Supplementary Materials

Neural Processing of Emotional-intensity Predicts Emotion Regulation Choice

Comparison between alternative models.

Model number	Intercept	Emotional-intensity predictor	Pre-choice-LPP predictor	Interaction between predictors	BIC	AIC
1	*fixed+random*	*fixed+random*	*fixed+random*	*no*	*3962.17*	*3956.28*
2	fixed+random	fixed+random	fixed+random	yes (fixed+randm)	3964.75	3956.68
3	fixed only	fixed+random	fixed+random	no	3978.35	3973.64
4	fixed+random	fixed only	fixed+random	no	3993.37	3988.65
5	fixed+random	fixed+random	fixed only	no	3965.17	3956.28

Table. S1. Estimation of alternative Logistic Mixed Effects Models to predict regulatory-choices, using Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) values.

Lower BIC and AIC values are indicative of better model fit. This Table shows that the characteristics of the model we report in the manuscript (model 1) show the best fit relative to other models.

Density of pre-choice-LPPs.

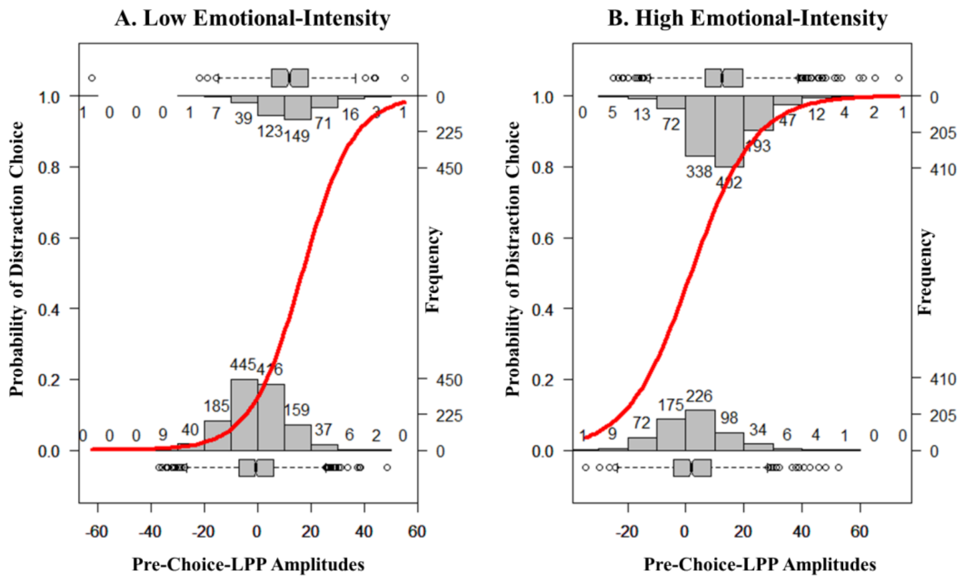

Fig. S4. Density of the pre-choice-LPP amplitudes in both low (A) and high (B) emotional-intensity categories. In both panels the x-axis represents the range of pre-choice-LPP amplitudes in microvolt (μV). The bottom histograms represent the frequency of reappraisal-chosen trails, and the upper inverted histograms represent the frequency of distraction-chosen trials (see also the right y-axis). For example, in panel B that represents high-intensity pictures, there were approximately 226 reappraisal-chosen trials and approximately 338 distraction-chosen trials in the 0 to 10 pre-choice-LPP amplitude range. The red line represents the probability of choosing distraction across pre-choice-LPP amplitudes (see also the left y-axis). For example, in panel B that represents high-intensity, for the 20 to 40 pre-choice-LPP amplitude range, the red line ranges between approximately 0.82 – 0.97 probability of distraction-choice. The box plots next to each histogram represent the interquartile range (between 25th and 75th percentile) of each distribution.

As can be seen, in both emotional intensities the majority of pre-choice-LPPs of distraction-chosen trials were higher than those of reappraisal-chosen trials.

Data from individual subjects.

