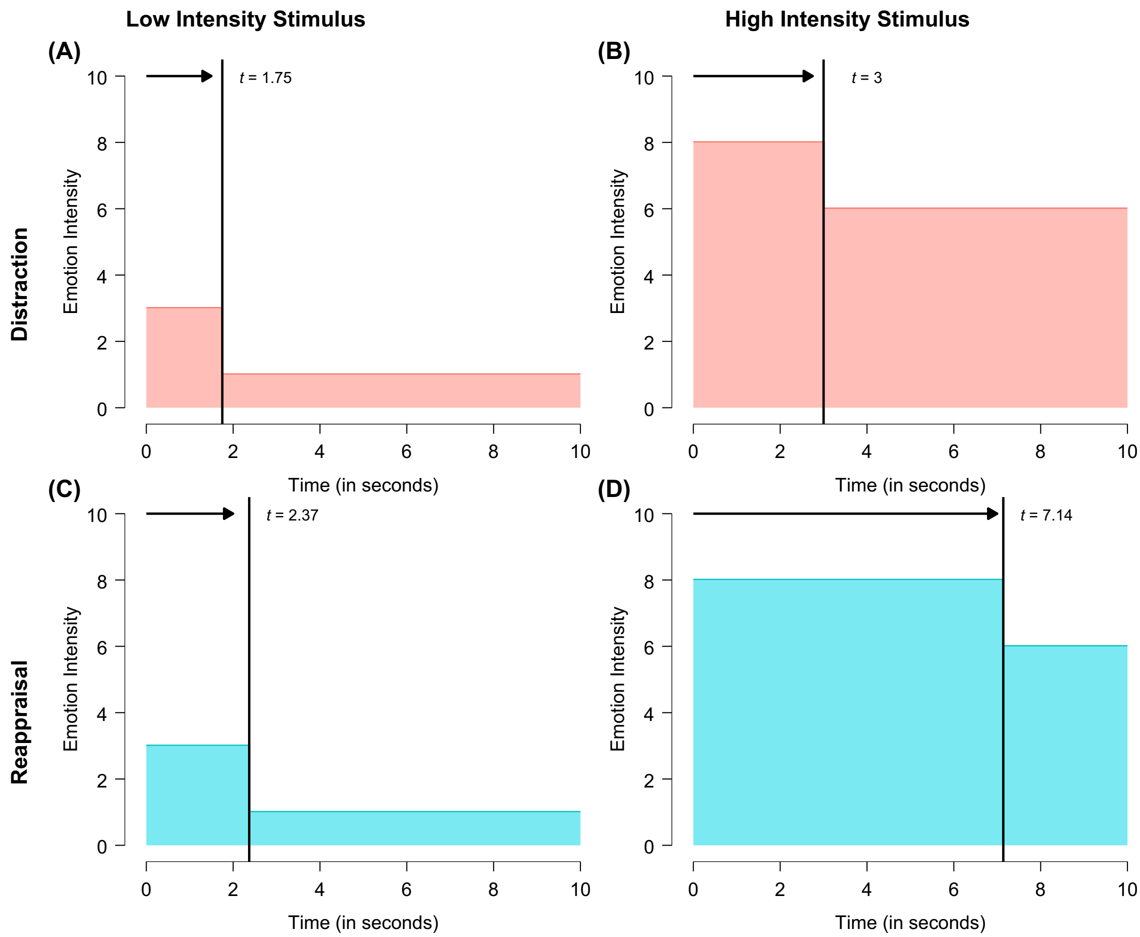
Method

Computational Model

As laid out above, the advantages of using each strategy play out on different timescales: within single stimulus encounters and across multiple encounters. Thus, to retrieve the optimal strategy for each

Figure 5

Illustration of the Short-Term Emotional Impact of Distraction and Reappraisal



Note. The *x*-axes show the time (in seconds). The *y*-axes show the intensity of negative affect. The shaded area indicates the total short-term emotional impact over one encounter with a stimulus. The vertical lines and the arrow highlight the time point at which the emotion regulation strategy takes effect. The values for time and emotional intensity are for illustrative purposes only. Panel A shows the effect of distraction for a low-intensity stimulus, Panel B of distraction for a high-intensity stimulus, Panel C of reappraisal for a low-intensity stimulus, and Panel D of reappraisal for a high-intensity stimulus. See the online article for the color version of this figure.

emotional intensity, the simulation must be able to map immediate as well as future rewards to the respective strategy choice, where the reward corresponds to the inverse of negative affect (i.e., a lower negative affect gives a higher reward). A natural model for finding the optimal solution (i.e., strategy choices) in such a complex and dynamic environment is a reinforcement learning model (Sutton & Barto, 2018). Specifically, to allow the model to anticipate future rewards, we employ the reinforcement learning method *Q-learning* (Watkins, 1989). Since we are not aiming to explicitly model the cognitive processes underlying the decision making, Q-learning suits our purpose well; it is a *model-free* approach that learns directly from experience without relying on an internal representation of the environment. While there are simpler methods to obtain the expected value of employing distraction and reappraisal under differing intensities, a reinforcement learning model also aligns with the second aim of our simulation, as we can use reinforcement learning to model human learning, allowing us to simulate developmental experiments.

