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The role of implicit learning and cue ambiguity on the subjective experience of affective predictions: a follow-up behavioral investigation

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ABSTRACT

People use their previous experience to predict present affective events. Since we live in ever-changing environments, affective predictions must generalize from past contexts (from which they are implicitly learned) to new, potentially ambiguous contexts. This study investigated how past (un)certain relationships influence subjective experience following new ambiguous cues, and whether past relationships can be learned implicitly. Two S1-S2 paradigms were employed as learning and test phases in two experiments. S1s were colored circles, S2s negative or neutral affective pictures. Participants (N = 121, 116) were assigned to the certain (CG) or uncertain group (UG), and they were presented with 100% (CG) or 50% (UG) S1-S2 congruency during an uninstructed (Experiment 1) or implicit (Experiment 2) learning phase. During the test phase both groups were presented with a new 75% S1-S2 paradigm, and ambiguous (Experiment 1) or unambiguous (Experiment 2) S1s. Participants were asked to rate the expected valence of upcoming S2s (expectancy ratings), or their experienced valence and arousal (valence and arousal ratings). In Experiment 1 ambiguous cues elicited less negative expectancy ratings, and less unpleasant valence ratings, independently from prior experience. In Experiment 2, participants in the CG reported more negative expectancy ratings after the S1s previously paired with negative stimuli. Overall, we found that in the presence of ambiguous cues subjective affective experience is dampened, and we confirmed that people are able to infer probabilistic relationships from the environment (and to use them later) at an implicit level.

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

1) INTRODUCTION

1.1) Emotions as predictions

People use their previous experience to predict and give meaning to present affective events. Since we live in multisensory ever-changing environments, affective predictions (and the associated subjective experience) must generalize from the specific features of past contexts (from which they are *implicitly* learned) to ever new and potentially *ambiguous* contextual features, in order to be effective in promoting survival and allostatic balance with the environment (Friston, 2010; Shipp, 2016). However, the specific mechanisms by which this process occurs remain unclear.

According to *predictive models of emotion* (Barrett, 2017; Seth & Friston, 2016), affective predictions are constructed along three distinct neurocomputational stages: prediction *generation*, in which prior experience is combined with present information to construct affective predictions; prediction *implementation*, in which predictions are used to pre-arrange the best action plans to deal with the expected situation; and prediction *updating*, in which current environmental inputs are compared with predictions, and in case of mismatch the unexpected information (encoded as a prediction error) acts as a feedback to adjust subsequent predictions. Predictive models are assumed to be (i) *probabilistic*, since they encode the statistical regularities within the observed inputs (Clark, 2013; Friston, 2010; Shipp, 2016); (ii) *generative*, because they generalize across sensory modalities, contexts, and time (Friston, 2010; Shipp, 2016); and (iii) *implicit*, since they act mostly outside of awareness, potentially emerging into it only in case of a prediction violation (Bar, 2007). It follows that human brains do not merely react to affective stimuli at the time of their occurrence, but rather, as a spontaneous activity, they are constantly busy in generating-implementing-updating predictions in the service of allostasis (Pezzulo et al., 2021; Sterling, 2012). Prediction

construction is assumed to represent the core mechanism on which the brain relies, in order to provide the body with optimal resources for growth, adaptation to the environment, and survival (Clark, 2013; Friston, 2010; Pezzulo et al., 2021; Sterling, 2012; Sterling & Laughlin, 2015). Previous experience (i.e., knowledge derived from the extraction of statistical regularities in the past environment) plays a pivotal role in the construction of new affective predictions: it interacts with momentary information (e.g., physical properties of the environment, contingencies experienced between present stimuli) in constraining and refining the pool of information used to generate predictions (Bar, 2007; Barrett, 2017; Clark, 2013; Friston, 2010).

Subjective experience of emotion is assumed to derive from the brain's spontaneous predictive activity, namely from the active process of making meaning of present stimuli by predicting and categorizing them on the basis of past experiences (Barrett, 2017). When this process draws on conceptual emotion knowledge to categorize actual incoming stimuli, the resulting predictive models and their associated affective responses can be subjectively experienced as emotions (Barrett, 2017; Barrett et al., 2014; Seth, 2013). It follows that subjective experience of emotion is sensitive to statistical regularities experienced in the past: the more certain the regularities, the more subjective expectancies will draw on them to accordingly predict upcoming stimuli (Del Popolo Cristaldi, Gambarota, et al., 2021). However, the role of previous probabilistic information on the construction of affective predictions from new, ambiguous environmental cues is still unclear. Moreover, it is not yet clear how previous experience might act at an implicit level (i.e., without explicitly focusing attention) in shaping subjective expectancies and reactions to new affective stimuli. The present work aimed to answer these open questions. As a first goal, we aimed to investigate if being exposed to certain vs. uncertain probabilistic relationships between stimuli might influence the subjective expectancies and reactions to new affective stimuli as a function of cue ambiguity.

As a second goal, we tackled whether people are able to implicitly extract (un)certain probabilistic information from the environment, and use it later to predict new affective events.

1.2) A novel experimental paradigm

To study the effects of previous experience on new affective predictions we have recently developed an experimental paradigm (Del Popolo Cristaldi, Gambarota, et al., 2021), which integrates the logic of traditional emotional S1-S2 paradigms (cf. Mercado et al., 2008 for a review) with an uninstructed learning component. In this novel paradigm two separate emotional S1-S2 paradigms are employed as a *learning* and *test* phase, respectively. As in typical emotional S1-S2 paradigms, a sequential presentation of two stimuli is implemented (both in the learning and test phases): the S1 (or *cue*) is a symbolic stimulus (i.e., red or blue circles), while the S2 (or *target*) is an emotional stimulus (i.e., negative or neutral affective pictures). The sequence of events in the S1-S2 paradigm allows to target the three stages of affective prediction construction: the S1 reflects the *generation* stage, the inter-stimulus interval (ISI) between S1 and S2 the *implementation* stage, and the S2 the *updating* stage (Del Popolo Cristaldi, Mento, et al., 2021). The contribution of this new paradigm is that it manipulates *actual previous experience* through *uninstructed* certain vs. uncertain probabilistic contingencies between S1 and S2 experienced during a separate learning phase. This approach is markedly different from extant S1-S2 paradigms that manipulate *explicitly labeled* probabilistic information while participants perform the task.

