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THE ROLE OF PROBABILISTIC INFORMATION ON AFFECTIVE PREDICTIONS:
NEURAL AND SUBJECTIVE CORRELATES AS MODULATED BY INTOLERANCE OF UNCERTAINTY

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"Prediction had become a privilege now lost to her.

Never mind the outside world, she could not even guess her own actions,

or the course of her thoughts.

Was this the true nature of emotion? she wondered.

The great defier of logic, of control—the whims of being human.

What lay ahead?"

Steven Erikson

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LIST OF ABBREVIATIONS

ACC	anterior cingulate cortex
aINS	anterior insula
ANS	autonomic nervous system
BA	Broadmann Area
BIS	behavioral inhibition system
BOLD	blood-oxygen-level-dependent
c	cluster statistic
CG	certain group
CI	confidence intervals
CMV	contingent magnetic variation
CNS	central nervous system
CNV	contingent negative variation
DF	degrees of freedom
dlPFC	dorsolateral prefrontal cortex
DMN	default mode network
dmPFC	dorsomedial prefrontal cortex
dPCC	dorsal posterior cingulate cortex
DV(s)	dependent variable(s)
EMG	electromyography
EMM(s)	estimated marginal mean(s)
EPN	early posterior negativity
ERD	event-related desynchronization
ERF(s)	event-related field(s)
ERP(s)	event-related potential(s)
fMRI	functional magnetic resonance imaging

FOTU	fear of the unknown
(G)LMM(s)	(generalized) linear mixed-effects model(s)
hd-EEG	high-density electroencephalography
HR(V)	heart rate (variability)
IA	Intolerance of Ambiguity
IADS	International Affective Digitized Sounds
IAPS	International Affective Picture System
ICA	Independent Component Analysis
IES	Inverse Efficiency Score
IFG	inferior frontal gyrus
IPS	intraparietal sulcus
ISI	inter-stimulus interval
ITI	inter-trial interval
IU	Intolerance of Uncertainty
IUS	Intolerance of Uncertainty Scale
lPFC	lateral prefrontal cortex
LPP	late positive potential
M	mean
MAD	Median Absolute Deviation
MEG	magnetoencephalography
mINS	mid-insula
MMCD	Mahalanobis-Minimum Covariance Determinant
MMN	mismatch negativity
mPFC	medial prefrontal cortex
MRCP(s)	movement related cortical potential(s)
NAPS	Nencki Affective Picture System

NEG	negative valence
NEU	neutral valence
OFC	orbitofrontal cortex
OSF	Open Science Framework
PCC	posterior cingulate cortex
PFC	prefrontal cortex
PFMC	posterior frontomedian cortex
pINS	posterior insula
POS	positive valence
ROI(s)	region(s) of interest
RQ	research question
rs-fc MRI	resting state functional connectivity magnetic resonance imaging
RT(s)	reaction time(s)
s	cluster size
sbps	subparietal sulcus
SCR	skin conductance response
SD	standard deviation
SE	standard error
SGC	subgenual cortex
sLORETA	standardized low-resolution brain electromagnetic tomography algorithm
SMA	supplementary motor area
SPN	stimulus preceding negativity
S-R	stimulus-response
STS	superior temporal sulcus
TPJ	temporo-parietal junction
UG	uncertain group

VAS(s) visual analogue scale(s)

VEF(s) visual evoked magnetic field(s)

vlPFC ventrolateral prefrontal cortex

vmPFC ventromedial prefrontal cortex

VPP vertex positive potential

OVERVIEW

Emotions have been recently reconsidered as interoceptive predictive models, "constructed" by the brain on the basis of contextual information and prior experience, with the aim to predict relevant stimuli or events, and to provide the organism with optimal resources for survival. Nevertheless, the specific mechanisms underlying the construction of affective predictions both at the neural and subjective experience level remain unclear. More specifically, both the role played by contextual information and prior experience on the one hand, and the potential interactions with dispositional characteristics such as Intolerance of Uncertainty (IU), which is considered a trans-diagnostic risk factor for affective disorders, on the other hand, have yet to be unraveled. The present thesis aimed to answer these open questions. As a first aim, we investigated how contextual information of different predictive value modulates the neural correlates of affective predictions construction. Second, we explored how prior probabilistic experience affects the construction of affective predictions at the subjective experience level. Third and last, we studied how individual differences in IU impact on the construction of affective predictions as a function of contextual information and prior experience.

In Chapter 1, a description of the predictive coding theoretical framework (Clark, 2013; Friston, 2010), and of its recent application to the emotion domain will be provided. More in detail, predictive coding will be introduced and discussed as a domain-general theory of brain functioning, and its application to the emotion domain, as conceptualized within the theory of constructed emotion (Barrett, 2017), will be presented. A detailed analysis on affective cueing paradigms (and the results they have collected) as useful tools for investigating affective predictions will follow. Finally, conceptual and empirical links between IU, its associated behavioral patterns and its shared features with affective psychopathology on the one hand, and affective prediction construction on the other hand will be reviewed.

The experimental body of this thesis will be presented in the following chapters. Chapter 2 will focus on the first research aim, by presenting results from a high-density EEG (hd-EEG) study (Study 1) investigating the neural correlates of affective predictions as constructed in presence of contextual information of different predictive value. In Chapter 3 we will focus on the second aim, as tackled by a set of studies (Studies 2 to 5) in which we manipulated prior experience in terms of affective contingency between stimuli, and we measured subjective affective ratings to subsequent affective predictions, both within and across sensory modalities. Last, in Chapter 4, the third aim will be covered investigating IU links with both the neural correlates of affective predictions as a function of contextual information (Study 6), and the subjective affective ratings to new predictions depending on previous experience (re-analysis of Studies 2 to 5 in relation to IU variable).

Taken together, this thesis contributes to untangling the dynamics of affective prediction construction at the neural and subjective experience level, as summarized in the General Discussion. Contextual information and prior experience were found to differently influence (depending on their predictive value), and to interact with IU, in shaping the neural correlates and the subjective experience of emotion along the construction of affective predictions. Thus, this work offers both a theoretical contribution to predictive models of emotion, by better clarifying the mechanisms subtending prediction construction at the neural and subjective experience levels, and potential clinical implications for the prevention and treatment of anxiety disorders, given the trans-diagnostic nature of IU as a risk factor for the development of affective psychopathology.

Keywords: *Emotion*, *predictive coding*, *hd-EEG*, *affective cueing paradigm*, *Intolerance of Uncertainty*

CHAPTER 1

GENERAL INTRODUCTION

"Predicting the future is a mug's game, but any game is improved when you can actually keep the score."

Douglas Adams

Imagine you are sitting in a café, in front of a person you don't find particularly attractive but who has asked you out on a date several times before you finally accepted. You suddenly realize you're blushing, your stomach is fluttering, your body is shaking, and you seem unable to stay focused on the conversation. You might think that all of these signs prove that, despite your initial resistance to dating this person, you are actually attracted to them as a potential partner. But, what if you come home from your date, with that exciting feeling that only the beginning of a love story can leave you with, and you realize you have a high fever? The same signs that made you think of a potential attraction to your date will suddenly take on a whole new meaning as you dial your GP's number to get a prescription for acetaminophen. Such things happen very often in our everyday lives, although we are not always aware of them. We continuously and spontaneously predict and make meaning of stimuli (coming from both inside and outside our bodies) based on the information available in the present context, and on previous experience that may guide our expectations and reactions; and this applies as much to sensory stimuli as to affective stimuli. These concepts, however, have rarely been brought into the focus of investigation by the prevailing theories in affective neuroscience, until the recent application of the predictive coding framework to the emotion domain.

1.1 THE PREDICTIVE CODING FRAMEWORK

During the last decade a growing interest has been raised towards the *predictive coding* framework (Bar, 2007; Clark, 2013; Friston, 2009, 2010; Friston & Kiebel, 2009; Huang & Rao, 2011; Knill & Pouget, 2004; Shipp, 2016). Predictive coding has been proposed as a *domain-general* theory of brain functioning, based on the assumption that the human brain evolved as a self-organizing system with the aim to ensure an efficient allostatic balance between the organism and its environment (Friston, 2010; McEwen & Wingfield, 2010; Sterling, 2012; Sterling & Laughlin, 2015). In order to continuously provide the human body with optimal resources for growth, survival and reproduction, the brain relies on a core mechanism: *prediction construction*. According to predictive coding, the brain does not merely react to stimuli at the time of their occurrence, but, as its spontaneous activity, it constantly and actively predicts future inputs starting from its internal models of inner and outer milieu (Clark, 2013; Friston, 2010; Pezzulo et al., 2021). Internal models are essential for every complex system to (self-)regulate, i.e., to achieve desirable outcomes (allostatic balance) net of all the potential disturbances (perturbations of allostasis) (Conant & Ross Ashby, 1970). In fact, they enable the brain to construct predictions in a dynamic and flexible way (Friston, 2005). Internal 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, namely the likelihood (i.e., the probability of an input, given its causes) and the prior (i.e., the a-priori probability of the causes of an input) (Clark, 2013; Friston, 2010; Shipp, 2016). They are also *hierarchical*, i.e., every input is specified at multiple levels of representation, and the best internal models available at higher levels of the hierarchy are used as the source of priors for models at subordinate levels (Clark, 2013; Friston, 2005; Shipp, 2016). The intrinsically generated internal models are therefore used to construct predictions approximating relevant features of future inputs in the service of homeostasis and allostasis (Bar, 2007; Friston, 2010; Shipp, 2016).

Prediction construction develops along three distinct neurocomputational stages (see Figure 1.1): prediction *generation*, in which currently available sensory and contextual information is extracted from the environment, and integrated with prior experience to construct predictions; prediction *implementation*, in which representations of potentially relevant inputs are pre-sensitized to facilitate perception and cognition, the best action plans to deal with the predicted situation are simulated, and the correspondent motor programs are prepared; prediction *updating*, in which predictions are tested against incoming inputs, with a possible match or mismatch (Bar, 2007; Knill & Pouget, 2004; Shipp, 2016). When the prediction is incomplete, or incompatible with actual inputs, the difference between predicted and observed input is encoded as a *prediction error*, and it is used to adjust the generative model by minimizing the error at every level of the hierarchy until the pan-hierarchical overall representation is refined (Bar, 2009; Friston, 2005, 2009; Shipp, 2016). Prediction errors can be minimized either by changing sensory input selectively sampling data conforming to predictions (i.e., through *action*), or by changing predictions so that they conform to actual input (i.e., through *perception*). Furthermore, the prediction error is weighted according to *precision*: *attention* modulates the magnitude of the prediction error by assigning greater weights to more reliable and informative prediction errors, thus leading them to a greater impact on the adjustment of generative models (Clark, 2013; Friston, 2009, 2010; Kok et al., 2019; Shipp, 2016; Yon & Frith, 2021). The generation-implementation-updating cycle occurs mostly *implicitly*, potentially emerging into awareness only in case of a mismatch (Bar, 2007). Moreover, it occurs *iteratively*, so that by means of the continuous exchange of information between top-down predictions and bottom-up prediction errors the system might efficiently pursue error minimization and generative models optimization, eventually ensuring survival and a flexible adaptation to the environment (Friston & Kiebel, 2009; Shipp, 2016; Sterling, 2012; Sterling & Laughlin, 2015).

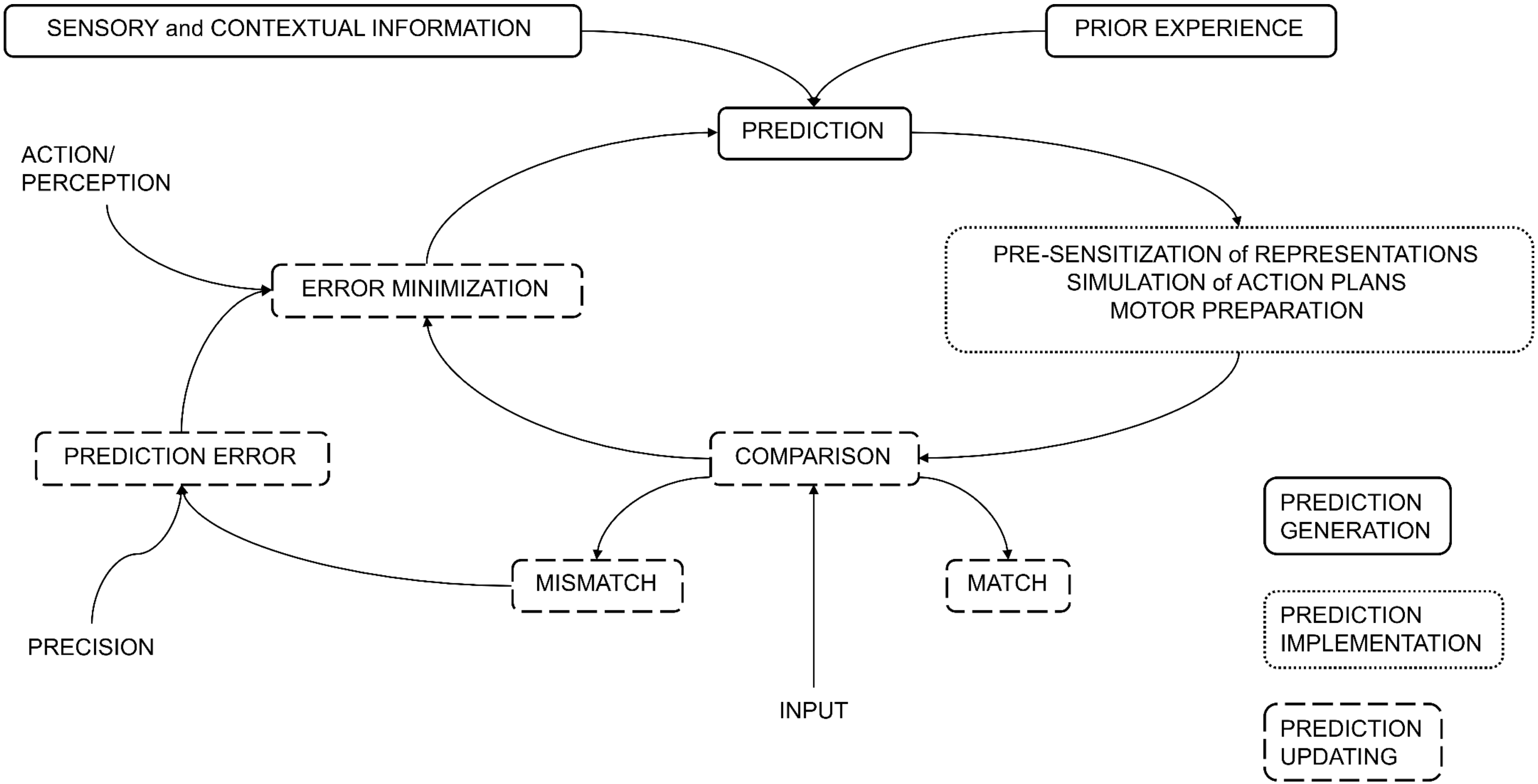

Figure 1.1 Schematic representation of the three stages of prediction construction.
During prediction *generation* (continuous-lined boxes) predictions are generated on the basis of prior experience and the available (sensory and contextual) information. During the *implementation* stage (dotted-lined boxes), representations of potentially relevant inputs are pre-sensitized, and action plans and correspondent motor programs are prepared. During prediction *updating* (dashed-lined boxes), the actual input is compared with predictions, and in case of mismatch a prediction error is encoded, minimized, and used to adjust future predictions.

