Electronic Supplementary Material

Thermal facial reactivity patterns predict social categorization bias triggered by unconscious and conscious emotional stimuli

Giorgia Ponsi, Maria Serena Panasiti, Giulia Rizza, Salvatore Maria Aglioti

Materials and Methods

Stimulus material

Table S1. Normative valence and arousal ratings for the IAPS[1] stimuli used in the affective priming task.

	Positive (N =62)		**Neutral (N =62)**		**Negative (N = 62)**	
Pictures	Mean	SD	Mean	SD	Mean	SD
Valence[a]	7.30	0.53	5.13	0.56	2.80	0.97
Arousal[b]	5.79	0.80	2.90	0.47	6.04	0.81

[a] Valence: positive > neutral (t = 23.86, df = 61, p<0.00), positive > negative (t = 39.15,df = 61, p< .00), neutral > negative (t = 17.45,df = 61, p< .00).

Valence (subliminal block): positive > neutral (t = 17.65, df = 30, p< .00), positive > negative (t = 24.81, df = 30, p< .00), neutral > negative (t = 10.26, df = 30, p< .00).

Valence (supraliminal block): positive > neutral (t = 15.94, df = 30, p< .00), positive > negative (t = 31.88, df = 30, p< .00), neutral > negative (t = 15.44, df = 30, p< .00).

[b] Arousal: positive > neutral (t = 25.00, df = 61, p< .00), positive = negative (t = -1.52, df = 61, p=.14), neutral < negative (t = -30.00, df = 61, p< .00).

Arousal (subliminal block): positive > neutral (t = 16.58, df = 30, p< .00), positive = negative (t = -0.97, df = 30, p= .34), neutral > negative (t = -18.43, df = 30, p< .00).

Arousal (supraliminal block): positive > neutral (t = 18.74, df = 30, p< .00), positive = negative (t = -1.15, df = 30, p= .26), neutral > negative (t = -25.24, df = 30, p< .00).

Procedure

Task and design

Cover story

We created a cover story in order to justify the employment of the masks, telling participants that the experiment aimed at investigating the effects of cognitive load on face categorization Thus, participants knew that they had to perform a same/different recognition task between mask 1 and mask 2 (which participants believed to be the task that required cognitive load) before making a categorization decision about the face. To make this “fake task” more persuasive, the two masks were identical in 50% of the trials (i.e. the squares composing them were equally displaced) and different in the other 50% of the trials (i.e. the squares composing them were differently displaced).

Procedure

Physiological recordings

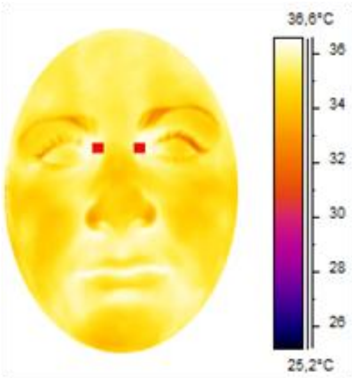

Figure S1. Infrared thermal image of the face of one participant. The red squares indicate the ROIs' positioning over the left and right periorbital regions.

Participants were required to avoid the intake of vasoactive substances (e.g. caffeine, nicotine and alcohol) for at least 3 hours prior to the experiment to prevent interference with basal sympathetic activity[2]. Once in the experimental room they waited 30 minutes before starting the experiment in order to let their skin temperature reach a thermal equilibrium[2].

Task and design

Memory recognition task

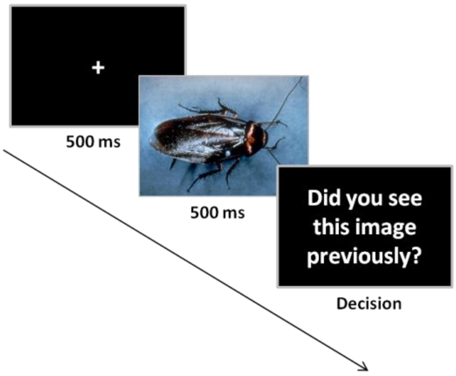

Figure S2. Timeline of the memory recognition task. Affective stimuli were taken from the IAPS[1].

Each trial in the memory recognition task included the following elements: 1) fixation cross (500 ms), 2) affective stimulus (500 ms), 3) yes/no memory recognition task (*"Did you see this image previously?"*) (see Figure S2). The affective stimuli were presented in a fully randomized order.

We fit the behavioral data in a multilevel logistic regression model predicting accuracy in the recognition memory task from the following categorical variables: valence (1 = positive, 2 = neutral, 3 = negative) and block (1= subliminal, 2 = supraliminal).

We also modelled the highest-order interaction as random slope over participants, as suggested in these guidelines[3] and in[4–6]. This model explained additional significant portion of variance respect to the saturated model without random slopes over participants (Chisq = 105.45, $p < .001$).