During the learning phase of our new paradigm, previous experience is manipulated between subjects by dividing participants into two experimental groups: the *certain* group (CG) and the *uncertain* group (UG). According to the group, they are presented with a 100% (CG) or 50% (UG) S1-S2 congruency, namely the probabilistic ratio between S1 color and S2 valence they are exposed to. During the test phase, all participants are then presented with a

new S1-S2 paradigm with a fixed 75% S1-S2 congruency. Here, they are asked to rate their subjective affective experience in terms of either the expected valence of upcoming S2s (*expectancy ratings*), or the experienced valence and arousal to S2s (*valence and arousal ratings*). Participants are left uninstructed about the probabilistic ratios they are exposed to during the whole paradigm.

1.3) Inconsistent evidence on subjective affective experience

As for *expectancy* measures related to the *generation-implementation* stages of affective prediction, in our previous research (Del Popolo Cristaldi, Gambarota, et al., 2021) we found that participants in the certain (100%) condition reported more negative expectancy ratings after the specific cues formerly paired with negative stimuli, and that this effect was generalizable across visual and auditory sensory modalities. In contrast, the literature implementing traditional S1-S2 paradigms found negatively-biased expectancy ratings in the uncertain (50%) condition (Dieterich et al., 2016; Grupe & Nitschke, 2011; Lin et al., 2018, 2020; Qiao et al., 2018; Sarinopoulos et al., 2010). Moreover, the only study manipulating cue ambiguity (Chen & Lovibond, 2016) found that ambiguous cues (i.e., cues with uninstructed 50% predictive value) elicited less negative expectancy ratings than unambiguous (i.e., instructed) cues.

Regarding the experienced *valence* and *arousal* to affective stimuli, as measured during the *updating* stage, results are also inconsistent. In our previous study (Del Popolo Cristaldi, Gambarota, et al., 2021) we did not find any significant effect of previous experience on valence and arousal ratings. This result is coherent with some extant evidence of null interaction between current (un)certainly and subjective valence ratings, collected by traditional S1-S2 paradigms (Bermppohl et al., 2006; Dieterich et al., 2016; Greenberg et al., 2015; Grupe & Nitschke, 2011; Lin et al., 2018; Qiao et al., 2018). Other S1-S2 studies, instead,

showed a more intense subjective experience (i.e., more pleasant valence ratings to positive S2s, more unpleasant valence ratings to negative S2s, and higher arousal) in the certain (100%) as compared to the uncertain (50%) condition (Bermpohl et al., 2006; Johnen & Harrison, 2019; Lin et al., 2020; Lin, Jin, et al., 2015; Lin, Xiang, et al., 2015). Opposed to the latter, one study reported more unpleasant ratings in the uncertain (50%) than in the certain (100%) condition (Lin et al., 2017). Furthermore, ambiguous cues were found to elicit more unpleasant post-experiment mood ratings than unambiguous cues (Chen & Lovibond, 2016).

A last S1-S2 study (Lin et al., 2018) is worth to be commented on, since it compared an explicit anticipation condition (in which participants were asked to give their expectancy ratings during the ISI) with an implicit anticipation condition (in which participants were asked to indicate a colored target number during the ISI). Concerning the target detection task presented during the ISI in the implicit condition, no effects of cue predictive meaning (100% vs. 50%) emerged on performance accuracy, whereas faster reaction times (RTs) were found in the certain condition. Finally, authors did not find any significant effect of cue predictive meaning (100% vs. 50%) nor anticipation pattern (explicit vs. implicit) on S2-valence ratings.

1.4) A follow-up research

Overall, evidence on the effects of past knowledge on subjective affective experience remains fragmentary, with our previous work (Del Popolo Cristaldi, Gambarota, et al., 2021) suggesting that a certain previous experience affects future expectancies (thus, the generation-implementation stage of new affective predictions construction), and S1-S2 studies suggesting that either certain (Bermpohl et al., 2006; Johnen & Harrison, 2019; Lin et al., 2020; Lin, Jin, et al., 2015; Lin, Xiang, et al., 2015) or uncertain (Chen & Lovibond, 2016; Dieterich et al., 2016; Grupe & Nitschke, 2011; Lin et al., 2017, 2018, 2020; Qiao et al., 2018; Sarinopoulos et al., 2010) environments can lead to an intensification of affect. Besides, little is known yet

about the potential effects of cue ambiguity on new affective predictions, nor on the actual possibility to learn environmental contingencies implicitly. Both these factors are nonetheless crucial to construct efficient affective predictions (cf. 1.1). In fact, since our environments are characterized by frequent changes, affective predictions must be flexible in adapting to new, and potentially ambiguous, contextual features (Bar, 2007; Barrett, 2017; Sterling, 2012). Moreover, in daily life people should be able to spontaneously learn contingencies from the environment, and to use them as priors for subsequent affective predictions, even in absence of explicit instructions and/or awareness of the contingencies themselves (Bar, 2007). However, despite the importance of both of these aspects for constructing efficient predictions, it remains unclear how they may influence the subjective experience of emotion.

Based on this, in the present research we implemented two follow-up experiments (pre-registered on the Open Science Framework - OSF; Experiment 1: <https://osf.io/gdr3b/>, Experiment 2: <https://osf.io/z5esb/>), in which we modified some features of our former paradigm. In particular, in order to investigate the construction of new affective predictions as a function of cue ambiguity, in Experiment 1 we introduced ambiguous cues in the test phase. Here, unbeknownst to participants, we presented two new reddish and bluish S1 colors (i.e., coral and turquoise) in addition to those already presented during the learning phase (i.e., red and blue). Further, to test if the probabilistic information available in the environment can be extracted and learned at an implicit level (i.e., not explicitly focusing attention on the probabilistic relationships between stimuli), in Experiment 2 we engaged participants in a distracting task (i.e., a parity judgment task) during the learning phase.

2) EXPERIMENT 1

Experiment 1 investigated how being exposed to certain vs. uncertain probabilistic relationships between stimuli might influence subjective reactions to new affective stimuli, as a function of cue ambiguity.

