

Monitoring in emotion regulation: behavioral decisions and neural consequences

Shirel Dorman Ilan,^{1,2} Roni Shafir,¹ Jeffrey L. Birk,^{3,4} George A. Bonanno,³ and Gal Sheppes^{1,5}

¹Department of psychology, School of Psychological Sciences, Tel Aviv University, Tel Aviv 6997801, Israel,

²The Child Psychiatry Division, Edmond and Lily Safra Children's Hospital, Sheba Medical Center, Tel

Hashomer 5266202, Israel, ³Department of psychology, Teachers College, Columbia University, New York, NY

10027, USA, ⁴Department of psychology, Columbia University Irving Medical Center, New York, NY 10027, USA,

and ⁵Sagol School of Neuroscience, Tel Aviv University, Tel Aviv 6997801, Israel

Correspondence should be addressed to Shirel Dorman Ilan or Gal Sheppes, The School of Psychological Sciences, Tel Aviv University, Tel Aviv 69978, Israel. E-mail: shireldorman@gmail.com; gsheppes@gmail.com

Abstract

Monitoring and deciding how to adjust an active regulatory strategy in order to maximize adaptive outcomes is an integral element of emotion regulation, yet existing evidence remains scarce. Filling this gap, the present study examined core factors that determine behavioral regulatory monitoring decisions and the neuro-affective consequences of these decisions. Using a novel paradigm, the initial implementation of central downregulation strategies (distraction, reappraisal) and the emotional intensity (high, low) were manipulated, prior to making a behavioral decision to maintain the initial implemented strategy or switch from it. Neuro-affective consequences of these behavioral decisions were evaluated using the Late Positive Potential (LPP), an electro-cortical measure of regulatory success. Confirming predictions, initial implementation of reappraisal in high intensity and distraction in low intensity (Strategy × Intensity combinations that were established in prior studies as non-preferred by individuals), resulted in increased behavioral switching frequency. Neurally, we expected and found that in high (but not low) emotional intensity, where distraction was more effective than reappraisal, maintaining distraction (relative to switching to reappraisal) and switching to distraction (relative to maintaining reappraisal) resulted in larger LPP modulation. These findings suggest that monitoring decisions are consistent with previously established regulatory preferences and are associated with adaptive short-term neural consequences.

Key words: emotion regulation; distraction; reappraisal; monitoring; consequences; late positive potential

Introduction

Imagine getting stuck in a massive traffic jam while driving to work. Anticipating being late, you feel that anger rises. Wanting to regulate your anger, you reappraise the situation by thinking that traffic jams often look worse than they are. While monitoring how anger regulation is faring, you realize that current

reappraisal attempts are not working well. This poses a dilemma of whether to continue reappraising or try a different course of action. You decide to switch to a different option and attempt to distract yourself by listening to the radio. Although still feeling some anger, you notice a sense of relief.

In thinking about the aforementioned situation, several factors can determine monitoring regulatory decisions to maintain

Received: 23 June 2018; Revised: 15 November 2019; Accepted: 6 December 2019

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a particular strategy or to switch from it to a different one, and their affective consequences. These factors may include elements of the emotional situation, such as the intensity of anger that is activated by the degree of traffic congestion, and the regulatory strategies one is monitoring, such as distraction vs reappraisal. Although monitoring appears fundamental in emotion regulation, existing studies remain scarce and indirect with regard to factors that determine monitoring decisions and their affective consequences.

Recent conceptual accounts suggest that emotion regulation is composed of several interacting and iterating valuation systems of key regulatory stages, in which emotion regulation-related decisions are made (e.g. Bonanno and Burton, 2013; Gross, 2015; Sheppes, 2020). Identification involves making the initial decision whether to regulate an emotion or not. If a decision to regulate was reached, a selection regulatory stage involves choosing one of several available regulatory strategies. Following the selection of a particular strategy, it is executed during an implementation stage. Only then monitoring begins, involving the decision whether and how to adjust an active implemented strategy across subsequent iterations, in order to maximize adaptive outcomes.

The conceptual extended process model of emotion regulation (Gross, 2015) specifies three monitoring decision options: (i) Maintenance: a decision to continue implementing a currently active strategy, conceptually involves subsequent iterations where regulation is positively valued during identification, and the specific active strategy is positively valued during selection. (ii) Switching: a decision to alter a currently active implemented strategy, conceptually involves subsequent iterations where regulation is positively valued during identification, but an alternative regulatory strategy is positively valued during selection. (iii) Stopping: a decision to cease regulation altogether, conceptually involves a subsequent iteration where regulation is negatively valued during identification. This model further argues that adequate monitoring decisions lead to adaptive outcomes.

Moving from conceptual grounds, existing empirical monitoring findings remain indirect. Paret et al. (2011) empirically supported a conceptual model (Kalisch, 2009), by providing neural correlates of regulatory maintenance across time. While important, these studies do not describe the switching and stopping monitoring decision options or how individuals decide between options.

Extending the scope beyond maintenance, one type of indirect studies (e.g. Yoon and Joormann, 2012; Peuters et al., 2019) examined the affective consequences of forced switching (i.e. instructing participants to implement two different strategies consecutively) and maintenance (i.e. instructing participants to implement the same strategy twice). While important, because participants could not freely decide between maintaining and switching, factors that influence monitoring decisions remain unexplored.

A second type of correlational studies indirectly examined individuals' decisions to maintain or switch from an initial implemented strategy. Kato (2012) found that individuals who reported more switching from an inefficient implemented strategy and reported decreased levels of psychopathology. Recently, utilizing experience sampling, Kalokerinos et al. (2017) demonstrated that switching from regulatory strategies that were inefficiently reduced negative affect, subsequently led to improved affect. Although important, these correlational studies that did not manipulate factors influencing monitoring decisions cannot reach causal conclusions.

Conceptual advances suggest potential factors that influence monitoring decisions (Bonanno and Burton, 2013). This framework focuses on individual differences in the sensitivity to the internal (e.g. subjective and physiological emotional states) and external (e.g. contextual or social cues) environment, which may influence the decision between the three core monitoring decision options (maintain, switch, stop).

Empirical support for this framework comes from a single study that examined the influence of the internal environment on the decision to maintain vs switch from an implemented strategy and its consequences for general well-being (Birk and Bonanno, 2016). Specifically, participants were asked to implement distraction or reappraisal while being physiologically monitored and were then given a choice between maintenance and switching.

Results showed that increased internal physiological intensity while implementing reappraisal, which denotes inefficient regulation, was associated with increased switching to distraction. Furthermore, participants who showed high correspondence between increased internal physiological intensity during reappraisal implementation and switching from reappraisal reported higher well-being.

While valuable, Birk and Bonanno (2016) did not manipulate participants' internal intensity and therefore could not evaluate the causal influence of this fundamental factor on monitoring decisions. Furthermore, focusing on the role of the internal environment leaves the important role of the external environment unexplored. Last, the evaluation of adaptive consequences of monitoring decisions was based on participants' self-reported well-being rather than on immediate behavioral or neural affective consequences. Despite many advantages, self-reports represent the endpoint, rather than online underlying mechanism, of emotional modulation and are susceptible to reporting biases.