In the reinforcement learning simulation, the simulated participants (i.e., agents) randomly encounter stimuli differing in intensity and select a regulation strategy (i.e., reappraise or distract). The agents then receive a reward, equal to the inverse of the cumulative negative affect within the stimulus encounter. Specifically, in Q-learning, a Q-table is created that contains values representing the expected total rewards, combining both immediate and future rewards, for taking each action given each stimulus intensity. When the actual reward for using a certain strategy differs from the stored reward value, an algorithm updates the Q-table. The function for updating the values is the Q-learning algorithm (Watkins, 1989), defined as Equation 8:

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha[R_{t+1} + \gamma \max Q(S_{t+1}, a) - Q(S_t, A_t)], \quad (8)$$

where S_t is the state at time point t, in the present model, the cumulative emotional intensity of the stimulus encounter. Here, it is important to note that a timestep t in Equation 8 corresponds to a stimulus encounter of the model, not a timestep within the duration of a stimulus encounter (l). A_t is the action at time point t, thus, in the present model, the selected regulation strategy, while a is the set of all possible actions (i.e., distraction and reappraisal); α is the learning rate, a parameter to determine how much the agent weighs new against old information. This means if we were to decrease α, it would have the effect that agents would only slowly update their expected rewards. Next, R_t is the reward at time point t, and γ is the discount factor—which influences how much future rewards are weighed against immediate rewards. This γ factor usually ranges from 0 to 1, with $\gamma = 0$ indicating that the agents only value immediate rewards, whereas $\gamma = 1$ means the agents value even rewards far in the future equally to immediate rewards.

Through iterations of this algorithm, the expected reward values in the Q-table start to approximate the average reward values of the strategies. The strategy selection in our model relies on the *epsilon-greedy policy*, which entails that the agent always selects the action with the highest expected value for the given stimulus intensity—except ε percent of the time, in which it selects a random strategy, that is, each strategy with probability .5 (Sutton & Barto, 2018). Hence, if $\varepsilon = .1$, the agent selects the current optimal action 90% of the time and a random action 10% of the time. This algorithm is necessary to resolve the explore-exploit dilemma, that is, to strike a balance between exploring new options for potentially better outcomes and exploiting the currently known best options. Random exploration is a strategy congruent with human decision making in this scenario (Wilson et al., 2014).

Simulation Parameters

The previously described assumptions and theoretical mechanisms are implemented in the model as flexible parameters. This makes it possible to manipulate them and evaluate the degree to which data patterns align with empirical findings. Table 3 shows the key simulation parameters.

Regarding properties of the environment, there is a parameter to control the length of the simulation (i.e., number of runs)—equal to the total number of stimuli encounters—and a parameter to control the number of agents, that is, the repetitions of the whole simulation. Regarding the stimulus characteristics, this includes a parameter to control the number of distinct stimuli (s) in the environment, one to control how often a stimulus may occur before being replaced (n_t), one to set the percentage of high reappraisal affordance compared to low reappraisal affordance stimuli, and one to set the duration of each stimulus encounter (l). Furthermore, there are parameters related to the properties of the agent. This includes the learning rate α, the discount factor γ, and the exploration factor ε. To simulate the differences in short-term impact between the strategies as described previously, we implemented a function based on the formal theory that computes a different immediate reward when using either strategy. To compute the long-term impact, we implemented a function that reduces the stimulus intensity permanently or improves the effect of reappraisal on the following encounter, when using reappraisal on a high or low reappraisal affordance stimulus, respectively. For these calculations of emotional impact, emotion intensity ranges from 0 (i.e., low-intensity) to 10 (i.e., high-intensity). The amount of emotion reduction that reappraisal (before adaptation) and distraction award, $r_{s,t=0}$ and d, respectively, as well as the long-term adaptive effect of reappraisal, adapt is also implemented as parameters and presented in Table 3. Any deviations from the values defined in Table 3 are noted throughout the rest of the section. The default values are all either standard values in Q-learning models (e.g., learning rate) or reasonable estimates assessed for their robustness (e.g., number of stimuli).

Table 3
Default Simulation Parameters

Parameter	Default value
Number of training runs	50,000
Number of agents	50
Number of training stimuli (s)	800
Maximum number of stimulus occurrences (n_t)	5
Proportion of high reappraisal affordance stimuli	0.5
Duration of trial (l)	10
Learning rate (α)	0.1
Discount factor (γ)	0.99
Exploration factor (ε)	0.1
Affect reduction of distraction (d)	2
Affect reduction of reappraisal ($r_{s,t=0}$)	2
Adaptive effect of reappraisal (adapt)	2

The time it takes both strategies to have an effect corresponds to the relationships illustrated in Figure 4. Scaled to our emotion scale ranging from 0 to 10 and after parameter tuning, the relationship between emotion intensity and time-to-effect of distraction is implemented as in Equation 9:

$$dTime(\text{intensity}) = 1 + 0.1\,\text{intensity}. \tag{9}$$

The relationship between emotion intensity and time-to-effect of reappraisal is implemented as in Equation 10:

$$\begin{aligned} r\text{Time}(\text{intensity}) = {} & 1 + 0.2\,\text{intensity} + 0.09\,\text{intensity}^2 \\ & + 0.002\,\text{intensity}^3, \end{aligned} \tag{10}$$

where in both functions, the output is the duration of the strategy to have an effect, given the input intensity.