We performed confirmatory analyses to test two a-priori formulated hypotheses (as pre-registered on OSF, <https://osf.io/gdr3b/>). The first hypothesis (H1) was that *ambiguous* cues would elicit less negative *expectancy ratings* (Chen & Lovibond, 2016). The second hypothesis (H2) was that *ambiguous* cues would elicit more unpleasant *valence ratings* (Chen & Lovibond, 2016), since ambiguity can contribute to a heightened anxious reaction to potential threats (cf. MacLeod & Mathews, 2012). As exploratory analyses, we tested whether *S1 color* modulated *expectancy ratings*, and whether *cue* ambiguity modulated *arousal ratings*.

2.1) Methods

2.1.1) Participants

We recruited 125 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/gdr3b/>) simulation-based power analysis for generalized linear mixed-effects models (GLMMs) (R package: *simr*; Green & MacLeod, 2016), estimating parameters from data of our previous study (Experiment 1, N = 185) (Del Popolo Cristaldi, Gambarota, et al., 2021). One participant was discarded according to the pre-registered exclusion criteria (<https://osf.io/gdr3b/>): 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. Data from 3 participants were discarded because of data collection failure.

The final sample was 121 participants (58 males, age: $M = 25.03$, $SD = 7.67$, range = 18-58). All participants gave their informed consent before starting the experiment, and were paid £1.93 for their participation. All experimental procedures were conducted in accordance with the Declaration of Helsinki, and approved by the Ethical Committee for the Psychological Research of the University of Padua (protocol no. 4177).

2.1.2) Stimulus material and procedure

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 in the learning and test phases. Only in the test phase, new ambiguous S1s were introduced: same-sized reddish and bluish (i.e., coral- and turquoise-colored) circles. In both learning and test phases, S2s were colored 800×600 px pictures from Nencki Affective Picture System (NAPS) (Marchewka et al., 2014). We manipulated picture valence at two levels: negative (neg) vs. neutral (neu). NAPS pictures used as S2s, sorted by valence, are listed in Supplementary Table S1. Negative and neutral pictures did not differ in luminance, contrast, complexity and color space indices (see Supplementary Table S2). An additional yellow circle and an additional 800×600 px picture depicting a pattern of black stripes on a transparent background were used in attention check trials as S1 and S2, respectively. Three Visual Analogue Scales (VASs) assessed *expectancy ratings* (i.e., the expected valence of upcoming S2s), *valence* and *arousal ratings* (i.e., subjective reactions to S2s). The expectancy VAS ranged 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. The valence VAS ranged from 0% “very negative” to 100% “very positive”, with 50% representing “neutral” valence. The arousal VAS ranged from 0% “relaxed” to 100% “aroused”, with 50% representing an intermediate level of activation.

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 optimal conditions for participation: they were asked to sit alone in a silent and private room, and to avoid distractions and interruptions. They were asked to run the study on a computer, ensuring that no one else could view the screen during the experiment due to the involvement of emotionally evocative material.

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 screen and pay attention to the relationship between S1 color and S2 valence. They were also instructed to press the ‘spacebar’ as fast as they could each time they saw a yellow circle (attention check trials). A practice session (4 trials) followed the instructions: here, participants received feedback on their performance to one attention check trial. Then, the learning session started. Each trial began with S1, presented for 250 msec, and displayed on a grey background. S1 was followed by a fixed ISI of 1000 msec, in which the screen remained grey, and then the S2, presented for 1000 msec. A white fixation cross was displayed in the center of the screen during the inter-trial interval (ITI), which randomly varied between 800 and 1200 msec. The total number of trials was 40, presented in random sequence. During the learning phase CG participants were exposed to a certain predictive relationship between S1 and S2: each S1 color (i.e., red and blue) was paired with the same S2 valence in 100% of the trials (100% S1-S2 congruency). UG participants, instead, were presented with an uncertain relationship: each S1 color was paired with negative S2s in 50% of the trials, and with neutral S2s in the other 50% (50% S1-S2 congruency). Color-valence pairings were counterbalanced between subjects, and participants were left uninstructed about the S1-S2 predictive ratios.

At the end of the learning phase participants were asked to wait and relax for 1 minute. Then, both groups were introduced to the same test phase. At the beginning of the test phase, participants were asked to look at the screen and pay attention to S1 color, trying to predict S2 emotional valence. Participants were instructed that, in some trials, they would be asked to rate how much they expected to see a negative picture after 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). After the instructions, participants performed a practice session (4 trials), in which they trained themselves to give their ratings, and received feedback on their performance to a single attention check trial. Then the test session started, with the same trial structure and timing as the learning phase, and a total number of 80 trials. The order of the trials was random. *S1 color* was manipulated within participants at four levels: red, blue, coral, and turquoise. *Cue ambiguity* was manipulated at two levels: ambiguous vs. unambiguous. In trials with *unambiguous* cues (N = 40) we employed the same S1 colors as the learning phase (i.e., red and blue), whereas in trials with *ambiguous* cues (N = 40) we employed the new reddish and bluish colors (i.e., coral and turquoise). Participants were not warned about the exposure to new colors. In the test phase, 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, and participants were left uninstructed about the S1-S2 predictive ratio. Notably, the new 75% ratio implied that CG participants moved from a reliable predictive relationship (100%, experienced during the learning phase), to a new, more uncertain context (in which the previously learned predictive models were sometimes violated). UG participants, instead, moved from an unreliable predictive relationship (50%), to a more predictive context. Moreover, the 75% is equidistant

from the predictive ratios experienced by the CG and the UG (it lies in the middle between 100% and 50%). All participants were asked to give either their *expectancy ratings* by answering the expectancy VAS during the ISI, or their *valence* and *arousal ratings*, by answering the valence/arousal VASs right after the S2. VASs response times were self-paced, and the two answer conditions were balanced for the number of trials (50%:50%) and randomly delivered. We chose to present the *expectancy* and the *valence/arousal ratings* in different trials to prevent the two kinds of ratings from influencing each other (see Figure 1a for a schematic representation of the experimental paradigm).