Overcoming these limitations, the present study provided two important contributions to the scant literature on regulatory monitoring. The first goal was to provide causal (rather than correlational) evidence for the influence of two core interconnected factors on monitoring regulatory decisions. The second goal was to provide evidence for neuro-affective (rather than self-reported) consequences of monitoring decisions.

We utilized our conceptual framework (Sheppes, 2020) that focuses on the combination of: (i) external generated emotional intensity (high, low) and (ii) regulatory strategy (distraction, reappraisal). Our conceptual framework has successfully explained the role of these two core factors in two other regulatory stages that precede the post-implementation/monitoring stage, namely, implementation and selection stages.

In the implementation regulatory stage, our framework (Sheppes and Gross, 2011) and supporting findings (e.g. Sheppes and Meiran, 2007; Shafir et al., 2015) indicated that in high-intensity situations, early attentional disengagement via distraction leads to a stronger emotional modulation, relative to reappraisal, which involves engaging with emotional information prior to a late semantic meaning reinterpretation. By contrast, in low-intensity situations, distraction and reappraisal are equally effective, but only reappraisal, that involves making sense of emotional events, may provide long-term benefits (Wilson and Gilbert, 2008; Thiruchselvam et al., 2011).

In the selection regulatory stage, our model (Sheppes and Levin, 2013) and supporting evidence (e.g. Sheppes et al., 2014; Shafir et al., 2016) repeatedly found that in high intensity, most individuals prefer distraction, which results in enhanced short-term emotional modulation, over reappraisal, and in

low-intensity, most individuals prefer reappraisal, which may provide long-term benefits, over distraction. These regulatory preferences appear very robust (Cohen's $d = \sim 2$, with 90% of individuals showing these patterns, see Sheppes, 2020 for review).

Drawing from these lines of research, our first research question was whether external emotional intensity (high, low) and regulatory strategies (distraction, reappraisal) influence regulatory decisions in a monitoring stage. To that end, we created a novel experimental paradigm that manipulates these two independent variables. In each trial, participants were initially instructed to implement distraction or reappraisal when facing images of low or high intensity (henceforth 'initial implementation') and were then asked to choose whether they wish to maintain the initial implemented strategy or switch from it (henceforth 'monitoring choice'). Participants then implemented their chosen option (henceforth 'post-choice implementation').

Consistent with our conceptual framework and previous findings (Sheppes, 2020), our first hypothesis was that initial implementation that is incongruent with averaged regulatory preferences obtained in prior studies (i.e. reappraisal in high intensity, distraction in low intensity) would result in increased switching frequency, relative to initial implementation that is congruent with previously established averaged regulatory preferences (i.e. distraction in high intensity, reappraisal in low intensity).

Our second research question was what are the neuro-affective consequences of monitoring decisions. To answer it, we utilized event-related potentials (ERPs), which have been extensively used in the study of emotion regulation (e.g. Hajcak et al., 2012). We focused on the late positive potential (LPP), a centroparietal electro-cortical component that reflects enhanced processing of emotionally arousing information. Attenuation of this component reflects downregulation success (Dennis and Hajcak, 2009) with good internal consistency (Moran et al., 2013).

We first wished to replicate prior neural findings (Shafir et al., 2015) by demonstrating that in high (but not low) intensity, initial distraction implementation would result in greater LPP modulation, relative to reappraisal. Importantly, this study was the first to examine the neuro-affective consequences (LPP modulation) of monitoring regulatory decisions. We hypothesized that exclusively in high intensity, where neural differences between distraction and reappraisal are evident (Shafir et al., 2015), maintaining distraction (relative to switching to reappraisal) and switching to distraction (relative to maintaining reappraisal) would each be associated with stronger LPP modulation.

Method

Below we report how we determined our sample size, all data exclusions, manipulations and measures in the study.

Ethical approval

This study was approved by the institutional review board of Tel Aviv University, and participants provided informed consent prior to inclusion in the study.

Participants

Thirty native Hebrew-speaking¹ subjects participated. Sample size was pre-determined based on a priori rule of collecting

data from 30 participants for ERP studies conducted in our lab (e.g. Shafir et al., 2015; Shafir and Sheppes, 2018; Shafir et al., 2018). Two participants were excluded prior to data analyses. One participant was not a Hebrew native speaker, and another participant did not comply with experimental instructions (see below). The main results reported below remain unchanged when including these two participants (all P s < 0.02). The final sample consisted of 28 participants (8 men, mean age = 23.27 years, s.d. = 2.08).

Stimuli

One hundred eighty negative pictures were chosen from previously validated pictorial datasets² (IAPS: Lang et al., 2008; EmoPicS: Wessa et al., 2010). High-intensity pictures ($n = 90$, $M_{arousal} = 6.45$, $M_{valence} = 2.04$) significantly differed in valence and arousal normative ratings from low-intensity pictures ($n = 90$, $M_{arousal} = 4.73$, $M_{valence} = 3.38$) (both F s > 423, P s < 0.001; c.f. Sheppes et al., 2011). Picture contents were matched for high- and low-intensity categories when possible. Importantly, analyses that decomposed interactions involving emotional intensity compared different regulation instructions within each intensity separately. Therefore, possible content differences between intensities have no bearing on the results.

Procedure

Following initial EEG setup, participants learned (four trials) and practiced (eight trials) distraction and reappraisal implementation (c.f., Sheppes et al., 2014). Adherence to regulatory instructions involved asking participants to talk out loud throughout implementation. Distraction instructions involved disengaging attention from emotional pictures by producing unrelated neutral thoughts (e.g. visualizing geometric shapes or daily chores). Reappraisal instructions involved engaging with the processing of emotional pictures, but reinterpreting their negative meaning (e.g. by thinking about less negative aspects of situations or that situations will improve over time) (c.f. Sheppes et al., 2014). Participants were asked not to form reality challenge reappraisals (i.e. interpret emotional events as fake; Qi et al., 2017).

The task consisted of 180 trials (divided into six equally long blocks, separated by breaks). Pictures of low and high intensity were presented in a random order, with no more than two consecutive trials of the same intensity, and were randomly assigned to reappraisal or distraction.