Outcome: Strategy Choices

The main outcome is the distribution of strategy choices across emotional intensities. Since the experimental paradigms used to establish the reference phenomenon generally refer to low- and high-intensity stimuli, we have dichotomized the discrete emotion scale ranging from 0 to 10 for the output, with stimuli of intensity five and below considered low-intensity and stimuli of intensity above five considered high-intensity.

Simulation Procedure

Assessing Adequacy by Reproducing Empirical Patterns. First, to confirm that the computational model generates data patterns in line with the empirical reference phenomenon, we ran simulations with the default model according to Table 3. After fully training the agents, we presented them with another 50 stimuli of varying intensities, and their regulation choices were recorded.

Assessing Model Parsimony. Second, to evaluate the quality of the formal theory, we need to understand whether it contains aspects that can be removed, while still producing data patterns in line with the reference phenomenon. Should this be the case, this suggests that model is needlessly complex, that is, parts of the theory are not necessary to explain the phenomenon (van Dongen et al., 2024). Thus, ideally, all mechanisms in the model are necessary to account for the empirical reference phenomenon. To test this, we have investigated the effect of removing either the short-term or the long-term differences from the model, hence one simulation in which both strategies have the same short-term impact, and one in which both strategies have the same long-term impact. Also in this environment, there is a training period until convergence is followed up with the presentation of 50 further stimuli for which the strategy choices are recorded.

Deriving Novel Predictions From the Model. Third, to showcase the possibility of deriving novel predictions through simulation, we use the reinforcement learning framework to simulate development. These precise predictions (in the form of data patterns) can then be put to a strong test in empirical research. For this, it is important to consider the behavioral change the model displays during different stages of the learning process. During learning, the preferred regulation strategy of the agents for stimuli of different intensities might still vary. The fully trained model, however, has only one preferred regulation strategy choice for each intensity. This difference in the learning status of the model could correspond to different real-life agents. Whereas the fully trained model would correspond to a fully developed, older adult, the model during training could correspond to a child or adolescent who is still developing their emotion regulation strategies. Since the reference phenomenon refers to healthy adults, we assume that they have learned to select the optimal strategies and hence inspect the output of the fully trained agents in the simulation. However, opportunities to investigate developmental trajectories emerge when studying the output of the model during training.

In the previous simulations, all agents in the model are the same. To showcase the possibility of introducing interindividual differences to the model, we want to generate data for agents with differences in reappraisal ability and reliability. Thus, instead of setting the affect reduction of reappraisal (before adaptation), $r_{s,t=0}$, and the adaptation effect, adapt, to constants, as suggested in Table 3, we will draw these parameters from a distribution every time the agents apply reappraisal. In our experiment, there are two groups, both of which draw from a normal distribution with $M = 2$, but the standard deviation of the distribution differs between groups. The group of agents for which reappraisal is a reliable strategy will draw from a normal distribution with a very low standard deviation ($M = 2$, $SD = 0.01$), whereas the group of agents for which reappraisal is a less reliable strategy will draw from a normal distribution with the same mean, but a higher standard deviation ($M = 2$, $SD = 1$). The effect of distraction will remain constant ($d = 2$) in this simulation.

We are not interested in the optimal solution, but in simulating real-life participants as closely as possible, and we intend to set a realistic duration for their learning period. Which number of negative stimuli corresponds to a person's day, month, or year might vary vastly and is thus an open question. There is some research measuring the relative frequency of negative emotions compared to positive emotions (Trampe et al., 2015; Zelenski & Larsen, 2000), yet we are not aware of any research that has specifically investigated the absolute frequency of negative emotional stimuli the average person experiences throughout their day. However, a study by Almeida et al. (2002) reported that people in their large population sample experience at least one stressful event on 40% of days and more than one stressful event on 10% of days. Further, the phenomenon that people prefer distraction over reappraisal for high-intensity stimuli but reappraisal for low-intensity stimuli is based on an experimental paradigm that uses very brief presentations of negative pictures. The number of negative stimuli relevant to the model is thus likely higher than what Almeida et al. (2002) considered a stressor. Thus, it appears reasonable to assume that people on average experience at least two to three negative stimuli per day that are comparable to the stimuli in the experimental paradigm that established the reference phenomenon. This estimate corresponds to a total of around 13,000–20,000 encountered negative stimuli in a person's life until the age of 18. We will thus set the duration of the learning period to 20,000 stimuli, to simulate an adolescent sample.

Transparancy and Openness

All data behind this simulation and analysis have been made publicly available on GitHub and can be accessed at https://github.com/JTPetter/emotionRegulationFastSlowComputationalModel. The simulation studies were conducted in Python 3.9 (Van Rossum & Drake, 1995). We used R 4.4.1 to analyze the generated data sets (R Core Team, 2021).