The model that guaranteed the best interpolation with our data showed significant main effects of valence (Chisq = 46.16, $p < .001$) and block (Chisq = 130.80, $p < .001$) which were qualified by a significant two-way interaction between these two factors (Chisq = 12.15, $p < 0.01$; see Figure S3).

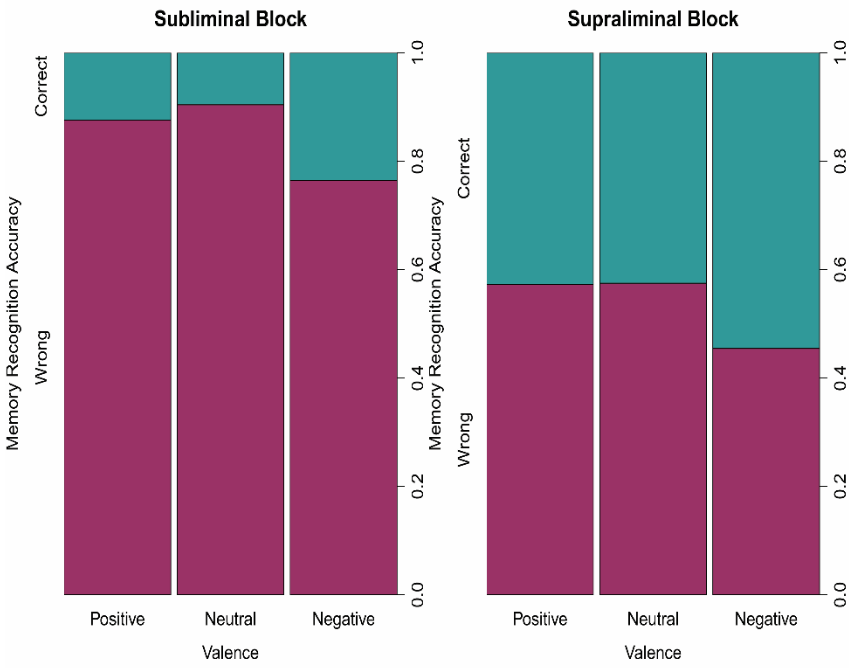

Figure S3. Accuracy in the recognition memory task.

Pairwise Bonferroni-corrected comparisons showed that all between block contrasts are significantly different from one another (ps < .001). Pairwise Bonferroni-corrected contrasts within the subliminal block show that negative stimuli are recognized better than neutral (b = -1.28, SE = 0.20, z = -6.51, p<.0001) and positive (b = -2.30, SE = 0.16, z = -14.06, p<.0001) stimuli, and that there is no difference in recognition between positive and neutral stimuli (b= 0.40, SE = 0.18, z = 2.24, p=0.38). Pairwise Bonferroni-corrected contrasts within the supraliminal block show exactly the same pattern: negative stimuli are recognized better than neutral (b = -0.62, SE = 0.15, z = -4.15, p<.001) and positive (b = -0.54, SE = 0.12, z = -4.51, p<.001) stimuli, while there is no difference in recognition between positive and neutral stimuli (b = 0.08, SE = 0.14, z = 0.58, p=1.00) (see Figure S3).

Recognition memory performance indicates that the subliminal and supraliminal presentation significantly affects the processing of affective stimuli, as supraliminal stimuli are correctly remembered much more often than subliminal ones. Moreover, we found a valence-related effect: negative stimuli are recognized more than positive and neutral ones (in both subliminal and supraliminal blocks). This suggests that threat-related visual material elicits enhancing effects on long-term memory[7]. Despite the absence of visual awareness, subliminal negative stimuli impact long-term memory significantly more than positive and neutral ones; this seems to be consistent with the finding that subliminally presented affective stimuli are able to impact implicit learning[8].

Procedure

Single trial generalized linear mixed models

In the multilevel logistic regression models, we fit the dependent variable (categorization choice: ingroup vs outgroup) with continuous and categorical independent variables. Our categorical dependent variable assumes a binomial distribution and as a consequence does not need to meet the assumption of normality. We considered the scalar effects of the participant (i.e. subject-specific random intercept) as a priori random factor because each individual possesses a unique decision style (i.e. he/she can be more prone to categorize the face as either ingroup or outgroup) that is independent from the face stimuli. Moreover, by way of a model comparison we checked whether it was necessary to include the random slopes for the significant within highest-order interaction in the model (as suggested in guidelines[3]). Reported main effects and interactions are based on model comparisons using the log-likelihood ratio statistics asymptotically approximated to a $\chi 2$ distribution. This allows for the computation of a p-value that reaches statistical significance if the data is better fitted to the more complex model[9]. In addition, we used a non-parametric bootstrap technique in order to have a more robust measure of our effects [10]. For 1000 times we randomly assigned each data to each condition, entered the data in the same generalized linear mixed model, computed the chi square for each main effect and for the interactions. Then, we compared our original chi square with the distribution under the null hypothesis of the bootstrap chi squares. The bootstrap p-level was calculated as the proportion of bootstrapped chi squares (included in the 95% confidence intervals) greater than the original chi squares [11].