At the end of the test phase, participants were redirected to a Qualtrics survey (Qualtrics, Provo, UT; www.qualtrics.com), in which they were asked 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, participants were thanked, and redirected to Prolific to 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 group (CG, UG). During the *learning phase* participants experienced a 100% (CG) vs. 50% (UG) affective contingency between S1 color (red or blue) and S2 valence (NEG or NEU), according to the group. During the *test phase* all participants were presented with unambiguous (i.e., red or blue) or ambiguous (i.e., coral or turquoise) S1s, and the S1-S2 affective contingency 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. **b)** Example sequence of events and their duration for a trial of Experiment 2, according to the phase (learning, test), and the group (CG, UG). During the *learning phase* participants experienced a 100% (CG) vs 50% (UG) affective contingency between S1 color (red or blue) and S2 valence (NEG or NEU), according to the group. Then, after the S2, they were presented with the parity judgement task. During the *test phase* the S1-S2 affective contingency 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 (*cue*, within-subjects: ambiguous vs. unambiguous) $\times$ 2 (*S2 valence*, within-subjects: neg vs. neu) mixed design. The analysis plan was pre-registered on OSF (<https://osf.io/gdr3b/>).

Univariate outliers (i.e., *expectancy ratings*) were detected through Median Absolute Deviation values ($MAD > 3$), and multivariate outliers (i.e., *valence* and *arousal ratings*) through the Mahalanobis-Minimum Covariance Determinant (MMCD, breakdown point 0.25) (R package: *Routliers*; Leys et al., 2019). We detected 12 univariate outliers. We visually inspected their ratings, and it emerged that they had reversed the poles of the rating scale (“error outliers”, cf. Leys et al., 2019). Thus, we chose to remove them from data analysis. We also detected 21 multivariate outliers. We visually inspected their ratings, and it emerged that they showed a slightly flattened or steeper relationship between valence and arousal ratings as compared to other participants. Nevertheless, none of them significantly impacted the models’ estimates (as assessed through Cook’s distance, see below). Thus, we chose to keep their data into the analysis (“potentially interesting outliers”, cf. Leys et al., 2019). Data from 109 participants were included into data analysis.

To test our hypotheses (H1, H2), we fitted the following linear mixed-effects models (LMMs) for each dependent variable (DV) (R package: *lme4*; Bates et al., 2015):

1. *expectancy ratings* (H1): *group*, *cue* and their interaction as fixed factors, random slopes for *cue* within participant;

2. *valence ratings* (H2): *group*, *cue*, *S2 valence* and their interaction as fixed factors, random slopes for *S2 valence* within participant.

As exploratory analyses, to investigate the effects of *S1 color* (within subjects: red, blue, coral, turquoise) on expectancy ratings, we fitted a LMM with *group*, *S1 color* and their interaction as fixed factors, and random slopes for *S1 color* within participants. To investigate the effects of *cue* ambiguity on subjective arousal, we fitted the H2 model on *arousal ratings*.

For each model, we evaluated influential cases 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/gdr3b/>). 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/gdr3b/>).

2.2) Results

Confirmatory models are summarized in Table 1 and Figure 2. For the *expectancy* model ($R^2_{\text{marginal}} = 0.006$, $R^2_{\text{conditional}} = 0.056$) testing H1, we found a main effect of *cue* ($F(1, 107) = 13.19$, $p < .001$): ambiguous cues elicited less negative expectancy ratings than unambiguous ones (ambiguous - unambiguous = -4.08 , $t(107) = -3.63$, $p < .001$, 95% $CI = [-6.28, -1.88]$). Thus, the expectancy model supports the hypothesis of less negative expectancy ratings to ambiguous cues (H1) within both groups. Moreover, for the exploratory expectancy model testing the effect of S1 color ($R^2_{\text{marginal}} = 0.155$, $R^2_{\text{conditional}} = 0.453$) we found a significant interaction between *group* and *S1 color* ($F(3, 107) = 9.49$, $p < .001$). Post-hoc contrasts showed that, in the CG only, red S1s elicited more negative expectancy ratings than blue (blue - red = -34.33 , $t(107) = -8.37$, $p < .001$), turquoise (red - turquoise = 32.28 , $t(107) =$

7.54, $p < .001$), and coral (coral - red = -7.71, $t(107) = -3.67$, $p = .002$); coral S1s elicited more negative ratings than blue (blue - coral = -26.63, $t(107) = -7.85$, $p < .001$), and turquoise (coral - turquoise = 24.57, $t(107) = 7.09$, $p < .001$); and no difference emerged between blue and turquoise S1s (blue - turquoise = -2.05, $t(107) = -1$, $p = .75$). Thus, we replicated our previous results (cf. Del Popolo Cristaldi, Gambarota, et al., 2021), finding more negative expectancy ratings in the CG after the unambiguous cues (i.e., red) which were previously paired with negative stimuli. We also found evidence in the CG for a generalization effect of the learned predictive meaning of cues to new, ambiguous ones (i.e., coral).

For the *valence* model ($R^2_{\text{marginal}} = 0.621$, $R^2_{\text{conditional}} = 0.704$) testing H2, we found a main effect of *cue* ($F(1, 4138) = 8.26$, $p = .004$), and a main effect of *S2 valence* ($F(1, 107) = 997.35$, $p < .001$), better specified by a significant interaction effect between *cue* and *S2 valence* ($F(1, 4138) = 7.45$, $p = .006$). In particular, we found evidence for more unpleasant valence ratings to neutral pictures presented after unambiguous cues as compared to ambiguous ones (neu: ambiguous - unambiguous = 2.74, $t(4138) = 3.96$, $p < .001$, 95% $CI = [1.38, 4.09]$), while valence ratings to negative pictures were not affected by cue ambiguity (neg: ambiguous - unambiguous = 0.071, $t(4138) = 0.103$, $p = .918$, 95% $CI = [-1.28, 1.43]$). Thus, cue ambiguity actually modulated valence ratings in both groups, but in the opposite direction as hypothesized (H2), with unambiguous cues leading subsequent neutral pictures to elicit more unpleasant subjective ratings.

For the exploratory *arousal* model ($R^2_{\text{marginal}} = 0.325$, $R^2_{\text{conditional}} = 0.566$) we only found a main effect of *cue* ($F(1, 4138) = 8.85$, $p = .003$): unambiguous cues elicited higher arousal ratings than ambiguous ones (ambiguous - unambiguous = -1.52, $t(4138) = -2.98$, $p = .003$, 95% $CI = [-2.53, -0.52]$).