All the neurocomputational stages of prediction construction are implemented within the structural and functional architecture of human brains, thanks to the bidirectional hierarchical organization of the cerebral cortex, and to the laminar differentiation between cortical layers. Pyramidal neurons encode the three core components of predictive coding in separate units: *prediction units*, which code for predictions; *error units*, encoding prediction errors; and *precision units*, which represent the reliability of predictions (Friston, 2010; Kok et al., 2019; Shipp, 2016). Moreover, the hierarchical organization of cortico-cortical connections ensures an optimal flow of top-down and bottom-up information, thanks to which prediction generation, implementation and updating are iteratively deployed. *Backward connections* from higher to lower levels of the hierarchy carry multimodal *predictions*, which are originated within cortical layers characterized by less laminar differentiation (agranular cortex, layer V), and propagate to areas with a greater laminar differentiation (dysgranular and granular cortex, layers I/II/III) changing the firing rates of their neurons (Barbas, 2015; Barbas & García-Cabezas, 2015; Barbas & Rempel-Clower, 1997; Barrett & Simmons, 2015; Friston, 2005; Rao & Ballard, 1999; Shipp, 2016). In this way, top-down predictions can shape the ongoing pattern of neural activity within lower levels of the hierarchy, anticipating sensory input through the pre-sensitization of potentially relevant representations, and preparing action (Bar, 2007; Barrett & Simmons, 2015). *Forward connections* from lower to higher levels of the hierarchy carry *prediction errors*, computed in more differentiated granular cortical areas, and projected back to less differentiated agranular layers, so that errors can be minimized, and the generative predictive models can be updated in a data-driven fashion according to new, bottom-up information (Barbas, 2015; Barbas & García-Cabezas, 2015; Barbas & Rempel-Clower, 1997; Barrett & Simmons, 2015; Friston, 2005; Rao & Ballard, 1999; Shipp, 2016). What needs to be passed forward along the system is only the unpredicted portion of information (i.e., the prediction error), because, according to the principle of efficient coding, the flow of information within the brain tends to a parsimonious encoding, and to redundancy reduction between sensory input and its representation (Clark, 2013; Friston, 2010). Last, *lateral connections* between *precision units* within the same hierarchical level mediate the influence of error units on prediction units, by dynamically modifying the synaptic gain of neurons computing the prediction error, eventually reducing or increasing the weight given to inputs as a function of the confidence put either in top-down predictions or in the reliability of bottom-up incoming stimuli (Barbas, 2015; Barbas & García-Cabezas, 2015; Barbas & Rempel-Clower, 1997; Barrett & Simmons, 2015; Friston, 2005).

It is thus easy to understand why predictive coding has emerged as a domain-general, coherent and neurobiologically plausible theoretical scaffolding (Hutchinson & Barrett, 2019). First, it relies on well-validated neuroanatomical pathways of information flow in the brain (Barbas, 2015; Barbas & Rempel-Clower, 1997; Friston, 2005). Second, it offers a parsimonious unified explanation for different phenomena, re-framing attention, perception and action as emergent properties of prediction construction (Friston, 2009). Third, it proved to be able to account for both explicit and implicit processes within several cognitive domains, such as visual perception (Alink et al., 2010; Friston, 2005; Huang & Rao, 2011; Kok et al., 2019; Rao & Ballard, 1999; Spratling, 2010; Stefanics et al., 2018), motor control (Duma et al., 2020; Kilner et al., 2007; Mento & Vallesi, 2016; Shipp et al., 2013), memory (Bar, 2009; Barron et al., 2020), auditory perception (Baldeweg, 2006; Carbajal & Malmierca, 2018; Denham & Winkler, 2020; Heilbron & Chait, 2018; Kumar et al., 2011), multisensory integration (Apps & Tsakiris, 2014; Shi & Burr, 2016; Talsma, 2015), language (Lewis et al., 2016; Lewis & Bastiaansen, 2015; Lupyan & Clark, 2015; Shain et al., 2020; Ylinen et al., 2017), interoception and emotion (Ainley et al., 2016; Barrett, 2017; Barrett & Simmons, 2015; Kleckner et al., 2017; Owens et al., 2018; Seth, 2013; Seth & Friston, 2016), and even psychopathology (Barrett et al., 2016; Brewer et al., 2021; Gerrans & Murray, 2020; Pang et al., 2019; Paulus et al., 2019; Smith et al., 2020; Sterzer et al., 2018, 2019; van de Cruys et al., 2014).

Of particular interest is the recent application of the predictive coding framework to the emotion domain, according to which emotions have been reconsidered as specific types of generative predictive models, based on interoception and developing along the three abovementioned neurocomputational stages (Barrett, 2017; Barrett & Simmons, 2015; Lee et al., 2021; Seth, 2013;

Seth & Friston, 2016). This approach dramatically shifted the perspective on the study of emotion. Extant emotion theories, in fact, traditionally considered emotions as innate response tendencies, eliciting autonomic and behavioral responses to salient stimuli or appraisals within a stimulus-response (S-R) pattern (Anderson & Adolphs, 2014; Damasio, 1994, 1998; Ekman, 1992b; Ekman & Cordaro, 2011; Izard, 2007, 2010, 2011; Levenson, 2011; Panksepp & Watt, 2011; Roseman, 2011; Russell, 2003; Scherer, 2009). According to the basic emotion perspective, in particular, each emotion had been assumed to be subtended by dedicated neural circuits and patterns of physiological correlates, which were considered as unique, universal, and relatively stable across time, cultures, and contexts (Ekman, 1992a, 1992b; Ekman et al., 1987; Ekman & Cordaro, 2011; Levenson, 2011; Panksepp & Watt, 2011). Predictive models of emotion, instead, have gone beyond the S-R conceptualization proposing an innovative approach: emotions are no longer considered as "reactions" to the world, triggered by eliciting stimuli and/or appraisals, and subtended by emotion-specific neural and physiological correlates; rather, they are reconceptualized as context-dependent "constructions" of the world, built by the brain within domain-general large-scale circuits, with the aim to make meaning of bodily sensations in relation to the inner and outer context (Barrett, 2017; Barrett & Satpute, 2019). One of the most prominent theories within predictive models of emotion is the *theory of constructed emotion* (Barrett, 2017), which will be presented in detail in the next section.

1.2 THE THEORY OF CONSTRUCTED EMOTION

The *theory of constructed emotion* (Barrett, 2017) is a brain-based, context-sensitive computational theory of emotion. It stands on the idea that emotions can be considered as particular types of predictive models, based on interoceptive signals (Barrett, 2017). Interoception is defined as the overall process of representing and making use of the sensations derived from the statistical regularities inferred from the internal milieu (Craig, 2015). In line with the assumptions of predictive coding, the theory of constructed emotion agrees that human brains, as their spontaneous activity, constantly generate-implement-update predictions (Pezzulo et al., 2021; Sterling, 2012), with the aim to identify (and categorize) inputs, to infer their causes, and to drive action. When the internal models refer to an emotion concept to make meaning of actual inputs, the resulting affective prediction is subjectively appraised as an instance of emotion (Barrett, 2017). Thus, conscious emotional experience, in the form of subjective feeling states, arises from affective predictive models about the likelihood and the priors of interoceptive signals (i.e., the most likely internal and/or external causes of observed changes in the physiological condition of the body) (Seth, 2013; Seth & Friston, 2016). Affective prediction errors are presumably computed out of awareness, until they are used to update the internal models eventually emerging in consciousness (Lee et al., 2021). In this light, emotional valence has been reconsidered as reflecting the degree of prediction updating, with a consequent effect on the learning rate needed to adjust internal models on the basis of new evidence: if sensory input fulfils predictions, this results in a positive valence, and in a decreasing of the learning rate; when sensory data violate predictions, emotional valence is negative, and the learning rate is increased (Joffily & Coricelli, 2013). Thus, in a broader perspective, valence may represent an index of the changes in the reliability of internal models: negatively-valenced states reduce reliance on prior expectations, while positively-valenced states increase reliance on prior expectations (Hesp et al., 2021).

The theory of constructed emotion developed from neuroscientific evidence that challenged the main tenets of traditional emotion theories, as it failed to find a consistent one-to-one mapping between each emotion and its neural and physiological correlates (Barrett & Satpute, 2013; Guillory & Bujarski, 2014; Lindquist et al., 2012; Siegel et al., 2018; Touroutoglou et al., 2015). The observed patterns of activation within the central and the peripheral nervous system did not clearly and univocally distinguish one emotion from another, and variability within emotion categories emerged as a core feature (Barrett, 2009, 2017; Barrett et al., 2014; Herschbach & Bechtel, 2014; Siegel et al., 2018). Variability might be a consequence of *degeneracy*, a property of complex systems (i.e., the human brain) thanks to which structurally distinct mechanisms (i.e., different sets of neurons) are able to perform the same function (i.e., give rise to the same instance of emotion) (Barrett, 2017;

Edelman & Gally, 2001). Therefore all instances within an emotion category are unlikely to share a common neural substrate, rather they result from the context-dependent activation of multiple spatiotemporal patterns in distributed neural populations (Barrett, 2017; Barrett & Satpute, 2019).

The domain-general large-scale brain circuits supporting homeostasis, allostasis and interoception (see Figure 1.2), and their hierarchical structural and functional architecture, have been suggested as the neural substrates for the construction of affective predictions (Barrett, 2017; Seth & Friston, 2016). Interoceptive *predictions* arise within agranular cortical regions such as the anterior cingulate cortex (ACC), the ventromedial prefrontal cortex (vmPFC), the orbitofrontal cortex (OFC), the anterior insula (aINS), the supplementary motor area (SMA), and the subgenual cortex (SGC), and they are projected to both primary sensory areas and (mostly subcortical) regions implementing homeostasis, such as the hypothalamus, the brainstem, and spinal cord nuclei (Barrett, 2017; Barrett & Simmons, 2015; Paulus et al., 2019; Seth & Friston, 2016). Within the latter areas the predicted metabolic requirements of the body (based on prior experience and on the estimation of necessary resources) are computed, eventually determining an allostatic adjustment; while the expected consequences of allostatic adjustments themselves, expressed in terms of interoceptive signals, are transmitted to the former sensory areas (Barrett & Simmons, 2015). Interoceptive *prediction errors* are computed in the granular cortex within mid- and posterior insula (mINS, pINS), amygdala, ventral striatum (which also carries information about rewards with an unexpected impact on homeostasis), and cerebellum (which also carries visceromotor information), and they are propagated back to the cortex in order to be minimized (Barrett, 2017; Barrett & Simmons, 2015; Seth & Friston, 2016). The regions involved in interoceptive predictions construction belong to three main brain networks. The vmPFC, together with the dorsomedial PFC (dmPFC) and the posterior cingulate cortex (PCC), is part of the *default mode network* (DMN) (Raichle, 2015). The vmPFC supports a sensory-visceromotor linking activity, by collecting sensory and interoceptive input from inside and outside the body, and by conveying it to subcortical structures (e.g., hypothalamus, amygdala, periaqueductal grey) (Raichle, 2015). The dmPFC is associated with subjective judgements about emotionallyvalenced stimuli (Raichle, 2015). The PCC, thanks to its connections with the hippocampal-parietal memory network, is involved in the recollection of prior experience (Raichle, 2015). Cortical regions as the aINS, the OFC and the temporal pole are part of the *salience network*, which supports interoceptive-autonomic processing by identifying relevant inputs, and by integrating this information with visceral and autonomic cues (Seeley et al., 2007). Last, areas such as the dorsolateral prefrontal cortex (dlPFC) and the intraparietal sulcus (IPS) are involved in the *frontoparietal control network* (Dosenbach et al., 2007). They build and maintain simulations, inhibiting those with low priors, and they tune internal models with prediction errors by supporting top-down control activity in response to feedback (Dosenbach et al., 2007). All these regions and networks, and the functions they subtend, play a pivotal role in upholding the constant cycle of generation-implementation-updating of affective predictions (Barrett, 2017).

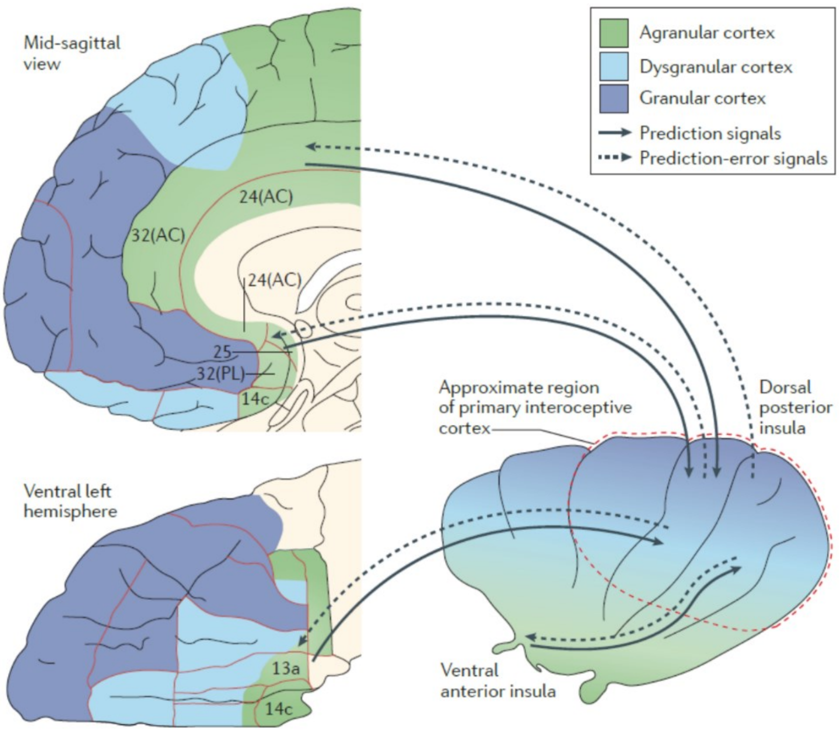

Figure 1.2 Neural circuits involved in interoceptive prediction construction.
Brodmann areas (BA) 24, 25, 32 = cingulate cortex, BA 14c = ventromedial prefrontal cortex (vmPFC), BA 13a = orbitofrontal cortex (OFC), AC = anterior cingulate, PL = prelimbic cortex. From “Interoceptive predictions in the brain”, by L. F. Barrett and W. K. Simmons, 2015, Nature Reviews Neuroscience, 16(7), p. 423.

Plentiful evidence from the last 10 years of neuroscience research seems to support the theory of constructed emotion. Task-related functional magnetic resonance imaging (fMRI) studies highlighted that (i) brain activations within the same emotion category differ as a function of the situation (e.g., internal vs. external focus, circumstances eliciting physical threat vs. social evaluation, typical vs. atypical instances of an emotion category) in which the emotion itself is experienced, eliciting context-specific (but not emotion-specific) neural activity (Oosterwijk et al., 2015; Wilson-Mendenhall et al., 2011, 2015); (ii) emotions (as induced through experimental paradigms involving scenario immersion) are subtended by variable patterns of activations within domain-general large-scale brain networks (Oosterwijk et al., 2012; Wilson-Mendenhall et al., 2011); (iii) emotional states are represented multimodally in the brain, independently of the specific sensory cues (e.g., faces, body movements, voices) from which they are perceived (Peelen et al., 2010). Moreover, resting-state functional connectivity MRI (rs-fc MRI) studies investigating brain's intrinsic activity demonstrated that (i) the existence of emotion-specific brain networks is poorly supported; rather, different emotional experiences seem to share common and distributed networks (Raz et al., 2016; Touroutoglou et al., 2015); (ii) connectivity patterns within large-scale networks might account for variability in the subjective experience of emotion, such as intensity ratings (Raz et al., 2016), or interoceptive accuracy (i.e., the level of concordance between objective and subjective measures of interoceptive signals) (Kleckner et al., 2017). Finally, several meta-analyses and reviews of neuroimaging data failed to find a coherent one-to-one mapping between each emotion category and the subtending activation patterns within the central nervous system (CNS) (Barrett & Satpute, 2013; Barrett & Wager, 2006; Clark-Polner et al., 2017; Lindquist et al., 2012; Wager et al., 2015), the autonomic nervous system (ANS) (Siegel et al., 2018), and even cortical electrical activity as recorded from intracranially implanted electrodes (Guillory & Bujarski, 2014). More specifically, no sound evidence has emerged on either *consistency* (i.e., increased activity within certain brain regions in association with *every* instance of an emotion category) or *specificity* (i.e., activation within certain brain regions in association with instances of *only one* emotion category) of brain activations, contrary to the predictions of the traditional locationist accounts (Lee et al., 2021; Lindquist et al., 2012).