To ensure adherence to regulatory instructions, participants provided five oral examples of each strategy during experimental breaks. Based on a priori exclusion criteria in our lab, participants who made more than 50% errors ($n = 1$) were excluded

2 Picture codes were as follows: Low intensity: IAPS: 224, 1111, 1270, 1271, 1274, 1275, 1280, 1301, 2120, 2278, 2312, 2399, 2456, 2457, 2490, 2590, 2682, 2691, 2692, 2700, 2718, 2722, 2753, 2795, 3216, 3280, 6010, 6190, 6561, 6562, 6825, 6836, 7092, 7135, 7359, 7360, 7361, 7520, 7521, 8231, 9001, 9002, 9008, 9010, 9031, 9041, 9045, 9046, 9090, 9101, 9102, 9110, 9120, 9145, 9160, 9171, 9180, 9182, 9168, 9190, 9270, 9280, 9290, 9291, 9330, 9331, 9341, 9342, 9360, 9373, 9390, 9404, 9415, 9417, 9726, 9427, 9440, 9445, 9452, 9469, 9470, 9471, 9530, 9584, 9590, 9592, 9594, 9610, 9912, 9926. High intensity: EmoPicS: 209, 210, 212, 231, 232, 233, 234, 235, 236, 238, 239, 240, 241, 242, 243, 244, 245, 246, 247, 248, 249, 250, 251, 252; IAPS: 2053, 2730, 2800, 3000, 3005.1, 3010, 3015, 3030, 3060, 3064, 3068, 3071, 3080, 3100, 3101, 3102, 3110, 3120, 3130, 3140, 3150, 3168, 3170, 3180, 3230, 3261, 3266, 3350, 3400, 3530, 3550, 6212, 6230, 6312, 6313, 6315, 6350, 6360, 6510, 6520, 6540, 6550, 6570, 6831, 6838, 9040, 9050, 9181, 9183, 9250, 9252, 9300, 9400, 9410, 9412, 9413, 9420, 9500, 9570, 9571, 9600, 9635.1, 9908, 9910, 9911, 9921.

1 We set an a priori native Hebrew proficiency inclusion rule, because understanding and implementing complex cognitive emotion regulation strategies require high verbal proficiency (c.f., Sheppes et al., 2011, 2014).

from data analyses. Average percentage of errors was minimal ($M = 0.05\%$, $s.d. = 0.08$).

Each trial (see Figure 1) began with a fixation cross (jittered between 2100 and 2900 ms) followed by a 2500 ms cue screen that signaled the intensity of the upcoming picture ('Intense' or 'Mild') and the initial strategy implementation ('Distraction' or 'Reappraisal') (c.f. Shafir et al., 2015), followed by a jittered 400–800 ms black screen. The picture was then presented (3000 ms), during which participants implemented the required strategy ('initial implementation'). Then, a choice screen was presented, where participants were asked to choose whether they wished to maintain the initial implemented strategy (i.e. choosing distraction following initial distraction implementation or choosing reappraisal following initial reappraisal implementation) or switch to the other regulatory option (i.e. choosing distraction following initial reappraisal implementation or choosing reappraisal following initial distraction implementation) ('monitoring choice'). Then, a 2000 ms cue screen presented both the chosen regulatory strategy and the intensity of the picture that was previously shown, followed by a jittered 400–800 ms black screen. The same picture was then presented again for 2000 ms, during which participants implemented their chosen strategy ('post-choice implementation'). The post-implementation window was 1000 ms shorter than the initial implementation window to balance adequate duration to observe LPP effects with maintaining a 5-s picture presentation per trial (c.f., Li et al., 2017).

To remind participants that monitoring decisions were aimed at reducing negative experience, the offset of 10% of pictures was followed by a Likert rating scale in which participants reported their negative experience (1 = 'not negative at all', 9 = 'extremely negative'). For complete explanation and analysis of partial self-report data, see Supplementary Materials, page 1.

Electrophysiological recordings and data reduction

EEG recordings used a Biosemi ActiveTwo recording system (Biosemi B. V., Amsterdam, The Netherlands), from 32 electrodes sites,³ and one electrode on each of the left and right mastoids. The horizontal electrooculogram (EOG) was recorded from two electrodes placed 1 cm to the left and right of the external canthi, and vertical EOG was recorded from an electrode placed beneath the left eye. The voltage from each electrode site was referenced online with respect to Common Mode Sense/Driven Right Leg electrodes. EEG data were sampled at 256 Hz.

Offline signal processing entailed EEGLAB and ERPLAB Toolboxes (Delorme and Makeig, 2004; Lopez-Calderon and Luck, 2014). Data from all electrodes were re-referenced to the average activity of the left and right mastoids. Continuous EEG data were then band-pass filtered (cutoffs: 0.05–20 Hz; 12 dB/oct rolloff). Eye movement artifacts were removed using independent component analysis (Delorme and Makeig, 2004; Mennes et al., 2010).

For the initial implementation LPP analysis, EEG was epoched into 3200 ms segments, starting 200 ms (baseline) before the picture appeared on the screen and lasting 3000 ms (end of the initial implementation). Similarly, for the post-choice implementation LPP analysis, EEG was epoched into 2200 ms segments, starting 200 ms (baseline) before the picture re-appeared on the

screen and lasting 2000 ms (end of post-choice implementation). All trials containing activity exceeding 80 μV within 200 ms were excluded.

The initial implementation LPP was defined as the mean amplitude between 300 (when the LPP becomes evident; Hajcak et al., 2010) and 3000 ms (end of the initial implementation stage). Similarly, the post-choice implementation LPP was defined as the mean amplitude between 300 and 2000 ms (end of the post-choice implementation stage). The LPP was measured as the average activity over centro-parietal electrode sites, where the LPP is typically maximal (CPz–CP1–CP2; c.f., Paul et al., 2015; Thiruchselvam et al., 2011).

Statistical analyses

Preliminary initial implementation analyses include data that precede monitoring decisions, where all analyzed factors are experimentally manipulated, resulting in the total number of trials ($n = 180$) equally divided across four conditions ($n = 45$ per condition). Slight variation in trial numbers across conditions is possible due to differential ERP trial rejection. However, rejections were minimal [Valid trials: low intensity/distraction: $M = 43.96$, $s.d. = 2.07$; low intensity/reappraisal: $M = 44.21$, $s.d. = 1.52$; high intensity/distraction: $M = 44.10$, $s.d. = 1.73$; high intensity/reappraisal: $M = 44.18$ trials, $s.d. = 1.48$]. Trial number did not significantly differ between conditions (all $F_s < 1$). Accordingly, to replicate prior implementation findings, preliminary initial implementation analyses employed a 2×2 analysis of variance (ANOVA) with emotional intensity (high, low) and initial implementation (distraction, reappraisal) as repeated-measures factors and LPP as a dependent variable.⁴

Trial numbers across conditions that constitute the first research question (behavioral regulatory monitoring decisions) are matched by experimental design. Accordingly, we employed a 2×2 ANOVA with emotional intensity (high, low) and initial implementation (distraction, reappraisal) as repeated-measures factors and switching frequency as a dependent variable.

