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Does your past define you? The role of previous visual experience in subjective reactions to new affective pictures and sounds.

Fiorella Del Popolo Cristaldi¹, Filippo Gambarota², Suzanne Oosterwijk^{3,4}

¹Department of General Psychology, University of Padua, Padua, Italy

²Department of Developmental Psychology and Socialization, University of Padua, Padua, Italy

³Department of Social Psychology, University of Amsterdam, Amsterdam, The Netherlands

⁴Amsterdam Brain and Cognition Centre (ABC), Amsterdam, The Netherlands

Corresponding author:

Fiorella Del Popolo Cristaldi

Department of General Psychology

Via Venezia 8, 35131 Padova, Italy

Phone: +39 0498276941

E-mail: fiorella.delpopolocristaldi@phd.unipd.it

ABSTRACT

According to predictive models of emotion, people use their previous experience to construct new affective predictions. We do not live in a stable world, however. Some environments are uncertain, others are not. This study investigated how experiencing certain vs. uncertain probabilistic relationships shapes subjective reactions to new affective stimuli, within and across sensory modalities. Two S1-S2 paradigms were employed as learning and test phases in two experiments. S1s were colored circles, S2s negative or neutral affective pictures or sounds. Participants (N = 192, 179) were assigned to the certain (CG) or uncertain group (UG), and they were presented with 100% (CG) or 50% (UG) S1-S2 congruency between visual stimuli during the learning phase. During the test phase both groups were presented with a new S1-S2 paradigm with a 75% S1-S2 congruency, and visual (Experiment 1) or auditory (Experiment 2) S2s. Participants were asked to rate the expected valence of upcoming S2s (expectancy ratings), or their experienced valence and arousal (valence and arousal ratings). In both experiments, participants in the CG reported more negative expectancy ratings after the S1s previously paired with negative stimuli, whereas no group differences emerged on valence and arousal ratings. Furthermore, when comparing the two experiments, no significant group by experiment interaction was found. Overall, and in line with predictive models, our results suggest that relying on a certain previous experience shapes subjective expectancies toward a coherent labeling of the predicted valence of future stimuli, and that this process develops similarly across sensory modalities.

Keywords: predictive coding, emotion, subjective experience, previous experience, S1-S2 paradigm

1) INTRODUCTION

Past experience can influence our subjective reactions to future affective stimuli. Let us imagine a person who is celebrating their birthday, and is about to unwrap their presents. From previous parties, they know that their parents often give very nice gifts. They will therefore predict a joyful experience when they unwrap their parent's present, and they will be particularly pleased if the present meets their expectation. Their aunt, however, has previously given both terrible and awesome gifts. Thus, they will not have any reliable previous experience about the likelihood of receiving cool or awful items from their aunt. As a result, it will be difficult to predict their subjective reaction when unwrapping their present, and maybe they will be particularly upset if the gift turns out to be an old-fashioned knitted sweater. This example highlights how being exposed to previous certain vs. uncertain scenarios could affect people's expectancies and subjective reactions to new affective events.

1.1) A predictive model of emotion

According to a *predictive model of emotion* (Barrett, 2017; Seth & Friston, 2016), people use their previous experience to construct affective predictive models (here we will refer to this process as the prediction *generation* stage), in order to predict incoming stimuli, and to prearrange action plans to efficiently deal with the expected situation (*implementation* stage). Actual environmental inputs are continuously tested against predictions: in case of a mismatch, the discrepancy is encoded as a prediction error, and used to adjust future predictions (*updating* stage). Predictive models are *generative*, in the sense that they generate predictions, and their modelling capacity generalizes across sensory modalities, contexts, and time (Friston, 2010; Shipp, 2016). They are *probabilistic*, which means that they encode the statistical structure of observed inputs (Clark, 2013; Friston, 2010; Shipp, 2016). They are also mostly *implicit*, potentially emerging into awareness only in case of a mismatch (Bar, 2007). The continuous cycle of *generation-implementation-updating* of (affective) predictions allows to (1) extract

relevant information from the environment, (2) combine it with previously acquired knowledge, (3) pre-allocate resources to face all the potential future scenarios, and (4) consistently adjust future predictions (Barrett, 2017). Thus, this ability is crucial to promote survival (Barrett, 2017; Sterling, 2012). When applied to the subjective experience of emotion, Barrett (2017) proposes that the brain actively constructs meaning in the present moment by predicting and categorizing incoming stimuli and sensations based on past experience. When conceptual emotion knowledge is used to make meaning of actual inputs, the resulting prediction and the associated affective reaction can be subjectively experienced as an instance of emotion (Barrett, 2017; Barrett et al., 2014; Seth, 2013).

Since subjective experience of emotion emerges from the meaning making of prediction construction (Barrett, 2017; Barrett et al., 2007), and (affective) predictive models encode the probabilistic structure of observed inputs (Clark, 2013; Friston, 2010; Shipp, 2016), it follows that subjective experience might be crucially affected by the degrees of uncertainty experienced in the past, and thus by the degree of reliability of the derived predictive models. In fact, we do not live in a stable world. Human organisms are embedded in constantly changing multisensory environments, experiencing different types of stimuli (e.g., visual, auditory), with different degrees of uncertainty (i.e., carrying more or less reliable information). Therefore, tapping into internal models which are based on past multimodal experience is crucial to our brains in order to construct predictions in a dynamic and flexible way (Barrett, 2017; Friston, 2005; Peelen et al., 2010). Nevertheless, it is an open question to what extent the construction of affective predictions in one sensory modality actually relies on (and integrates) information in another sensory modality, previously experienced in uncertain vs. certain environments. Furthermore, it is still unclear how (un)certain previous experience affects future affective predictions at the level of subjective experience. The present paper aims to answer these questions. Our first goal is to examine which type of previously experienced environment (certain vs. uncertain) will

lead to an intensification of subjective reactions during future predictions. Our second goal is to examine whether new affective predictions develop similarly across sensory modalities.

1.2) Manipulating previous experience

Most studies in the extant literature have not manipulated previous experience directly, but have focused on how explicit probabilities of affective stimuli occurrence (based on the instructed meaning of a preceding cue) may impact affective processing. These studies mostly employed emotional S1-S2 paradigms in the visual modality. This paradigm implements a sequential presentation of two stimuli: the S1 (or *cue*) is typically a symbolic stimulus (e.g., geometric shapes, or letters), while the S2 (or *target*) is an emotional stimulus (e.g., affective pictures, or faces). Usually, S2 valence is manipulated at two levels, and a response is required to each S2 (e.g., emotion categorization, subjective valence and arousal ratings) (see Mercado et al., 2008 for a review on emotional S1-S2 paradigms). The S1-S2 paradigm allows to effectively investigate the three stages of affective prediction construction, with S1 processing reflecting the *generation* stage, the inter-stimulus interval (ISI) between S1 and S2 the *implementation* stage, and S2 the prediction *updating* (Del Popolo Cristaldi et al., 2021). Extant literature focused on the role of *currently available* probabilistic information on affective processing, by manipulating *explicitly labeled* certain (100%) vs. uncertain (50%) relationships between S1 and S2. Thus, in existing paradigms participants are explicitly instructed about the probabilistic ratios they will be exposed to. Such S1-S2 paradigms do not implement the role of *actual previous experience* in generating future predictions. Furthermore, they do not resemble more realistic everyday contexts, in which people automatically learn contingencies from their environments, and infer probabilistic information to use in their affective predictions, by means of exposure (Bar, 2007). The present study instead will utilize a novel experimental paradigm that directly manipulates previous experience in terms of uninstructed certain vs. uncertain emotional congruency between stimuli.

1.3) Mixed evidence from S1-S2 paradigms

The literature employing S1-S2 paradigms led to fragmentary evidence on subjective experience. Focusing on expectancy measures related to the *generation-implementation* stages (i.e., either trial-by-trial expectancy ratings about the expected valence of the upcoming S2, or post-experiment estimation of the percentage of uncertain cues followed by a negative S2), it was consistently shown that an uncertain probabilistic ratio was associated with negatively-biased expectancies about the forthcoming S2 valence, which means an overestimation of negative S2s occurrence following uncertain S1s (Dieterich et al., 2016; Grupe & Nitschke, 2011; Lin et al., 2018, 2020; Qiao et al., 2018; Sarinopoulos et al., 2010). Regarding the *updating* stage, some inconsistencies emerged when considering the modulating effects of the probabilistic information on S2-subjective ratings. Some studies found more pleasant valence ratings to certain positive as compared to uncertain positive S2s, and more unpleasant ratings to certain negative as compared to uncertain negative S2s (Johnen & Harrison, 2019; Lin et al., 2020; Lin, Jin, et al., 2015; Lin, Xiang, et al., 2015); one study reported more unpleasant ratings to uncertain negative as compared to certain negative S2s (Lin et al., 2017); and still others found no significant interactions between probabilistic information and subjective valence ratings (Berpohl et al., 2006; Dieterich et al., 2016; Greenberg et al., 2015; Grupe & Nitschke, 2011; Lin et al., 2018; Qiao et al., 2018). The only study assessing emotional intensity (Berpohl et al., 2006) found a stronger self-reported emotional intensity after certain as compared to uncertain emotional S2s. Lastly, two studies (Lin et al., 2017; Lin, Xiang, et al., 2015) investigated how experiencing a certain vs. uncertain anticipation pattern (acquired through the emotional S1-S2 paradigm during an encoding phase) could influence the subsequent recognition and the neural correlates of S2 processing during an unexpected old/new recognition task. At the neural level, it emerged that a certain anticipation pattern led to an enhanced processing of negative S2s (Lin, Xiang, et al., 2015), while an uncertain

anticipation pattern led to a reduced recognition of neutral S2s features (Lin et al., 2017). However, it is still not clear if experiencing different degrees of (un)certainty during the encoding phase could influence subsequent subjective reactions, since the authors did not measure S2-affective ratings during the recognition phase.