Thus, taken together, recent evidence supports some of the main claims of the theory of constructed emotion: emotions are "constructions" deriving from context-specific, multimodal interoceptive predictions; they are subtended by neural activity within domain-general, distributed brain networks, which are not emotion-specific nor consistent; and they are, together with other mental processes, the "by-product" of the brain's core task of continuously and implicitly constructing predictions in the service of homeostasis and survival (Barrett, 2017). As a main consequence, thus, and in line with predictive coding (see Figure 1.1), both *contextual information* (i.e., the combination of sensory input from inside and outside the body, and the associated probabilistic structure) and *prior experience* (i.e., the knowledge deriving from the extraction of repeating patterns and statistical regularities from the environment) emerge as crucial factors in shaping the process of affective prediction construction. Previous learning experiences and context-specific inputs constantly interact in constraining and refining the pool of information used to generate affective predictions, eventually causing a cascade effect also on the implementation and updating stages. Nevertheless, despite the contribution of contextual information in modulating affective predictions is viewed as fundamental at the theoretical level, the specific role played by contextual information and prior experience in the construction of affective predictions has scarcely been studied at the empirical level. Research, instead, has typically focused on the experimental investigation of the anticipation of emotional stimuli. This literature draws mainly on traditional theoretical accounts, highlighting how the function of emotion is not only restricted to the generation of responses, but it also involves the anticipation of relevant stimuli in the environment, by promoting behavioral approach/avoidance of potential rewards/threats, and by pre-organizing adaptive bodily changes before the actual stimulus delivery (Castelfranchi & Miceli, 2011; van Boxtel & Böcker, 2004). Even though this line of evidence does not directly refer to predictive models of emotion, and it largely preceded the recent formalization of the theory of constructed emotion (Barrett, 2017), its results and experimental paradigms can still be informative in unraveling the influential role of (at least some) contextual factors on the construction of affective predictions. For this reason, in the next section the extant literature investigating emotional anticipation will be reviewed, particularly focusing on a specific type of experimental paradigm, the *affective cueing paradigm*. This paradigm, by allowing to separately investigate the three stages of affective predictions, and requiring the probabilistic manipulation of affective contingencies (see § 1.3), might represent a valuable tool for the empirical investigation of the construction of affective predictions within a predictive theoretical framework.

1.3 The affective cueing paradigm

In the last 20 years several studies investigated emotional anticipation with event-related potentials (ERPs), fMRI, magnetoencephalography (MEG), and/or peripheral psychophysiological measures (see Table 1.1). Authors mostly employed *affective cueing paradigms* (e.g., S1-S2 paradigm, threat-of-shock paradigm), in which a sequential presentation of two stimuli is typically implemented. The *S1* (or *cue*) is a warning stimulus, which signals with strong or weak certainty the imminent delivery of a relevant stimulus; while the *S2* (or *target*) is an emotional stimulus, such as affective pictures or faces, or painful stimuli (see Mercado et al., 2008 for a review). The relationship between specific S1 types and the emotional valence of S2s or the probability of painful S2s (i.e., *affective contingency*) is typically manipulated so that in a certain (i.e., fully predictive) experimental condition each S1 type is always paired with the same S2's emotional valence or probability; in an uncertain (i.e., non-predictive) condition, S1s are absent or not informative about S2's valence or probability. Although it has been originally developed for different purposes, the affective cueing paradigm is particularly suited to effectively investigate the construction of affective predictions. First, it allows to target the three stages of prediction construction separately, and to explore their reciprocal relationships, with S1-processing reflecting prediction *generation*, the processes developing in the inter-stimulus interval (ISI) between S1 and S2 representing the *implementation* stage, and S2-processing indexing the *updating* stage. Second, it might allow to grasp the generative, probabilistic and hierarchical nature of affective predictive models: by employing different types of stimuli (e.g., visual, auditory), contexts, and/or stimulus timing it is possible to study how predictive models generalize across sensory modalities, contexts, and time; while by manipulating probabilistic relationships between S1 and S2 at a global (block-wise) or local (trial-by-trial) level (as commonly done in S1-S2 paradigms within other cognitive domains; see Braem et al., 2019 for an example) it becomes possible to explore whether and how the statistical structure of inputs is extracted, and used for the construction of current or future affective predictions.

Table 1.1 Studies investigating emotional anticipation and relative details about experimental stimuli, tasks, and manipulations.
Affective contingency is expressed in terms of percentage of experimental trials in which S1 was paired with the same S2 valence: 100% represents the certain condition, between 80% and 70% a moderately predictive condition, and 50% the uncertain condition. The last column shows which paradigm stages (S1, ISI, S2) and ERP/ERF/psychophysiological indices have been analyzed. CMV = contingent magnetic variation, CNV = contingent negative variation, EMG = electromyography, EPN = early posterior negativity, ERD = event-related desynchronization, ERF = event-related field, ERP = event-related potential, HR = heart rate, LPP = late positive potential, MRCPs = movement related cortical potentials, NEG = negative, NEU = neutral, POS = positive, SCR = skin conductance response, SPN = stimulus preceding negativity, VEF = visual evoked magnetic fields, VPP = vertex positive potential.

ERPs							
Study	**S1/cue**	**S2/target**	**S1/cue emotional valence**	**S2/target emotional valence**	**S1-S2/cue-target affective contingency**	**Experimental paradigm**	**Stages investigated (and ERP components targeted for each)**
(Brown et al., 2008)	Cue words	Laser heat stimuli	NEG, uncertain	NEG	100% vs. 50%	Threat of shock	ISI (SPN), S2 (P2)
(Buodo et al., 2012)	Affective words	Affective pictures	POS, NEG, NEU	POS, NEG, NEU	100%	S1-S2	S1 (P3), ISI (SPN), S2 (P3, LPP)
(Casement et al., 2008)	Symbolic visual cues	Affective adjectives	POS, NEG, NEU, uncertain	POS, NEG, NEU	100% (and 50%, not analyzed)	S1-S2	ISI (CNV)
(Dieterich et al., 2016)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	S2 (P2, LPP)
(Gole et al., 2012)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	S1 (P2), S2 (P2, N2, LPP)
(Jin et al., 2013)	Geometric shapes	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 20%	S1-S2	S2 (N1, P2, N2)
(Johnen & Harrison, 2019)	Symbolic visual cues	Affective pictures	POS, NEG, uncertain	POS, NEG	70% vs. 50%	S1-S2	S1 (P2, EPN), ISI (SPN), S2 (P2, N2, EPN, LPP)
(Johnen & Harrison, 2020)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs 70% vs 50%	S1-S2	ISI (SPN), S2 (P2, EPN, LPP)
(Klorman & Ryan, 1980)	Acoustic tones	Affective pictures	NEG, NEU	NEG, NEU	100%	S1-S2	S1 (N1, P2, P3), ISI (CNV)
(Lin et al., 2012)	Symbolic visual cues	Affective pictures	POS, NEG	POS, NEG	100% vs. no cue	S1-S2	S2 (P2, N2, LPP)
(Lin, Gao, et al., 2014)	Symbolic visual cues	Affective pictures	POS, NEG, uncertain	POS, NEG	100% vs. 50%	S1-S2	S1 (N2), ISI (CNV)
(Lin, Liang, et al., 2014)	Symbolic visual cue	Affective pictures	POS, NEG, no cue	POS, NEG	100% vs. no cue	S1-S2	S2 (N2, LPP)
(Lin, Jin, et al., 2015)	Symbolic visual cues	Affective pictures	POS, NEG, uncertain	POS, NEG	100% vs. 50%	S1-S2	S2 (P2, N2, LPP)

(Lin, Xiang, et al., 2015)	Symbolic visual cues	Affective pictures	NEG, NEU, no cue	NEG, NEU	100% vs. no cue	S1-S2, followed by a old/new recognition task	S2 (P2, P3)
(Lin, Schulz, et al., 2015)	Symbolic visual cues	Affective facial expressions	NEG, NEU	NEG, NEU	75%	S1-S2	S2 (N170, P3)
(Lin et al., 2016)	Symbolic visual cues	Affective facial expressions	NEG, NEU	NEG, NEU	75%	S1-S2	S2 (N2, EPN, LPP)
(Lin et al., 2017)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2, followed by a old/new recognition task	S2 (P2, N2, P3, LPP)
(Lin et al., 2018)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	S2 (P2, N2, LPP)
(Lin et al., 2020)	Affective vs. scrambled facial expressions	Affective pictures	POS, NEG, NEU/uncertain	POS, NEG	100% vs 50%	S1-S2	S2 (60-1000 ms)
(Lin & Liang, 2020)	Symbolic visual cues	Affective pictures	NEG, NEU	NEG, NEU	75%	S1-S2, followed by a old/new recognition task	S2 (P2, LPP)
(Nelson et al., 2015)	Acoustic probes	Electric shocks	Predictable (P), unpredictable (U), no probe (N)	NEG, no shock	/	Threat of shock	S1 (N1, P3)
(Nelson & Hajcak, 2017)	Acoustic probes	Electric shocks vs. affective pictures	Predictable (P), unpredictable (U), no probe (N)	NEG, no S2	/	Threat of shock	S1 (N1, P3), S2 (P3, LPP)
(Peng et al., 2012)	Affective words	Affective facial expressions	NEG, NEU	NEG, NEU	75% vs. 50%	S1-S2	ISI (SPN), S2 (N1, P1, P2, N3, P3, N170)
(Perri et al., 2014)	Keypress	Affective picture	POS, NEG, NEU, scrambled	POS, NEG, NEU, scrambled	100%	Self-paced exposure task	ISI (MRCPs), S2 (P2, N2, LPP)
(Poli et al., 2007)	Affective words	Affective pictures	POS, NEG, NEU	POS, NEG, NEU	100%	S1-S2	S1 (P3, LPP), ISI (SPN)
(Qiao et al., 2018)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	ISI (SPN), S2 (P2, LPP)
(Recio et al., 2014)	Affective facial expressions	Affective facial expressions (displayed)	NEG, POS	NEG, POS	80% vs. 20%	Display an emotional facial expression	ISI (CNV), S2 (P2, N2, P3, LPP)
(Takeuchi et al., 2005)	Geometric shapes	Affective pictures	POS, NEG, NEU	POS, NEG, NEU	100%	S1-S2	ISI (SPN)
(Vallet et al., 2019)	Geometric shapes	Affective pictures	POS, NEG, NEU	POS, NEG, NEU	100%	Time perception task	S1 (P1, N1, N150, N2, P3), ISI (CNV, LPP)

(Yang et al., 2012)	Affective pictures	Affective facial expressions	NEG, NEU, no cue	NEG, NEU	100% vs. no cue	S1-S2	S1 (P3-like, LPP-like), S2 (N1, P2/VPP, N2/N3)
MEG							
Study	**S1/cue**	**S2/target**	**S1/cue emotional valence**	**S2/target emotional valence**	**S1-S2/cue-target affective contingency**	**Experimental paradigm**	**Stages investigated (and ERF components targeted for each)**
(Onoda et al., 2006)	Geometric shapes	Affective pictures	POS, NEG, uncertain, no cue	POS, NEG	100% vs. 50% vs. no cue	S1-S2	ISI (CMV), S2 (VEF)
(Onoda et al., 2007)	Geometric shapes	Affective pictures	POS, NEG, uncertain, no cue	POS, NEG	100% vs. 50% vs. no cue	S1-S2	ISI (ERD)
fMRI							
Study	**S1/cue**	**S2/target**	**S1/cue emotional valence**	**S2/target emotional valence**	**S1-S2/cue-target affective contingency**	**Experimental paradigm**	**Stages investigated**
(Bermpohl et al., 2006a)	Symbolic visual cues	Affective pictures	Emotional, NEU, no cue	POS, NEG, NEU	100%	S1-S2	ISI, S2
(Bermpohl et al., 2006b)	Symbolic visual cues	Affective pictures	Emotional, NEU, no cue	POS, NEG, NEU	100%	S1-S2	ISI, S2
(Greenberg et al., 2015)	Symbolic visual cues	Affective movie clips	POS, NEG, NEU, uncertain	POS, NEG, NEU	100% vs. 50%	S1-S2	ISI
(Grupe et al., 2013)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	ISI
(Herwig, Kaffenberger, et al., 2007)	Symbolic visual cues	Affective pictures	POS, NEG, NEU, uncertain	POS, NEG, NEU	75% vs. 50%	S1-S2	ISI
(Herwig, Abler, et al., 2007)	Symbolic visual cues	Affective pictures	POS, NEG, NEU	POS, NEG, NEU	100%	S1-S2	ISI
(Kaffenberger et al., 2010)	Symbolic visual cues	Affective pictures	POS, NEG, NEU, uncertain	POS, NEG, NEU	100% vs. 50%	S1-S2	S2
(Motzkin et al., 2014)	Symbolic visual cue	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	ISI
(Nitschke et al., 2006)	Symbolic visual cues	Affective pictures	NEG, NEU	NEG, NEU	100%	S1-S2	ISI, S2
(Onoda et al., 2008)	Acoustic tone	Affective pictures	NEG, POS, uncertain	POS, NEG	100% vs. 50%	S1-S2	ISI
(Ran et al., 2016)	Affective words	Affective facial expressions	POS, NEG, uncertain	POS, NEG	100% vs. 50%	S1-S2	S2
(Sarinopoulos et al., 2010)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	ISI, S2

(Schienle et al., 2010)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	S2
(Simmons et al., 2004)	Auditory tones	Affective pictures	NEG	NEG	100%	S1-S2 contemporary to a discrimination task	ISI
(Ueda et al., 2003)	Geometric shapes	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	ISI
(M. Walter et al., 2009)	Symbolic visual cues	Affective pictures	POS, NEG, NEU, no cue	POS, NEG, NEU	100%	S1-S2	ISI
Peripheral psychophysiological indices							
Study	**S1/cue**	**S2/target**	**S1/cue emotional valence**	**S2/target emotional valence**	**S1-S2/cue-target affective contingency**	**Experimental paradigm**	**Stages investigated (and peripheral indices targeted for each)**
(Chen & Lovibond, 2016)	Symbolic visual cue	Affective pictures	NEG, NEU, uncertain, ambiguous	NEG, NEU	100% vs. 50%	S1-S2	ISI (SCR)
(Grupe & Nitschke, 2011)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	S2 (SCR)
(Klorman & Ryan, 1980)	Acoustic tones	Affective pictures	NEG, NEU	NEG, NEU	100%	S1-S2	ISI (HR)
(Nelson et al., 2015)	Acoustic probes	Electric shocks	Predictable (P), unpredictable (U), no probe (N)	NEG, no shock	/	Threat of shock	S1 (startle)
(Nelson & Hajcak, 2017)	Acoustic probes	Electric shocks vs. affective pictures	Predictable (P), unpredictable (U), no probe (N)	NEG, no S2	/	Threat of shock	S1 (startle)
(Poli et al., 2007)	Affective words	Affective pictures	POS, NEG, NEU	POS, NEG, NEU	100%	S1-S2	ISI (HR)
(Schumacher et al., 2015)	Symbolic visual cue	Affective pictures	POS, NEG, NEU, uncertain	POS, NEG, NEU	100% vs. 50%	S1-S2	ISI (SCR, HR, EMG), S2 (SCR, HR, EMG)
(Vanderhasselt et al., 2014)	Cue words	Affective pictures	POS, NEG	POS, NEG	100%	S1-S2	ISI (pupillary dilation)

A heterogeneous set of central and peripheral psychophysiological indices, as well as fMRI blood-oxygen-level-dependent (BOLD) signal within specific regions of interest (ROIs) have been targeted to explore emotional anticipation within affective cueing paradigms. Amongst ERPs, both early (< 250 msec) and late (> 250 msec) components, as well as S1- and S2-locked ERPs have been investigated. The *P1* and *N1* components have been mostly analyzed as indices of early visual and perceptual processing: both are typically distributed over lateral occipital sites, with a latency of 100-150 msec, and they can be modulated by selective attention and subjective arousal, and by spatial attention, respectively (Hillyard et al., 1998; Hopf et al., 2002; Luck et al., 2000; Luck, 2005; Mangun, 1995; Ritter et al., 1979; Vogel & Luck, 2000). The N1 has been recently proven to be also modulated by unexpected perceptual events, showing dose-dependent sensitivity to expectancy violation (Robinson et al., 2018).