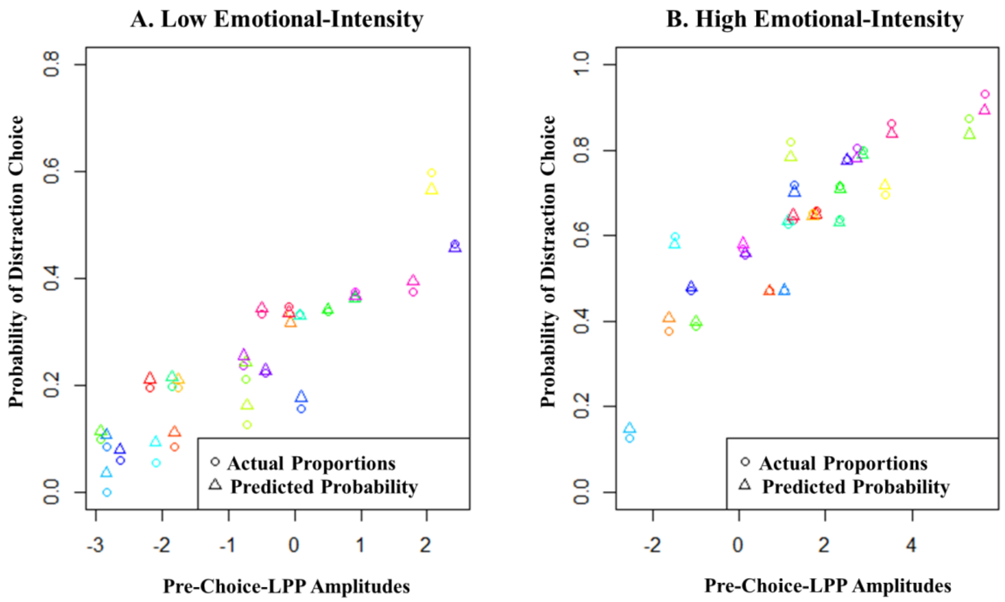

Fig. S5. Individual actual proportions (circles) and predicted probabilities (triangles) of choosing distraction (y-axis) in both low (A) and high (B) emotional-intensity categories. The x-axis represents pre-choice-LPP amplitudes in microvolt (μV). For each individual, the value on the x-axis represents their mean pre-choice-LPP amplitudes in each emotional-intensity category (i.e., in graphs A and B, these values represent mean pre-choice-LPP amplitudes for each individual in low and high emotional-intensity, respectively). Each individual is represented by a different color. Note that the distance between actual proportions and predicted probabilities provides visual representation of model fit.

Bayesian analyses.

Does Neural Processing of Emotional-intensity Improve Regulatory-Choice Prediction?

Bayes factors (BFs) were calculated to compare our model, which contains both subjective emotional-intensity category and pre-choice-LPP amplitude as regulatory-choice predictors, with two alternative models containing each of these predictors alone. BFs were calculated based on BIC approximation, where differences in BICs are converted into an approximate BF (e.g., Raftery, 1995; Wagenmakers, 2007 for details). BFs were interpreted based on Jeffreys (1961) interpretation guidelines.

Supporting our pre-choice-LPP effect, $BF_{\text{both predictors/emotional-intensity category only}} = 4.48$ (interpreted as "substantial support") suggested that the data were 4.48 times more likely to occur under a model including both predictors (emotional-intensity category and pre-choice-LPP), rather than a model including only emotional-intensity category.

Supporting our emotional-intensity category effect, $BF_{\text{both predictors/ pre-choice-LPP amplitudes only}} = 335120256$ (interpreted as "decisive support") suggested that the data were 335120256 times more likely to occur under a model including both predictors (emotional-intensity category and pre-choice-LPP), rather than a model including only the pre-choice-LPP.

Do Regulatory-Choices Have Adaptive Consequences?

Bayesian repeated measures analyses of variance (ANOVAs) ware conducted using JASP (version 0.7.5.5. See JASP, 2014).

Modulation of neural processing during implementation

For the implementation-LPP analysis, an estimated BF suggested that the data were 6.24 times more likely to occur under the Emotional-Intensity main effect than the null model (interpreted as reflecting "substantial support" for H1). Additionally, the Regulatory-Choice main effect model was preferred over the null model (BF = 68.77, "very strong support"). Finally, BF suggested that the data were 3.68 times more likely to occur under a model including two main effects (Emotional-Intensity and Regulatory-Choice), rather than a model including two main effects and an interaction ("substantial support").