Overall, these results are in contrast with the literature suggesting that uncertainty intensifies affective experience, by pushing towards a polarization of both positive and negative affect, and thus leading to increased attention and emotional engagement towards uncertain events (Bar-Anan et al., 2009; Carleton, 2016a, 2016b; Einstein, 2014). Nevertheless, they can be explained within the *predictive framework* (Barrett, 2017; Seth & Friston, 2016). In certain contexts, the brain can generate reliable affective predictions based on previously learned contingencies, thus pre-activating the expected affective experience, which in turn could lead to an intensification of subjective reactions. Within uncertain contexts, instead, reliable affective predictions (and correspondent experience pre-activation) cannot be constructed, and the brain's resources are deployed in prediction error detection and encoding, thus potentially leading to dampened subjective reactions.

1.4) The present study

This brief literature review unveils some important gaps that the present study aims to fill. First, the impact of previous experience on new affective predictions has never been systematically investigated, although, according to the *predictive framework* (Barrett, 2017; Seth & Friston, 2016), prior experience is crucial to generate predictions and to make meaning of the emotional events in the present moment. Second, subjective affective ratings in the extant S1-S2 paradigms have mainly assessed the valence dimension, while arousal is under-represented, despite being an equally important dimension of affective experience. Third, extant S1-S2 paradigms are typically instructed: participants are explicitly informed about the probabilistic ratios between S1 and S2 prior to the experiment. This could arouse concerns on

the generalizability of results. In daily life, people are usually able to spontaneously learn contingencies from the environment, and to use them as priors for subsequent affective predictions, without any need to be instructed. And finally, fourth, cross-modality effects have never been studied within the extant literature. If affective predictions integrate multisensory information, then it is possible that learned certain and uncertain probabilities of affective events in one modality generalize to another modality.

In the light of these considerations, we here propose a purposely developed online experimental design, which combines emotional S1-S2 paradigms with a learning component. Our paradigm investigates the impact of (un)certain previous experience in constructing new affective predictions in a new, moderately certain probabilistic context, both within and across sensory modalities. A first emotional S1-S2 paradigm was employed as a learning phase, in which prior experience was manipulated via uninstructed certain vs. uncertain S1-S2 emotional congruency. Participants were assigned to the *certain* or *uncertain* experimental group, in which they were presented with a 100% vs. 50% probabilistic ratio between visual stimuli (i.e., colored dots as S1s, and affective pictures as S2s), respectively. A second emotional S1-S2 paradigm with a fixed 75% S1-S2 probabilistic ratio, and visual (Experiment 1) or auditory (Experiment 2) affective stimuli as S2s, was then employed as a test phase. Here, we investigated the effects of previously learned probabilistic relationships on subjective affective experience in a new, moderately certain (75%) probabilistic context. Participants were asked to rate the expected valence of upcoming S2s (*expectancy ratings*), or the experienced valence and arousal to S2s (*valence* and *arousal ratings*).

We performed confirmatory analyses to test three a-priori formulated hypotheses (as pre-registered on the Open Science Framework – OSF; Experiment 1: <https://osf.io/ef9q7/>, Experiment 2: <https://osf.io/wcy9r/>). The first hypothesis (H1) was that participants in the *uncertain* group would show more negative expectancy ratings (Dieterich et al., 2016; Grupe

& Nitschke, 2011; Herwig et al., 2007; Qiao et al., 2018; Schumacher et al., 2015), as compared to participants in the certain group. The second hypothesis (H2a) was that participants in the *uncertain* group would show higher *arousal* and more unpleasant *valence ratings* to S2s (Bar-Anan et al., 2009; Carleton, 2016a, 2016b; Einstein, 2014; Lin et al., 2017) than participants in the certain group. The third hypothesis (H2b), opposed to H2a, was that participants in the *certain* group would show higher *arousal* and more unpleasant *valence ratings* to S2s (Berpohl et al., 2006; Johnen & Harrison, 2019; Lin et al., 2020; Lin, Jin, et al., 2015; Lin, Xiang, et al., 2015), as compared to participants in the uncertain group.

Furthermore, if previously learned visual contingencies effectively generalize to novel auditory stimuli, then we expected to find similar patterns of results in Experiment 1 (visual to visual) and Experiment 2 (visual to auditory). Finally, we explored whether S1-S2 *congruency* played a modulating role on S2-subjective reactions, by comparing *valence* and *arousal ratings* of congruent trials (i.e., trials of the test phase in which the S1-S2 pairing was more likely, i.e., 75%) with ratings of incongruent trials (i.e., trials of the test phase in which S1-S2 pairing was less likely, i.e., 25%).

2) EXPERIMENT 1

Experiment 1 investigated how being exposed to certain vs. uncertain probabilistic relationships between visual stimuli might influence subjective affective experience to new affective predictions in the same (i.e., visual) sensory modality.

We tested the pre-registered hypotheses H1, H2a, H2b (<https://osf.io/ef9q7/>).

2.1) Methods

2.1.1) Participants

We recruited 200 adult participants through the provider platform Prolific (Prolific, Oxford, UK; www.prolific.co). The sample size was estimated through an a priori pre-registered (<https://osf.io/ef9q7/>) simulation-based power analysis for generalized linear mixed-effects models (GLMMs) (R package: *simr*; Green & MacLeod, 2016), estimating parameters from pilot data ($N = 27$). Data from 8 participants were discarded according to the following pre-registered exclusion criteria (<https://osf.io/ef9q7/>): scoring lower than 75% accuracy on attention check items (see 2.1.2 below), reporting experienced technical issues in more than 25% of the experimental trials.

The final sample was 192 participants (73 males, age: $M = 33.07$, $SD = 11.46$, range = 18-62). All participants gave their informed consent before starting the experiment, and were paid £2.50 for their participation. All experimental procedures were approved by the Ethical Committee for the Psychological Research of the University of Padua (protocol no. 4012), and were conducted in accordance with the Declaration of Helsinki.

2.1.2) Stimulus material and procedure

Stimuli and rating scales. Two emotional S1-S2 paradigms were employed as a learning and a test phase, respectively. Colored red and blue 1 cm diameter circles were employed as S1s. An additional yellow 1 cm diameter circle was used as S1 in attention check trials. Colored 800×600 px pictures (60 negative, 60 neutral) from Nencki Affective Picture

System (NAPS) (Marchewka et al., 2014) were employed as S2s. NAPS pictures names, sorted by emotional valence, are listed in Supplementary Table S1. Negative and neutral pictures did not differ in terms of luminance, contrast, complexity, and color space (see Supplementary Table S2). An additional 800×600 px picture, depicting a pattern of black stripes on a transparent background, was used as S2 in attention check trials.

A Visual Analogue Scale (VAS) assessed *expectancy ratings* (i.e., the expected valence of upcoming S2s), ranging from 0% (“I definitely expect to see a neutral picture”) to 100% (“I definitely expect to see a negative picture”), with 50% representing not knowing what to expect. Two more VASs were used to collect *valence* and *arousal ratings* to S2s. The valence scale ranged from 0% “very negative” to 100% “very positive”, with 50% representing “neutral”. The arousal scale ranged from 0% “relaxed” to 100% “aroused”, with 50% representing an intermediate level of activation.

Learning phase. Before the learning phase, participants were randomly assigned to one of two experimental groups: the *certain* group (CG), and the *uncertain* group (UG). At the beginning of the learning phase, participants were instructed to look at the computer screen and pay attention to the relationship between S1 color and S2 valence. Furthermore, they were instructed to press the ‘spacebar’ as fast as they could each time they saw a yellow circle (attention check trials). The instructions were followed by a practice session (4 trials) in which participants received feedback on their performance to one attention check trial. Then, the learning session started. Each trial was displayed on a grey background, and it began with S1, presented for 250 msec. A fixed ISI of 1000 msec followed, in which the screen remained grey, then S2 was presented for 1000 msec. The inter-trial interval (ITI), in which a white fixation cross was displayed in the center of the screen, randomly varied between 800 and 1200 msec. The total number of trials was 40. The order of the trials was random.

During the learning phase, participants in the CG were presented with a 100% S1-S2 congruency: each S1 color was paired with the same S2 valence in 100% of the trials, thus they learned a highly predictive relationship between S1 and S2. The UG, instead, experienced a 50% congruency level: each S1 color was paired with negative S2s in 50% of the trials, and with neutral S2s in the other 50%, thus they learned an uncertain relationship. Color-valence pairings were counterbalanced between subjects. Participants were left uninstructed about the S1-S2 probabilistic relationship.

Test phase. At the end of the learning phase participants were asked to wait and relax for 1 minute, after which they were introduced to the test phase, identical for both the experimental groups. At the beginning of the test phase participants were instructed about the second S1-S2 paradigm: they were asked to look at the computer screen and pay attention to S1 color, trying to predict S2 emotional valence. Participants were explained that, in some trials, they would be asked to rate how much they expected to see a negative picture after the S1, by answering a 0-100% rating scale; while in other trials they would be asked to assess the subjective valence and arousal elicited by the S2, by answering a 0-100% rating scale for each dimension. They were also instructed to press the ‘spacebar’ as fast as they could each time they saw the yellow circle (attention check). Instructions were followed by a practice session (4 trials) in which participants trained themselves to give their ratings, and they received feedback on their performance to one attention check trial. Then, the test session started. Trial structure and timing were the same as the learning phase. The total number of trials was 80. S1-S2 congruency was fixed at 75%, that is S1 color was moderately predictive of S2 valence (same S1 color-S2 valence pairings in 75% of the trials). Color-valence pairings were counterbalanced between subjects. Participants were left uninstructed about the S1-S2 probabilistic relationship in the test phase.

Participants were asked to answer the VASs either during the ISI for half of the trials (*expectancy ratings*), or right after the S2 for the other half of the trials (*valence* and *arousal ratings*). The order of the trials was random. Response time for the VASs was self-paced. The *expectancy ratings* and the *valence/arousal ratings* were presented in different trials to prevent the two ratings from influencing each other (see Figure 1a for a schematic representation of the experimental paradigm).