The *P2* component is distributed over anterior/central sites, and peaks around 200 msec from stimulus onset; it is sensitive to simple perceptual features of target stimuli and their frequency, with larger amplitudes to target and infrequent stimuli (Luck, 2005; Luck & Hillyard, 1994), and it also signals the degree of updating of internal models after experiencing a novel event (Gómez et al., 2019; Kimura & Takeda, 2015).

Face-specific ERPs, such as the *N170* and the Vertex Positive Potential (*VPP*), have also been investigated in studies employing face stimuli: they reflect structural encoding and a coarse emotional processing of facial expressions, and they can be considered as the opposite sides of the same dipole, both peaking around 170 msec, with the first component distributed over lateral (typically right) occipital sites, and the second over central midline sites (Bentin et al., 1996; Blau et al., 2007; Jeffreys, 1989; Luck, 2005; Robinson et al., 2018; Rossion et al., 2003). As the N1, the N170 has shown a dose-dependent modulation as a function of expectancy violation (Robinson et al., 2018).

As an early index of conflict monitoring and selective attention, sensitive to mismatching attended stimuli, studies often targeted the anterior *N2* component, distributed over frontocentral sites and peaking around 200 msec from stimulus onset (Folstein & Petten, 2008; Luck, 2005). As a further index, distributed over frontocentral midline sites, peaking between 160 and 220 msec, and sensitive to mismatching stimuli, the Mismatch Negativity (*MMN*) has been widely employed, indexing violations of statistical regularities during perceptual learning and their associated prediction error (Chennu et al., 2013; Luck, 2005; Stefanics et al., 2018). Within the same time range, the Early Posterior Negativity (*EPN*), distributed over occipital sites, has been frequently studied as an index of additional recruitment of perceptual processing resources, specific for emotion-inducing (especially positive) stimuli (Luck, 2005; Schupp et al., 2003; Weinberg & Hajcak, 2010).

Another widely investigated component is the *P3*, which represents a family of distinguishable ERP sub-components, showing either a frontal or a parietal distribution, and peaking around 300 msec. The P3 is assumed to reflect the allocation of resources for categorization/working memory updating processes; it is sensitive to stimulus probability (showing a larger amplitude to infrequent stimuli), and it has recently been reconceptualized as an index of prediction error encoding (Chennu et al., 2013; Donchin, 1981; Luck, 2005; Polich, 2012).

Last, three slow cortical potentials have been targeted as indices of sustained processing: (i) the Stimulus Preceding Negativity (*SPN*), typically measured as the mean amplitude over 200 msec before a relevant and expected stimulus, and reflecting affective-motivational anticipation processes (Brunia et al., 2011; Brunia & Van Boxtel, 2001; van Boxtel & Böcker, 2004); (ii) the Contingent Negative Variation (*CNV*), typically measured in S1-S2 paradigms as the mean amplitude of the slow wave developing during the ISI, which reflects attention orienting towards motivationally relevant stimuli (early CNV) and motor preparation for a required or possible action (late CNV), as well as being sensitive to the probabilistic and temporal structure of the experimental task (Chennu et al., 2013; Gómez et al., 2019; Mento, 2013; Mento et al., 2015; W. G. Walter et al., 1964); (iii) the Late Positive Potential (*LPP*), an index of sustained motivated attention to emotional stimuli, also sensitive to stimulus predictability (Hajcak et al., 2010; Johnen & Harrison, 2019; Lin et al., 2020; Schupp et al., 2000).

Amongst *peripheral indices*, skin conductance response (SCR), heart rate (HR) acceleration, and pupil diameter dilation have been employed as indices of arousal, since they show increased activity in association with emotional stimuli, independently from valence (Bradley et al., 1990, 2008; Greenwald et al., 1989; Lang et al., 1993). As valence-specific indices, instead, zygomaticus muscle electromyographic (EMG) activity is typically increased in response to positive stimuli; while HR deceleration and corrugator EMG activity are larger, and startle eyeblink reflex is potentiated, in association to negative stimuli eliciting defensive motivation (Bradley et al., 1990; Cacioppo et al., 1986; Dimberg, 1982, 1986; Gomez et al., 2009; Greenwald et al., 1989; Hare et al., 1970; Libby et al., 1973; Reynaud et al., 2012, 2012). The startle reflex has proven to be sensitive also to threat predictability, showing potentiation in anticipation of unpredictable relative to predictable threat (Gorka et al., 2016; Nelson et al., 2015).

This rich literature (see Table 1.1) has yielded inconsistent results. Concerning the prediction *generation* stage, some studies found emotional (especially negative) S1s to elicit a greater processing (subtended by larger P2, N2, P3 and LPP amplitudes), and a heightened defensive motivation (as indexed by startle reflex potentiation to negative stimuli), than neutral S1s (Johnen & Harrison, 2019; Klorman & Ryan, 1980; Poli et al., 2007; Vallet et al., 2019; Yang et al., 2012), and to a greater extent in the uncertain condition (Lin, Gao, et al., 2014) or in conditions of unpredictable threat (Nelson et al., 2015; Nelson & Hajcak, 2017). Other studies, instead, found no effects of emotional valence or predictive meaning of cues on S1-ERPs amplitudes (Buodo et al., 2012; Gole et al., 2012). Interestingly, none of the fMRI studies focused on S1-related brain activations.

Moving to prediction *implementation*, anticipatory resources as indexed by both ERPs/event-related fields (ERFs) and peripheral indices were found to be modulated by (i) the emotional valence of S2s, with a larger pre-allocation before highly arousing (Poli et al., 2007) and emotional (Buodo et al., 2012; Perri et al., 2014; Vanderhasselt et al., 2014) stimuli, especially when fully predicted and negatively-valenced (Brown et al., 2008; Chen & Lovibond, 2016; Klorman & Ryan, 1980; Lin, Gao, et al., 2014; Onoda et al., 2007; Peng et al., 2012; Qiao et al., 2018; Schumacher et al., 2015; Takeuchi et al., 2005; Vallet et al., 2019); and (ii) stimulus predictability, with a larger pre-allocation within the fully predictive condition (Johnen & Harrison, 2020). Some isolated studies found a larger pre-allocation of resources also towards positively-valenced stimuli (Casement et al., 2008; Schumacher et al., 2015), while others found null results (Johnen & Harrison, 2019; Onoda et al., 2006; Recio et al., 2014).

The anticipation of emotional stimuli seems to be subtended by neural activity within the following ROIs: right aINS, dlPFC, parahippocampal gyrus, ACC, SMA, parieto-occipital sulcus, bilateral OFC, thalamus, caudate nucleus, inferior parietal cortex, inferior prefrontal cortex (PFC), amygdala (Bermpohl et al., 2006b; Greenberg et al., 2015; Grupe et al., 2013; Nitschke et al., 2006; Sarinopoulos et al., 2010; Simmons et al., 2004). Valence-specific activations have been found within left dlPFC, medial prefrontal cortex (mPFC), right cerebellum, and nucleus accumbens when anticipating positively-valenced stimuli (Greenberg et al., 2015; Ueda et al., 2003); and within parahippocampal gyrus, right inferior PFC, right mPFC, right amygdala, left ACC, bilateral visual cortex, mINS, thalamus, hypothalamus, and striatum when anticipating negatively-valenced stimuli (Greenberg et al., 2015; Herwig, Abler, et al., 2007; Simmons et al., 2004; Ueda et al., 2003). Moreover, expecting a negative stimulus with high certainty (certain condition) was found to be associated with increased activation in ACC, ventrolateral PFC (vlPFC), insula and amygdala (Onoda et al., 2008). Predictive context-specific neural activations have also been found, with activity in the mPFC, inferior PFC, dlPFC, and dmPFC associated with certain experimental conditions (Ueda et al., 2003; M. Walter et al., 2009); and activity in the bilateral insula, right inferior frontal gyrus (IFG), thalamus and red nucleus linked to uncertain anticipation (i.e., non-predictive condition), independently from the emotional valence of subsequent S2 (Herwig, Kaffenberger, et al., 2007; Motzkin et al., 2014).

As for the prediction *updating* stage, most studies replicated the well-known effect of enhanced sensory and attentional processing, as indexed by ERPs/ERFs and peripheral indices, for emotional than neutral stimuli (Buodo et al., 2012; Perri et al., 2014), with a valence-specific advantage of negative stimuli (Brown et al., 2008; Gole et al., 2012; Johnen & Harrison, 2019; Lin et al., 2012, 2017; Lin, Jin, et al., 2015; Lin, Liang, et al., 2014; Lin, Schulz, et al., 2015; Lin, Xiang, et al., 2015; Peng et al., 2012; Qiao et al., 2018; Schumacher et al., 2015); while only a few studies found a valence-specific advantage also for positive over negative and neutral S2s (Lin et al., 2012; Lin, Jin, et al., 2015; Lin, Liang, et al., 2014; Schumacher et al., 2015). S2 emotional processing in affective cueing paradigms seems to be subtended by activity within the following ROIs: amygdala, aINS, ACC, mPFC, lateral PFC (lPFC), right dlPFC, right OFC, cerebellum, and occipitotemporal areas (Bermpohl et al., 2006b, 2006a; Nitschke et al., 2006). Regarding the predictive context-specific effects, evidence is highly controversial: some studies found enhanced attentional engagement towards S2s, independently from emotional valence, in the certain condition (Gole et al., 2012; Johnen & Harrison, 2020; Lin et al., 2012, 2017; Lin, Jin, et al., 2015; Lin, Liang, et al., 2014; Lin, Schulz, et al., 2015); whereas other studies found the opposite (Dieterich et al., 2016; Gole et al., 2012; Johnen & Harrison, 2019; Lin, Schulz, et al., 2015; Lin & Liang, 2020; Qiao et al., 2018; Recio et al., 2014), especially in females (Jin et al., 2013), with processing under uncertainty supported by dlPFC, ACC, and mPFC activity (Schienle et al., 2010).

Last, when considering the interactions between predictive context and S2 emotional valence, results remain controversial: there is evidence of enhanced processing of either negative (Lin et al., 2016, 2020; Lin, Jin, et al., 2015; Lin, Liang, et al., 2014; Lin, Schulz, et al., 2015; Lin, Xiang, et al., 2015; Peng et al., 2012) or positive (Recio et al., 2014; Schumacher et al., 2015) S2s in the certain than in the uncertain condition, but also opposing results suggesting a greater allocation of processing resources to either negative (Grupe & Nitschke, 2011; Lin et al., 2016, 2017, 2018; Lin, Jin, et al., 2015; Nelson & Hajcak, 2017; Onoda et al., 2006; Peng et al., 2012; Recio et al., 2014; Yang et al., 2012) or positive (Lin et al., 2020; Lin, Jin, et al., 2015) S2s in the uncertain as compared to the certain condition. Unexpected negative stimuli (i.e., negative S2s in the uncertain condition) seem to be processed by a brain network including the insula, the amygdala, and the right dlPFC (Ran et al., 2016; Sarinopoulos et al., 2010); while the processing of positive stimuli is subtended by left dlPFC activity in the certain condition (Ran et al., 2016), and by vlPFC, caudate nucleus, premotor and temporal cortex activity in the uncertain condition (Kaffenberger et al., 2010).

Of all the studies, only a few investigated the reciprocal relationships either between the three stages of generation-implementation-updating, or between neural activity and subjective affective experience, mood ratings, or personality traits. It emerged that neural activity during the generation stage, as indexed by N2 amplitude, positively predicted CNV amplitude during the implementation stage (Vallet et al., 2019); while the relationship between implementation and updating might be either direct, with ISI-SPN amplitude positively predicting S2-P2 in the certain condition (Brown et al., 2008), or inverse, with ISI-locked pupil dilation and ACC activation negatively predicting S2-locked pupil dilation and insula/amygdala activations, respectively (Sarinopoulos et al., 2010; Vanderhasselt et al., 2014). Moreover, concerning the implementation-related neural activity, ISI-SPN amplitude has been found to positively predict subjective mood ratings (Qiao et al., 2018); right dlPFC and OFC activity positively predicted levels of positive and negative affect (Nitschke et al., 2006); and brain areas associated with uncertain anticipation positively predicted participants' depressiveness and neuroticism scores in the uncertain condition (Herwig, Kaffenberger, et al., 2007). Finally, updating-related left amygdala activity was found to positively predict subjective arousal ratings in response to emotional stimuli (Bermpohl et al., 2006a), while no significant relationship between S2-LPP amplitude and subjective valence ratings emerged (Johnen & Harrison, 2019).

Overall, this large body of evidence can be re-interpreted within the predictive framework, offering some important insights about the neurocomputational processes developing along the three stages of the construction of affective predictions. In line with predictive coding, the data suggest that during prediction *generation* contextual information is extracted, presumably within unimodal and domain-specific sensory neural circuits under the top-down influence of multimodal agranular cortical regions. This process particularly favors the processing of negative stimuli, because of their motivational salience: negative valence, in fact, impacts on internal models' adjustment more than positive valence (Joffily & Coricelli, 2013), decreasing confidence on priors (Hesp et al., 2021).

Furthermore, more processing effort is required to generate affective predictions when the predictive context conveys uncertain/unreliable probabilistic information. Since the available evidence lacks statistical regularity, more effort is needed to infer and encode the statistical structure of the observed inputs, in order to generate reliable and effective predictive models. The depth of information processing during prediction generation also influences the following implementation stage, coherently with predictive coding assumptions: predictions are used to predispose action, thus the more (and the more precisely) features are extracted from environmental cues during the generation stage, the more anticipatory resources are allocated during implementation.

In the *implementation* stage the brain is kept busy with the pre-sensitization of relevant representations and with action preparation, consistently with predictive coding predictions: expecting an emotional stimulus with high certainty brings to a maximization of the pre-allocation of anticipatory resources, in order to "stay ready" to face the predicted scenarios. This process is coherently supported by the activation of brain areas involved in motor preparation, homeostasis/interoceptive adjustments, and cognitive control, and located both within the salience and the frontoparietal control networks. The amount of resources pre-allocated during the implementation stage is also related to the subjective experience of emotion, with a larger pre-allocation of resources resulting in a more intense reported experience.

Lastly, during prediction *updating*, emotional stimuli (especially negative) are prioritized, thus eliciting greater allocation of attentional resources, independently from stimuli being predicted or not. This is coherent with their motivational relevance, their potential impact on survival, and the subtended neural activation of the salience network; and it is correlated with subjective affective experience, since a larger neural activity during the updating stage predicts higher arousal ratings to stimuli. Nonetheless, when coming to differences between affective stimuli that match or mismatch predictions, the evidence is controversial. On the one hand, stimuli that match predictions have been found to elicit heightened processing, supported by activity of the salience network: this might be the consequence of the pre-sensitization of potentially relevant stimuli accomplished during the implementation stage, which can leave some representations active, eventually facilitating their subsequent processing if they actually occur. This interpretation is supported by studies reporting a positive correlation between the amount of anticipatory resources during implementation and the depth of information processing during updating. On the other hand, stimuli that match predictions have been found to elicit reduced processing, a phenomenon known as "silencing" (Kok et al., 2019): predicted sensory signals are attenuated, and a good match between predictions and actual inputs results in less neural activity than a mismatch, where instead a prediction error arises, which must be minimized and projected back to higher levels of the hierarchy in order to update the internal models. This interpretation is supported by the coherent activation of the frontoparietal control network, and by evidence of a negative correlation between the amount of anticipatory resources during the implementation stage and the depth of information processing during updating.