To examine the second research question (short-term neural consequences of monitoring decisions), we first created a neural consequence LPP outcome variable. For each trial, we subtracted the post-choice implementation LPP amplitude from the respective initial implementation/pre-choice LPP amplitude in that trial, with higher scores indicating stronger LPP attenuation (i.e. higher regulatory success). Note that each trial consists of a pre-choice implementation phase and a post-choice implementation phase and thus the subtraction that constitutes the dependent variable occurs within each individual trial. The neural consequence LPP variable was created to adjust for initial implementation LPP differences between distraction and reappraisal (see results below and c.f. Shafir et al., 2016). Notably, the main results reported below remain unchanged when re-conducting the analysis on the post-choice implementation LPP, without performing these subtractions (i.e. the predicted Emotional Intensity \times Initial Implementation \times Monitoring Choice interaction remains significant [$b = 3.82$, $SE = 1.72$, 95% CI (0.45, 7.20), $F(1, 4254) = 4.94$, $P = 0.026$]).

4 A significance level of 5% (two-sided) was selected for the two analyses of variance (ANOVAs) used to replicate prior implementation findings and to examine the first research question (behavioral regulatory monitoring decisions). In both ANOVAs, we used only 2×2 (or $2 \times 2 \times 2$) experimental designs, which do not require any tests of sphericity (Mordkoff, 2015).

3 The 32 EEG scalp electrodes sites were as follows: Fp1, Fp2, Fpz, Af3, Af4, Afz, F1, F3, Fz, Fc1, Fc2, Fcz, C1, C3, C2, C4, Cz, Cp1, Cp2, Cpz, P1, P3, P2, P4, Pz, O1, O2, Poz, T7, T8, F2, F4.

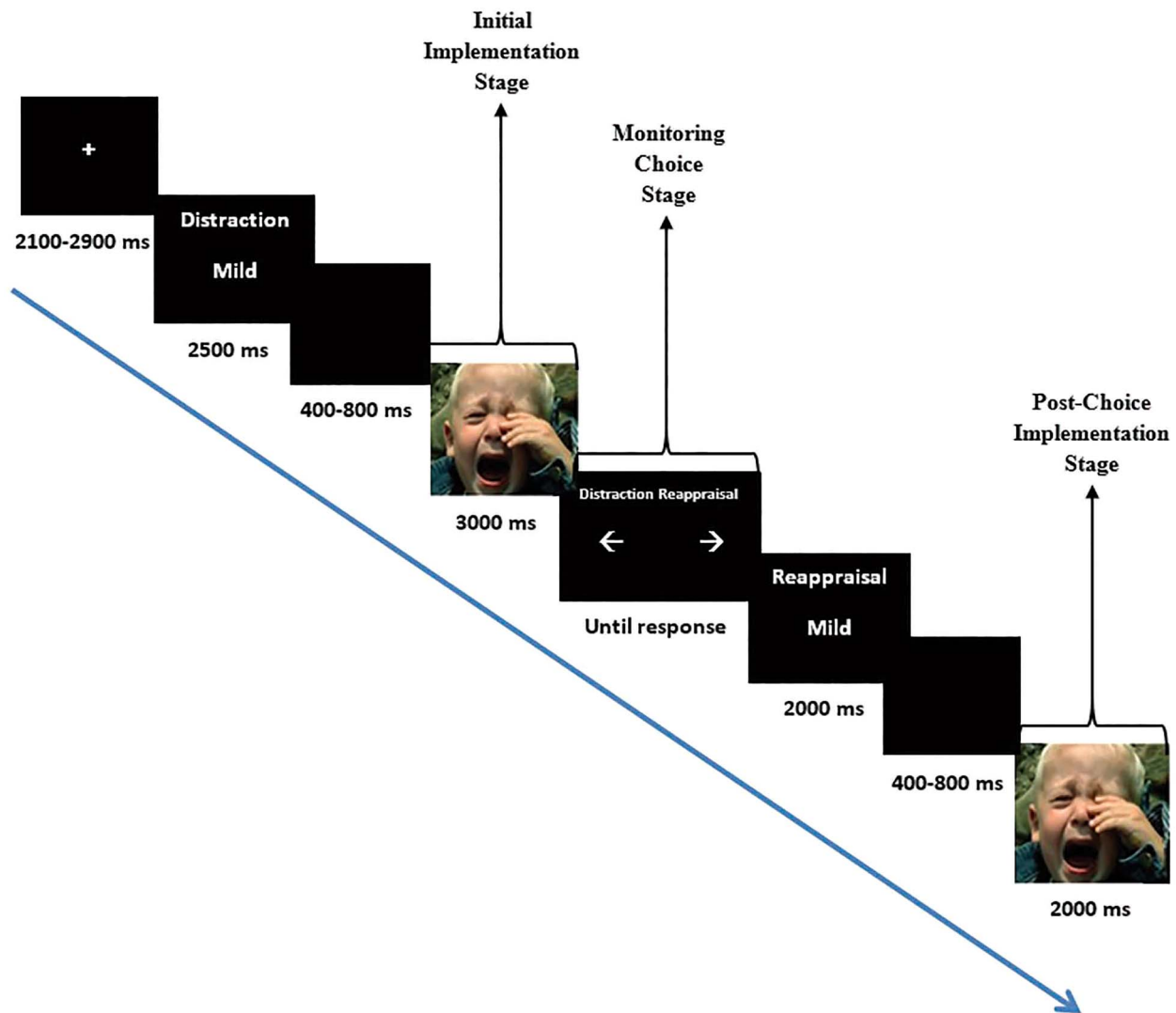


Fig. 1. Trial structure: An example of a low-intensity trial, where distraction was the initial implemented regulatory strategy, and the participant chose to switch to reappraisal. Note that this choice pattern is consistent with regulatory preferences for reappraisal over distraction in low intensity.

Because the neural consequence measure takes into account LPPs that are measured following monitoring decisions, trial numbers across conditions cannot be experimentally controlled (Table 1 for all values). This element potentially biases conventional ANOVAs. Accordingly, the analyses of the second research question were performed on individual trials (rather than on condition averages across trials) of the neural consequence LPP, using linear mixed models (LMMs, using PROC MIXED procedure in SAS version 9.4 for Windows; Galwey, 2014; Boisgontier and Cheval, 2016). LMM is a widely accepted method that accounts for unequal trial numbers in experimental designs, by treating between-subject variance in the outcome measure as a random effect, in addition to modeling the within-subjects effects (e.g. Cohen et al., 2011; Radel et al., 2018; Smedley and Smith, 2018). LMMs also make use of all available data, which protects from reduced power and reliability of averaged estimates of cells with considerable amount of discarded observations.

Our LMM modeling approach involved balancing accuracy with parsimony by starting with a maximum random effect structure, followed by separate steps that decrease in complexity (first examining the random three-way interaction, then random two-way interactions, then random main effects), involving the

removal of random effects not supported by the data. Each step applies multiple iterations and likelihood evaluations to achieve convergence of the final model estimates. At the end of this convergence process, there are cases when the final model estimates a random effect as one of its boundary constraints, such as exactly zero. We adopted a conservative approach of only removing random effects that explained exactly zero variance c.f., Bates et al., 2015 (see Supplementary Table S3 for all non-zero random effects). Kenward-Roger approximation for degrees of freedom, which entails a Satterthwaite approximation (SAS Institute Inc., 2013), was computed as recommended for unbalanced designs (Schaalje et al., 2001). We removed correlations between random effects to achieve model convergence.