Modulation of self-reported post regulatory implementation arousal

For the self-reported arousal analysis, an estimated BF suggested that the data were 20.72 times more likely to occur under the Emotional-Intensity main effect than the null model ("strong support"). Additionally, the Regulatory-Choice main effect model was preferred over the null model (BF = 929.79, "decisive support"). Finally, BF suggested that the data were 1.6 times more likely to occur under a model including two main effects (Emotional-Intensity and Regulatory-Choice) and an interaction, rather than a model including two main effects ("anecdotal support"). Although this result is not consistent with our prediction, we do not discuss it further because it is anecdotal.

Modulation of self-reported post regulatory implementation valence

For the self-reported valence analysis, an estimated BF suggested that the data were 1.16 times more likely to occur under the Emotional-Intensity main effect than the null model ("anecdotal support"). Additionally, the Regulatory-Choice main effect model was preferred over the null model (BF = 15235.89, "decisive support").

Finally, BF suggested that the data were 2.6 times more likely to occur under a model including two main effects (Emotional-Intensity and Regulatory-Choice), rather than a model including two main effects and an interaction ("anecdotal support").

Single-trial & single-subject level outliers.

Cook's distance function of the R package ‘influence.ME’ was used to identify outliers at the single-trial level as well as the single-subject level.

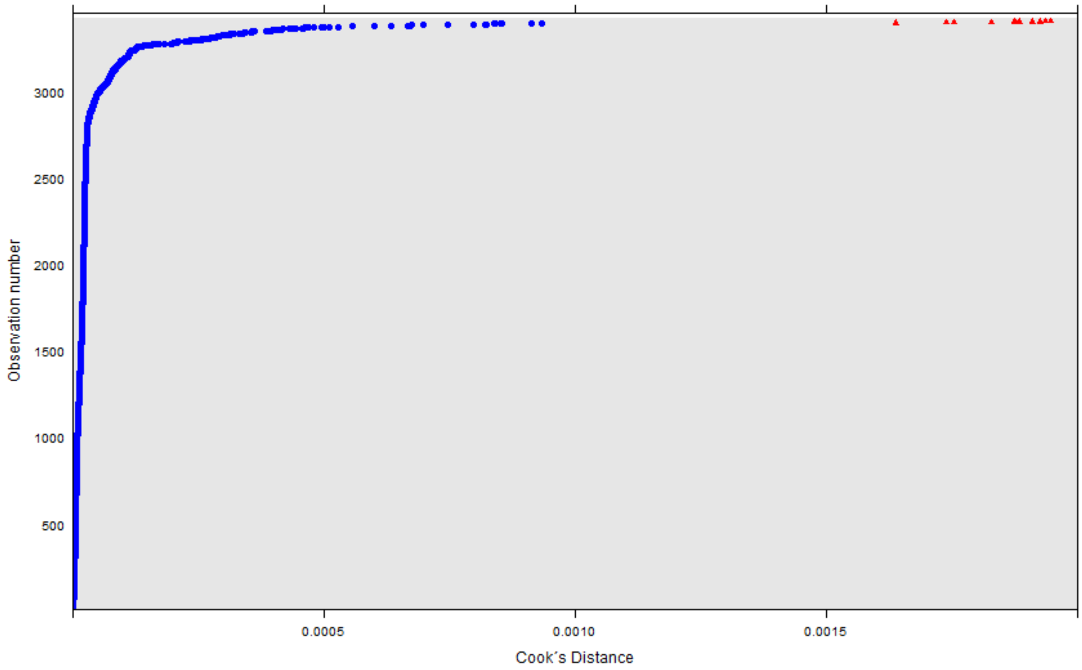

Fig. S6. Single trial-level Cook’s distance. The x-axis represents single-trial Cook's distance values. In our case, the cut-off value of Cook’s distance (4/n) equals 4/3425=0.001167. The y-axis represents each of the 3425 single-trials in the data, arranged by their Cook's distance values (smallest to largest). As can be seen, the results seem to be most strongly influenced by 10 observations (represented by the red triangles) that were identified as outliers.