Despite its potentially crucial contribution, deriving from critically re-interpreting the body of evidence within a predictive coding framework, the literature on the anticipation of emotional stimuli presents some important gaps and methodological flaws. First, there is a huge variability in the kind of stimuli (some of which are not even emotional per se) and experimental tasks/paradigms, making it hard to compare results between studies. Second, studies mostly employed visual stimuli (with some exceptions using auditory tones as S1s), thus the construction of affective predictions within other sensory modalities, as well as potential cross-modality generalization effects, have never been investigated. Third, only extreme predictive contexts (certain vs. uncertain) have been typically implemented, while experimental conditions conveying more realistic, moderately predictive probabilistic information are rare. Fourth, studies investigating the whole process of construction of affective predictions, including all the three stages, their reciprocal relationships, and their potential correlation with subjective affective experience, are also rare. Fifth, affective contingency has been manipulated only at a global (block-wise) level, and never at a local (trial-by-trial) level. Sixth, affective cueing paradigms are typically instructed, i.e., participants are explicitly told the exact probabilistic ratio of affective contingencies prior to the experiment, leading to potential concerns about the generalizability of results. In daily life, in fact, people automatically and implicitly learn contingencies from the environment, and infer the subtending statistical structure, by means of mere exposure. Seventh, the impact of prior experience on new affective predictions has never been investigated by directly manipulating it, although it is a crucial factor in prediction generation. Last, it is still under-investigated whether and how individual differences in potentially relevant behavioral, temperamental, and/or personality traits might interact with the construction of affective predictions. Amongst these traits, Intolerance of Uncertainty (IU) may be particularly influential in shaping affective predictions under various conditions of uncertainty, as it can interfere with the ability to assess levels of uncertainty in the present environment, and thus to extract the statistical regularities needed to build reliable internal models. Moreover, IU is increasingly viewed as a trans-diagnostic risk factor for a wide range of affective disorders, amongst which anxiety disorders (Carleton, 2016a, 2016b; Einstein, 2014; Shihata et al., 2016; Tanovic, Gee, et al., 2018). For these reasons, the next paragraph will focus on IU, its relationships with peculiar behavioral patterns and psychopathology, and the experimental evidence investigating IU within affective cueing paradigms.

1.4 INTOLERANCE OF UNCERTAINTY

Intolerance of uncertainty (IU) is the dispositional characteristic that reflects individual differences in tolerating and adapting to uncertain situations (Carleton, 2012, 2016a, 2016b). It is defined as the inability to tolerate the aversive state triggered by a perceived lack of sufficient or salient information, sustained by the related perception of uncertainty (Carleton, 2016a, 2016b). In order to get a clearer definition of IU a distinction must be made between *uncertainty* and *ambiguity*: net of their partial conceptual overlaps (see Grenier et al., 2005 for a review), ambiguity is more focused on the *here and now*, thus it refers to situations characterized by ambiguous or equivocal features; while uncertainty is more focused on *future* events, i.e., situations eliciting potentially negative outcomes (Carleton, 2012). Two different components, involving separate psychological factors, are assumed to equally contribute to IU: a *prospective* component, subtended by a cognitive factor of desire for predictability and for threat appraisal, and an *inhibitory* component, subtended by a behavioral factor of uncertainty-related action inhibition (Einstein, 2014; Shihata et al., 2016). IU builds upon the latent fear of the unknown (FOTU), a fundamental dispositional fear, expressed as the propensity to experience feelings of fear about the perceived absence of information at any level of information processing (Carleton, 2016a, 2016b). FOTU represents a common substrate shared by IU and several other higher-order constructs (see Carleton, 2016a for a comprehensive review), and it is assumed to be inherent, since uncertainty is appraised as intrinsically aversive without any need of a-priori learning, and evolutionarily supported, since a certain amount of fear when facing unknown situations might be adaptive for survival (Carleton, 2016a).

IU is characterized by several cognitive, behavioral, psychophysiological, and neural facets that may broadly impact on affective experience at both implicit and explicit levels. Amongst the *cognitive* facets, individuals high in IU show increased attention to, and hypervigilance for, threatening and uncertain stimuli (Grupe & Nitschke, 2013; Shihata et al., 2016; Tanovic, Gee, et al., 2018); they tend to appraise uncertainty as threatening irrespective of its probability and outcomes, and to consider the possibility of the occurrence of a negative event as unacceptable (Carleton, 2012, 2016a; Dugas et al., 2005; Einstein, 2014; Grupe & Nitschke, 2013; Pepperdine et al., 2018; Shihata et al., 2016; Tanovic, Gee, et al., 2018); they systematically overestimate threat probability and cost (Grupe & Nitschke, 2013; Shihata et al., 2016; Tanovic, Gee, et al., 2018); they report heightened subjective certainty when anticipating the possible negative outcomes of an uncertain situation (Miranda et al., 2008; Shihata et al., 2016); they show deficient safety learning (Tanovic, Gee, et al., 2018), and a reduced ability to use their safety appraisals (when accomplished) in order to inhibit anxiety (Cupid et al., 2021); they use avoidance and information seeking as coping strategies to face uncertainty (Carleton, 2016b; Grupe & Nitschke, 2013; Shihata et al., 2016; Tanovic, Gee, et al., 2018); they typically engage more in worry and ruminations (Carleton, 2012; Koerner & Dugas, 2008; Shihata et al., 2016; Tanovic, Gee, et al., 2018); they are characterized by a reduced distress tolerance (Fergus et al., 2013); and they show an intensified subjective affective experience and an increased fear response to uncertain situations (Einstein, 2014), with potential impact on problem-solving skills and cognitive tasks' performance (Carleton, 2012).

At the *behavioral* level, IU is associated with the activation of the behavioral inhibition system (BIS) and the fight-flight-freeze defensive response (Carleton, 2016b); the tendency to prefer immediate rather than delayed rewards (Shihata et al., 2016); reduced confidence towards risky decisions, and reduced propensity to change a decision in front of new information (Shihata et al., 2016); slower decision times (Shihata et al., 2016); and uncertainty avoidance (Carleton, 2016a; Grupe & Nitschke, 2013; Tanovic, Gee, et al., 2018).

At the *psychophysiological* level, higher IU is related to heightened physiological arousal (Shihata et al., 2016); either reduced or increased amplitudes in ERP components related to error or reward processing, and startle potentiation in conditions of uncertain threat (Carleton, 2016a; Tanovic, Gee, et al., 2018); reduced heart rate variability (HRV) during worry (Tanovic, Gee, et al., 2018); increased SCRs to both safety and threat cues (Tanovic, Gee, et al., 2018); reduced emotional modulation of the LPP (MacNamara, 2018).

Last, individuals high in IU have shown atypical *neural* activity within some brain areas: hyperactivation of amygdala, hippocampus, insula, ACC, OFC, vmPFC, dlPFC, right superior temporal sulcus (STS), and increased gray matter volume in the right superior temporal pole (Carleton, 2016a; Einstein, 2014; Shihata et al., 2016; Tanovic, Gee, et al., 2018).

In addition to the abovementioned facets, IU has been recently shown to be able to account for statistically significant variance in several higher-order personality and temperamental traits (e.g., neuroticism, pessimism, anxiety sensitivity, trait anxiety, and negative affectivity), as well as in symptoms of affective psychopathology (e.g., anxiety disorders, depressive disorders, obsessive-compulsive disorders, trauma- and stressor-related disorders, eating disorders, substance-use disorders) (Carleton, 2012, 2016a, 2016b; Einstein, 2014; Pepperdine et al., 2018; Shihata et al., 2016). Thus, IU is increasingly considered as a broad trans-diagnostic cognitive vulnerability and maintaining factor for a wide range of affective disorders (Carleton, 2012; Einstein, 2014; Hong &

Cheung, 2015; Shihata et al., 2016). This paved the way for some interesting clinical implications, proposing IU as a potential early marker to identify people at risk of developing psychopathology, as well as a potential outcome measure to assess treatments' effectiveness. Teaching people at risk how to minimize perceived uncertainty and/or how to increase their ability to tolerate uncertainty seems to be effective in supporting a significant reduction in clinically relevant symptoms of affective disorders, especially anxiety (Carleton, 2012, 2016b; Einstein, 2014; Shihata et al., 2016).

Despite its prominent role as a clinically relevant risk factor, and despite its associated cognitive, behavioral, psychophysiological and neural patterns suggesting the presence of an altered underlying mechanism in the construction of affective predictions, a clear understanding of how individual differences in IU may interact with the assessment of environmental uncertainty in modulating affective predictions is far from being fully addressed by the literature. The studies that investigated the effects of IU within affective cueing paradigms are few (see Table 1.2), and even more scarce are the theoretical contributions that attempted to explain some typical IU facets by adopting concepts from the predictive coding framework (Tanovic, Gee, et al., 2018). Amongst the existing studies, IU has been mainly measured through the Intolerance of Uncertainty Scale (IUS), either in its original (27-item) (Freeston et al., 1994) or short (12-item) (Carleton et al., 2007) forms. Furthermore, as a common practice when dealing with continuous variables (see Iacobucci et al., 2015 for more details), authors mostly divided their samples into two groups (high- vs. low-IU) according to the IUS scores distribution.

Table 1.2 Studies investigating IU with affective cueing paradigms and relative details about experimental stimuli, tasks, and manipulations.
Affective contingency is expressed in terms of percentage of experimental trials in which S1 was paired with the same S2 valence: 100% represents the certain condition, between 80% and 70% a highly predictive condition, and 50% the uncertain condition. The last column shows which paradigm stages (S1, ISI, S2) and ERPs/psychophysiological indices have been analyzed. EMG = electromyography, LPP = late positive potential, NEG = negative, NEU = neutral, POS = positive, SCR = skin conductance response, SPN = stimulus preceding negativity.

ERPs							
Study	**S1/cue**	**S2/target**	**S1/cue emotional valence**	**S2/target emotional valence**	**S1-S2/cue-target affective contingency**	**Experimental paradigm**	**Stages investigated (and ERP components targeted for each)**
(Gole et al., 2012)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	S1 (P2), S2 (P2, N2, LPP)
(Tanovic, Pruessner, et al., 2018)	Card	Electric shocks	Certain shock, certain no-shock, uncertain	NEG	from 0% to 100%	Threat of shock	S1 (P2), ISI (SPN)
fMRI							
Study	**S1/cue**	**S2/target**	**S1/cue emotional valence**	**S2/target emotional valence**	**S1-S2/cue-target affective contingency**	**Experimental paradigm**	**Stages investigated**
(Morriss et al., 2021)	Symbolic visual cue	Electric shocks	Certain shock, certain no-shock, uncertain	NEG	100% vs 50%	Threat of shock	S1
(Schienle et al., 2010)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	S2
(Simmons et al., 2008)	/	/	/	/	/	Wall of faces	ISI
Peripheral psychophysiological indices							
Study	**S1/cue**	**S2/target**	**S1/cue emotional valence**	**S2/target emotional valence**	**S1-S2/cue-target affective contingency**	**Experimental paradigm**	**Stages investigated (and peripheral indices targeted for each)**
(Bennett et al., 2018)	Acoustic tones	Electric shocks	Certain shock, certain no-shock, uncertain	NEG	100% vs 50%	Threat of shock	S1 (startle)
(Chen & Lovibond, 2016)	Symbolic visual cue	Affective pictures	NEG, NEU, uncertain, ambiguous	NEG, NEU	100% vs. 50%	S1-S2	ISI (SCR)
(Chin et al., 2016)	Symbolic visual cues	Electric shocks	/	NEG	50% vs 75% reinforcement rate	Fear conditioning	S1 (startle)
(Grupe & Nitschke, 2011)	Symbolic visual cues	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs. 50%	S1-S2	S2 (SCR)
(Morriss, 2019)	Symbolic visual cue	Affective pictures	NEG, NEU, uncertain	NEG, NEU	100% vs 50%	S1-S2	S1 (SCR, EMG), S2 (SCR, EMG)

(Morriss et al., 2020)	Symbolic visual cue	Electric shocks,	Certain shock, certain no-shock, uncertain	NEG	100% vs 50%	Threat of shock	S1 (SCR, pupil dilation, EMG)
(Morriss et al., 2021)	Symbolic visual cue	Electric shocks	Certain shock, certain no-shock, uncertain	NEG	100% vs 50%	Threat of shock	S1 (SCR)
(Nelson & Shankman, 2011)	Acoustic tones	Electric shocks	Certain shock, certain no-shock, uncertain	NEG	100% vs 50%	Threat of shock	S1 (startle)
(Nelson et al., 2016)	Acoustic tones	Electric shocks	Certain shock, certain no-shock, uncertain	NEG	100% vs 50%	Threat of shock	S1 (startle)
Behavioral indices							
Study	**S1/cue**	**S2/target**	**S1/cue emotional valence**	**S2/target emotional valence**	**S1-S2/cue-target affective contingency**	**Experimental paradigm**	**Stages investigated**
(Kirschner et al., 2016)	Symbolic visual cues	Affective pictures	NEG, POS, uncertain	NEG, POS, ambiguous	100% vs 50%	S1-S2	S2
(Ranney et al., 2019)	/	Affective film clips	/	NEG	/	Affective clips viewing	Anticipation period, S2

The results reported in this literature (see Table 1.2) are fragmentary and sometimes in conflict with what can be reasonably predicted according to the theoretical models of IU (Carleton, 2016a; Einstein, 2014; Grupe & Nitschke, 2013; Shihata et al., 2016). Regarding the *generation* stage, higher IU was found to be associated with either heightened defensive system activation, early automatic attentional allocation, and negative mood in conditions of uncertain threat (Chen & Lovibond, 2016; Chin et al., 2016; Gole et al., 2012; Nelson et al., 2016); or attenuated processing and aversive response to uncertain threat (Morriss et al., 2020; Nelson & Shankman, 2011; Tanovic, Pruessner, et al., 2018). Other studies, instead, found no differences between high- and low-IU participants in S1-locked psychophysiological responses (Bennett et al., 2018; Morriss, 2019). The S1-derived estimation of threat, based on instructed uncertain contingencies, was subtended by an increased phasic activation of mPFC and dmPFC in high-IU individuals (Morriss et al., 2021).

Focusing on prediction *implementation*, some studies found no significant effects of IU on neural processing and expectancy ratings during the ISI (Grupe & Nitschke, 2011; Morriss et al., 2021; Tanovic, Pruessner, et al., 2018); while others found that high-IU participants showed increased threat expectancy (Chen & Lovibond, 2016), heightened distress and worry (Ranney et al., 2019), and increased insula activation (Simmons et al., 2008) during the anticipation period.

As for prediction *updating* stage, some evidence suggest that IU might be associated with either dampened processing of affective uncertain stimuli (Gole et al., 2012); or intensified threat appraisal, retrospective estimation of threat occurrence, and subjective affective ratings, subtended by an increased activity in the amygdala and a reduced activity in dlPFC, mPFC and ACC (Chen & Lovibond, 2016; Kirschner et al., 2016; Schienle et al., 2010). Other studies, instead, failed to find significant effects of IU on S2-locked psychophysiological responses (Grupe & Nitschke, 2011; Morriss, 2019). Evidence suggesting an attenuated processing of both cues and targets in uncertain conditions is in contrast with the assumption that uncertainty is aversive per se and is associated with a more intense subjective affective experience and a heightened physiological reactivity, as predicted by the theoretical models of IU (Carleton, 2016a; Einstein, 2014; Grupe & Nitschke, 2013; Shihata et al., 2016).

Altogether, re-interpreting results within a predictive framework, data suggest that during prediction *generation* individuals with high IU levels deploy more processing resources towards environmental cues conveying uncertain/unreliable (and thus, potentially threatening) probabilistic information, due to their attentional bias prioritizing threat and activation of the defensive system. At a qualitative level, the processes involved in the generation stage seem to be unaffected by IU, since they are the same as those previously found in affective cueing paradigms independently from individual differences in IU (cf. § 1.3); but at the quantitative level the amount of processing resources allocated seems to differ as a function of IU, increasing with higher levels of IU. Nevertheless, the estimation of uncertainty levels and threat probability which should be derived from environmental cues is likely disrupted in individuals with high IU levels, since they show a systematic overestimation of threat and a consequent heightened deployment of resources (in the attempt to solve the perceived uncertainty) during the subsequent *implementation* stage. Thus, it seems that higher IU results in a less efficient use of contextual information (inferred during the generation stage) in top-down regulating the processes developing during implementation (i.e., pre-sensitization of relevant stimuli representations, simulation of action plans, motor preparation; cf. Figure 1.1). Finally, the evidence supports an overall affect intensification effect in high-IU individuals (both at the neural and subjective levels) during prediction *updating*, coherently with what predicted by theoretical models of IU (Einstein, 2014). Furthermore, people characterized by high IU levels might show also a disrupted prediction error signaling during prediction updating (Paulus & Stein, 2006; Tanovic, Gee, et al., 2018). This disruption could be subtended by altered connectivity patterns between the dorsal portion of the ACC (responsible of the initial comparison and mismatch detection between predicted and actual incoming signal) and the rostral portion of the ACC (allocating later attentional control resources) on the one hand, and the insula (which integrates information transmitted by the ACC with somatic arousal states and threat expectancy estimates) on the other hand (Einstein, 2014).