The initial maximum random effect structure converged ($-2*LL = 42705.9$, $AIC = 42731.9$). In the first model complexity reduction step, the random effect of the Emotional Intensity \times Initial Implementation \times Monitoring Choice three-way interaction was estimated to be zero. Therefore, in the next model complexity reduction step, this random interaction was removed. This new model converged with unchanged fit statistics ($-2*LL = 42705.9$, $AIC = 42731.9$) while also revealing that the two-way interaction of Emotional Intensity \times Initial

Table 1. Trial means, standard deviations, max and min values for each experimental condition in the post-choice implementation analyses

| | High Intensity | | | | Low Intensity | | | |
|---------|----------------|------------|-----------|-----------|---------------|-----------|-----------|-----------|
| | Dist→Dist | Reap →Dist | Dist→Reap | Reap→Reap | Dist→Dist | Reap→Dist | Dist→Reap | Reap→Reap |
| Average | 34.57 | 20.43 | 10.43 | 24.54 | 27.07 | 8.50 | 17.89 | 36.46 |
| SD | 7.12 | 8.95 | 7.12 | 8.92 | 9.53 | 6.07 | 9.49 | 6.10 |
| Max | 45 | 42 | 25 | 41 | 44 | 29 | 36 | 44 |
| Min | 20 | 4 | 0 | 3 | 9 | 1 | 1 | 16 |

Note: Repeated-measures factors include emotional intensity (high, low), initial regulatory strategy (distraction, reappraisal) and monitoring regulatory choice (maintain, switch), and the dependent variable is 'neural consequence' LPP. Note: Dist→Dist: maintaining distraction following initial distraction implementation; Reap→Dist: switching to distraction following initial reappraisal implementation; Dist→Reap: switching to reappraisal following initial distraction implementation; Reap→Reap: maintaining reappraisal following initial reappraisal implementation.

Note: The LPP is considered a large robust component, and even in our smallest cell the average exceeds the recommended number of trials required to produce a reliable LPP (Moran et al., 2013).

Implementation was zero. Therefore, in the next model complexity reduction step, this random interaction was removed. This new model converged with unchanged fit statistics as before ($-2*LL = 42705.9$, $AIC = 42731.9$) and revealed that the main effect of monitoring choice was zero.

Accordingly, the final model consisted of all fixed effects together with the following random effect structure: intercept, Emotional Intensity, Initial Implementation, Initial Implementation \times Monitoring Choice and Emotional Intensity \times Monitoring Choice. This final model converged ($-2*LL = 42705.9$, $AIC = 42731.9$) and had comparable model fit to a similar model that allowed random effects to correlate (-2 log likelihood = 42693.5, $AIC = 42735.5$; $\Delta -2*LL = 12.4$, $df = 10$, $P = 0.26$).

Results

Replicating prior neural findings during initial implementation

We first wished to replicate prior findings (e.g. Shafir et al., 2015) demonstrating that in high (but not low) emotional intensity, initial implementation of distraction would result in greater LPP modulation, relative to reappraisal. The ANOVA yielded a predicted Emotional Intensity \times Initial Implementation interaction that was marginally significant [$F(1, 27) = 3.36$, $P = 0.07$, $\eta_p^2 = 0.11$; Figure 2, Supplementary Table S1 for all effects]. Follow-up analyses supported predictions in showing that in high intensity [$F(1, 27) = 13.43$, $p = 0.001$, $\eta_p^2 = 0.33$], distraction implementation resulted in decreased LPPs ($M = 4.07$, $SE = 1.08$), relative to reappraisal implementation ($M = 6.50$, $SE = 0.97$). As expected, in low intensity, there were no differences [$F(1, 27) < 1$, $P = 0.45$, $\eta_p^2 = 0.02$] in LPPs between distraction ($M = 0.93$, $SE = 0.92$) and reappraisal implementation ($M = 1.58$, $SE = 0.86$).

Regulatory preferences predict regulatory choices to switch vs maintain an implemented strategy during post-implementation monitoring

Our first research question examined whether initial implementation that is incongruent with regulatory preferences (i.e. distraction in low intensity, reappraisal in high intensity) results in increased switching frequency, relative to initial implementation that is congruent with regulatory preferences (i.e. reappraisal in low intensity, distraction in high intensity)?

Prior to hypothesis testing, we confirmed using ANOVAs previously established regulatory preferences, in finding that in a monitoring context, intensity increase from low-to-high was associated with increased preference for distraction over reappraisal (i.e. increased preference to maintain distraction or

switch to distraction from reappraisal) [$t(27) = -7.81$, $P < 0.001$, $d = 1.47$]. Confirming our main prediction, we found a significant Emotional Intensity \times Initial Implementation interaction [$F(1, 27) = 60.99$, $P < 0.001$, $\eta_p^2 = 0.69$; see Figure 3 and Supplementary Table S2 for all effects]. Follow-up analyses showed that in high intensity, initial reappraisal implementation (the non-preferred strategy) resulted in higher switching frequency ($M = 45.41\%$, $SE = 0.04$), compared to initial distraction implementation (the preferred strategy, $M = 23.22\%$, $SE = 0.03$) [$F(1, 27) = 16.14$, $P < 0.001$, $\eta_p^2 = 0.37$]. A mirrored pattern emerged in low intensity, where initial distraction implementation (the non-preferred strategy) resulted in higher switching frequency ($M = 39.62\%$, $SE = 0.40$), compared to initial reappraisal implementation (the preferred strategy, $M = 18.87\%$, $SE = 0.02$) [$F(1, 27) = 19.68$, $P < 0.001$, $\eta_p^2 = .42$].

Neuro-affective consequences of monitoring regulatory decisions

Our second research question examined the short-term neural consequences (LPP modulation) of monitoring regulatory choices. We expected to show that in high intensity, where distraction is more effective than reappraisal (Sheppes and Meiran, 2007; Shafir et al., 2015, 2016), choosing to maintain (or switch to) distraction would result in greater LPP modulation, compared to choosing to maintain (or switch to) reappraisal. By contrast, in low intensity, where distraction and reappraisal are equally effective, choosing one strategy over the other was not expected to result in differential LPPs.

Results using LMMs showed the expected Emotional Intensity \times Initial Implementation \times Monitoring Choice interaction [$b = 5.99$, $SE = 2.50$, 95% CI (1.09, 10.89), $F(1, 3653) = 5.75$, $P = 0.017$, Figure 4 for LPP waveforms and LPP topographical distribution and Supplementary Table S3 for all effects].⁵ Follow-up analyses explored lower-order effects in the context of a full model (using 'estimate' statements in the SAS syntax). Despite having clear a priori predictions, when decomposing this three-way interaction, we corrected for multiple comparisons by applying the well-established Benjamini-Hochberg procedure that adjusts the criterion for significance by controlling for the false discovery rate (Benjamini and Hochberg, 1995).