Congruency. In the test phase, trials in which the pairing between S1 color and S2 valence was more likely (i.e., 75%) were coded as congruent, while trials in which the pairing between S1 color and S2 valence was less likely (i.e., 25%) were coded as incongruent. Thus, congruent trials are those trials in which, according to the new 75% probabilistic ratio, a stronger expectancy about the valence of the forthcoming S2 should be generated and implemented, leading to an *expectancy confirmation* when updating the internal model to the actual S2. In incongruent trials, instead, the lower likelihood of the S1-S2 association should determine an *expectancy violation* when updating the internal model to the actual S2. Therefore, the *S2 congruency* factor allowed us to investigate if ratings were different between expected and unexpected S2s, combining the new contingencies with the contingencies learned in the learning phase. Notably, the 75% ratio implied participants in the CG to transition from a totally reliable predictive context (100%, experienced during the learning phase), to a new context in which the predictive models they had previously learned were confirmed in the congruent trials and disconfirmed in the incongruent trials. Participants in the UG, instead, transitioned from a totally unreliable predictive context (50%), to a more predictive situation. Importantly, the 75% ratio is equidistant from the probabilistic relationships experienced both by the CG and the UG, laying exactly in the middle between 100% and 50%.

Procedure. The experiment was run online, through OpenSesame (Mathôt et al., 2012) and the JATOS hosting server (Lange et al., 2015). Participants were instructed to ensure that

their environment was optimal for participation: they were asked to sit alone in a silent and private room, and to avoid all potential distractions and interruptions. Furthermore, they were asked to perform the study on a computer, and to ensure that no one else could view the computer screen during the experiment due to the involvement of emotionally evocative material.

At the end of the test phase, participants were redirected to a Qualtrics survey (Qualtrics, Provo, UT; www.qualtrics.com). They were asked to fill a few demographic questions (age, gender). They were also asked whether and in how many trials they had experienced any issues with the internet connection and/or with pictures uploading. At the end of the survey, all participants were thanked for their participation, and redirected to Prolific to complete the study submission and receive their payment.

a) EXPERIMENT 1

b) EXPERIMENT 2

Figure 1. a) Example sequence of events and their duration for a trial of Experiment 1, according to the phase (learning, test), and the experimental group (CG, UG). During the *learning phase* participants experienced a 100% (CG) vs. 50% (UG) probabilistic relationship between S1s (red or blue circles) and S2s (negative or neutral emotional pictures), according to the experimental group. During the *test phase* the S1-S2 probabilistic relationship was fixed at 75% for both groups. Participants were asked to answer the VASs either during the ISI for half of the trials (*expectancy ratings*), or right after the S2 for the other half of the trials (*valence and arousal ratings*). Response times were self-paced. **b)** Example sequence of events and their duration for a trial of Experiment 2, according to the phase (learning, test), and the experimental group (CG, UG). During the *learning phase* participants experienced a 100% (CG) vs 50% (UG) probabilistic relationship between S1s (red or blue circles) and S2s (negative or neutral affective pictures), according to the experimental group. During the *test phase* S2s were negative or neutral affective sounds, and the S1-S2 probabilistic relationship was fixed at 75%. Participants were asked to answer the VASs either during the ISI for half of the trials (*expectancy ratings*), or right after the S2 for the other half of the trials (*valence and arousal ratings*). Response times were self-paced.

ISI = inter-stimulus interval, ITI = inter-trial interval, VAS = visual analogue scale. The text is not drawn to scale.

2.1.3) Data analysis

The study has a 2 (*group*, between-subjects: CG vs. UG) $\times$ 2 (*S2 valence*, within-subjects: negative - neg vs. neutral - neu) mixed design. The analysis plan was pre-registered on OSF (<https://osf.io/ef9q7/>). We ran an additional analysis to investigate if *expectancy ratings* in the two groups differed as a function of the *S1 color* (within-subjects: red vs. blue). In fact, based on the way the paradigm is constructed, the color of the circle had a different

(uninstructed) predictive value depending on the experimental group. Each color had an actual predictive meaning for participants in the CG, since they experienced a totally reliable S1-S2 congruency ratio during the learning phase (for example, they learned that a red circle always preceded a negative picture, and a blue one always preceded a neutral picture). For participants in the UG, instead, the color of the circle had no predictive value, since during the learning phase each color was paired equally often with either negative or neutral pictures. To compensate for the counterbalancing of S1 color-S2 valence pairings, in the analysis we recoded as *red* all the trials in which the circle preceded a negative picture, and as *blue* all the trials in which the circle preceded a neutral picture, independently from the actual circles' color.

Outliers were detected through Median Absolute Deviation values ($MAD > 3$) when univariate (i.e., *expectancy ratings*), and through the Mahalanobis-Minimum Covariance Determinant (MMCD, breakdown point 0.25) when multivariate (i.e., *valence* and *arousal ratings*) (R package: Routliers; Leys et al., 2019). Data from 7 participants were detected as univariate outliers. From visual inspection of their ratings, it emerged that these participants had reversed the poles of the rating scale ("error outliers", cf. Leys et al., 2019), thus they were removed from data analysis. Data from 68 participants were detected as multivariate outliers. From visual inspection of their ratings, it emerged that these participants were characterized by a slightly flattened or steeper relationship between valence and arousal ratings as compared to other participants. Thus, since none of them significantly impacted the models' estimates (as assessed through Cook's distance, see below), we chose not to discard them ("potentially interesting outliers", cf. Leys et al., 2019). Data from 185 participants entered data analysis.

In order to test our a-priori hypotheses (H1, H2a, H2b), for each dependent variable (DV) we fitted the following linear mixed-effects models (LMMs) (R package: lme4; Bates et al., 2015):

1. *expectancy ratings* (H1): *group*, *S1 color* and their interaction as fixed factors, random slopes for *S1 color* within participant;
2. *valence* and *arousal ratings* (H2a vs. H2b): *group*, *S2 valence* and their interaction as fixed factors, random slopes for *S2 valence* within participant.

Furthermore, to assess the differences between expected and unexpected S2s, we ran the following exploratory analysis: we added *S2 congruency* (within-subjects: congruent vs. incongruent), and its interaction with *group* and *S2 valence* as fixed factors to the confirmatory models for *valence* and *arousal ratings*.

Influential cases for each confirmatory model were evaluated through Cook's distance (>1). No influential cases emerged. Models effects were evaluated using *F*-test and *p*-values, calculated via Satterthwaite's degrees of freedom method ($\alpha = .05$, R package: lmerTest; Kuznetsova et al., 2017). For each model we reported the estimated parameters with 95% confidence intervals (CI). We also reported marginal and conditional R^2 (estimated as in Nakagawa et al., 2017), that represent the variance explained by *fixed effects* and by *fixed plus random effects*, respectively.

2.1.4) Transparency and openness

The study has been pre-registered on OSF (<https://osf.io/ef9q7/>). The experiment's file (containing all the stimulus material), the pilot pre-processed dataset, and the power analysis R syntax are included in the pre-registration. The final pre-processed dataset, and the analysis R syntax are available at the GitHub repository linked to the pre-registration (<https://osf.io/ef9q7/>).

2.2) Results

All confirmatory models are summarized in Table 1 and Figure 2. For the *expectancy* model ($R^2_{\text{marginal}} = 0.216$, $R^2_{\text{conditional}} = 0.496$), we found a main effect of *S1 color* ($F(1, 183) = 90.2$, $p < 0.001$) and an interaction between *S1 color* and *group* ($F(1, 183) = 65.30$ $p < 0.001$).

In line with the assumption that participants learned probabilistic relationships in the learning phase, we found that participants in the CG reported significantly more negative expectancy ratings after the red color (i.e., circles preceding negative pictures) as compared to the blue color (i.e., circles preceding neutral pictures) (blue - red = -35.2, $t(183) = -13.12$, $p < 0.001$, 95% CI = [-40.54, -29.94]), whereas in the UG no differences in expectancy ratings as a function of the S1 color emerged (blue - red = -2.8, $t(183) = -0.96$, $p = 0.34$, 95% CI = [-8.72, 3.03]). Contrary to H1, however, we did not find any significant main effect of *group* ($F(1, 183) = 0.02$, $p = 0.9$). Thus, the expectancy model does not support the hypothesis of more negative expectancy ratings in the UG as compared to the CG (H1).

For both *valence* ($R^2_{\text{marginal}} = 0.622$, $R^2_{\text{conditional}} = 0.723$) and *arousal* ($R^2_{\text{marginal}} = 0.293$, $R^2_{\text{conditional}} = 0.556$) models testing H2a vs. H2b, we found a main effect of *S2 valence*, with both groups reporting significantly greater unpleasantness ($F(1, 183) = 1393$, $p < 0.001$, neg - neu = -47.55, SE = 1.27, $t(183) = -37.32$, $p < 0.001$, 95% CI = [-50.06, -45.03]) and higher arousal ($F(1, 183) = 332.68$, $p < 0.001$, neg - neu = 26.69, SE = 1.46, $t(183) = 18.24$, $p < 0.001$, 95% CI = [23.79, 29.57]) towards negative pictures. However, in contrast with H2a and H2b, we found no evidence for the interaction effect between *S2 valence* and *group* both for *valence* ($F(1, 183) = 0.07$, $p = 0.799$) and *arousal ratings* ($F(1, 183) = 0.82$, $p = 0.364$). Thus, neither valence nor arousal models support the hypothesis of an affect intensification in the UG (H2a) or in the CG (H2b) as compared to the other group.

Exploratory models are summarized in Table 2.