A persistent alteration in prediction error signaling might evolve in a chronic inability to effectively reduce perceived uncertainty, and thus in an increased allostatic load, which can eventually contribute to systemic and neural damage or malfunction, making high-IU individuals more likely to develop (psycho)pathologies (Peters et al., 2017).

Hence, from the literature review it emerged that the mechanisms underlying the interaction between IU and the construction of affective predictions are still unclear. A better understanding of how individual differences in IU might impact on the construction of affective predictions could therefore represent a valuable contribution not only to advancing knowledge about the mechanisms of affective predictions per se, but also to unraveling whether high-IU individuals may be characterized by specific alterations in affective predictions (thus, predisposing to psychopathology), eventually leading to promising clinical implications. As a further critical element, dichotomizing IUS scores into groups (a common practice in research dealing with continuous variables) might have contributed to the flattening of individual differences and to loss of information and statistical power (Royston et al., 2006), thus calling into question the generalizability and effective theoretical contribution of existing results.

Then, considering the affective cueing literature published to date, future research should try to overcome the limitations of existing studies by reframing extant paradigms within a predictive coding framework. If predictions are a constitutive feature of affective experience, then it could be beneficial to develop new experimental designs that systematically investigate whether stimuli (un)predictability contribute to subjective affective experience and its neural correlates (Lee et al., 2021). In doing so, new research might take advantage of the potential strengths offered by affective cueing paradigms in validly and flexibly approximating the process of construction of affective predictions (including all the stages and their reciprocal relationships), and in allowing to potentially manipulate several crucial modulating factors (e.g., contextual probabilistic information, sensory modality involved, prior experience). The present research project was purposely designed to implement novel applications of (and to develop some modifications to) the existing affective cueing paradigms, with the aim to unravel the neural and subjective mechanisms underlying the construction of affective predictions as a function of either *contextual information* or *prior experience*, and individual differences in *IU*.

1.5 The research project

The present research project aimed to answer three main research questions:

RQ1. How does *contextual information* of different predictive value modulate the neural correlates of affective predictions construction?

RQ2. How does *prior experience* affect the construction of new affective predictions, both within and across sensory modalities, at the subjective experience level?

RQ3. How do individual differences in *Intolerance of Uncertainty* modulate the construction of affective predictions as a function of contextual information and prior experience?

To answer these questions we ran two hd-EEG studies (Study 1, Study 6), and four behavioral studies pre-registered on the Open Science Framework (OSF) (Study 2, Study 3, Study 4, Study 5) (see Table 1.3). In Studies 1 and 6 we measured cortical activity during an uninstructed, passive viewing S1-S2 paradigm, in which unbeknownst to participants we manipulated the predictive value of S1 in terms of certain (100%), moderately predictive (75%), and uncertain (50%) affective contingency between S1 and S2. We manipulated emotional valence at three levels, employing standardized affective faces and pictures with positive (POS), negative (NEG), or neutral (NEU) valence as S1s and S2s, respectively. In Study 6 we also measured individual differences in IU through the IUS. In Studies 2 to 5, instead, we employed two different S1-S2 paradigms as a learning and a test phase, respectively. We used colored circles as S1s. We manipulated emotional valence at two levels, employing NEG or NEU standardized affective pictures (Studies 2, 4 and 5) or sounds (Study 3) as S2s. Participants were randomly assigned to the certain (CG) or the uncertain (UG) experimental groups, and the learning phase was either uninstructed (Studies 2, 3, 4) or implicit (Study 5). During the learning phase participants in the CG were presented with a certain (100%) S1-

S2 affective contingency, while the UG experienced an uncertain (50%) affective contingency. During the test phase both groups were presented with a new S1-S2 paradigm with a more realistic 75% affective contingency, ambiguous (Study 4) or unambiguous (Studies 2, 3 and 5) S1s, and visual (Studies 2, 4 and 5) or auditory (Study 3) S2s. In Studies 2 to 5 we also collected IUS scores. We focused on the subjective affective experience reported during the test phase, as assessed in terms of the expected valence of the upcoming S2s (i.e., expectancy ratings) and the experienced valence and intensity of S2s (i.e., valence and arousal ratings).

Study 1 aimed to answer RQ1, by investigating the modulating role of contextual information on the neural correlates of affective predictions construction. Studies 2 to 5 aimed to answer both RQ2, by directly manipulating prior experience in terms of certain vs. uncertain affective contingency, and RQ3, by analyzing how individual differences in IU might affect these processes. Study 6 aimed to answer RQ3, by exploring if IU predicted the neural correlates of affective predictions' construction depending on contextual uncertainty levels.

Table 1.3 Studies of the research project.
For each study we report the research question (RQ) tackled, the type (hd-EGG vs. behavioral), the sample size (N), the type of stimuli employed as S1s and S2s, the main variables measured, and the permanent links to data repository and/or OSF pre-registration.

Study	RQ	Type	N	S1	S2	Main variables measured	Data/OSF link
Study 1	RQ1	hd-EEG	31	Affective faces	Affective pictures	ERPs, brain sources activity	https://doi.org//10.6084/m9.figshare.12951782
Study 2	RQ2, RQ3	Behavioral	200	Colored circles	Affective pictures	Expectancy ratings, valence ratings, arousal ratings, IUS	https://osf.io/ef9q7/
Study 3	RQ2, RQ3	Behavioral	200	Colored circles	Affective pictures (learning phase) and affective sounds (test phase)	Expectancy ratings, valence ratings, arousal ratings, IUS	https://osf.io/wcy9r/
Study 4	RQ2, RQ3	Behavioral	125	Colored circles (ambiguous vs. unambiguous in the test phase)	Affective pictures	Expectancy ratings, valence ratings, arousal ratings, IUS	https://osf.io/gdr3b/
Study 5	RQ2, RQ3	Behavioral	125	Colored circles	Affective pictures	Expectancy ratings, valence ratings, arousal ratings, IUS	https://osf.io/z5esb/
Study 6	RQ3	hd-EEG	36	Affective faces	Affective pictures	ERPs, brain sources activity, IUS	https://doi.org//10.6084/m9.figshare.13560569

CHAPTER 2

THE ROLE OF CONTEXTUAL INFORMATION

"Oft expectation fails, and most oft there /

Where most it promises"

William Shakespeare

2.1 INTRODUCTION

Imagine you see a masked person running towards you at night. If you are walking down a lonely street, where you do not expect to meet anyone, you will likely experience a feeling of fear. If it is Halloween night, instead, you probably will not even notice the masked man, since you reasonably expect to see a lot of masked people. You may therefore make meaning of the same sensory input (i.e., a masked person) tapping into different conceptual knowledge. This can eventually lead to opposite affective experiences (i.e., fear vs. enjoyment), depending on the available contextual probabilistic information (i.e., how likely it is to encounter certain kind of stimuli in a specific context).

This example suggests how affective experience can remarkably change depending on what you expect to face. Recently, the role of expectancy has been redescribed within predictive models of emotion (Barrett, 2017; Seth & Friston, 2016), according to which the brain, starting from its internal models, builds predictions about incoming (affective) stimuli, and continuously tests them against inputs. Events that meet predictions are silenced, and their processing is inhibited; while unpredicted information is encoded as a prediction error, and used to adjust future predictions (see § 1.2). Prediction construction, thus, requires three neurocomputational stages: prediction *generation*, *implementation*, and *updating* (see Figure 1.1).

The brain system supporting allostasis and interoception has been suggested as the neural substrate for the construction of affective predictions (Barrett, 2017; Seth & Friston, 2016) (see § 1.2). This system includes several cortical regions, which are part of three main networks: the DMN (Raichle, 2015), the salience network (Seeley et al., 2007), and the frontoparietal control network (Dosenbach et al., 2007). All these networks, and the functions they subtend, play a pivotal role in upholding the constant cycle of generation-implementation-updating of emotional predictions (Bar, 2007; Knill & Pouget, 2004). Nevertheless, it is still unclear how this neurocomputational model displays in the construction of affective predictions across conditions of different predictive value.

Therefore, in Study 1 we aimed to unravel how different probabilistic *contextual information* can modulate the neural correlates of affective predictions construction (see RQ1, § 1.5). We built on the logic of extant affective cueing paradigms (cf. § 1.3) by implementing a novel S1-S2 paradigm, in which we manipulated the predictive value of S1 in terms of certain (100%), moderately predictive (75%), and uncertain (50%) affective contingency between S1 and S2. Furthermore, we employed standardized emotional faces and pictures, with positive (POS), negative (NEG), or neutral (NEU) valence, as S1s and S2s, respectively. This paradigm allowed us to separately investigate the three stages of prediction construction, with S1 processing reflecting prediction generation, the ISI between S1 and S2 the implementation stage, and S2 the updating stage (see § 1.3).

Extant ERP literature investigating emotional anticipation (see Table 1.1) is controversial. Some studies found emotional (especially negative) S1s eliciting a greater attentional engagement than neutral S1s (Johnen & Harrison, 2019; Klorman & Ryan, 1980; Poli et al., 2007; Yang et al., 2012), and to a greater extent in the uncertain condition (Lin, Gao, et al., 2014); while other studies found no effects of emotional valence on S1 processing (Buodo et al., 2012; Gole et al., 2012). Focusing on ISI, anticipatory resources were found to be modulated by (i) the emotional valence of upcoming S2s, with a larger pre-allocation before highly arousing (Poli et al., 2007) and emotional (Buodo et al., 2012) stimuli, especially when expected and negatively-valenced (Klorman & Ryan, 1980; Lin, Gao, et al., 2014; Peng et al., 2012; Qiao et al., 2018; Takeuchi et al., 2005); and (ii) stimuli predictability, with a larger mobilization within the certain condition (Johnen & Harrison, 2020). As for S2 processing, some studies found an attention enhancement towards expected S2s (Gole et al., 2012; Johnen & Harrison, 2020; Lin et al., 2012), while others found the opposite (Dieterich et al., 2016; Johnen & Harrison, 2019; Qiao et al., 2018; Recio et al., 2014). Emotional valence seemed to interact with stimuli predictability, leading attention to an enhancement towards positive and to a reduction towards negative S2s within the certain condition (Lin et al., 2020).

Amongst the fMRI studies investigating emotional anticipation (see Table 1.1), the bilateral insula and the ACC were found to be consistently associated with the anticipation of unexpected (especially negative) stimuli (Greenberg et al., 2015; Motzkin et al., 2014; Sarinopoulos et al., 2010), while the PFC was involved in the anticipation of expected (negative) stimuli (Onoda et al., 2008; Ueda et al., 2003). Nevertheless, these studies suffered from the fMRI coarse temporal resolution, due to which it is difficult to disentangle the temporal dynamics of the processes developing within the various stages of prediction construction. For these reasons, in Study 1 we chose to employ hd-EEG. Due to its optimal compromise between spatial and temporal resolution (Michel & Murray, 2012), it allowed to provide a compelling comprehensive evidence on affective prediction construction, narrowing the gap between low-density ERP and fMRI studies.

Based on extant ERP research employing affective cueing paradigms (see Table 1.1), we chose to target the following ERP components for each stage of prediction construction. Covering the prediction generation stage, we focused on S1-N170 component, which is sensitive to stimuli predictability, and reflects structural encoding and a coarse processing of emotional facial expressions (Bentin et al., 1996; Blau et al., 2007; Robinson et al., 2018; Wieser & Brosch, 2012). Concerning prediction implementation, we targeted the CNV (W. G. Walter et al., 1964), which reflects the orientation of attention towards motivationally relevant stimuli (early CNV) and the motor preparation for a required or possible action (late CNV), and it is sensitive to predictive complexity or temporal expectancy (Chennu et al., 2013; Gómez et al., 2019; Mento, 2013; Mento et al., 2015). Regarding prediction updating, we marked both early and late S2-ERPs, such as the MMN, indexing the early automatic processing of stimulus deviance and its associated prediction error (Chennu et al., 2013; Stefanics et al., 2018); the P2, signaling the degree of updating of internal models after experiencing a new event (Gómez et al., 2019; Kimura & Takeda, 2015); and the LPP, an index of motivated and sustained attention to emotional stimuli, also sensitive to stimulus predictability (Hajcak et al., 2010; Johnen & Harrison, 2019, 2020; Lin et al., 2020; Schupp et al., 2000).

Consistently with previous ERP literature (cf. § 1.3), in the prediction *generation* stage we hypothesized (H1a) emotional (especially negative) S1s to elicit a larger N170 (Bentin et al., 1996; Blau et al., 2007; Johnen & Harrison, 2019; Klorman & Ryan, 1980; Poli et al., 2007; Yang et al., 2012), with (H1b) stronger effects in less predictable conditions (Lin, Gao, et al., 2014; Robinson et al., 2018). In the *implementation* stage we expected to find (H2) a larger CNV in the certain condition (100%) (Johnen & Harrison, 2020), especially for negative stimuli (Klorman & Ryan, 1980; Lin, Gao, et al., 2014; Peng et al., 2012; Qiao et al., 2018; Takeuchi et al., 2005). Lastly, within the *updating* stage we hypothesized (H3a) incongruent S2s in moderately predictive (75%) and uncertain (50%) conditions to elicit lager P2/MMN amplitudes, signaling the prediction error (Chennu et al., 2013; Kimura & Takeda, 2015; Stefanics et al., 2018). We also expected (H3b) LPP to be larger in the certain (100%) condition (Johnen & Harrison, 2020) and, (H3c) within this condition, to find larger amplitudes to positive and smaller amplitudes to negative S2s (Lin et al., 2020).

STUDY 1

2.2 METHODS

2.2.1 PARTICIPANTS

Italian-speaking volunteer undergraduates at the University of Padua completed an online survey evaluating inclusion criteria for the study: absence of neurological/psychiatric disorders; normal or corrected-to-normal vision; no medication taken; right-handedness, as assessed by the Edinburgh Handedness Inventory (Oldfield, 1971); no high blood-injection-injury fear, as assessed by the Fear Survey Schedule (Wolpe & Lang, 1964). Since some stimuli depicted gory scenes, we included the last criterion for ethical reasons, to discard highly fearful participants who scored 4 on items concerning blood, injuries, weapons (0-4 score).

Among the students screened, 31 participants met the inclusion criteria and took part in the study. The sample size was based on previous ERP research using affective cueing paradigms (Johnen & Harrison, 2020; Lin et al., 2020). Data from 5 participants were discarded after Emotional Recognition Task scoring (see § 2.2.2).

The final sample included 26 participants (10 males, age: *M* = 23.42, *SD* = 2, range = 20-29). All participants signed an informed consent; the study was approved by the Ethical Committee for the Psychological Research of the University of Padua (protocol no. 2859) and was conducted in accordance with the Declaration of Helsinki.

2.2.2 Stimulus material and procedure

Upon arrival, participants seated in a dimly lit room, at a viewing distance of 90 cm from a computer screen. They received information about EEG montage and the experimental task. Then, an elastic 128-channel EEG net was applied.

A computerized S1-S2 paradigm was presented on a 24-inch monitor (1280 × 1024 pixel resolution). Emotional faces from the NimStim Set of Facial Expressions (Tottenham et al., 2009) were employed as S1s, and affective pictures from the International Affective Picture System (IAPS) (Lang et al., 2008) as S2s. S1s were 24 different colored pictures depicting 4 male and 4 female Caucasian models, each posing fearful, happy and neutral expressions. Each facial expression (fearful, happy, and neutral) was presented four times with the male faces, and four times with the female faces. Every picture was repeated 15 times within the whole experiment. S2s were 120 colored pictures: 40 high-arousing negative, 40 high-arousing positive, and 40 low-arousing neutral pictures. Every picture was repeated 3 times within the whole experiment. Two additional S1s (1 male and 1 female, posing angry and surprised expressions) and 4 additional S2s (2 low-arousing positive and 2 low-arousing negative) were selected for practice trials. NimStim and IAPS pictures numbers, sorted by emotional valence, are listed in Table 2.1. Positive and negative pictures did not differ for mean arousal standardized ratings (mean (*M*) = 6.43 and 6.44, standard deviation (*SD*) = 0.46 and 0.62, respectively; $t(93) = 0.12$, $p = .9$). S1s and S2s were presented pseudo-randomly (no more than 3 subsequent same-valence couplings) in their original size, in the center of the screen against a black background, through E-prime software (Schneider et al., 2010).