5 To mitigate concerns that our findings depend on a large DF value, we also tested the same model using a between-within (i.e. $ddf = BETWITHIN$) minimal value of degrees of freedom. Results in this alternative model remained identical, including the three-way interaction of interest [$b = 5.99$, $SE = 2.48$, 95% CI (0.88, 11.10), $F(1, 25) = 5.83$, $P = 0.023$].

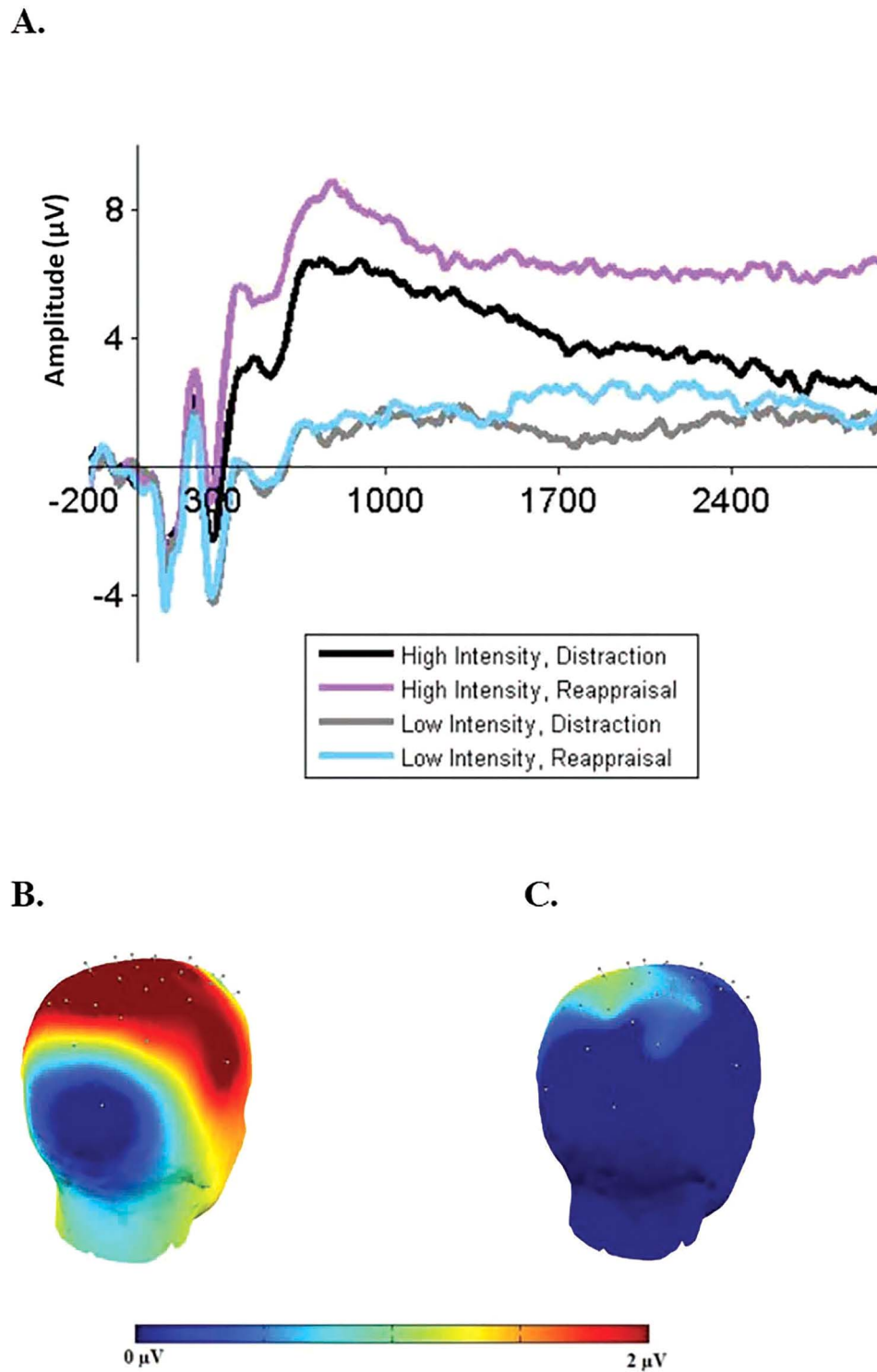


Fig. 2. (A) Initial implementation findings. LPP amplitudes during initial implementation of distraction and reappraisal in high and low emotional intensities. Waveforms are averages across CPz, CP1 and CP2 electrodes. The x-axis runs from the beginning of the baseline (200 ms before picture onset) to the end of the picture presentation (3000 ms). (B, C) Head maps of the LPP topographical distribution. Voltage difference score for the initial implementation of distraction and reappraisal in high (B) and low (C) emotional intensities was calculated as: (averaged initial reappraisal implementation)–(averaged initial distraction implementation).

Decomposing the three-way interaction revealed that, consistent with our prediction, in high intensity [$b = 8.22$, $SE = 1.84$, 95% CI (4.60, 11.83), $t(246) = 4.48$, $P < 0.001$, $\alpha_{\text{adjusted}} = 0.013$], but not in low intensity [$b = 2.23$, $SE = 1.88$, 95% CI (–1.47, 5.92), $t(306) = 1.19$, $P = 0.237$, $\alpha_{\text{adjusted}} = 0.050$], there was an Initial Imple-

mentation \times Monitoring Choice interaction, such that choosing to maintain (or switch to) distraction, relative to maintain (or switch to) reappraisal, resulted in larger LPP modulation. Specifically, in high intensity, switching to distraction following initial reappraisal implementation resulted in substantially