Model	Parameter	Estimate	SE	<i>t</i>	df	<i>p</i>	95% CI	
Expectancy ratings	Intercept	52.96	0.57	93.46	183.00	< 0.001	51.84	54.08
	UG - CG	-0.15	1.13	-0.13	183.00	0.897	-2.38	2.09
	blue - red	-19.04	2.00	-9.50	182.99	< 0.001	-23.00	-15.09
	color x group	-32.40	4.01	-8.08	182.99	< 0.001	-40.31	-24.49
	σ ID	6.98						
	σ color	26.37						
	σ residual	20.04						
Valence ratings	Intercept	45.49	0.40	112.42	183.00	< 0.001	44.69	46.28
	UG - CG	-0.73	0.81	-0.90	183.00	0.369	-2.33	0.87
	neg - neu	-47.55	1.27	-37.32	183.00	< 0.001	-50.06	-45.04
	valence x group	0.65	2.55	0.26	183.00	0.799	-4.38	5.68
	σ ID	4.87						
	σ valence	16.49						
	σ residual	15.87						
Arousal ratings	Intercept	47.67	0.63	75.12	183.00	< 0.001	46.42	48.93
	UG - CG	0.17	1.27	0.13	183.00	0.894	-2.33	2.67
	neg - neu	26.69	1.46	18.24	183.00	< 0.001	23.80	29.57
	valence x group	-2.66	2.93	-0.91	183.00	0.364	-8.44	3.11
	σ ID	8.19						
	σ valence	19.11						

Table 1. Results of confirmatory LMMs on *expectancy*, *valence* and *arousal* ratings in Experiment 1. For each model, we reported the unstandardized regression coefficients, standard errors (SE), 95% confidence intervals (CI), and the associated *t*-test.

Figure 2. Box-plot of *expectancy*, *valence* and *arousal* ratings in Experiment 1 according to the *group* (CG vs. UG), and the *S1 color* (red vs. blue, for expectancy ratings) or the *S2 valence* (neg vs. neu, for valence and arousal ratings). Points represent the mean estimated value for each participant and condition.

Model	Parameter	Estimate	SE	<i>t</i>	df	<i>p</i>	95% CI	
Valence ratings	Intercept	46.44	0.42	111.05	208.84	< 0.001	45.62	47.27
	UG - CG	-0.52	0.84	-0.62	208.84	0.535	-2.17	1.13
	neg - neu	-45.60	1.29	-35.30	193.21	< 0.001	-48.14	-43.05
	congruent - incongruent	-3.83	0.42	-9.06	7,026.01	< 0.001	-4.66	-3.00
	valence x group	1.10	2.58	0.43	193.21	0.669	-3.99	6.20
	group x congruency	-0.84	0.85	-0.99	7,026.01	0.322	-2.50	0.82
	valence x congruency	-7.82	0.85	-9.24	7,026.01	< 0.001	-9.47	-6.16
	group x valence x congruency	-1.82	1.69	-1.07	7,026.01	0.283	-5.14	1.50
	σ ID	4.88						
	σ valence	16.51						
	σ residual	15.68						
Arousal ratings	Intercept	47.33	0.64	73.48	194.20	< 0.001	46.06	48.60
	UG - CG	0.17	1.29	0.13	194.20	0.893	-2.37	2.71
	neg - neu	25.53	1.48	17.26	191.40	< 0.001	22.62	28.45
	congruent - incongruent	1.36	0.44	3.09	7,026.00	0.002	0.50	2.23
	valence x group	-2.47	2.96	-0.83	191.40	0.405	-8.31	3.37
	group x congruency	-0.01	0.88	-0.02	7,026.00	0.987	-1.74	1.71
	valence x congruency	4.61	0.88	5.22	7,026.00	< 0.001	2.88	6.33
	group x valence x congruency	-0.77	1.76	-0.44	7,026.00	0.663	-4.22	2.69

σ ID	8.19
σ valence	19.11
σ residual	16.33

Table 2. Results of exploratory LMMs investigating the effect of *S2 congruency* (congruent vs. incongruent) on *valence* and *arousal ratings* in Experiment 1. For each model, we reported the unstandardized regression coefficients, standard errors (SE), 95% confidence intervals (CI), and the associated *t*-test.

2.3) Discussion

Experiment 1 demonstrated that within the visual sensory modality previous probabilistic information shaped the subjective experience of the expected valence of future stimuli (i.e., the *generation-implementation* stages of affective prediction construction), but not of their experienced valence and intensity (i.e., the *updating* stage). Participants in the CG - who during the learning phase were exposed to totally reliable S1-S2 relationships - during the test phase reported more negative expectancy ratings after the cues whose color was previously paired with negative pictures; whereas expectancy ratings of participants in the UG were not modulated by the color of the cue. This suggests that, within the visual modality, experiencing a past environment conveying certain probabilistic information leads people's subjective expectancies to subsequently rely on previous experience to consistently *generate* and *implement* new affective predictions. Having learned that a specific environmental cue reliably predicts a negative stimulus will thus coherently modulate subjective expectancies towards a more negative valence. Contrary to our hypothesis (H1), however, we did not find any evidence of negatively-biased expectancy ratings in the UG. This unexpected result can be explained by the differences between our experimental paradigm and the extant literature from which we derived our hypothesis (Dieterich et al., 2016; Grupe & Nitschke, 2011; Herwig et al., 2007;

Qiao et al., 2018; Schumacher et al., 2015). The latter measured expectancy in relation to *currently available, instructed* probabilistic information; whereas in our experimental paradigm participants *previously* learned *uninstructed* certain or uncertain contingencies, and only in a subsequent moment they were asked to express their expectancy ratings within a different probabilistic context. It is possible that experiencing a high uncertainty level (i.e., 50%) in the *here and now* might push subjective experience towards a negative bias (as it has been found in the literature), whereas this effect might be dampened when uncertain *past* experience is used at a later time to generate and implement new predictions (as it happens in our paradigm).

Regarding the *updating* stage, we found no evidence for an affect intensification effect strictly related to previous experience. In fact, no significant group differences emerged on valence and arousal ratings. This result is in contrast with our hypotheses (H2a and H2b), which were derived from the literature assessing subjective experience with regard to currently available, instructed probabilistic information (Johnen & Harrison, 2019; Lin et al., 2017, 2020; Lin, Jin, et al., 2015; Lin, Xiang, et al., 2015). It is however consistent with some extant evidence of null interactions between probabilistic information and subjective valence ratings (Bermpohl et al., 2006; Dieterich et al., 2016; Greenberg et al., 2015; Grupe & Nitschke, 2011; Lin et al., 2018; Qiao et al., 2018). Thus, subjective reactions during the *updating* stage do not seem to be affected by previous (un)certain learning, showing only a valence-dependent modulation, with both groups reporting greater unpleasantness and higher arousal towards negative stimuli. This can be partially ascribed to a ceiling effect, such that the intrinsic differences in valence between negative and neutral visual stimuli were so prominent that they might have eventually captured most of the variance in the valence and arousal ratings.

Thus, given that results of Experiment 1 suggested that previous experience shaped the subjective reactions to new affective predictions only with regards to the *generation-*

470 *implementation* stages, whereas it did not lead to an intensification of affect during the *updating*
471 stage, in Experiment 2 we tested if these results hold when previous experience and new
472 predictions tap into different sensory modalities.

473

3) EXPERIMENT 2

Experiment 2 investigated how being exposed to certain vs. uncertain probabilistic relationships between stimuli in one sensory modality (i.e., visual) might influence the subjective affective experience to new affective predictions when it crosses over to a different sensory modality (i.e., auditory).

We tested the same a-priori and pre-registered (<https://osf.io/wcy9r/>) hypotheses as in Experiment 1 (H1, H2a, H2b). Furthermore, we explored whether the influence of previous experience on subjective affective ratings differed between Experiment 1 and Experiment 2.

3.1) Methods

3.1.1) Participants

According to an a-priori power-analysis (see 2.1.1 for details), we recruited 200 adult participants through the provider platform Prolific (Prolific, Oxford, UK; www.prolific.co). Data from 17 participants were discarded according to the pre-registered exclusion criteria (<https://osf.io/wcy9r/>). Furthermore, data from 3 participants were discarded because of data collection failure, and 1 participant reported to be affected by hearing impairment, thus they were excluded from data analysis.

The final sample was 179 participants (97 males, age: $M = 26.05$, $SD = 7.86$, range = 18-59). All participants gave their informed consent before starting the experiment, and were paid £2.67 for their participation. All experimental procedures were approved by the Ethical Committee for the Psychological Research of the University of Padua (protocol no. 4012), and were conducted in accordance with the Declaration of Helsinki.

3.1.2) Stimulus material and procedure

The experiment was run online, through OpenSesame (Mathôt et al., 2012) and the JATOS hosting server (Lange et al., 2015). Two S1-S2 paradigms were employed as a learning and a test phase, respectively. S1s were the same as in Experiment 1. NAPS pictures (20

negative, 20 neutral) (Marchewka et al., 2014) were employed as S2s for the learning phase. Affective sounds (40 negative, 40 neutral) from International Affective Digitized Sounds (IADS-2) (Bradley & Lang, 2007) were employed as S2s for the test phase. NAPS pictures names, and IADS-2 sounds numbers, sorted by valence, are listed in Supplementary Table S3. Negative and neutral pictures, and sounds did not differ in terms of physical properties (i.e., luminance, contrast, complexity, and color space for pictures; max dB, min dB, and peak dB for sounds) (see Supplementary Table S4). During attention check trials, a white noise sound was used as S2 for the test phase. Three VASs were used to collect *expectancy* (from 0% “I definitely expect to hear a neutral sound” to 100% “I definitely expect to hear a negative sound”), *valence* (from 0% “very negative” to 100% “very positive”) and *arousal* (from 0% “relaxed” to 100% “aroused”) *ratings*.

Before the learning phase participants were randomly assigned to the CG or the UG. They were instructed to ensure silent and private environmental conditions for participation: they were asked to avoid potential distractions and interruptions, and to perform the study alone, where no one else could view the computer screen nor hear the sounds due to the involvement of emotionally evocative material. The learning phase was identical to Experiment 1.

At the end of the learning phase participants were asked to wait and relax for 1 minute, and then they were introduced to the test phase, identical for both groups. Instructions, practice trials, and trial number and structure of the test phase were the same as in Experiment 1 (adapting the wording from visual to auditory modality). S1, ISI, and ITI timings were unchanged, whereas S2s were presented in their full length of 6000 msec (see Figure 1b for a schematic representation of the experimental paradigm).