Results

Model Convergence

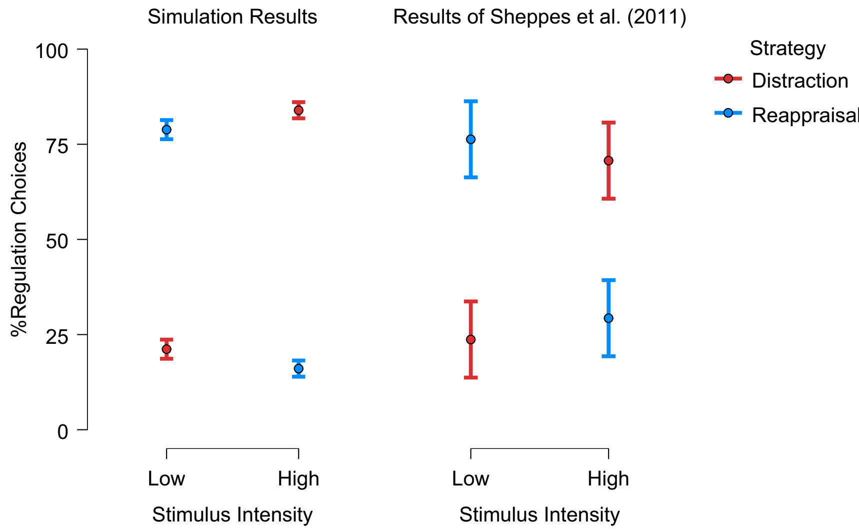
The agents appear to reach a stable state after approximately 40,000 runs. Details of the model convergence estimation are presented in Appendix A.

Assessing Adequacy by Reproducing Empirical Patterns

The left panel of Figure 6 shows the proportion of strategy choices for low- and high-intensity stimuli in the fully trained model. The right panel shows data from an exemplary experimental study that established the reference phenomenon (Sheppes et al., 2011). In line with the reference phenomenon, agents in the model select distraction for high-intensity stimuli 83.9% of the time, CI [81.8, 86.1], but select reappraisal for low-intensity stimuli 78.8% of the time, CI [76.3, 81.4]. While the agents can only have a single preferred action per stimulus intensity, we still see variance in the strategy choices. This variance comes through the randomness inherent in the simulation, as not all agents had the same number of stimuli of each intensity in their environment during training.

To investigate the robustness of these results to the simulation parameters, we have conducted a Sobol sensitivity analysis. Sobol sensitivity analysis is a technique used to assess the contribution of all parameters to the output variance of a model, considering all parameters simultaneously rather than one at a time, capturing both individual effects and interactions (Zhang et al., 2015). The results of the Sobol sensitivity analysis are presented in Appendix B. From the first-order sensitivity indices, which indicate the individual contribution of each parameter to the outcome variance, it appears

Figure 6
The Proportion of Strategy Choices of the Default Model



Note. The *x*-axis shows the intensity of the presented stimuli. The *y*-axis shows the percentage of choices of a regulation strategy of the total strategy choices. The error bars indicate 95% confidence intervals. See the online article for the color version of this figure.

that the number of stimuli and the maximum stimulus occurrence are relatively influential parameters. This makes intuitive sense, as both directly influence how well the long-term effect of reappraisal can play out. However, the total-order sensitivity indices, which indicate the contribution of each parameter in interaction with other parameters, show that most variation in the outcome is accounted for through interactions of parameters in combination with each other.

Assessing Model Parsimony

Next, we turn to the results of the simulation when removing parts of the theory. As explained previously, this is necessary to evaluate whether the model is parsimonious, that is, all its aspects are needed to reproduce the expected data pattern. The right panel of Figure 7 shows the proportion of regulation choices of the fully trained agent, when both strategies have the same short-term impact. In line with our expectations, we can see that the agent, in this case, prefers reappraisal for high- and low-intensity stimuli, selecting it 96.8% and 78.3% of the time, CI [95.6, 97.9] and [76.0, 80.6]. The left panel of Figure 7 shows the strategy choices when both strategies have the same long-term impact. Again, as expected, we can see that the agents, in this case, prefer distraction for high- and low-intensity stimuli, selecting it 99.1% and 74.0% of the time, CI [98.6, 99.6] and [71.5, 76.4]. This gives support for the idea that the present model is not needlessly complex, and all its parts are necessary to reproduce the expected data pattern.

Deriving Novel Predictions From the Model

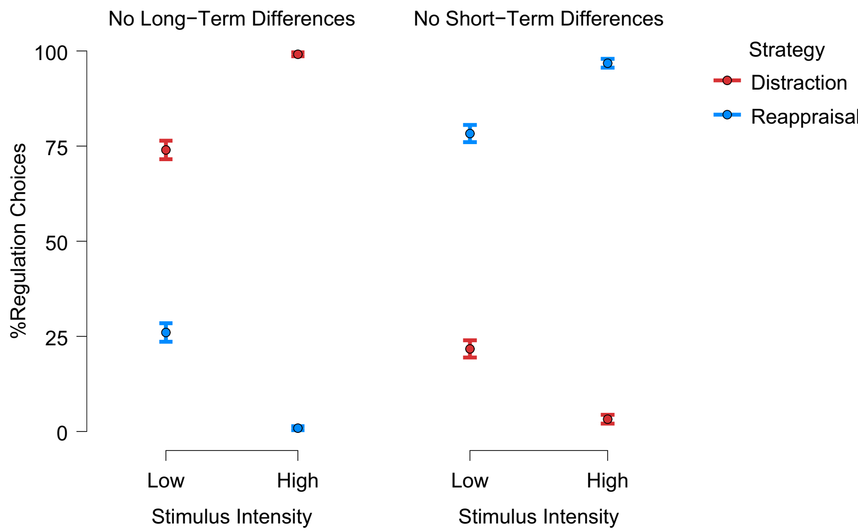
To model individual differences in reappraisal ability, we simulated two levels of variance (i.e., low and high variance) in the effect of reappraisal. Agents in this simulation were not fully converged, as they were trained only on 20,000 stimuli. These agents are intended to correspond to people still learning which emotion regulation strategies are optimal, such as adolescents. Figure 8 shows the results of this simulation. In such an environment, the group of agents for whom the effect of reappraisal has a large variance learn to prefer distraction for high-intensity as well as low-intensity stimuli. The group of agents for whom the effect of reappraisal has a smaller variance learn to prefer reappraisal for low-intensity, but distraction for high-intensity stimuli—although with a weaker preference compared to the fully trained agents in Figure 6.