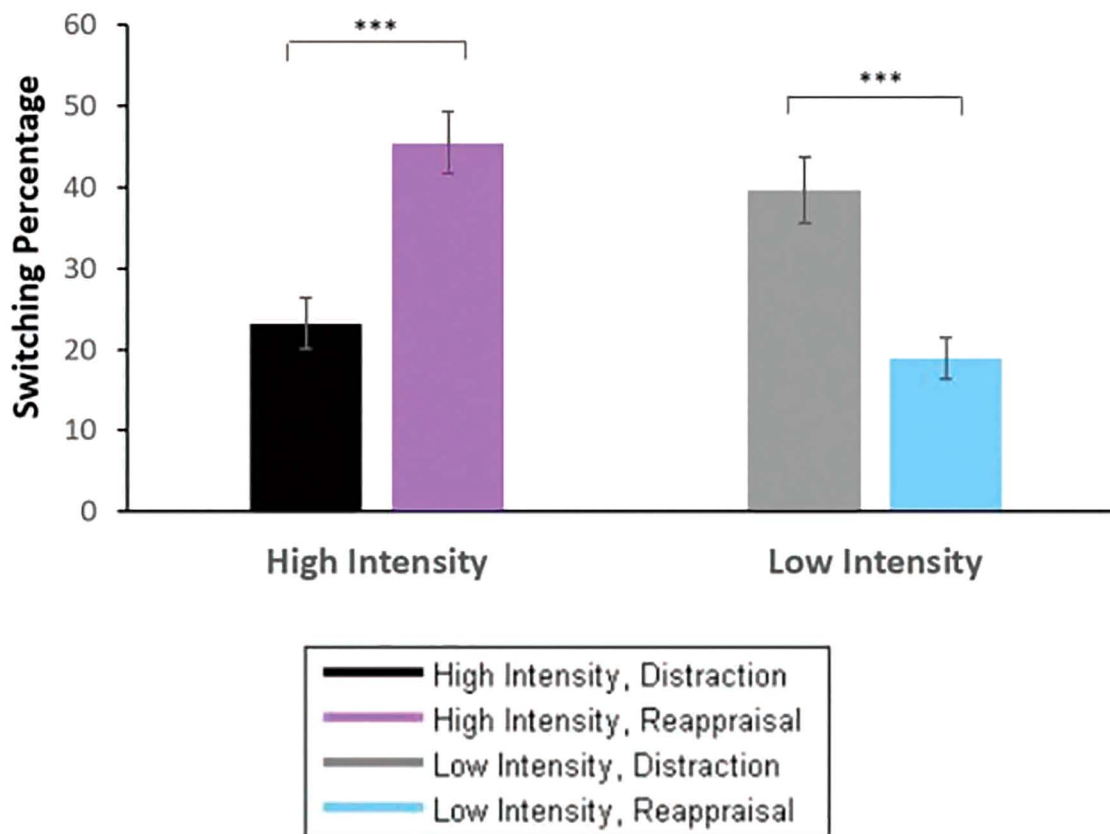


Fig. 3. Percentage of trials (y-axis) during which participants chose to switch (vs maintain) following initial implementation of distraction and reappraisal in high and low emotional intensities. *** $P < 0.001$.

stronger LPP modulation ($M = 7.03$, $SE = 1.10$), relative to maintaining reappraisal ($M = 2.62$, $SE = 0.94$) [$b = 4.41$, $SE = 1.20$, 95% CI (2.02, 6.80), $t(93.3) = 3.66$, $P < 0.001$, $\alpha_{\text{adjusted}} = 0.025$]. Complimentary, in high intensity, maintaining distraction following initial distraction implementation resulted in stronger LPP modulation ($M = 2.95$, $SE = 0.86$), relative to switching to reappraisal ($M = -0.85$, $SE = 1.49$) [$b = 3.81$, $SE = 1.51$, 95% CI (0.80, 6.81), $t(74.9) = 2.52$, $P = 0.014$, $\alpha_{\text{adjusted}} = 0.038$]. A similar pattern of findings emerged when using an alternative LMM with a more minimal random effect structure or a repeated-measures ANOVA (Supplementary Material, pages 4–7).

Discussion

While a monitoring regulatory stage is considered an integral part of emotion regulation and successful functioning, empirical evidence remains scarce. Our first research question was whether previously established regulatory preferences (i.e. the combination of emotional intensity and initial regulatory strategy) influence the decision to maintain vs switch from the implemented strategy. Supporting predictions, initial implementation that is incongruent with regulatory preferences (i.e. distraction in low intensity, reappraisal in high intensity) resulted in increased switching frequency, relative to initial implementation that is congruent with regulatory preferences (i.e. reappraisal in low intensity, distraction in high intensity). Our second research question was what are the neuro-affective consequences (LPP modulation) of monitoring regulatory decisions. We predicted and found that in high (but not low) emotional intensity, where distraction is more effective than reappraisal, choosing distrac-

tion (either by maintaining or switching to distraction) resulted in adaptive neural consequences (i.e. greater LPP modulation).

Considering our first research question, results extend our conceptual account and selection findings (Sheppes, 2020), by elucidating the role of regulatory preferences for the unexplored monitoring regulatory stage. In each emotional intensity, initial implementation that is incongruent with regulatory preferences, led to increased switching, relative to initial implementation that is congruent with regulatory preferences.

Although monitoring decisions were strongly determined by regulatory preferences, we also observed considerable inertial effects. Even in cases where the initial implemented strategy was non-preferred and less effective (reappraisal in high intensity), it was nonetheless maintained in a notable amount of trials. It seems that an initial implemented strategy may function as a strong default. This notion is further supported by studies demonstrating that presenting individuals with a 'default' option leads to disproportionately sticking with it (e.g. Hartman et al., 1991; Suri et al., 2015).

Considering our second research question, we evaluated adaptive consequences of monitoring decisions using neural measures, transcending prior self-report findings (Birk and Bonanno, 2016). These results extend prior neural findings (Shafir et al., 2015) by showing that in the monitoring regulatory stage, choosing to maintain (or switch to) distraction in high intensity results in adaptive neural consequences. These results are consistent with the notion that in high intensity, early attentional disengagement via distraction is more effective in the short term, compared to late operating reappraisal (Sheppes and Gross, 2011).