At the end of the test phase, participants were redirected to the Qualtrics survey (see 2.1.2), and then back to Prolific to complete the study submission and receive their payment.

3.1.3) Data analysis

The study has a 2 (*group*, between-subjects: CG vs. UG) $\times$ 2 (*S2 valence*, within-subjects: negative - neg vs. neutral - neu) mixed design. The analysis plan was pre-registered on OSF (<https://osf.io/wcy9r/>).

Data from 11 participants were detected as univariate outliers ($MAD > 3$). From visual inspection of their ratings, it emerged that 7 of them had reversed the poles of the rating scale (“error outliers”, cf. Leys et al., 2019), thus they were excluded from data analysis. Data from 54 participants were detected as multivariate outliers (MMCD, breakdown point 0.25). From visual inspection of their ratings, 1 of them was identified as having reversed the rating scales’ poles (“error outlier”, cf. Leys et al., 2019), and removed from data analysis. The remaining 57 outliers were characterized by a slightly flattened or steeper relationship between valence and arousal ratings as compared to other participants. Thus, since none of them significantly impacted the models’ estimates (as assessed through Cook’s distance), we chose to keep them into data analysis (“potentially interesting outliers”, cf. Leys et al., 2019). Data from 171 participants entered data analysis.

In order to test our a-priori hypotheses (H1, H2a, H2b), for each DV we fitted the following LMMs (R package: lme4; Bates et al., 2015):

1. *expectancy ratings* (H1): *group*, *S1 color* and their interaction as fixed factors, random slopes for *S1 color* within participant;
2. *valence* and *arousal ratings* (H2a vs. H2b): *group*, *S2 valence* and their interaction as fixed factors, random slopes for *S2 valence* within participant.

Furthermore, we ran some exploratory analyses. To assess the differences between expected and unexpected S2s, we added *S2 congruency*, and its interaction with *group* and *S2 valence* as fixed factors to the confirmatory models for *valence* and *arousal ratings*. To compare results from Experiment 1 and Experiment 2, we merged the two datasets, and added

the *study* (between-subjects: Experiment 1 vs. Experiment 2) as a fixed factor to the confirmatory LMMs.

For each confirmatory model no influential cases emerged, as evaluated through Cook's distance (>1). Models effects were evaluated using *F*-test and *p*-values, calculated via Satterthwaite's degrees of freedom method ($\alpha = .05$, R package: lmerTest; Kuznetsova et al., 2017). For each model we reported the estimated parameters with 95% CI. We also reported marginal and conditional R^2 (estimated as in Nakagawa et al., 2017), that represent the variance explained by *fixed effects* and by *fixed plus random effects*, respectively.

3.1.4) Transparency and openness

The study has been pre-registered on OSF (<https://osf.io/wcy9r/>). The experiment's file (containing all the stimulus material) is included in the pre-registration. The final pre-processed dataset, and the analysis R syntax are available at the GitHub repository linked to the pre-registration (<https://osf.io/wcy9r/>).

3.2) Results

All confirmatory models are summarized in Table 3 and Figure 3. For the *expectancy* model ($R^2_{\text{marginal}} = 0.145$, $R^2_{\text{conditional}} = 0.468$) replicating the finding from Experiment 1, we found a main effect of *SI color* ($F(1, 183) = 73.25$, $p < 0.001$), and an interaction between *SI color* and *group* ($F(1, 183) = 18.45$, $p < 0.001$). In particular, we found that participants reported significantly more negative expectancy ratings after the red color (i.e., circles preceding negative sounds) as compared to the blue one (i.e., circles preceding neutral sounds), both in the CG (blue - red = -27.97 , $t(183) = -8.86$, $p < 0.001$, 95% CI = $[-34.20, -21.73]$) and in the UG (blue - red = -9.28 , $t(183) = -3.09$, $p = 0.002$, 95% CI = $[-15.19, -3.36]$) condition. To better understand these two contrasts we computed a standardized effect size, dividing the mean difference between blue and red cues within each group by the total estimated variability from the LMM (as in Westfall et al., 2014). The blue vs. red standardized difference was -0.81

in the CG and -0.269 in the UG. Thus, despite both contrasts being statistically significant, the standardized difference between red and blue cues is clearly greater (and therefore of relevant interest for the purposes of an interpretation) in the CG. Contrary to H1, we did not find any significant main effect of *group* ($F(1, 183) = 0.35, p = 0.56$). Therefore, the expectancy model does not support the hypothesis of more negative expectancy ratings in the UG as compared to the CG (H1).

For both *valence* ($R^2_{\text{marginal}} = 0.471, R^2_{\text{conditional}} = 0.540$) and *arousal* ($R^2_{\text{marginal}} = 0.274, R^2_{\text{conditional}} = 0.398$) models testing H2a vs. H2b, we found a main effect of *S2 valence*, with both groups reporting significantly greater unpleasantness ($F(1, 169) = 1490.65, p < 0.001$, neg - neu = -37.67, SE = 0.98, $t(183) = -38.61, p < 0.001$, 95% CI = [-39.59, -35.74]) and higher arousal ($F(1, 169) = 870.40, p < 0.001$, neg - neu = 25.24 SE = 0.86, $t(183) = -37.32, p < 0.001$, 95% CI = [23.55, 26.93]) towards negative sounds. We also found evidence for interaction between *S2 valence* and *group* on both *valence* ($F(1, 169) = 4.72, p = 0.031$) and *arousal* models ($F(1, 169) = 5.30, p = 0.022$), as hypothesized (H2a and H2b). However from post-hoc contrasts we did not find evidence for significant differences between the CG and the UG within each *S2 valence* level for both *valence* (neu: CG - UG = 2.54, SE = 1.32, $t(169) = 1.92, p = 0.056$, 95% CI = [-0.06, 5.14]; neg: CG - UG = -1.70, SE = 1.22, $t(169) = -1.39, p = 0.166$, 95% CI = [-0.22, 0.03]) and *arousal ratings* (neu: CG - UG = -2.07, SE = 1.31, $t(169) = -1.58, p = 0.117$, 95% CI = [-4.67, 0.52]; neg: CG - UG = 1.86, SE = 1.56, $t(169) = 1.19, p = 0.235$, 95% CI = [-1.22, 4.97]). Thus, neither valence nor arousal models support the hypothesis of an affect intensification in the UG (H2a) or in the CG (H2b) as compared to the other group.

Experiment 2 exploratory models are summarized in Table 4.

Model	Parameter	Estimate	SE	t	df	p	95% CI	
Expectancy ratings	Intercept	53.40	0.54	99.62	169	< 0.001	52.34	54.46
	UG - CG	0.63	1.07	0.59	169	0.557	-1.48	2.75
	blue - red	-18.62	2.18	-8.56	169	< 0.001	-22.92	-14.33
	color x group	-18.69	4.35	-4.30	169	< 0.001	-27.28	-10.10
	σ ID	6.28						
	σ color	27.73						
	σ residual	19.56						
Valence ratings	Intercept	41.46	0.41	101.44	169	< 0.001	40.65	42.26
	UG - CG	0.42	0.82	0.51	169	0.609	-1.19	2.03
	neg - neu	-37.67	0.98	-38.61	169	< 0.001	-39.59	-35.74
	valence x group	-4.24	1.95	-2.17	169	0.031	-8.09	-0.39
	σ ID	4.45						
	σ valence	11.30						
	σ residual	18.59						
Arousal ratings	Intercept	59.94	0.58	102.68	169	< 0.001	58.79	61.09
	UG - CG	-0.10	1.17	-0.09	169	0.931	-2.41	2.20
	neg - neu	25.24	0.86	29.50	169	< 0.001	23.55	26.93
	valence x group	3.94	1.71	2.30	169	0.022	0.56	7.32
	σ ID	7.03						
	σ valence	9.48						

Table 3. Results of confirmatory LMMs on *expectancy*, *valence* and *arousal* ratings in Experiment 2. For each model we reported the unstandardized regression coefficients, standard errors (SE), 95% confidence intervals (CI), and the associated *t*-test.

Figure 3. Box-plot of *expectancy*, *valence* and *arousal* ratings in Experiment 2 according to the *group* (CG vs. UG), and the *S1 color* (red vs. blue, for expectancy ratings) or the *S2 valence* (neg vs. neu, for valence and arousal ratings). Points represent the mean estimated value for each participant and condition.

Model	Parameter	Estimate	SE	<i>t</i>	df	<i>p</i>	95% CI	
Valence ratings	Intercept	42.13	0.43	98.30	204.39	< 0.001	41.29	42.98
	UG - CG	0.44	0.86	0.52	204.39	0.607	-1.25	2.13
	neg - neu	-35.69	1.01	-35.36	193.50	< 0.001	-37.68	-33.70
	congruent - incongruent	-2.70	0.52	-5.22	6,494.00	< 0.001	-3.71	-1.69
	valence x group	-3.52	2.02	-1.74	193.50	0.083	-7.50	0.46
	group x congruency	-0.09	1.03	-0.09	6,494.00	0.929	-2.12	1.93
	valence x congruency	-7.93	1.03	-7.68	6,494.00	< 0.001	-9.96	-5.91
	group x valence x congruency	-2.87	2.07	-1.39	6,494.00	0.165	-6.92	1.18
	σ ID	4.47						
	σ valence	11.32						
	σ residual	18.47						
Arousal ratings	Intercept	59.48	0.60	99.45	186.22	< 0.001	58.30	60.66
	UG - CG	-0.15	1.20	-0.12	186.22	0.903	-2.51	2.21
	neg - neu	23.85	0.89	26.67	201.72	< 0.001	22.09	25.61
	congruent - incongruent	1.83	0.52	3.52	6,494.00	< 0.001	0.81	2.86
	valence x group	3.40	1.79	1.90	201.72	0.058	-0.12	6.93
	group x congruency	0.18	1.04	0.17	6,494.00	0.866	-1.87	2.22
	valence x congruency	5.56	1.04	5.34	6,494.00	< 0.001	3.52	7.60

group x valence x congruency	2.15	2.08	1.03	6,494.00	0.303	-1.94	6.23
σ ID	7.03						
σ valence	9.49						
σ residual	18.62						

Table 4. Results of exploratory LMMs investigating the effect of *S2 congruency* (congruent vs. incongruent) on *valence* and *arousal ratings* in Experiment 2. For each model, we reported the unstandardized regression coefficients, standard errors (SE), 95% confidence intervals (CI), and the associated *t*-test.