Model	Parameter	Estimate	SE	<i>t</i>	df	<i>p</i>	95% <i>CI</i>	
Expectancy ratings	Intercept	52.17	0.61	85.91	107.00	< .001	50.97	53.38
	UG - CG	-0.39	1.21	-0.32	107.00	.746	-2.80	2.01
	ambiguous - unambiguous	-4.08	1.12	-3.63	107.00	< .001	-6.31	-1.85
	group × cue	2.51	2.25	1.12	107.00	.266	-1.94	6.97
	σ ID	4.62						
	σ cue	7.89						
	σ residual	27.27						
Valence ratings	Intercept	44.67	0.49	90.57	107.53	< .001	43.70	45.65
	UG - CG	0.98	0.99	0.99	107.53	.322	-0.97	2.94
	ambiguous - unambiguous	1.40	0.49	2.87	4,138.00	.004	0.45	2.36
	neg - neu	-46.35	1.47	- 31.58	107.23	< .001	- 49.26	- 43.44
	group × cue	0.85	0.98	0.87	4,138.00	.383	-1.06	2.77
	valence × group	-5.50	2.94	-1.87	107.23	.064	- 11.32	0.32
	cue × valence	-2.67	0.98	-2.73	4,138.00	.006	-4.58	-0.75
	group × cue × valence	-2.40	1.95	-1.23	4,138.00	.219	-6.23	1.43
	σ ID	4.47						

Model	Parameter	Estimate	SE	<i>t</i>	df	<i>p</i>	95% CI
	σ valence	14.43					
	σ residual	16.03					

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), the *cue* (ambiguous vs. unambiguous), and *S2 valence* (neg vs. neu, for valence and arousal ratings only). Points represent the mean value for each participant and condition.

2.3) Discussion

Results of Experiment 1 suggested that cue ambiguity per se (regardless of cue predictive meaning) did not interact with uncertainty of previous experience in shaping subjective expectancies and reactions to new affective stimuli. In fact, no significant group by cue interaction was found in any of the models. We found instead that ambiguous cues elicited less negative expectancy ratings in the *generation-implementation* stage (coherently with H1), less unpleasant valence ratings (contrary to H2) and lower arousal during the *updating* stage, regardless of previous experience. Thus, cue ambiguity appears to be associated at all stages with a dampened subjective experience of emotion. With regards to subjective expectancy (i.e., expectancy ratings) these results are consistent with our hypotheses (H1, Chen & Lovibond, 2016), with regards to subjective reactions to new stimuli (i.e., valence and arousal ratings) they are instead partially in contrast (H2, Chen & Lovibond, 2016). It must be noted, however, that in our paradigm we asked for a trial-by-trial rating of experienced valence (and arousal) to S2s, whereas Chen and Lovibond (2016) asked for a post-experiment mood rating. Thus, the different nature of the ratings requested to participants may be accountable for the opposing effects found. Moreover, another S1-S2 study (Kirschner et al., 2016) manipulating ambiguity of the target affective pictures, found that ambiguous pictures were rated as less unpleasant and less arousing than unambiguous pictures, coherently with what we found following ambiguous cues. These effects can be explained in light of the time-related distinction between ambiguity and uncertainty (as proposed in Grenier et al., 2005). Ambiguity, on the one hand, refers to a static feature of the *here and now*, embedded in the present moment: an ambiguous situation or stimulus is characterized by novelty, unpredictability and also uncertainty (Grenier et al., 2005). Uncertainty, on the other hand, refers to a *future-oriented* feature, characterized by unpredictability but not necessarily also by ambiguity (Carleton, 2012; Grenier et al., 2005). In Experiment 1, we manipulated uncertainty during the learning phase (where participants were

not asked for any rating), and ambiguity during the test phase (where we asked for subjective affective ratings). As a consequence, and in line with the results of our previous research (Del Popolo Cristaldi, Gambarota, et al., 2021), it might be that *current* (i.e., ambiguous vs. unambiguous) information prevailed over *past* information (i.e., certain vs. uncertain) in shaping subjective affective experience.

Moreover, when testing the effects of cue predictive meaning (*S1 color*) on expectancy ratings, an interesting result emerged: CG participants - who had previously been exposed to a reliable S1-S2 relationship - reported more negative expectancy ratings both after unambiguous cues whose same color had previously been paired with negative images (e.g., red), and after ambiguous cues whose color resembled (but was not identical to) that previously paired with negative images (e.g., coral). Thus, it seems that previous reliable learnings (i.e., the certain association between unambiguous cue color and picture valence experienced during the learning phase) may be used in a future moment to give meaning not only to the same cues, but also to new, ambiguous ones. This result supports the idea that (affective) predictions can indeed generalize from the specific features of past contexts, to new and potentially ambiguous contextual features, as hypothesized within the predictive framework (Barrett, 2017; Friston, 2010; Shipp, 2016).

3) EXPERIMENT 2

Experiment 2 investigated whether experiencing *implicit* certain vs. uncertain probabilistic relationships between stimuli might influence the subjective reactions to new affective predictions. More specifically, to ensure an implicit exposure to the probabilistic relationship between S1 and S2, during the learning phase we engaged participants in a distracting task (a parity judgement task, see 3.1.2 below for details). Then, we tested if participants were able to implicitly extract the (un)certain probabilistic information available

during the learning phase, and to use it in the test phase to rate the expected valence of new affective events, or the subjective valence and arousal to new affective stimuli.

We performed confirmatory analyses to test seven a-priori and pre-registered (<https://osf.io/z5sesb/>) hypotheses. The first two hypotheses concerned the behavioral performance to the parity judgement task. We hypothesized to find (H1a) faster *RTs* in the *CG* as compared to the *UG*, and (H1b) no differences in *accuracy* between the groups (Lin et al., 2018). The remaining hypotheses regarded the test phase. As third hypothesis (H2a), we expected to find more negative *expectancy ratings* in the *UG* as compared to the *CG* (Dieterich et al., 2016; Grupe & Nitschke, 2011; Herwig et al., 2007; Qiao et al., 2018; Schumacher et al., 2015). The fourth hypothesis (H2b), opposed to H2a, was that participants in the *CG* would show more negative *expectancy ratings* after the cues which were previously paired with a negative picture during the learning phase (Del Popolo Cristaldi, Gambarota, et al., 2021). The fifth hypothesis (H3a) was that participants in the *UG* would show higher *arousal* and more unpleasant *valence ratings* to S2s (Lin et al., 2017) than participants in the *CG*. The sixth hypothesis (H3b), opposed to H3a, was that participants in the *CG* would show higher *arousal* and more unpleasant *valence ratings* to S2s (Bermppohl 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 *UG*. The last hypothesis (H3c), opposed to both H3a and H3b, was to find only a main effect of S2 valence, with significantly higher *arousal* and more unpleasant *valence ratings* to *negative* S2s independently from the experimental group (Lin et al., 2018).