Summary of Results

Implementing the formal theory in a computational model closely reproduces the empirical findings concerning the relationship between stimulus intensity and strategy choice. Fully trained agents in the model learn to prefer distraction for high-intensity stimuli, but reappraisal for low-intensity stimuli. This confirms that the present formal theory does indeed account for the phenomenon it intends to explain. Furthermore, we conclude that all aspects of the theory are indeed necessary. Removing the short-term impact theory from the model results in agents preferring reappraisal across the board, whereas removing the long-term impact theory results in a general preference for distraction. Lastly, we can see that the model is useful for deriving novel predictions. Modeling an environment in which agents are not trained until convergence leads to different preferences depending on the variance of the reappraisal effect. Agents have a general preference for distraction when the effect of reappraisal has a large variance, but a preference for distraction only for high-intensity stimuli when the effect has a small variance. This makes sense intuitively, as when the effect of reappraisal varies substantially, agents need more time to learn that it is on average more beneficial than when the effect has little or no variance. This prediction could correspond to the development of regulation strategy choices in adolescents, comparing a group that consistently

Figure 7

The Proportion of Strategy Choices When Modeling No Long- or Short-Term Differences Between Strategies



Note. The *x*-axis shows the intensity of the presented stimuli. The *y*-axis shows the percentage of choices of a regulation strategy of the total strategy choices. The error bars indicate 95% confidence intervals. See the online article for the color version of this figure.

comes up with effective reappraisal to a less consistent group. It may be interesting to investigate this prediction empirically.

General Discussion

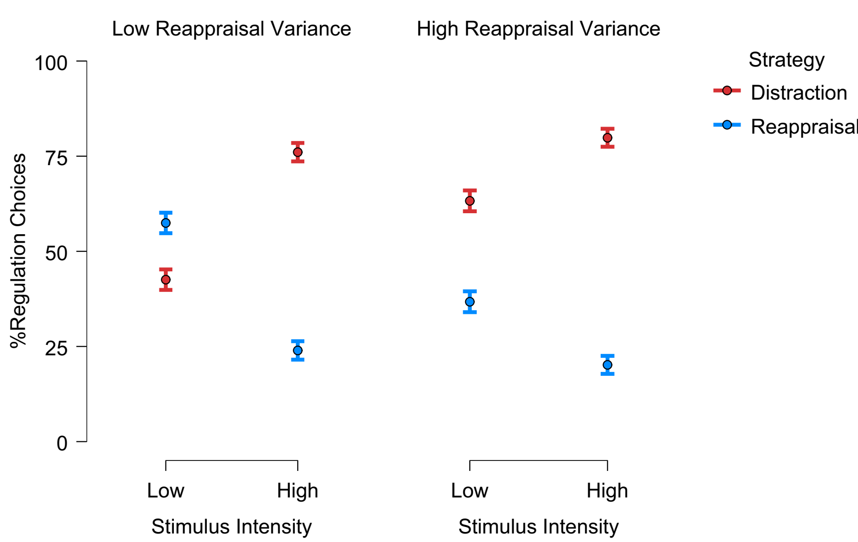
Developing the present model of emotion regulation strategy selection has raised several questions with the potential to deepen our understanding of emotion regulation. However, it is also important to note several limitations and future extensions of this work.

Formal Theory Contributions

First, the formalization of the long-term effects of reappraisal has raised a question about the underlying mechanism(s): Does

Figure 8

The Proportion of Strategy Choices When Modeling Varying Reappraisal Effects



Note. The *x*-axis shows the intensity of the presented stimuli. The *y*-axis shows the percentage of choices of a regulation strategy of the total strategy choices. The error bars indicate 95% confidence intervals. See the online article for the color version of this figure.

a successful reappraisal directly alter the subsequent emotional appraisal (i.e., emotional impact) of the same stimulus or does this initial appraisal remain the same while subsequent reappraisals become more effective in reducing negative affect? We proposed that both mechanisms are likely to take place but depend on the ability of a person to find a believable compared to a generic reappraisal, which in turn depends on the reappraisal affordances of the stimulus. That is, for stimuli with high reappraisal affordances, it might be possible to find believable reappraisals that permanently reduce the emotional impact. For stimuli with low reappraisal affordances, one might only be able to find generic reappraisals and improve the efficacy of these reappraisals over time. In the most extreme form of low reappraisal affordances, some stimuli might be impossible to reappraise even once. Investigating these proposed working mechanisms of reappraisal further and how reappraisal affordances relate to them might clarify how people generate believable reappraisals—also for stimuli with low reappraisal affordances—and which other factors play a role in this process. Knowledge of the stimulus content might, for instance, also relate to the process of finding believable reappraisals. A medical doctor might be able to generate more believable reappraisals for stimuli related to severe injuries, as they have a lot of knowledge about their treatment. In this sense, a lack of such knowledge could interfere with people generating believable reappraisals, as they cannot come up with realistic alternative outcomes. Understanding more precisely which factors besides the reappraisal affordances of a stimulus allow people to generate believable reappraisals could inform interventions, including for instance education about stimulus-related content to allow construction of more believable reappraisals.