Results

Models formulas

The expression within parenthesis (e.g. Variable name | Subject). indicates the random effects defined in the model. The expression outside parenthesis refers to the fixed effects. Colons between effects are used to indicate interactions.

a. Temperature subliminal model

The model was computed as follows: Group categorization decision = Valence + Mean periorbital temperature (100-600 ms) + Mean periorbital temperature (600-1100 ms) + Valence : Mean periorbital temperature (100-600 ms) + Valence : Mean periorbital temperature (600-1100 ms) + (1 | Subject).

The model including the random slope of the highest-order significant interaction was computed as follows: Group categorization decision ~ Valence + Mean periorbitalperiorbital temperature (100-600 ms) + Mean periorbitalperiorbital temperature (600-1100 ms) + Valence : Mean periorbitalperiorbital temperature (100-600 ms) + Valence : Mean periorbitalperiorbital temperature (600-1100 ms) + (Valence : Mean periorbital temperature (600-1100 ms) | Subject).

b. Temperature supraliminal model

The model was computed as follows: Group categorization decision = Valence + Mean periorbital temperature (100-600 ms) + Mean periorbital temperature (600-1100 ms) + Mean periorbital temperature (1100-1600 ms) + Valence : Mean periorbital temperature (100-600 ms) + Valence : Mean periorbital temperature (600-1100 ms) + Valence : Mean periorbital temperature (1100-1600 ms) + (1 | Subject).

The model including the random slope of the highest-order significant interaction was computed as follows: Group categorization decision = Valence + Mean periorbital temperature

(100-600 ms) + Mean periorbital temperature (600-1100 ms) + Mean periorbital temperature (1100-1600 ms) + Valence : Mean periorbital temperature (100-600 ms) + Valence : Mean periorbital temperature (600-1100 ms) + Valence : Mean periorbital temperature (1100-1600 ms) + (Valence : Mean periorbital temperature (600-1100 ms) | Subject).

c. Individual differences

Main analysis

The model was computed as follows: Group categorization decision = Valence + Emotional Awareness + Mean periorbital temperature (600-1100 ms) + Block + Valence : Emotional Awareness + Valence : Mean periorbital temperature (600-1100 ms) + Emotional Awareness : Mean periorbital temperature (600-1100 ms) + Valence : Block + Emotional Awareness : Block + Mean periorbital temperature (600-1100 ms) : Block + Valence : Emotional Awareness : Mean periorbital temperature (600-1100 ms) + Valence : Emotional Awareness : Block + Valence : Mean periorbital temperature (600-1100 ms) + Emotional Awareness : Mean periorbital temperature (600-1100 ms) : Block + Valence : Emotional Awareness : Mean periorbital temperature (600-1100 ms) : Block + (1 | Subject).

The model including the random slope of the within highest-order significant interaction was computed as follows: Group categorization decision = Valence + Emotional Awareness + Mean periorbital temperature (600-1100 ms) + Block + Valence : Emotional Awareness + Valence : Mean periorbital temperature (600-1100 ms) + Emotional Awareness : Mean periorbital temperature (600-1100 ms) + Valence : Block + Emotional Awareness : Block + Mean periorbital temperature (600-1100 ms) : Block + Valence : Emotional Awareness : Mean periorbital temperature (600-1100 ms) + Valence : Emotional Awareness : Block + Valence : Mean periorbital temperature (600-1100 ms) + Emotional Awareness : Mean periorbital temperature (600-1100 ms)

: Block + Valence : Emotional Awareness : Mean periorbital temperature (600-1100 ms) : Block + (Valence : Mean periorbital temperature (600-1100 ms) : Block | Subject).

Low- and high-EA participants

The model was computed as follows: Group categorization decision ~ Valence + Mean periorbital temperature (600-1100 ms) + Block + Valence : Mean periorbital temperature (600-1100 ms) + Valence : Block + Mean periorbital temperature (600-1100 ms) : Block + Valence : Mean periorbital temperature (600-1100 ms) : Block + (1 | Subject) .

The model including the random slope of the highest-order significant interaction was computed as follows: Group categorization decision ~ Valence + Mean periorbital temperature (600-1100 ms) + Block + Valence : Mean periorbital temperature (600-1100 ms) + Valence : Block + Mean periorbital temperature (600-1100 ms) : Block + Valence : Mean periorbital temperature (600-1100 ms) : Block + (Valence : Mean periorbital temperature (600-1100 ms) : Block | Subject). The models were computed separately for low- and high- EA sub-sample.

d. Memory recognition task

The model was computed as follows: Accuracy ~ Valence + Block + Valence : Block + (1 | Subject).

The model including the random slope of the highest-order significant interaction was computed as follows: Accuracy ~ Valence + Block + Valence: Block + (Valence : Block | Subject).

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