3.1) Methods

3.1.1) Participants

We computed the required sample size through an a priori pre-registered (<https://osf.io/z5sesb/>) power analysis for GLMMs (see 2.1.1), estimating parameters from pilot

data ($N = 18$). We recruited 126 adult participants through the provider platform Prolific (Prolific, Oxford, UK; www.prolific.co). In order to be included in Experiment 2, participants must not have taken part in Experiment 1. Data from 10 participants were discarded according to the pre-registered exclusion criteria (<https://osf.io/z5esb/>): scoring lower than $-2 SD$ from the mean accuracy in the parity judgement task, reporting internet/uploading issues in more than 25% of the experimental trials, reporting to have caught the exact probabilistic relationship between S1 color and S2 valence during the learning phase. The final sample was 116 participants (58 males, age: $M = 25.06$, $SD = 7.63$, range = 18-55). All participants gave their informed consent before starting the experiment, and were paid £2.13 for their participation. All experimental procedures were conducted in accordance with the Declaration of Helsinki, and approved by the Ethical Committee for the Psychological Research of the University of Padua (protocol no. 4177).

3.1.2) Stimulus material and procedure

Two S1-S2 paradigms were employed as a learning and a test phase, respectively. S1s and S2s were the same as in Experiment 1 (see 2.1.2 above), but we employed in Experiment 2 only unambiguous (i.e., red and blue) cues. During the learning phase, single digits from 1 to 9 were employed as stimuli for the parity judgment task. Three VASs were used to collect *expectancy* (from 0% “I definitely expect to see a neutral picture” to 100% “I definitely expect to see a negative picture”), *valence* (from 0% “very negative” to 100% “very positive”) and *arousal* (from 0% “relaxed” to 100% “aroused”) ratings during the test phase.

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 silent and private conditions for participation, and to avoid distractions and interruptions. They were also

asked to perform the study where no one else could view the computer screen, due to the involvement of emotionally evocative material.

Before the learning phase participants were randomly assigned to the CG or the UG. The learning phase was the same as in Experiment 1, except for the introduction of the parity judgement task. Participants were informed that they would see a sequence of stimuli on the screen: a colored circle, followed by a picture, and then a number. They were instructed to look at the screen and judge if the number was odd or even, by pressing the 'Z' or 'M' keys. Response keys were counterbalanced between subjects. A practice session (3 trials) followed the instructions. Here, participants trained themselves to give their parity judgments, and they received feedback on their performance. Then, the learning session started, with the same trial structure, timing and number as in Experiment 1. After the S2, a second ISI with a random duration between 500 and 800 msec followed, in which the screen remained grey. Then, a random digit between 1 and 9 was presented in the center of the screen for 200 msec, and participants had up to 1500 msec to judge the digit's parity by pressing the 'Z' or 'M' keys. Participants were left uninstructed about the S1-S2 ratios (100% for the CG, 50% for the UG) they were exposed to.

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. Cue ambiguity was not manipulated (thus, only red and blue circles were employed) (see Figure 1b for a schematic representation of the experimental paradigm).

At the end of the test phase, participants were directed to the Qualtrics survey (see 2.1.2). Here, we added an open question as a manipulation check: participants were asked whether they caught any relationship between the color of the circle and the emotional valence

of the pictures during the learning phase. Participants were then redirected 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: neg vs. neu) mixed design. The analysis plan was pre-registered on OSF (<https://osf.io/z5esb/>).

During data pre-processing, participants' verbatim responses to the manipulation check question (see 3.1.2 above) were qualitatively analyzed by the experimenter, and coded as “yes” or “no” according to their content. No response was coded as “yes”, suggesting that no participants reported to have caught the probabilistic relationship between S1 and S2.

We detected 4 univariate outliers ($MAD > 3$), which had reversed the poles of the rating scale (“error outliers”, cf. Leys et al., 2019). Thus, they were excluded from data analysis. We also detected 36 multivariate outliers (MMCD, breakdown point 0.25). From visual inspection of their ratings, it emerged that 2 of them had reversed the scales' poles (“error outliers”, cf. Leys et al., 2019), and they were therefore removed from data analysis. The remaining multivariate outliers showed a slightly flattened or steeper relationship between valence and arousal ratings as compared to other participants. Thus, we chose to keep them into data analysis (“potentially interesting outliers”, cf. Leys et al., 2019), since none of them impacted the models' estimates (as assessed through Cook's distance). Data from 110 participants were included into data analysis.

Before performing the analyses, we pre-processed RTs to the parity judgement task according to the following pre-registered steps (<https://osf.io/z5esb/>): (i) trimming RTs between 100 and 1500 msec (Ratcliff, 1993); (ii) discarding RTs of incorrect trials; (iii)

adjusting RTs for the speed-accuracy trade off by means of Inverse Efficiency Score (IES) transformation (Vandierendonck, 2017); (iv) log-transforming IES to account for their skewed distribution (Ratcliff, 1993; Wilcox et al., 2018).

In order to test our a-priori hypotheses (H1a and H1b on parity judgement task; H2a, H2b, H3a, H3b and H3c on test phase ratings), for each DV we fitted the following (G)LMMs (R package: lme4; Bates et al., 2015):

1. *log-transformed IES* (H1a): *group* as fixed factor, random intercept for participant;
2. *accuracy* (H1b): logistic regression with *group* as fixed factor, random intercept for participant;
3. *expectancy ratings* (H2a, H2b): *group*, *S1 color* and their interaction as fixed factors, random slopes for *S1 color* within participant;
4. *valence* and *arousal ratings* (H3a, H3b, H3c): *group*, *S2 valence* and their interaction as fixed factors, random slopes for *S2 valence* within participant.

For each model no influential cases emerged, as evaluated through Cook's distance (>1). LMMs 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), GLMMs effects were evaluated through Type II Analysis of Deviance (R package: car; Fox & Weisberg, 2019). For each model we reported the estimated parameters with 95% *CI* (for the IES model parameters are reported in the logit scale), marginal and conditional R^2 (estimated as in Nakagawa et al., 2017).