Table 2.1 List of NimStim and IAPS picture numbers used as S1s and S2s in Studies 1 and 6, sorted by valence. POS = positive, NEG = negative, NEU = neutral

Valence	NimStim	IAPS
POS	01F_HA_O; 03F_HA_O; 06F_HA_O; 09F_HA_O; 28M_HA_O; 33M_HA_O; 34M_HA_O; 36M_HA_O	4647; 4651; 4652; 4653; 4656; 4658; 4659; 4664; 4666; 4669; 4670; 4672; 4680; 4683; 4687; 4690; 4694; 4695; 4800; 4810; 5621; 8021; 8030; 8031; 8034; 8040; 8080; 8160; 8161; 8178; 8179; 8180; 8185; 8186; 8193; 8200; 8210; 8370; 8400; 8490
NEG	01F_FE_O; 03F_FE_O; 06F_FE_O; 09F_FE_O; 28M_FE_O; 33M_FE_O; 34M_FE_O; 36M_FE_O	3000; 3010; 3015; 3030; 3051; 3053; 3060; 3068; 3071; 3080; 3100; 3102; 3110; 3120; 3130; 3140; 3150; 3400; 3550; 6190; 6200; 6210; 6211; 6213; 6230; 6242; 6243; 6250; 6260; 6300; 6312; 6313; 6315; 6350; 6360; 6510; 6530; 6540; 6550; 9405
NEU	01F_NE_O; 03F_NE_O; 06F_NE_O; 09F_NE_O; 28M_NE_O; 33M_NE_O; 34M_NE_O; 36M_NE_O	7000; 7002; 7004; 7006; 7009; 7010; 7020; 7025; 7030; 7031; 7034; 7035; 7036; 7037; 7039; 7040; 7041; 7050; 7052; 7056; 7060; 7080; 7090; 7100; 7110; 7130; 7140; 7150; 7170; 7175; 7211; 7217; 7224; 7233; 7234; 7235; 7491; 7495; 7500; 7510

At the beginning of the task participants read the on-screen instructions at their own pace. They were told that they would see a face followed by a picture and that they only had to look at the screen, trying to move as little as possible. Practice session began as they pressed the spacebar, and it included 2 congruent (i.e., same-valence S1-S2 pairs) and 2 incongruent (i.e., different-valence S1-S2 pairs) trials.

Each S1 was presented for 500 msec, followed by a fixed ISI of 2000 msec, in which the screen remained black. Then S2 was presented for 1500 msec. The inter-trial interval (ITI) – a white fixation cross against a black background – randomly varied between 800 and 1200 msec. The total number of trials was 360.

S1-S2 affective contingency was manipulated through 3 blocks of 120 trials each. In 100% block, S1 and S2 were always congruent, that is S1 was fully predictive of S2 valence. In 75% block, S1 and S2 were congruent in the 75% of the trials, that is S1 was moderately predictive of S2 valence. In 50% block, S1 was randomly followed by a positive, negative, or neutral S2, that is S1 was unpredictive of S2 valence. Blocks were presented seamlessly, with brief random breaks and a between-subjects counterbalanced order. No explicit information was given to participants about the different between-blocks S1-S2 probabilistic ratio.

After the S1-S2 paradigm, participants completed a self-paced computerized Emotional Recognition Task. For each S1, presented in random order, participants had to select which emotion best represented the facial expression, choosing between anger, disgust, fear, happiness, sadness, surprise, and no emotion. The order of choice options was random to avoid automaticity in responding. Percentage of correct responses was computed for each participant. The Emotional Recognition Task was used to check whether S1 valence was correctly recognized by all participants, and participants who scored less than 60% accuracy were discarded.

At the end of the task, the experimenter orally asked each participant if during the S1-S2 paradigm they had caught any relationship between the face and the picture. Participants answers were verbatim written down by the experimenter, and qualitatively analyzed after the experiment. This interview aimed to ensure that the exact S1-S2 probabilistic ratio had remained implicit for each participant, and to discard those who might have caught the experimental manipulation. Participants only reported to have caught a general within-trials affective congruency/incongruency, but none of them reported the precise probabilistic ratios of the blocks. At the end of the session each participant was given information about the research and thanked for the participation (see Figure 2.1 for a schematic representation of the experimental paradigm).

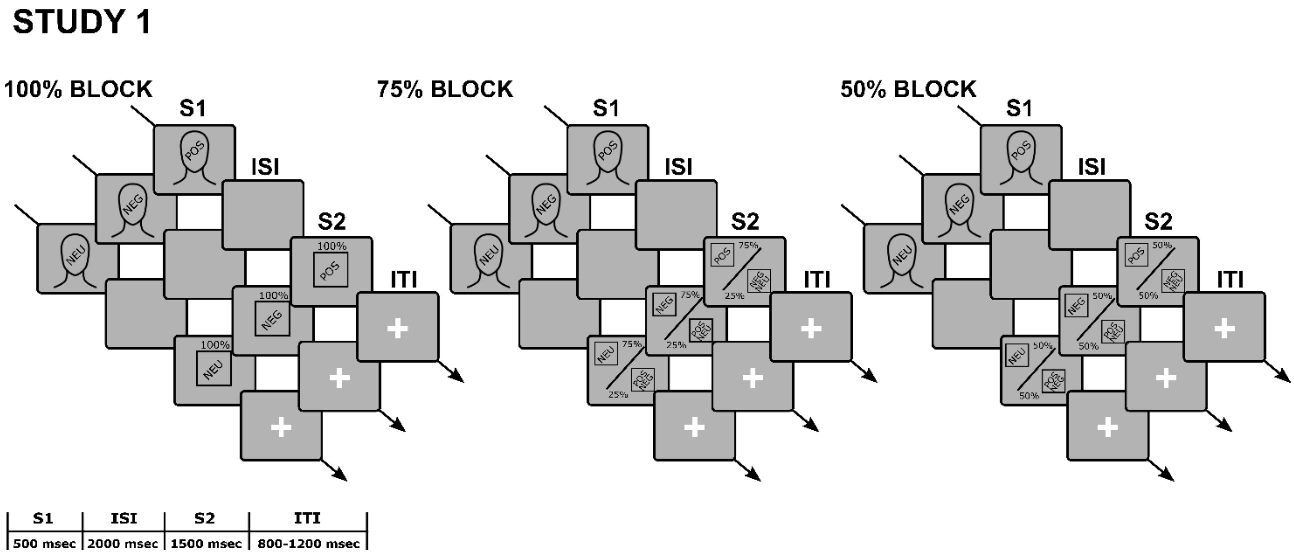

Figure 2.1 Schematic representation of Study 1 experimental paradigm.
Example sequence of events and their duration for a trial, according to the block (100%, 75%, 50%), S1 valence (POS, NEG, NEU) and S2 valence (POS, NEG NEU). In 100% block the face (S1) was followed by a picture (S2) of the same valence in 100% of the trials; in 75% block the face (S1) was followed by a picture (S2) of the same valence in 75% of the trials, and of different valence in 25% of the trials; in 50% block the face (S1) was followed by a picture (S2) of the same valence in 50% of the trials, and of different valence in the other 50% of the trials. Participants were asked to passively view the stimuli while their EEG signal was recorded.
ISI = inter-stimulus interval, ITI = inter-trial interval. The text is not drawn to scale.

2.2.3 Electrophysiological recordings, brain source modelling and data analysis

The study has a 3 (*block*: 100%, 75% and 50%) × 3 (*S1* or *S2 valence*: POS, NEG, NEU) within-subjects design. Trials of the 75% and 50% blocks in which the S1 and the S2 had the same valence were coded as congruent, whereas trials in which the S1 and the S2 had different valence were coded as incongruent (*S2 congruency*, within-subjects: congruent vs. incongruent).

During the S1-S2 paradigm, EEG was continuously recorded using a Geodesic hd-EEG System (EGI® GES-300), through a pre-cabled 128-channel HydroCel Geodesic Sensor Net (HCGSN-128). All electrodes were referenced online to the vertex. Scalp voltages were amplified through a 24-bit DC amplifier. The sampling rate was 500 Hz. The impedance was kept below 60 kΩ for each sensor. EEG recordings were preprocessed using the MATLAB toolbox EEGLAB 14.1.2b (Delorme & Makeig, 2004). EEG signal was downsampled at 250 Hz and filtered with a digital band-pass filter (0.01-40 Hz, -6dB) using a Hamming windowed sinc finite impulse response filter (filter order = 82500). To compute ERPs, continuous EEG was segmented into 4500 msec epochs from 500 msec before to 4000 msec after S1 onset. Signal was then baseline-corrected from 500 msec before to S1 onset for S1-locked ERP analysis, and from 200 msec before to S2 onset for S2-locked ERP analysis. Epochs were digitally inspected through the TBT EEGLAB plug-in, applied to electrodes from E40 to E100. The TBT algorithm performed an automatic rejection of epochs and interpolation of channels on an epoch-by-epoch basis: channels that exceeded a differential average amplitude of ±150 μV on more than 30% of all epochs were marked as bad, excluded and subsequently interpolated with the spherical spline interpolation method (Ferree, 2006; Perrin et al., 1989). Epochs having more than 10 bad channels were also excluded. Artifact-reduced data were then subjected to Independent Component Analysis (ICA) (Stone, 2002) using the Infomax algorithm (Bell & Sejnowski, 1995). All independent components were visually inspected to discard those related to eye blinks, eye movements, heartbeat, and muscular signals, according to their morphology and scalp distribution. The remaining components were projected back to the electrode space. Epochs were further visually inspected and residual artifact-contaminated trials were rejected. Experimental conditions did not differ for final number of epochs, except for *S2 congruency*, which necessarily implies a different numerosity between congruent and incongruent trials (see Table 2.2). Data were finally re-referenced to the average of all electrodes. Individual average and grand average ERPs were computed for all experimental conditions, applying a weighted average in order to control for any potential unbalanced number of epochs per condition (Kotowski et al., 2019; Leski, 2002).

Table 2.2 Means (M), standard deviations (SD), test statistics (*F*), and associated *p*-values (*p*) of the final number of epochs accepted for each experimental condition in Study 1.
Results showed no significant differences between conditions, except for *S2 congruency*.

Block	**100%**		**75%**		**50%**		***F*(2,75)**	***p***
	M	*SD*	*M*	*SD*	*M*	*SD*	1.53	.22
	114.5	5.8	116.73	3.24	115.58	4.4		

S2 congruency	**Congruent**		**Incongruent**		***F*(1, 102)**	***p***
	M	*SD*	*M*	*SD*	101.7	**< .001**
	72.71	15.12	43.44	14.46		

Valence	**POS**		**NEG**		**NEU**		***F*(2, 75)**	***p***
S1	*M*	*SD*	*M*	*SD*	*M*	*SD*	0.6	.55
	115.12	4.3	116.23	3.18	115.46	3.73		
S2	*M*	*SD*	*M*	*SD*	*M*	*SD*	0.58	.56
	115.15	4.07	116.23	3.05	115.42	4.04		

The ERPs statistical analysis was performed via Brainstorm software, using the Fieldtrip functions (Oostenveld et al., 2011; Tadel et al., 2011). Given the amount of spatiotemporal data of hd-EEG, a whole-brain paired two-tailed *t*-test ($\alpha = .05$) permutation approach (Fields & Kuperberg, 2020; Groppe et al., 2011) was used, performing 1000 Monte-Carlo cluster-based corrected permutations over all 128 channel locations. This approach allows to effectively control the familywise error rate, and it can be used also for complex factorial designs, since providing greater statistical power than traditional spatiotemporal averaging approaches when applied to a-priori defined time windows (Fields & Kuperberg, 2020; Groppe et al., 2011; Luck & Gaspelin, 2017). The permutations were computed over 7 a-priori time windows, corresponding to 5 distinguishable ERP components: S1-locked N170 (140-180 msec) for prediction *generation*; S1-locked early (1500-2000 msec) and late CNV (2000-2500 msec) for prediction *implementation*; S2-locked MMN (100-250 msec), P2 (200-300 msec), early (400-600 msec) and late LPP (600-800 msec) for prediction *updating*. Interaction effects were tested through a difference-based strategy widely used in the literature, which allowed to further reduce the familywise error rate (Luck & Gaspelin, 2017).

All the planned pairwise comparisons performed are summarized as follows:

- to test for the presence of overall *block* effects, we performed the pairwise comparisons 100% vs. 75%, 100% vs. 50%, 50% vs. 75% blocks, collapsing emotional valence across blocks;
- to test for the presence of overall *valence* effects, we performed the pairwise comparisons POS vs. NEU, NEG vs. NEU, NEG vs. POS on both S1 and S2 valence, collapsing blocks across emotional valence;
- to test for the presence of *S2 congruency* effects, we performed the pairwise comparison incongruent vs. congruent S2s, separately per block (75%, 50%) and S2 valence;
- in order to assess the *interaction* effects between S1 and S2 valence, congruency and block, the same contrasts (POS vs. NEU, NEG vs. NEU, NEG vs. POS) were performed separately per block (100%, 75%, 50%) and S2 congruency (congruent, incongruent). Furthermore, for both S1- and S2-ERPs difference waves were computed (POS-NEU, NEG-NEU, and NEG-POS) and compared between blocks.

To investigate the relationships between the stages of affective prediction construction, linear mixed-effects models (LMMs) (R package: lme4; Bates et al., 2015) with individual random intercept were estimated separately per block and S2 congruency, with N170, early and late CNV, and their interaction with S2 valence as fixed factors; P2, early and late LPP as dependent variables (DVs). The maximum likelihood method was employed to analyze the contribution of each factor within the model, and the strength of their evidence was estimated as the difference in AIC between the model with and the model without the parameter (ΔAIC).

Cortical sources of ERP activity were reconstructed via Brainstorm (Tadel et al., 2011). ICBM152 anatomical template (Evans et al., 2012) was used for the approximation of individual anatomies and warped to the EEG channel positions through rigid rotations and translations of digitized landmarks. Conductive head volume was modelled according to the realistic forward model OpenMEEG BEM (Gramfort et al., 2010). Solution space was constrained to the cerebral cortex and modelled as a 3D grid of 15002 fixed dipole triplets normally oriented to cortical surface. Inverse modelling was based on sLORETA (standardized low-resolution brain electromagnetic tomography algorithm), implemented with default parameters. Noise covariance matrix was computed from the average of EEG baselines. For each participant, sources were projected to a standard anatomical template (MNI) and their activity was transformed in absolute *z* scores relative to baselines. Cortical activations were located according to the anatomical Destrieux atlas (Destrieux et al., 2010) adapted for cortical space solution. Finally, a spatial smooth with a FWHM of 3 mm, was applied to each source.

2.3 RESULTS

2.3.1 ERPS AND CORTICAL SOURCES RECONSTRUCTION

2.3.1.1 Prediction generation stage – N170 (140-180 msec) to S1 onset

A significant negative parietal-occipital cluster, reflecting a larger N170, was found in 100% block when comparing fearful with neutral faces, and in 75% block when comparing fearful with positive and neutral faces. No significant differences were found in 50% block, nor on difference waves (see Table 2.3 and Figure 2.2, panel A).

N170 source reconstruction highlighted an emotional modulation on the right STS, showing a maximum pattern of activation after fearful faces (see Figure 2.2, panel B). This pattern replicated consistently in 100% and 75% blocks.

Table 2.3 ERP results from Study 1 during the prediction *generation* stage in the N170 time window (140-180 msec). Means (*M*), standard deviation (*SD*), cluster statistic (*c*), cluster size (*s*), and the associated *p*-values for each planned comparison (POS vs. NEU, NEG vs. NEU, NEG vs. POS) within each block (100%, 75%, 50%) are reported.