To evaluate trial outlier influence we re-ran the Logistic Mixed Effects Model (using PROC GLIMMIX procedure in SAS 9.3) excluding these 10 trials, and results remained essentially unchanged. Specifically, we found a main effect of subjective emotional-intensity category [b = 1.89, 1/8 LI [1.5, 2.28], $F(1,23) = 112.2$, $p < .001$, OR = 6.65, p < .001, 95% CI: [4.59, 9.62]] as well as pre-choice-LPP amplitudes [b = 0.02, 1/8 LI [0.01, 0.03], F(1,23) = 17.5, p < .001, OR = 1.02, p < .001, 95% CI: [1.009, 1.028]]. Additionally, the sigtest function of the R package 'influence.ME' was used to estimate the influence of each single-trial on the observed results. The analysis confirmed that none of the single trials influenced the significance of the effects we originally observed (i.e., the subjective emotional-intensity category and the pre-choice-LPP effects).

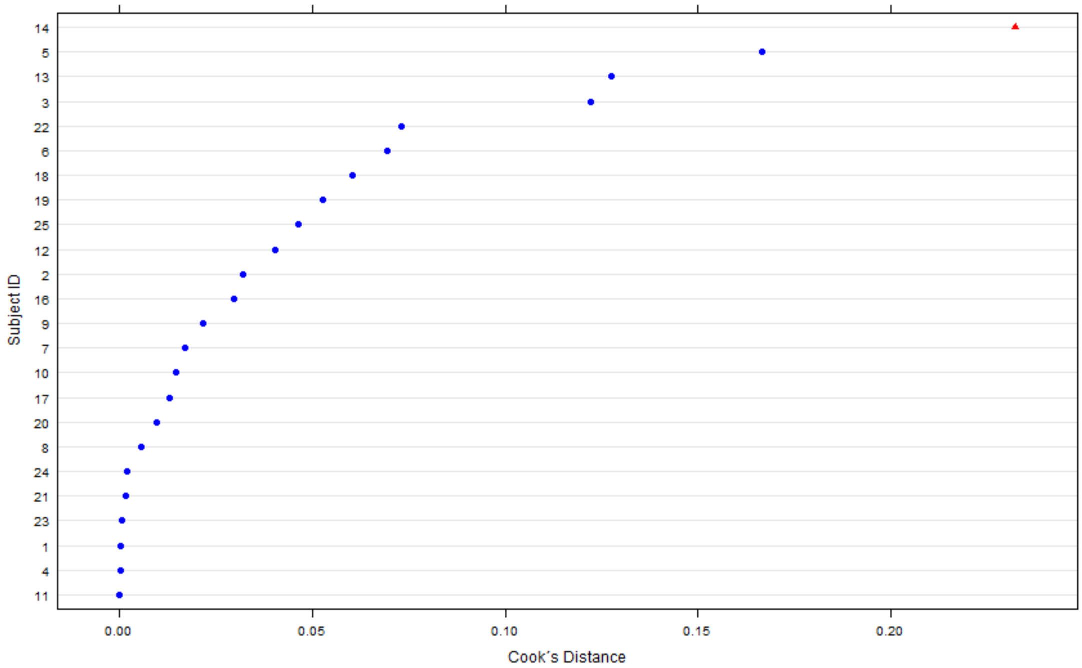

Fig. S7. Single-subject level Cook's distance. The x-axis represents single-subject Cook's distance values. In our case, the cut-off value of Cook's distance (4/n) equals 4/24=0.16667. The y-axis represents each of the 24 single subjects, arranged by their Cook's distance values (smallest to largest). As can be seen, the results seem to be most strongly influenced by one subject (number 14, represented by the red triangle) who was identified as an outlier.

Similar to the previous trial-level analyses, to evaluate subject outlier influence we first re-ran the Logistic Mixed Effects Model (using PROC GLIMMIX procedure in SAS 9.3) excluding subject 14, and results remained essentially unchanged. Specifically, we found a main effect of subjective emotional-intensity category [b = 1.9, 1/8 LI [1.49, 2.28], $F(1,22) = 108.44$, $p < .001$, OR = 6.59, $p < .001$, 95% CI: [4.53, 9.6] as well as pre-choice-LPP amplitudes [b = 0.02, 1/8 LI [0.01, 0.03], $F(1,22) = 16.26$, $p < .001$, OR = 1.02, $p < .001$, 95% CI: [1.009, 1.028]]. Additionally, the sigtest function of the R package ‘influence.ME’ was used to estimate the influence of each single subject on the observed results. This function tests whether excluding the influence of each single subject changes the statistical significance of any of the predictors in the model. The analysis confirmed that none of the single subjects influenced the significance of the effects we originally observed (i.e., the subjective emotional-intensity category and the pre-choice-LPP effects).

References

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