Exploratory models comparing results of Experiment 1 and 2 are summarized in Figure 4. For the *expectancy* model ($R^2_{\text{marginal}} = 0.184$, $R^2_{\text{conditional}} = 0.483$) we found evidence for a three-way interaction ($F(1, 352) = 5.385$, $p = 0.021$) between *study*, *group* and *S1 color*. However, none of the post-hoc comparisons between Experiment 1 and Experiment 2 emerged as statistically significant. For the *valence* model ($R^2_{\text{marginal}} = 0.559$, $R^2_{\text{conditional}} = 0.645$) we found an interaction between *study* and *S2 valence* ($F(1, 352) = 37.09$, $p < 0.001$). In particular, neutral sounds were rated as more unpleasant than neutral pictures (neu: Experiment 1 - Experiment 2 = 8.969, SE = 1.054, $z = 8.508$, $p < 0.001$)¹. Finally, for *arousal* model ($R^2_{\text{marginal}} = 0.327$, $R^2_{\text{conditional}} = 0.512$) we only found a main effect of *study*, with sounds rated overall as more arousing than visual stimuli independently from valence (Experiment 1 - Experiment 2 = -12.3, $z = -14.16$, SE = 0.87, $p < 0.001$)¹. Thus, none of the exploratory comparisons between Experiment 1 and Experiment 2 collected evidence in favor of a different effect of our experimental manipulation of previous experience as a function of the sensory modality involved.

¹ We are using *z*-test for post hoc-comparison given that the computation of degrees of freedom is memory intensive due to the LMM computed on data from two experiments.

627

628 **Figure 4.** Top: box-plot of *expectancy ratings* according to the *study* (Experiment 1 vs.
629 Experiment 2), the *group* (CG vs. UG), and the *S1 color* (red vs. blue). Middle: box-plot of
630 *valence ratings* according to the *study* (Experiment 1 vs. Experiment 2), and *S2 valence* (neg
631 vs. neu). Bottom: box-plot of *arousal ratings* according to the *study* (Experiment 1 vs.
632 Experiment 2). Points represent the mean estimated value for each participant and condition.

3.3) Discussion

Experiment 2 (visual to auditory) demonstrated that previous visual probabilistic information shaped the subjective experience of the expected valence of future auditory stimuli (i.e., *generation-implementation* stages), but not of their experienced valence and intensity (i.e., *updating* stage), similarly as it occurred in Experiment 1 (visual to visual). In Experiment 2 we replicated results of Experiment 1, with participants in the CG showing more negative expectancy ratings after the cues whose color was previously paired with negative stimuli. Surprisingly, more negative expectancy ratings were found to follow red cues also in the UG. Nevertheless, since the effect size for the red-blue contrast within the CG (-0.81) is three times the effect within the UG (-0.269), this last result should be interpreted with caution. In fact, in the UG the cue color had no real predictive value, because during the learning phase each color was paired equally often with either negative or neutral stimuli, thus participants could not learn any reliable S1-S2 relationship. Therefore, considering the effect sizes of both contrasts and the absence of an actual predictive meaning of cues in the UG, the red-blue contrast within this group may be considered of negligible significance. Overall, according to our results, experiencing a past certain environment in one sensory modality (i.e., visual) leads people's subjective expectancies to subsequently rely on previous experience to consistently *generate* and *implement* new affective predictions also in a different sensory modality (i.e., auditory).

Regarding the *updating* stage, as in Experiment 1 we found no evidence of an affect intensification effect related to previous experience. Even though we found a significant group by valence interaction in both valence and arousal models, post-hoc comparisons between groups did not reach statistical significance. Therefore, subjective reactions during the *updating* stage do not seem to be affected by previous (un)certain learning also when the learning occurs

in a different sensory modality (i.e., visual) from the one involved in the present moment (i.e., auditory).

Last, no evidence of a difference between sensory modalities in the influence of previous experience on subjective reactions emerged. No meaningful group by study interaction was found in the exploratory models run on the merged dataset (Experiment 1 + Experiment 2). Thus, consistently with the *predictive framework* (Barrett, 2017; Friston, 2010; Seth & Friston, 2016; Shipp, 2016), this supports the claim that affective predictions develop similarly across sensory modalities. Only a general effect of sensory modality emerged with regards to the *updating* stage, with neutral sounds eliciting more unpleasant valence ratings than neutral pictures, and sounds eliciting higher arousal ratings than pictures regardless of valence. These effects may be due to the heightened ambiguity of affective sounds as compared to pictures (Shinkareva et al., 2014), which can produce a greater allocation of processing resources towards sounds, and which can thus eventually turn into a more intense subjective reaction. Alternatively, they may be ascribed to the longer presentation length of auditory stimuli (i.e., 6 sec) as compared to visual ones (i.e., 1 sec).

4) GENERAL DISCUSSION

Our study represents to our knowledge the first attempt to empirically investigate the role of previous experience in the construction of new affective predictions, both within and across sensory modalities, and with a specific focus on subjective experience. We employed a novel experimental paradigm, purposely developed to address our research questions, and to fill some of the gaps in the existing literature. First, our experimental design combined the logic of emotional S1-S2 paradigms with an uninstructed learning component. This allowed our paradigm to implement the role of *actual previous experience* in constructing new predictions, by manipulating the experienced (un)certain probabilistic relationships between stimuli. Second, it allowed us to target all the stages of the (affective) prediction construction process (*generation-implementation-updating*), and to study *cross-modality generalization* between the visual and auditory modalities. Last, by leaving participants *uninstructed* about the specific contingency ratios they were exposed to, our paradigm allowed us to specifically target subjective experience more similarly to how it spontaneously develops in everyday life contexts.

Overall, we found that being exposed to certain vs. uncertain previous experience affected the *generation-implementation* stages of future prediction construction, but not the *updating* stage. In both the experiments, participants who had previously experienced certain probabilistic relationships between stimuli, reported more negative expectancy ratings after the specific cues which were previously paired with negative stimuli. According to the *predictive framework* (Barrett, 2017; Seth & Friston, 2016), this supports the claim that learning certain probabilistic relationships between stimuli could make the derived internal models highly reliable. As a consequence, when constructing new affective predictions, subjective expectancies will fully tap into previously acquired knowledge, coherently labeling the expected valence of future stimuli. Furthermore, in line with *predictive models* assumptions

(Barrett, 2017; Friston, 2010; Shipp, 2016), this process emerged to develop similarly (and thus, to be generalizable) across the visual and auditory sensory modalities, supporting the idea that (affective) predictive models are represented multimodally (Barrett, 2017; Friston, 2005; Peelen et al., 2010).

Surprisingly, we found no evidence about an intensification of subjective reactions during the *updating* stage as a function of the uncertainty degrees previously experienced. According to the *predictive framework* (Barrett, 2017; Seth & Friston, 2016), it could be expected that having at one's disposal a reliable predictive model would lead to a pre-activation of the expected affective experience, with the consequence of producing an intensification of subjective reactions when the expected stimuli actually occur. Our results, however, only partially support this claim. In fact, in both the experiments we did not find any evidence of an affect intensification effect strictly related to previous experience (i.e., the two experimental groups did not significantly differ in terms of their valence and arousal ratings during the test phase). However, an interesting result emerged from exploratory models assessing the differences between expected and unexpected S2s by comparing affective ratings between congruent and incongruent test trials (see Tables 2 and 4). In both the experiments and in both the groups, congruent negative stimuli (i.e., negative stimuli more strongly expected) were rated as more unpleasant and more arousing than incongruent ones (i.e., negative stimuli violating expectancies), thus leading to an intensification of subjective experience. Restating the differences between *currently available* and *previously learned* probabilistic information (see 2.3), it is possible that experiencing a sufficient certainty level in the *here and now* (i.e., contingencies experienced during the test phase, 75%) might drive subjective reactions towards an affect intensification, whereas this effect is dampened when referring to the uncertainty degrees experienced in the *past* (i.e., contingencies experienced during the learning phase, 100% vs. 50%). Thus, it may be that subjective experience in the *updating* stage is more

prominently modulated by currently available probabilistic information rather than by past learnings.

Summarizing, our results add a further piece of knowledge about the mechanisms by which previous information shapes the subjective experience of emotion, as defined within a *predictive framework* (Barrett, 2017; Seth & Friston, 2016). We demonstrated that, without the need of any explicit instruction, people are able to build affective predictive models from the simple exposure to contingencies between stimuli (learning phase). This presumably happens thanks to associative learning mechanisms, which are assumed to be amongst the primary mechanisms on which prediction construction relies (Bar, 2007; Dale et al., 2012). Those affective predictive models, and their associated reliability value, are then used in a subsequent moment (test phase) to coherently predict (and make meaning of) relevant events in the present environment: the more reliable the available predictive model, the more subjective expectancies draw on it to make meaning of environmental cues and predict the emotional valence of upcoming stimuli. Furthermore, we demonstrated that this process is generalizable across sensory modalities, since the available predictive models (derived from the exposure to contingencies in the visual modality) proved to shape subjective expectancies of future stimuli also within a different (auditory) sensory modality. However, although previous experience did indeed modulate the *generation-implementation* of new affective predictions, it proved ineffective in shaping subjective reactions to new affective stimuli during prediction *updating*. The actual stimuli incoming during the updating stage represent the information array that must be tested against predictions, in order to adjust future predictions (Barrett, 2017; Seth & Friston, 2016). Thus, in making meaning of them, it might be more crucial to draw on the information available in the *here and now* (i.e., if the new stimuli actually confirm or violate predictions, according to the present context), rather than to draw on *past* experience.