3.1.4) Transparency and openness

The study has been pre-registered on OSF (<https://osf.io/z5esb/>). 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/z5esb/>).

3.2) Results

Models are summarized in Table 2 and Figure 3. For the *IES* model ($R^2_{\text{marginal}} = 0.018$, $R^2_{\text{conditional}} = 0.818$) testing H1a, we did not find any effect of *group* ($F(1, 104) = 2.42$, $p = .123$). Thus, the IES model does not support the hypothesis of faster RTs in the CG as compared to the UG (H1a). We found the same result for the *accuracy* model ($R^2_{\text{marginal}} = 0.012$, $R^2_{\text{conditional}} = 0.506$) testing H1b, with no significant effect of *group* emerging ($\chi^2 = 2.409$, $p = .121$). Therefore, we confirmed our hypothesis (H1b) of not finding group differences in accuracy scores to the parity judgement task.

For the *expectancy* model ($R^2_{\text{marginal}} = 0.033$, $R^2_{\text{conditional}} = 0.273$) testing H2a vs. H2b, we found a main effect of *S1 color* ($F(1, 108) = 11.89$, $p < .001$) and an interaction between *S1 color* and *group* ($F(1, 108) = 10.02$, $p = .002$). In particular, in the CG, we found significantly more negative expectancy ratings after the red color (i.e., circles preceding negative pictures) as compared to the blue one (i.e., circles preceding neutral pictures) (blue - red = -14.43, $t(108) = -4.68$, $p < .001$, 95% $CI = [-20.55, -8.31]$), whereas in the UG no differences in expectancy ratings as a function of the S1 color emerged (blue - red = -0.618, $t(108) = -0.2$, $p = .842$, 95% $CI = [-6.73, 5.5]$). Thus, the expectancy model supports the hypothesis of more negative expectancy ratings in the CG after the cues which were previously paired with negative stimuli (H2b).

For both *valence* ($R^2_{\text{marginal}} = 0.593$, $R^2_{\text{conditional}} = 0.669$) and *arousal* ($R^2_{\text{marginal}} = 0.351$, $R^2_{\text{conditional}} = 0.517$) models testing H3a vs. H3b vs. H3c, we found a main effect of *S2 valence*, with both groups reporting significantly greater unpleasantness ($F(1, 108) = 1113.46$, $p < .001$; NEG - NEU = -47, $t(108) = -33.37$, $p < .001$, 95% $CI = [-49.8, -44.2]$) and higher arousal ($F(1, 108) = 391.67$, $p < .001$; NEG - NEU = 30.9, $t(108) = 19.79$, $p < .001$, 95% $CI = [27.8, 34]$) towards negative pictures. Thus, valence and arousal models support the hypothesis of significantly higher arousal and more unpleasant valence ratings to negative S2s independently from the experimental group (H3c).

Model	Parameter	Estimate	SE	statistics	df	<i>p</i>	95% <i>CI</i>	
IES	Intercept	6.33	0.03	211.83	104.62	< .001	6.27	6.39
	UG - CG	-0.09	0.06	-1.55	104.62	.123	-0.21	0.03
	σ ID	0.31						
	σ residual	0.15						
Accuracy	Intercept	2.32	0.19	12.41		< .001	1.95	2.69
	UG - CG	0.58	0.37	1.55		0.12	-0.15	1.30
	σ ID	1.81						
Expectancy ratings	Intercept	53.05	0.90	59.08	108.00	< .001	51.27	54.83

	UG - CG	0.45	1.80	0.25	108.00	.801	-3.11	4.01
	blue - red	-7.52	2.18	-3.45	108.01	< . .001	- 11.85	-3.20
	color × group	-13.81	4.36	-3.17	108.01	.002	- 22.46	-5.16
	σ ID	8.62						
	σ color	21.59						
	σ residual	24.01						
Valence ratings	Intercept	44.95	0.54	83.00	108.01	< .001	43.88	46.02
	UG - CG	0.31	1.08	0.29	108.01	.772	-1.83	2.46
	neg - neu	-47.01	1.41	-33.37	108.00	< . .001	- 49.80	- 44.22
	valence × group	0.61	2.82	0.22	108.00	.83	-4.98	6.19
	σ ID	4.96						
	σ valence	13.69						
	σ residual	17.56						
Arousal ratings	Intercept	49.02	0.75	65.22	107.95	< .001	47.53	50.51

UG - CG	-0.62	1.50	-0.41	107.95	.679	-3.60	2.36
neg - neu	30.89	1.56	19.79	107.98	< .001	27.79	33.98
valence × group	1.42	3.12	0.46	107.98	.65	-4.77	7.61
σ ID	7.34						
σ valence	15.33						
σ residual	18.12						

Table 2. Results of confirmatory (G)LMMs on *IES*, *accuracy*, *expectancy*, *valence* and *arousal ratings* in Experiment 2. For each model we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated statistics (*t*-test for LMMs, *z*-test for GLMMs).

Figure 3. Box-plot of *IES*, *accuracy*, *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 value for each participant and condition.

3.3) Discussion

Experiment 2 demonstrated that probabilistic information can be extracted from the environment at an implicit level, and that this information is then used to coherently generate and implement (but not to update) new affective predictions, similarly as when information is extracted at an explicit level (cf. Del Popolo Cristaldi, Gambarota, et al., 2021). As hypothesized (H2b), experiencing a reliable S1-S2 relationship during the learning phase led participants in the CG to subsequently rely on the implicitly learned associations to accordingly *generate* and *implement* new predictions about the valence of the upcoming stimuli. In fact, the CG reported more negative expectancy ratings to the cues formerly paired with a negative picture, while the UG did not show any expectancy modulation depending on the cue color.

Moreover, consistent with our previous findings (Del Popolo Cristaldi, Gambarota, et al., 2021) and with the S1-S2 study employing an implicit anticipation pattern (Lin et al., 2018), implicit previous experience was ineffective in influencing the subjective reactions during the *updating* stage, in which both valence and arousal ratings showed only the hypothesized (H3c) valence-dependent modulation.