Second, formalizing the long-term adaptive effect of reappraisal also raised the question of whether there is a limit to how much a stimulus can be regulated. Previous research suggests it is unlikely that every person can reappraise every negative stimulus so effectively that it eventually becomes emotionally neutral (Yuan et al., 2015)—besides that this is not usually what people aim for. What determines which stimuli continue to evoke negative emotions is probably highly individual. For some people, it might be the reminder of losing a loved one; for others, it might be a failed business venture that continues to haunt them. Effective reappraisals might make people feel better about the event, but they usually will not completely neutralize the negative affect. Assuming that there indeed is a limit for how much certain people can reappraise certain stimuli, an interesting follow-up question is how they deal with the remainder of their negative affect. They might need to switch to other strategies if the negative affect remains high enough to evoke the motivation for emotion regulation. Alternatively, people might try to improve their reappraisals further with the help of others. Either way, understanding what happens when people reach the limit of their reappraisal is valuable, as this might be another point at which people could resort to maladaptive regulation strategies.

Last, the formal model not only raised new questions during its creation but also permitted the generation of simulated data to directly make clear predictions. These model-derived predictions might be especially helpful in answering questions concerning the development of certain strategy patterns as the model agents also learn regulation strategy patterns over time. This might include questions about how children and adolescents learn to regulate their emotions in adverse environments, where they encounter an increased number of high-intensity negative stimuli (Rudenstine et al., 2019). A reliable computational model could be especially valuable in this area of research, given that these questions are usually difficult to study experimentally.

Limitations and Possible Extensions

Naturally, simplifications are needed to make creating a first formal theory feasible. It also requires a high degree of specificity about aspects of emotion regulation that are not well-researched. While this offers opportunities for future research, it also results in some limitations.

First and foremost, while the proposed mechanism that the stimulus intensity affects how quickly reappraisal has an effect does account for a difference in short-term emotional impact between reappraisal and distraction, there is only limited empirical evidence for this explanation. Multiple studies provide indirect evidence for this idea (Schonfelder et al., 2014; Shafir et al., 2015; Sheppes, Brady, & Samson, 2014; Thiruchselvam et al., 2011) but no research to date directly demonstrates that distraction corresponds to a faster reduction of the subjective experience of negative affect compared to reappraisal and how this timing differs at low and high negative affect intensity. Future research is thus needed to investigate this mechanism in more detail.

Second, it is important to note that the output of the computational model can only be interpreted based on its qualitative characteristics. That is, the simulated data indicate a preference for reappraisal over distraction at low emotional intensities and for distraction at high emotional intensities. Moreover, this qualitative difference appears robust to changes in parameter settings. On the other hand, the quantitative strength of this preference depends strongly on the selected parameters. To illustrate, keeping all other parameters constant, a stronger relationship (i.e., steeper curve) between emotional intensity and the time-to-effect of reappraisal than distraction leads to distraction becoming the more valuable strategy at some value of emotional intensity. However, the exact value of emotion intensity at which distraction becomes the more valuable strategy depends on the specific form of both curves. Other parameters, such as the scale on which emotional intensity is measured, also play a role. To produce results that can be interpreted quantitatively, the key will be to ground these parameter values in future empirical research. This research needs to clarify where exactly the threshold at which distraction becomes more valuable should be. This threshold might also differ between individuals, and these differences might have implications that characterize adaptive or maladaptive emotion regulation choice.

Third, in the current model, the stimulus characteristics are limited to intensity. And while intensity has been established as an important factor in driving emotion regulation choice, it is certainly not the only one. Other factors, such as the discrete emotion a stimulus evokes or the previously mentioned reappraisal affordances, have also been shown to influence the regulation choice (Matthews et al., 2021). Adding a more complex stimulus representation to the model could allow us to simulate these effects and extend the model's capability to account for emotion regulation choices in a wider range of scenarios. This might for instance entail implementing a different effect of reappraisal depending on the discrete emotion (e.g., reappraisal works well for anger, but less for sadness). Further, a more complex representation of the stimuli would allow us to model the transfer of long-term reappraisal effects to stimuli with similar properties. It might for instance be possible to fully transfer certain reappraisals to very similar stimuli or to partially transfer reappraisals to distinct stimuli that share a property, such as the discrete emotion they evoke.