Concluding, some limitations of the present study must be addressed. First, we employed unambiguous symbolic stimuli as S1s, and unimodal affective stimuli as S2s. Although this choice makes our paradigm similar (and thus, comparable) with the emotional S1-S2 paradigms existing in the literature, it still remains quite artificial as compared to the multifaceted environments we are embedded in our everyday lives. Employing ambiguous cues, multimodal or dynamic affective stimuli, and/or different environments might allow future S1-S2 paradigms to reach a better ecological validity. Second, even though our paradigm employed more realistic (i.e., uninstructed) probabilistic ratios, participants were however invited to pay attention to the relationships between stimuli they were exposed to. Therefore, our paradigm did not allow us to understand if contingencies might be effectively learned at a fully *implicit* level, as it should occur according to the *predictive framework* (Bar, 2007). Thus, we encourage future research to overcome these limitations by employing also different kinds of affective stimuli (e.g., ambiguous, multimodal, dynamic), and by making the exposure to previous experience fully implicit (e.g., by engaging participants in a distracting task during the learning phase). Furthermore, as a future line of research, it could be interesting also to combine the assessment of the overt subjective experience with the measurement of more covert (psychophysiological or neural) indices.

5) AUTHOR NOTE

All materials, data and analysis code reported in this manuscript have been made publicly available on OSF and can be accessed at the links <https://osf.io/ef9q7/> and <https://osf.io/wcy9r/>.

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7) REFERENCES

- Bar, M. (2007). The proactive brain: Using analogies and associations to generate predictions. *Trends in Cognitive Sciences*, 11(7), 280–289. <https://doi.org/10.1016/J.TICS.2007.05.005>
- Bar-Anan, Y., Wilson, T. D., & Gilbert, D. T. (2009). The Feeling of Uncertainty Intensifies Affective Reactions. *Emotion*, 9(1), 123–127. <https://doi.org/10.1037/a0014607>
- Barrett, L. F. (2017). The theory of constructed emotion: An active inference account of interoception and categorization. *Social Cognitive and Affective Neuroscience*, 12(1), 1–23. <https://doi.org/10.1093/scan/nsw154>
- Barrett, L. F., Mesquita, B., Ochsner, K. N., & Gross, J. J. (2007). The Experience of Emotion. *Annual review of psychology*, 58, 373–403. <https://doi.org/10.1146/annurev.psych.58.110405.085709>
- Barrett, L. F., Wilson-Mendenhall, C. D., & Barsalou, L. W. (2014). The conceptual act theory: A roadmap. In L. F. Barrett & J. A. Russell (A c. Di), *The psychological construction of emotion* (pagg. 83–110). Guilford Press.
- Bates, D., Mächler, M., Bolker, B. M., & Walker, S. C. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1). <https://doi.org/10.18637/jss.v067.i01>
- Berpohl, F., Pascual-Leone, A., Amedi, A., Merabet, L. B., Fregni, F., Gaab, N., Alsop, D., Schlaug, G., & Northoff, G. (2006). Attentional modulation of emotional stimulus processing: An fMRI study using emotional expectancy. *Human Brain Mapping*, 27(8), 662–677. <https://doi.org/10.1002/hbm.20209>
- Bradley, M. M., & Lang, P. J. (2007). The International Affective Digitized Sounds (2nd Edition; IADS-2): Affective ratings of sounds and instruction manual. *Technical report B-3. University of Florida, Gainesville, Fl.*

801 Carleton, R. N. (2016a). Fear of the unknown: One fear to rule them all? *Journal of*
802 *Anxiety Disorders*, 41, 5–21. <https://doi.org/10.1016/j.janxdis.2016.03.011>

803 Carleton, R. N. (2016b). Into the unknown: A review and synthesis of contemporary
804 models involving uncertainty. *Journal of Anxiety Disorders*, 39, 30–43.
805 <https://doi.org/10.1016/j.janxdis.2016.02.007>

806 Clark, A. (2013). Whatever next? Predictive brains, situated agents, and the future of
807 cognitive science. *Behavioral and Brain Sciences*, 36(3), 181–204.
808 <https://doi.org/10.1017/S0140525X12000477>

809 Dale, R., Duran, N. D., & Morehead, J. R. (2012). Prediction during statistical learning,
810 and implications for the implicit/explicit divide. *Advances in Cognitive Psychology*, 8(2), 196–
811 209. <https://doi.org/10.2478/v10053-008-0115-z>

812 Del Popolo Cristaldi, F., Mento, G., Buodo, G., & Sarlo, M. (2021). What's next?
813 Neural correlates of emotional predictions: A high-density EEG investigation. *Brain and*
814 *Cognition*, 150, 105708. <https://doi.org/10.1016/j.bandc.2021.105708>

815 Dieterich, R., Endrass, T., & Kathmann, N. (2016). Uncertainty is associated with
816 increased selective attention and sustained stimulus processing. *Cognitive, Affective, &*
817 *Behavioral Neuroscience*, 16(3), 447–456. <https://doi.org/10.3758/s13415-016-0405-8>

818 Einstein, D. A. (2014). Extension of the Transdiagnostic Model to Focus on Intolerance
819 of Uncertainty: A Review of the Literature and Implications for Treatment. *Clinical*
820 *Psychology: Science and Practice*, 21(3), 280–300. <https://doi.org/10.1111/cpsp.12077>

821 Friston, K. (2005). A theory of cortical responses. *Philosophical transactions of the*
822 *Royal Society B: Biological sciences*, 360(1456), 815–836.
823 <https://doi.org/10.1098/rstb.2005.1622>

824 Friston, K. (2010). The free-energy principle: A unified brain theory? *Nature Reviews*
825 *Neuroscience*, 11(2), 127–138. <https://doi.org/10.1038/nrn2787>

826 Green, P., & MacLeod, C. J. (2016). SIMR: An R package for power analysis of
827 generalized linear mixed models by simulation. *Methods in Ecology and Evolution*, 7(4), 493–
828 498. <https://doi.org/10.1111/2041-210X.12504>

829 Greenberg, T., Carlson, J. M., Rubin, D., Cha, J., & Mujica-Parodi, L. (2015).
830 Anticipation of high arousal aversive and positive movie clips engages common and distinct
831 neural substrates. *Social Cognitive and Affective Neuroscience*, 10(4), 605–611.
832 <https://doi.org/10.1093/scan/nsu091>

833 Grupe, D. W., & Nitschke, J. B. (2011). Uncertainty is associated with biased
834 expectancies and heightened responses to aversion. *Emotion*, 11(2), 413–424.
835 <https://doi.org/10.1037/a0022583>

836 Herwig, U., Kaffenberger, T., Baumgartner, T., & Jäncke, L. (2007). Neural correlates
837 of a «pessimistic» attitude when anticipating events of unknown emotional valence.
838 *NeuroImage*, 34(2), 848–858. <https://doi.org/10.1016/j.neuroimage.2006.09.035>

839 Johnen, A. K., & Harrison, N. R. (2019). The effects of valid and invalid expectations
840 about stimulus valence on behavioural and electrophysiological responses to emotional
841 pictures. *International Journal of Psychophysiology*, 144, 47–55.
842 <https://doi.org/10.1016/j.ijpsycho.2019.08.002>

843 Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2017). lmerTest Package:
844 Tests in Linear Mixed Effects Models. *Journal of Statistical Software*, 82(13), 1–26.
845 <https://doi.org/10.18637/jss.v082.i13>

846 Lange, K., Kühn, S., & Filevich, E. (2015). "Just Another Tool for Online Studies"
847 (JATOS): An Easy Solution for Setup and Management of Web Servers Supporting Online
848 Studies. *PLOS ONE*, 10(6), e0130834. <https://doi.org/10.1371/journal.pone.0130834>

- Leys, C., Delacre, M., Mora, Y. L., Lakens, D., & Ley, C. (2019). How to Classify, Detect, and Manage Univariate and Multivariate Outliers, With Emphasis on Pre-Registration. *International Review of Social Psychology*, 32(1). <https://doi.org/10.5334/irsp.289>
- Lin, H., Jin, H., Liang, J., Yin, R., Liu, T., & Wang, Y. (2015). Effects of Uncertainty on ERPs to Emotional Pictures Depend on Emotional Valence. *Frontiers in Psychology*, 6(1927). <https://doi.org/10.3389/fpsyg.2015.01927>
- Lin, H., Liang, J., Jin, H., & Zhao, D. (2018). Differential effects of uncertainty on LPP responses to emotional events during explicit and implicit anticipation. *International Journal of Psychophysiology*, 129, 41–51. <https://doi.org/10.1016/j.ijpsycho.2018.04.012>
- Lin, H., Liang, J., Liu, T., Liang, Z., & Jin, H. (2020). Cue Valence Influences the Effects of Cue Uncertainty on ERP Responses to Emotional Events. *Frontiers in Human Neuroscience*, 14, 140. <https://doi.org/10.3389/fnhum.2020.00140>
- Lin, H., Xiang, J., Li, S., Liang, J., & Jin, H. (2015). Anticipation of negative pictures enhances the P2 and P3 in their later recognition. *Frontiers in Human Neuroscience*, 9, 646. <https://doi.org/10.3389/fnhum.2015.00646>
- Lin, H., Xiang, J., Li, S., Liang, J., Zhao, D., Yin, D., & Jin, H. (2017). Cued uncertainty modulates later recognition of emotional pictures: An ERP study. *International Journal of Psychophysiology*, 116, 68–76. <https://doi.org/10.1016/j.ijpsycho.2017.03.004>
- Marchewka, A., \Zurawski, \Lukasz, Jednoróg, K., & Grabowska, A. (2014). The Nencki Affective Picture System (NAPS): Introduction to a novel, standardized, wide-range, high-quality, realistic picture database. *Behavior Research Methods*, 46(2), 596–610. <https://doi.org/10.3758/s13428-013-0379-1>
- Mathôt, S., Schreij, D., & Theeuwes, J. (2012). OpenSesame: An open-source, graphical experiment builder for the social sciences. *Behavior Research Methods*, 44(2), 314–324. <https://doi.org/doi:10.3758/s13428-011-0168-7>

874 Mercado, F., Hinojosa, J. A., Peñacoba, C., & Carretié, L. (2008). The emotional S1-
875 S2 paradigm for exploring brain mechanisms underlying affective modulation of expectancy.
876 In *Brain Mapping Research Developments* (pagg. 197–209). Nova Science Publishers.