These results cannot be explained by any potential unexpected difference in the way implicit learning occurred in the two groups. In fact, no significant group effects emerged on the performance to the parity judgment task, as measured through RTs (cf. H1a) and accuracy (cf. H1b), suggesting that the distracting task acted similarly in the two groups. Moreover, from the post-experiment manipulation check question (see 3.1.2), it was confirmed that none of the participants actually caught the exact probabilistic ratio they were exposed to during the learning phase. Thus, it can be concluded that Experiment 2 results reflect the effects of actual implicit previous experience, and that they must be specifically ascribable to the different probabilistic ratios (100% vs. 50%) experienced by the two experimental groups.

4) GENERAL DISCUSSION

This follow-up study represents an attempt to shed further light on the construction of the subjective experience of emotion as conceived within the recent *predictive models of emotion* (Barrett, 2017; Seth & Friston, 2016), covering both some gaps in the existing literature and some limitations of our previous research (Del Popolo Cristaldi, Gambarota, et al., 2021). Indeed, little was known about how subjective affective experience was shaped when faced with new, ambiguous environmental cues, or whether it could be influenced by implicitly experienced probabilistic information. Moreover, no studies had investigated whether these processes might interact with the (un)certainty of previous experience (and thus, with the reliability of the derived predictive models). However, implicitly extrapolating present

statistical regularities to generate (affective) predictive models, and subsequently using these models in new and potentially ambiguous contexts, are both crucial skills for constructing efficient predictions (Friston, 2010; Shipp, 2016).

Regarding the construction of new predictions under *ambiguity* (Experiment 1), we found that subjective affective experience in all the stages (generation-implementation and updating) was dampened when facing ambiguous cues, and that this effect was independent of (un)certainty of previous learnings. Thus, it seems that when it comes to evaluating affective ambiguity, the processing resources are mostly employed to analyze the novelty of the present situation, and thus the information available in the *here and now* prevails over *past* knowledge. When presented with unambiguous cues (for which one might have formerly constructed a reliable internal model), people showed more intense subjective ratings, probably due to a pre-activation of the expected affective experience (as it might be supposed according to Barrett, 2017 and Seth & Friston, 2016). When faced with ambiguous cues (for which no reliable internal model could have been constructed from previous experience), instead, subjective affective experience was dampened, since it could not have been coherently pre-activated on the basis of the available information. Moreover, we demonstrated that previous reliable learnings may be used in a later moment to predict and give meaning both to unambiguous and ambiguous environmental cues, supporting the idea that affective predictions generalize from the specific features of past contexts to new ambiguous ones, as hypothesized by the predictive framework (Barrett, 2017; Friston, 2010; Shipp, 2016).

For what concerns the role of *implicit* information on subjective expectancies and reactions to new affective stimuli (Experiment 2), we confirmed that statistical knowledge can be actually inferred from the environment without any explicit instruction and focus of attention, as stated by the predictive framework (Bar, 2007). Participants who were exposed to

a reliable and implicit association between stimuli then tapped into it to coherently *generate* and *implement* (but not to update) new affective predictions, even though none of them explicitly reported to have caught any S1-S2 relationship. We thus confirmed that, even in the case of implicit learning, relying on certain prior experience can lead to a pre-activation of the expected valence of future stimuli, as it occurs when prior learning is explicit (Del Popolo Cristaldi, Gambarota, et al., 2021).

Although the present research has further developed our paradigm, overcoming some previous limitations (Del Popolo Cristaldi, Gambarota, et al., 2021), some facets could still be improved. First, even in this advanced version, the paradigm remains quite artificial with respect to real-life situations, in which the affective stimuli people are exposed to are often multimodal and dynamic. Second, previous experience is manipulated only in terms of (un)certain probabilistic relationships between stimuli (i.e., S1-S2 congruency). However, other characteristics of previous experience, such as the frequency of exposure, or the familiarity with the physical environment in which the stimuli are embedded, may be of interest, too. Third, we have only manipulated ambiguity with respect to cues, but also ambiguity of targets can have a great impact on subjective affective experience. Last, in our line of research we only focused on subjective experience, as overtly rated by participants, but more subtle modulations may be experimentally caught by measuring also covert processing indices (e.g., psychophysiological measures, neural activity).

In conclusion, and net of the present limitations, our results seem to partially support the assumptions of *predictive models of emotion* (Barrett, 2017; Seth & Friston, 2016), further deepening our understanding of the mechanisms involved in the subjective affective experience, as constructed from prior knowledge. We confirmed that people are able to infer the regularities necessary to generate affective predictive models even at an *implicit* level, being

exposed to reliable or unreliable associations between stimuli without an explicit focus of attention. This is presumably ascribable to associative learning mechanisms acting mostly implicitly, on which prediction construction primarily relies (Bar, 2007; Dale et al., 2012). The affective predictive models thus generated, if sufficiently reliable, are then used at a later time, every time a new unambiguous situation must be faced, to predict potentially salient events accordingly (implementation stage). When it comes over to *ambiguous* situations, processing resources in the here and now are presumably allocated to scan the environment. Assessing environmental ambiguity in order to update existing predictive models may thus turn into a dampened subjective affective experience, regardless of past learnings. Nevertheless, having experienced reliable relationships between stimuli in the past leads future subjective expectancies to effectively generalize also to new ambiguous cues, in line with the predictive framework (Barrett, 2017; Friston, 2010; Shipp, 2016). Thus, subjective experience under ambiguity seems to be affected by the reliability of prior experience in the *generation-implementation* stages, while it is more prominently modulated by currently available contextual information in the *updating* stage.

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/gdr3b/> and <https://osf.io/z5esb/>.

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8) SUPPLEMENTARY MATERIAL

Valence	NAPS pictures names
neg	<p>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</p>
neu	<p>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</p>

Table S1. List of NAPS picture names used as S2s, sorted by valence (neg = negative, neu = neutral).

Measure	neg		neu		<i>t</i> (118)	<i>p</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>		
luminance	114.149	27.503	116.943	27.615	-0.555	.58
contrast	65.682	11.569	66.225	11.490	-0.258	.797
jpeg_size	350012.367	118541.318	331739.683	120579.766	0.837	.404
entropy	7.579	0.338	7.608	0.311	-0.489	.626
LABL	47.078	11.035	48.411	11.090	-0.66	.511
LABA	1.684	4.6	0.541	7.901	0.969	.335
LABB	7.444	9.766	7.492	11.416	-0.025	.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.