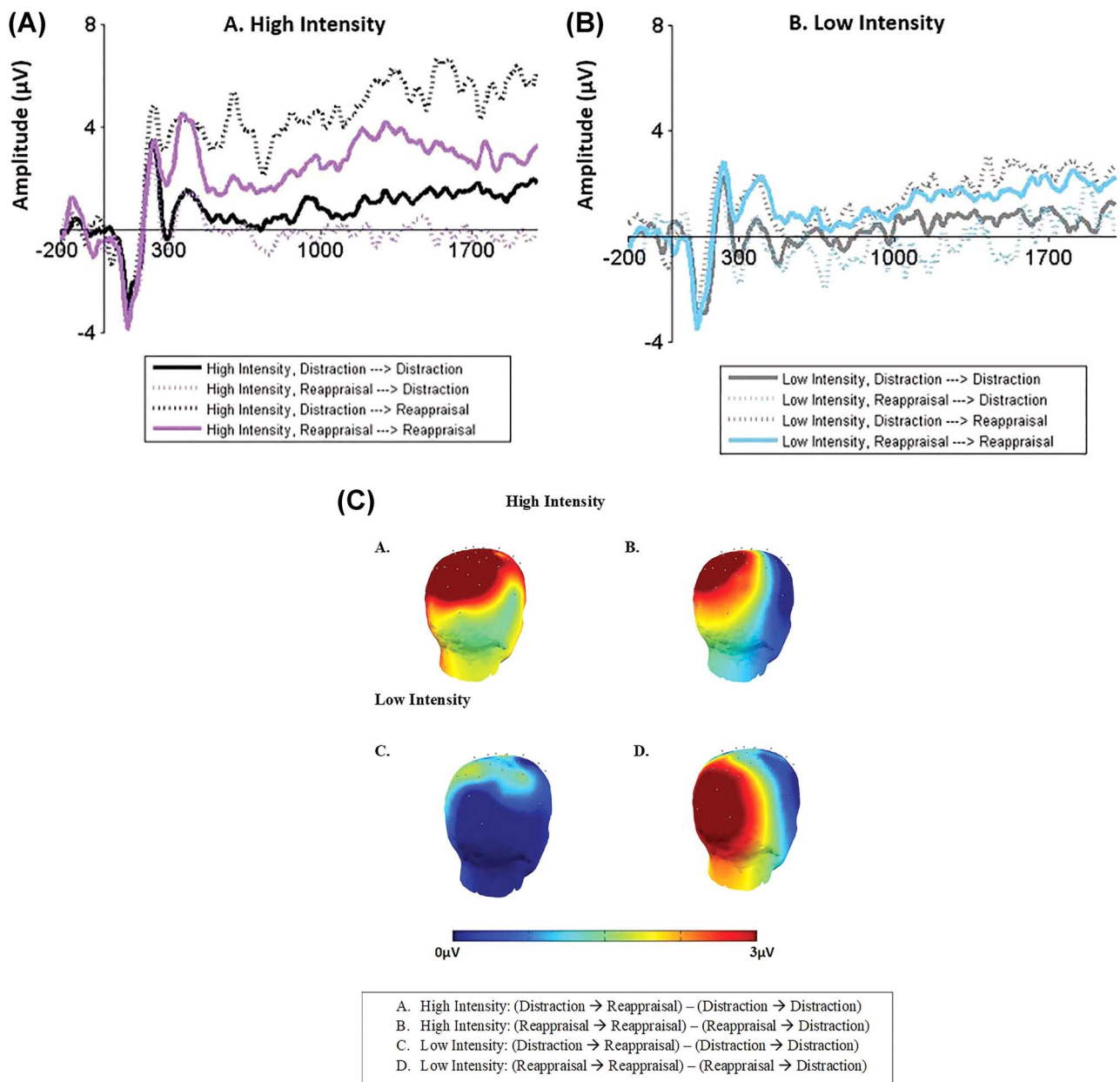


Fig. 4. (a,b) Post-choice implementation findings. LPP amplitudes during post-choice implementation for distraction and reappraisal in high (A) and low (B) emotional intensities. The x-axis runs from the beginning of baseline (200 ms before picture onset) to the end of the picture presentation (2000 ms). Note that these waveforms represent post-choice implementation LPP averaged amplitudes without subtractions from initial implementation LPP amplitudes, which were only performed for the statistical analyses. Notably, higher LPP amplitudes represent decreased emotional modulation (i.e. lower regulatory success). Note: Distraction→Distraction: maintaining distraction following initial distraction implementation; Reappraisal→Distraction: switching to distraction following initial reappraisal implementation; Distraction→Reappraisal: switching to reappraisal following initial distraction implementation; Reappraisal→Reappraisal: maintaining reappraisal following initial reappraisal implementation. (c) Post-choice implementation findings. Head maps of the LPP topographical distribution during post-choice implementation of distraction and reappraisal for high (A, B) and low (C, D) emotional intensities. (A) and (C) were calculated as: (averaged initial distraction implementation followed by post-choice reappraisal implementation) – (averaged initial distraction implementation followed by post-choice distraction implementation). (B) and (D) were calculated as: (averaged initial reappraisal implementation followed by post-choice reappraisal implementation) – (averaged initial reappraisal implementation followed by post-choice distraction implementation). Note: Distraction→Distraction: maintaining distraction following initial distraction implementation; Reappraisal→Distraction: switching to distraction following initial reappraisal implementation; Distraction→Reappraisal: switching to reappraisal following initial distraction implementation; Reappraisal→Reappraisal: maintaining reappraisal following initial reappraisal implementation.

Accordingly, distraction may serve as a ‘first aid’ tool in highly intense situations, not only during initial implementation (Shafir et al., 2015) but also following monitoring decisions. Notably, however, distraction has significant shortcomings in the long term (Wilson and Gilbert, 2008). Thus, future studies should examine the benefits of maintaining reappraisal in the

long term, where reappraisal is predicted to be more beneficial (e.g. Thiruchselvam et al., 2011).

Our results have clinical implications. Repeated failure to make flexible monitoring decisions that are sensitive to contextual demands (i.e. failing to switch from inefficient strategies or failing to maintain efficient strategies) constitutes

a form of emotional dysregulation that may be associated with psychopathology (Sheppes *et al.*, 2015). However, studies investigating monitoring decisions and their consequences in clinical populations are crucially needed.

The current study has several limitations. First, we focused on the combination of two elements—external negative emotional intensity (high, low) and two regulatory strategies (distraction, reappraisal). Based on our conceptual framework (Sheppes and Levin, 2013) and prior findings (Shafir *et al.*, 2015), we had the clearest predictions regarding these two elements. Nonetheless, future studies should explore additional factors, including positive emotional intensity and other strategies that may influence monitoring decisions.

Second, we focused on two monitoring decision options (maintaining and switching), leaving the third option—stopping to regulate—unexplored. Future studies should examine factors that determine decisions to stop regulating and the neuro-affective consequences of stopping.

Third, our *a priori* design decisions led to being able to evaluate neural, but not subjective experience consequences, of regulatory decisions. To evaluate consequences of regulatory decisions, one has to obtain pre-choice and post-choice implementation indices (c.f., Shafir *et al.*, 2016). The pre-choice index is crucial to account for well-established differences between reappraisal and distraction during initial implementation (e.g. Shafir *et al.*, 2015; see also a replication above). While our design involved pre-choice and post-choice LPP measurements (collected continuously and unobtrusively), we did not collect a pre-choice measure of self-reported negative experience. This *a priori* decision (c.f., *all* prior regulatory selection studies, e.g. Sheppes *et al.*, 2011, 2014) to refrain from asking participants to provide pre-choice ratings immediately prior to making regulatory decisions is based on a concern that this explicit reporting will bias naturally occurring choices. Conceptually, providing baseline self-reports shifts the focus from examining our causal externally manipulated intensity to the examination of the influence of (measured) internal intensity (Birk and Bonanno, 2016).

Fourth, choosing to maintain (or switch to) reappraisal under low intensity may not necessarily reflect a clear preference for reappraisal. Participants may prefer distraction-over-reappraisal under high intensity, because distraction is more effective than reappraisal. However, given that in low intensity, there are no short-term efficacy differences between the strategies, participants may prefer reappraisal because they strive to balance their overall preferences, or they feel they are expected to use both strategies. More generally, providing participants with only two decision options yields choice preferences that are not fully independent from one another.

Last, prior to initial implementation, participants received information regarding the emotional intensity and the instructed strategy. This may have influenced participants' later monitoring decisions. However, consistent with prior paradigms (Shafir *et al.*, 2015, 2018), providing information on both variables equates the saliency of each prior to upcoming monitoring decision.

Supplementary data

Supplementary data are available at SCAN online.

Funding

G. Sheppes is supported by the Israel Science Foundation (Grant No. 1130/16).

Conflict of interest

None declared.

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