877 Nakagawa, S., Johnson, P. C. D., & Schielzeth, H. (2017). The coefficient of
878 determination R² and intra-class correlation coefficient from generalized linear mixed-effects
879 models revisited and expanded. *Journal of The Royal Society Interface*, 14(134), 20170213.
880 <https://doi.org/10.1098/rsif.2017.0213>

881 Peelen, M. V., Atkinson, A. P., & Vuilleumier, P. (2010). Supramodal Representations
882 of Perceived Emotions in the Human Brain. *Journal of Neuroscience*, 30(30), 10127–10134.
883 <https://doi.org/10.1523/JNEUROSCI.2161-10.2010>

884 Qiao, Z., Geng, H., Wang, Y., & Li, X. (2018). Anticipation of uncertain threat
885 modulates subsequent affective responses and covariation bias. *Frontiers in Psychology*, 9,
886 2547. <https://doi.org/10.3389/fpsyg.2018.02547>

887 Sarinopoulos, I., Grupe, D. W., Mackiewicz, K. L., Herrington, J. D., Lor, M., Steege,
888 E. E., & Nitschke, J. B. (2010). Uncertainty during anticipation modulates neural responses to
889 aversion in human insula and amygdala. *Cerebral Cortex*, 20(4), 929–940.
890 <https://doi.org/10.1093/cercor/bhp155>

891 Schumacher, S., Herwig, U., Baur, V., Mueller-Pfeiffer, C., Martin-Soelch, C., Rufer,
892 M., & Brühl, A. B. (2015). Psychophysiological responses during the anticipation of emotional
893 pictures. *Journal of Psychophysiology*, 29(1), 13–19. [https://doi.org/10.1027/0269-](https://doi.org/10.1027/0269-8803/a000129)
894 [8803/a000129](https://doi.org/10.1027/0269-8803/a000129)

895 Seth, A. K. (2013). Interoceptive inference, emotion, and the embodied self. *Trends in*
896 *Cognitive Sciences*, 17(11), 565–573. <https://doi.org/10.1016/j.tics.2013.09.007>

897 Seth, A. K., & Friston, K. J. (2016). Active interoceptive inference and the emotional
898 brain. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 371(1708),
899 20160007. <https://doi.org/10.1098/rstb.2016.0007>

900 Shinkareva, S. V., Wang, J., Kim, J., Facciani, M. J., Baucom, L. B., & Wedell, D. H.
901 (2014). Representations of modality-specific affective processing for visual and auditory
902 stimuli derived from functional magnetic resonance imaging data. *Human Brain Mapping*,
903 35(7), 3558–3568. <https://doi.org/10.1002/hbm.22421>

904 Shipp, S. (2016). Neural elements for predictive coding. *Frontiers in Psychology*, 7,
905 1792. <https://doi.org/10.3389/fpsyg.2016.01792>

906 Sterling, P. (2012). Allostasis: A model of predictive regulation. *Physiology &*
907 *Behavior*, 106(1), 5–15. <https://doi.org/10.1016/j.physbeh.2011.06.004>

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SUPPLEMENTARY MATERIAL

Valence	NAPS pictures names
Neg	Animals_001_h; Animals_024_h; Animals_025_h; Animals_027_h; Animals_033_h; Animals_038_h; Animals_054_h; Animals_068_h; Animals_071_h; Animals_074_h; Animals_077_h; Animals_078_h; Faces_146_h; Faces_150_h; Faces_152_h; Faces_170_h; Faces_271_h; Faces_272_h; Faces_285_h; Faces_290_h; Faces_291_h; Faces_293_h; Faces_294_h; Faces_302_h; Landscapes_002_h; Landscapes_004_h; Landscapes_005_h; Landscapes_007_h; Landscapes_010_h; Landscapes_011_h; Landscapes_014_h; Landscapes_017_h; Landscapes_022_h; Landscapes_026_h; Landscapes_139_h; Landscapes_177_h; Objects_001_h; Objects_002_h; Objects_003_h; Objects_007_h; Objects_011_h; Objects_022_h; Objects_125_h; Objects_132_h; Objects_139_h; Objects_149_h; Objects_283_h; Objects_285_h; People_001_h; People_008_h; People_020_h; People_022_h; People_118_h; People_127_h; People_136_h; People_140_h; People_200_h; People_215_h; People_225_h; People_226_h
Neu	Animals_109_h; Animals_114_h; Animals_122_h; Animals_125_h; Animals_126_h; Animals_136_h; Animals_165_h; Animals_169_h; Animals_170_h; Animals_197_h; Animals_202_h; Animals_206_h; Faces_184_h; Faces_186_h; Faces_188_h; Faces_282_h; Faces_304_h; Faces_314_h; Faces_316_h; Faces_326_h; Faces_329_h; Faces_331_h; Faces_335_h; Faces_343_h; Landscapes_009_h; Landscapes_041_h; Landscapes_048_h; Landscapes_050_h; Landscapes_089_h; Landscapes_100_h; Landscapes_107_h; Landscapes_127_h; Landscapes_143_h; Landscapes_149_h; Landscapes_163_h; Landscapes_172_h; Objects_025_h; Objects_033_h; Objects_041_h; Objects_069_h; Objects_075_h; Objects_078_h; Objects_079_h; Objects_103_h; Objects_254_h; Objects_262_h; Objects_263_h; Objects_270_h; People_069_h; People_089_h; People_099_h; People_101_h; People_109_h; People_153_h; People_162_h; People_167_h; People_173_h; People_178_h; People_194_h; People_250_h

Table S1. List of NAPS picture names used as S2s in Experiment 1, sorted by valence (Neg = negative, Neu = neutral).

Measure	Neg		Neu		t_{118}	p
	M	SD	M	SD		
luminance	114.149	27.503	116.943	27.615	-0.555	0.58
contrast	65.682	11.569	66.225	11.490	-0.258	0.797
complexity						
jpeg_size	350012.367	118541.318	331739.683	120579.766	0.837	0.404
entropy	7.579	0.338	7.608	0.311	-0.489	0.626
color space						
LABL	47.078	11.035	48.411	11.090	-0.66	0.511
LABA	1.684	4.6	0.541	7.901	0.969	0.335
LABB	7.444	9.766	7.492	11.416	-0.025	0.980

Table S2. Means (M), standard deviations (SD), and results of two-tailed t-tests assuming unequal variance in luminance, contrast, complexity indices (i.e., JPEG size, entropy), and color space indices (i.e., LABL, LABA, LABB), referred to negative (Neg) and neutral (Neu) NAPS pictures employed as S2s in Experiment 1.

Valence	NAPS pictures names	IADS-2 sounds numbers
Neg	Animals_074_h, Animals_077_h, Animals_078_h, Animals_024_h, Faces_293_h, Faces_290_h, Faces_302_h, Faces_152_h, Landscapes_139_h, Landscapes_005_h, Landscapes_026_h, Landscapes_002_h, Objects_139_h, Objects_125_h, Objects_149_h, Objects_003_h, People_226_h, People_022_h, People_140_h, People_127_h	105, 106, 115, 116, 241, 242, 244, 255, 276, 277, 279, 283, 285, 286, 289, 290, 292, 293, 295, 296, 420, 422, 423, 424, 501, 502, 600, 611, 624, 625, 626, 703, 709, 711, 712, 713, 714, 719, 730, 732
Neu	Animals_170_h, Animals_206_h, Animals_125_h, Animals_109_h, Faces_304_h, Faces_316_h, Faces_331_h, Faces_326_h, Landscapes_127_h, Landscapes_149_h, Landscapes_163_h, Landscapes_107_h, Objects_262_h, Objects_254_h, Objects_263_h, Objects_078_h, People_194_h, People_099_h, People_173_h, People_101_h	107, 109, 113, 120, 132, 150, 152, 170, 171, 172, 206, 225, 254, 262, 270, 355, 360, 361, 363, 364, 365, 370, 374, 375, 377, 378, 400, 403, 601, 602, 610, 698, 704, 705, 716, 721, 724, 725, 726, 808

Table S3. List of NAPS pictures names and IADS-2 sounds numbers used as S2s in Experiment 2, sorted by valence (Neg = negative, Neu = neutral).

Measure	Neg		Neu		t_{38}	p
	M	SD	M	SD		
luminance	110.232	23.168	121.242	24.168	-1.471	0.150
contrast	65.834	10.017	61.919	10.617	1.199	0.238
jpeg_size	345480.200	115725.462	357945.550	111068.563	-0.348	0.730
entropy	7.623	0.399	7.663	0.216	-0.394	0.695
LABL	45.552	9.136	50.539	9.667	-1.677	0.102
LABA	2.089	4.294	-1.576	10.822	1.408	0.167
LABB	5.316	5.992	6.630	15.278	-0.358	0.722
Measure	Neg		Neu		t_{78}	p
	M	SD	M	SD		
min dB	-0.673	0.058	-0.657	0.094	-0.916	0.362
max dB	0.668	0.052	0.681	0.116	-0.638	0.526
peak dB	-93.125	566.920	-3.582	1.347	-0.999	0.321

Table S4. Means (M), standard deviations (SD), and results of two-tailed t -tests assuming unequal variance in luminance, contrast, complexity indices (i.e., JPEG size, entropy), and color space indices (i.e., LABL, LABA, LABB) for affective pictures, and in physical properties (i.e., min dB, max dB, peak dB) for affective sounds, referred to negative (Neg) and neutral (Neu) NAPS pictures and IADS-2 sounds employed as S2s in Experiment 2.