Fourth, our affective calculus is grounded in the assumption that the value of a regulation strategy corresponds to the cumulative affective state it yields, that is, the AUC. While this might appear intuitive, the *peak-end rule* introduces additional complexity to this assumption (Fredrickson, 2000; Kahneman et al., 1993). The peak-end rule refers to the robust finding that when evaluating a situation's unpleasantness at a later point, people do generally not appear to calculate their cumulative affective state throughout the situation. Instead, in most cases, the overall unpleasantness rating of a situation appears to be predicted well by the peak and final level of negative affect. The peak-end rule has direct relevance to our model. It aligns well, for instance, with our distinction in mechanisms behind the long-term adaptation of reappraising high reappraisal affordance versus low reappraisal affordance stimuli. We proposed that reappraising a high reappraisal affordance stimulus might reduce the peak negative intensity, as well as the end negative intensity on future encounters. For low reappraisal affordance stimuli, reappraisal might only affect the end negative intensity, while the initial peak remains constant. Assuming that a combination of reducing the peak and end intensity is the optimal outcome, reappraisal should be especially valuable for high reappraisal affordance stimuli. The peak-end rule, furthermore, conflicts partially with our conceptualization of the short-term effects of distraction and reappraisal. According to the peak-end rule, people should not prefer distraction over reappraisal at high intensities simply because it reduces the cumulative negative affect—as our model proposes. However, as the peak-end rule refers to the post hoc evaluation of negative affect, it is not entirely clear whether it applies similarly to affective forecasting. Also, further research has shown that besides the peak and the end level of negative affect, the velocity of negative affect reduction influences the rating of the overall unpleasantness of an experience (Hsee & Abelson, 1991). Thus, it might be that distraction not only works earlier at high intensities but also reduces negative affect more rapidly. It might be helpful in the future to refine the model to align better with the peak-end rule and the velocity relation and create a more complex algorithm to determine the value of a strategy—not only based on the cumulated negative affect levels but also taking the peak and end levels and the change rates into account.

Last, the model in its current form has limited possibilities to account for individual differences between the human agents it models. While the model can account for individual differences in future discounting, learning speed, and regulatory effectiveness, several more important individual differences could be included. Differences in emotional reactivity, for instance, may be included by incorporating a parameter in the model that determines how the agents perceive stimuli. Currently, this is a one-to-one mapping, that is, a stimulus of intensity five is perceived as emotional intensity five. But some people have stronger emotional reactions; thus, for them, perceiving stimuli of intensity five might lead to an emotional reaction of intensity eight. Extending the model in this manner could enhance its ability to make predictions about subgroups with specific characteristics or even about individuals.

Fortunately, a formal theory is well-suited to address these shortcomings in future work. Its precise mathematical expression makes it possible to build on the existing model without the risk of accidentally modifying or misinterpreting any other aspects of the theory. Furthermore, the possibility of simulating data from the model allows us to continuously assess all its predictions. This opens up the possibility of creating even very complex extensions while ensuring that the model still aligns with all phenomena it is supposed to account for. Even if future research fails to find evidence for the mechanism that is fundamental to the model in its current form—the proposed relationship between stimulus intensity and time-to-effect of distraction and reappraisal—this could be resolved through a straightforward extension of the present model. Likely, this would necessitate explicitly including the cognitive characteristics in the value calculation of the strategy—in line with the theory by Sheppes, Scheibe, et al. (2014) that includes the cognitive characteristics in the cost–benefit profile.

Conclusion

That people prefer distraction over reappraisal for high-intensity emotional stimuli but reappraisal for low-intensity stimuli is one of the most robust findings in the field of affective science. Researchers have proposed theories to explain this phenomenon, formulated in natural language. Formalizing these verbal theories may make more precise predictions possible and may suggest new predictions. To address these possibilities, the present study developed a formal theory building on a modified version of the verbal theory by Sheppes, Scheibe, et al. (2014). The formal model we proposed for analyzing emotion regulation choice uses a simple explanation that accounts well for the effect of stimulus intensity on strategy choice. However, one of the main explanatory mechanisms—an increase in the time it takes reappraisal to have an effect at high emotional intensities—is not yet firmly grounded in empirical evidence. This should be addressed before considering our formal theory fully adequate. However, if future empirical work indeed finds support for the mechanisms we proposed in the model, there are promising possibilities to derive novel predictions or extend the explanatory scope of the theory.

In conclusion, we believe that the present study has shown the benefits of formal modeling for the field of emotion regulation. Our formalized theory explains the effect of stimulus intensity on strategy choice well. Unlike the verbal theory we took as a starting point, it is unambiguous about the relationships between all included factors, due to its precise specification through mathematical equations. Even if not all of the model's aspects are supported by empirical evidence yet, the precise specification allows for strong tests to investigate its value. Besides the theory itself, the effort of modeling has brought up interesting questions, answers to which might deepen our understanding of emotion regulation strategy choice. Investigating these questions and understanding the underlying mechanisms in detail have the potential to help people with emotion regulation difficulties. It could inform more effective interventions in clinical and nonclinical populations that reduce suffering and other consequences associated with maladaptive regulation choices.

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(*Appendices follow*)

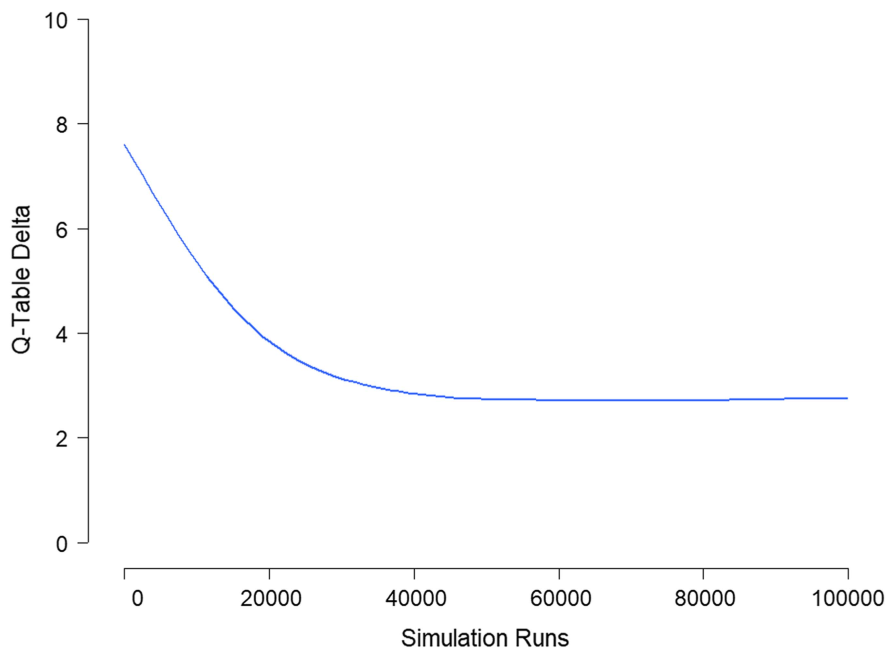
Appendix A

Model Convergence

We are interested in determining whether the expected values of the agent reach a stable optimum state if it continues to learn. To determine this, we look at the development of the Q-table difference values, that is, the difference between the sum of all values in the Q-table at timepoint t and timepoint $t + 1$. Once the expected reward values in the Q-table start to approach the actual reward values, this difference approaches zero. However, the simulation has random elements, such as the reoccurrence of reappraised stimuli. The Q-table will, therefore, not approach a fixed state but continuously change within a certain range. Thus, instead of taking a Q-table δ of zero as the benchmark, we inspect its development and estimate the point at which the learning curve becomes flat (Sutton & Barto, 2018). The development of the Q-table difference values is presented in Figure A1.

Figure A1

The Development of Q-Table Difference Values Across Time



Note. The x-axis shows the time of the simulation in runs. The y-axis shows the Q-table δ, that is, the difference between the sum of all Q-values at the current timepoint and the previous timepoint. The Q-table δ values are averaged across 50 repetitions of the simulation. See the online article for the color version of this figure.

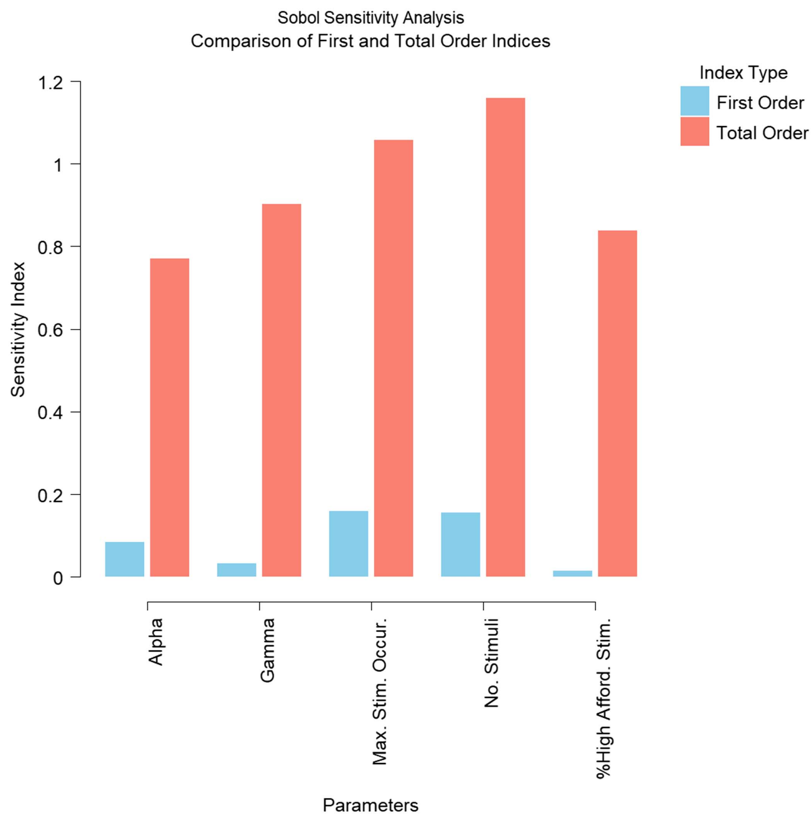
(*Appendices continue*)

Appendix B

Sensitivity Analysis

Figure B1

Results of the Sobol Sensitivity Analysis



Note. The figure shows first-order and total-order sensitivity indices for parameters in the model. First-order indices represent the individual contributions of each parameter to the output variance, while total-order indices account for both the individual and interactive contributions. Bar colors represent the type of index: blue for first-order and red for total-order. Max. = Maximum; Stim. = Stimulus; Occur. = Occurrences; No. = Number; Afford. = Affordances. See the online article for the color version of this figure.

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