Block	**N170**						
	POS		**NEU**		*c*	*s*	*p*
	M	*SD*	*M*	*SD*			
100%	2.21	0.39	2.76	0.39	-356	125	.08
75%	2.39	0.55	2.61	0.55	-94	42	.432
50%	2.12	0.23	2.52	0.23	-263	108	.134
	NEG		**NEU**		*c*	*s*	*p*
	M	*SD*	*M*	*SD*			
100%	2.00	0.39	2.76	0.39	-711	204	**.004**
75%	1.56	0.55	2.61	0.55	-1194	318	**.002**
50%	2.13	0.23	2.52	0.23	-219	88	.148
	NEG		**POS**		*c*	*s*	*p*
	M	*SD*	*M*	*SD*			
100%	2.00	0.39	2.21	0.39	-146	54	.214
75%	1.56	0.55	2.39	0.55	-527	193	**.018**
50%	2.13	0.23	2.12	0.23	-129	51	.318

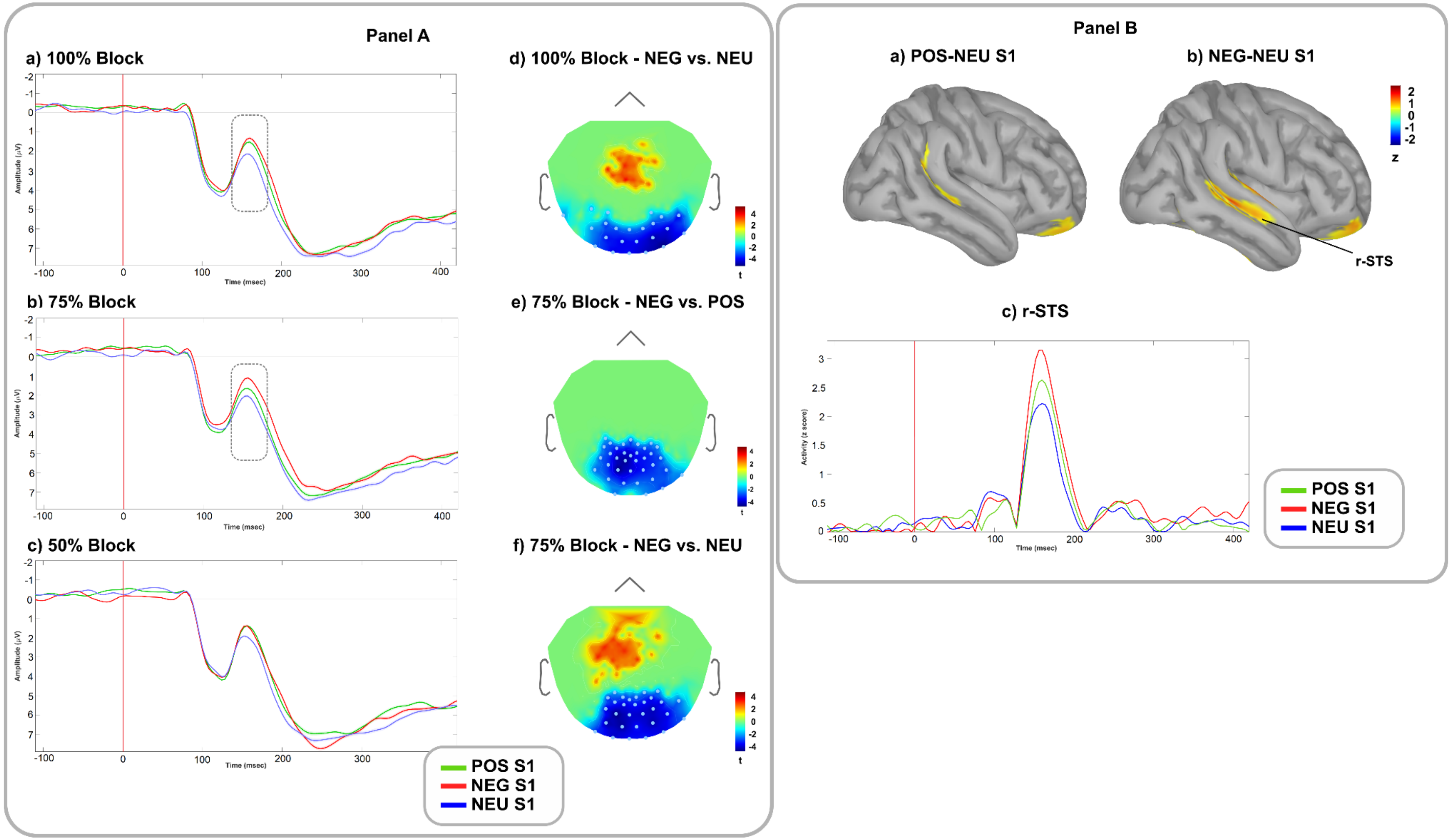

Figure 2.2 Modulation of ERPs and brain sources during prediction *generation* stage in Study 1.
Panel A. On the left, grand average ERP waveforms following NEG (red lines), POS (green lines) and NEU (blue lines) faces (S1) in the (a) 100%, (b) 75% and (c) 50% blocks. Waveforms are plotted from a parietal-occipital cluster of electrodes (E70, E71, E73, E74, E75, E76, E81, E82, E83, E88). Shaded areas denote standard error (*SE*). The N170 was computed between 140 and 180 msec from S1 onset (time 0). On the right, cluster-based N170 ERP activity averaged across the electrodes exceeding the critical *t*-score threshold for statistical significance for the contrasts (d) 100% block – NEG vs. NEU, (e) 75% block – NEG vs. NEU, and (f) 75% block – NEG vs. POS. **Panel B**. On the top, cortical maps reconstruction of the (a) POS-NEU and (b) NEG-NEU differences in brain activations in the N170 temporal window (140-180 msec), regardless of blocks. On the bottom, time course of (c) right STS activations to POS (green lines), NEG (red lines), and NEU (blue lines) faces, regardless of blocks. r-STS = right superior temporal sulcus.

2.3.1.2 Prediction implementation stage – early (1500-2000 msec) and late (2000-2500 msec) CNV to S1 onset

A significant negative left-central cluster indexed a larger early and late CNV in 50% than in 75% block (cluster statistic (c) = -6075, cluster size (s) = 2071, p = .014) (see Figure 2.3, panel A). No other significant effects were found when comparing valence and congruency levels, and difference waves.

CNV source analysis showed the involvement of a left network, extending over the ACC, the SMA, and an area in between dorsal PCC (dPCC) and the subparietal sulcus (sbps), showing larger activity in 50% than in 75% block (see Figure 2.3, panel B).

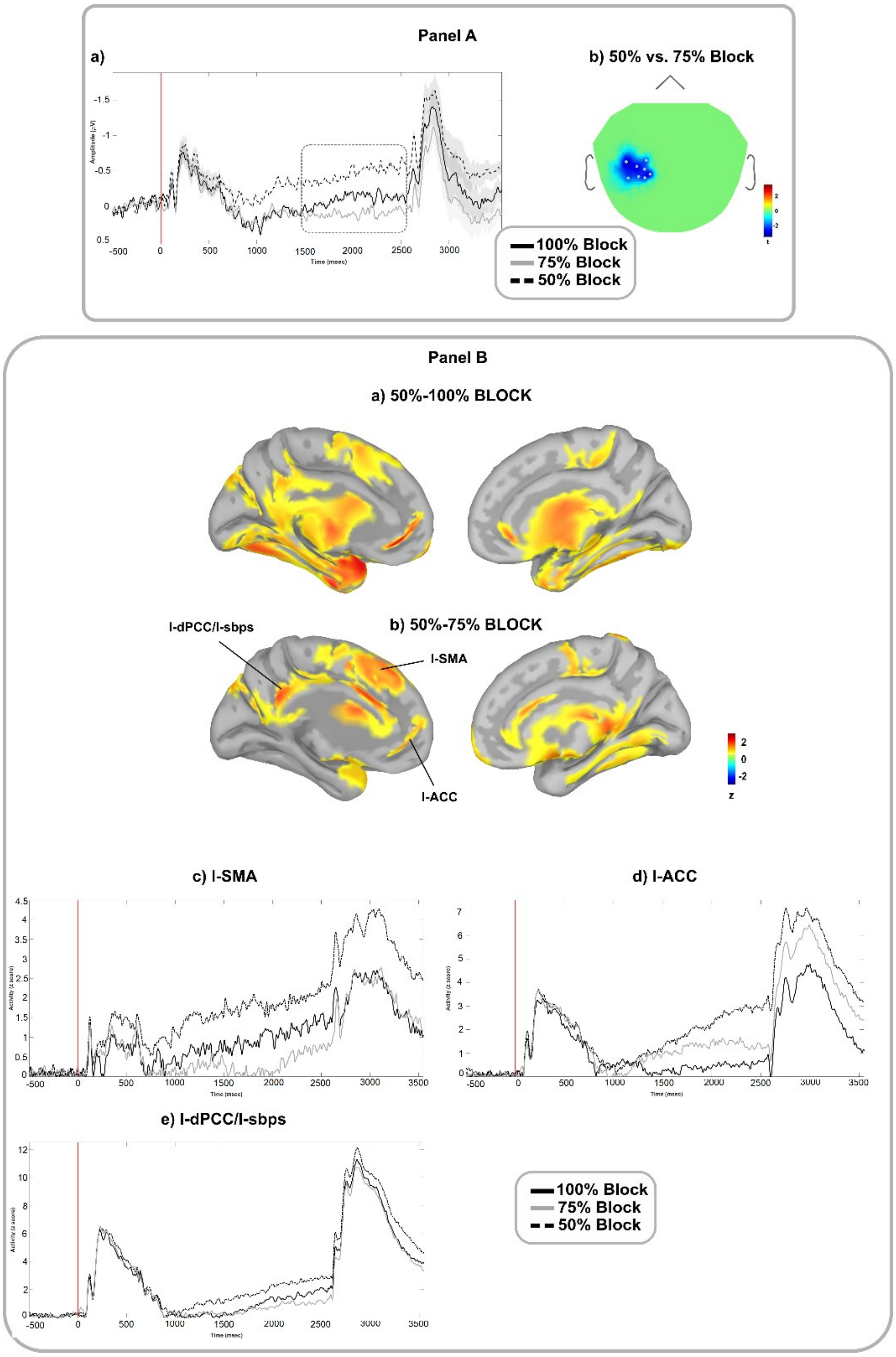

Figure 2.3 Modulation of ERPs and brain sources during prediction *implementation* stage in Study 1.
Panel A. On the left, (a) grand average ERP waveforms during prediction implementation in the 100% (continuous black line), 75% (continuous grey line), and 50% (dashed black line) blocks. Waveforms are plotted from a central cluster of electrodes (E39, E40, E41, E42, E45, E46, E47). Shaded areas denote *SE*. CNV was computed between 1500 and 2500 msec from S1 onset (time 0). For visualization purposes, waveforms were low-pass re-filtered at 10 Hz. On the right, (b) cluster-based CNV ERP activity averaged across the electrodes exceeding the critical *t*-score threshold for statistical significance for the contrast 50% vs. 75% block. **Panel B.** On the top, cortical maps reconstruction of the (a) 50%-100% block and (b) 50%-75% block differences in brain activations in the total CNV temporal window (1500-2500 msec). On the bottom, time course of (c) left SMA, (d) left ACC and (e) left dPCC/l-sbps activations to 100% (continuous black lines), 75% (continuous grey lines), and 50% (dashed black lines) blocks. l-SMA = left supplementary motor area, l-ACC = left anterior cingulate gyrus and sulcus, l-dPCC = left posterior-dorsal part of cingulate gyrus, l-sbps = left subparietal sulcus.

2.3.1.3 Prediction updating stage – MMN (100-200 msec), P2 (200-300 msec), early (400-600 msec) and late LPP (600-800 msec) to S2 onset

No significant effects were found in MMN window.

A significant negative centro-parietal cluster was found, signaling a reduced positivity to positive and negative, and so a larger P2 to neutral pictures in all the blocks and S2 congruency levels (see Table 2.4 and Figure 2.4, panel A). No significant effects were found on difference waves.

P2 source reconstruction highlighted a larger activation of bilateral temporo-parietal junction (TPJ) and an area in between paracentral gyrus and precuneus to neutral than emotional pictures in all the blocks and S2 congruency levels (see Figure 2.4, panel B).

A significant positive centro-parietal cluster was found, confirming the effect of S2 valence on LPP: positive and negative pictures elicited a larger early and late LPP than neutral pictures in all the blocks and S2 congruency levels (see Table 2.4 and Figure 2.4, panel A). The analysis of difference waves revealed that the emotional modulation of late LPP was larger in 100% than in 50% block (NEG-NEU: $c = 2028$, $s = 868$, $p = .041$; POS-NEU: $c = 2074$, $s = 909$, $p = .048$). Finally, a larger late LPP was found comparing positive congruent vs. incongruent pictures in 50% block ($c = 1746$, $s = 692$, $p = .036$).

LPP source analysis showed that, as compared with neutral, emotional stimuli elicited a larger activation of the right OFC and the right temporal pole in all the blocks and S2 congruency levels (see Figure 2.4, panel C). Modelling the sources of difference waves (NEG-NEU, POS-NEU), the same areas showed a between-blocks modulation within the right hemisphere, with larger activation in 100% than in 50% block. Interestingly, regardless of emotional valence, in 50% block, incongruent S2s elicited a larger activation than congruent S2s in the above-mentioned areas of the right hemisphere, while in the left hemisphere OFC showed a larger activation to congruent than incongruent S2s.

Table 2.4 ERP results from Study 1 during the prediction *updating* stage in the P2 (200-300 msec) and LPP (400-800 msec) time window.
Means (*M*), standard deviation (*SD*), cluster statistic (*c*), cluster size (*s*), and the associated *p*-values for each planned comparison (POS vs. NEU, NEG vs. NEU, NEG vs. POS) within each block (100%, 75%, 50%) and congruency level (congruent, incongruent) are reported.

Block	**P2**							**LPP**						
	POS		**NEU**		*c*	*s*	*p*	**POS**		**NEU**		*c*	*s*	*p*
	M	*SD*	*M*	*SD*				*M*	*SD*	*M*	*SD*			
100%	6.23	0.32	6.85	0.32	-2874	778	**.002**	8.07	1.51	5.62	1.51	25807	5260	**.002**
75% (congruent)	6.22	0.15	7.23	0.22	-3498	927	**.002**	8.40	0.13	5.86	0.10	22117	4543	**.002**
75% (incongruent)	6.43	0.15	7.53	0.22	-1418	546	**.028**	8.22	0.13	6.00	0.10	14544	4109	**.002**
50% (congruent)	6.43	0.22	6.88	0.25	-1913	665	**.004**	7.97	0.37	6.01	0.24	16375	4122	**.002**
50% (incongruent)	6.12	0.22	6.53	0.25	-994	372	**.034**	7.46	0.37	5.66	0.24	20110	4851	**.002**
	NEG		**NEU**		*c*	*s*	*p*	**NEG**		**NEU**		*c*	*s*	*p*
	M	*SD*	*M*	*SD*				*M*	*SD*	*M*	*SD*			
100%	6.40	0.32	6.85	0.32	-4342	1057	**.002**	8.37	1.51	5.62	1.51	29890	5574	**.002**
75% (congruent)	6.40	0.19	7.23	0.22	-4635	1004	**.002**	8.42	0.20	5.86	0.10	29128	5838	**.002**
75% (incongruent)	6.66	0.19	7.53	0.22	-1965	743	**.002**	8.16	0.20	6.00	0.10	15072	4276	**.002**
50% (congruent)	6.22	0.22	6.88	0.25	-1940	645	**.006**	8.00	0.04	6.01	0.24	19069	4649	**.002**
50% (incongruent)	5.91	0.22	6.53	0.25	-2435	779	**.006**	7.95	0.04	5.66	0.24	27657	5564	**.002**
	NEG		**POS**		*c*	*s*	*p*	**NEG**		**POS**		*c*	*s*	*p*
	M	*SD*	*M*	*SD*				*M*	*SD*	*M*	*SD*			
100%	6.40	0.32	6.23	0.32	-754	250	.348	8.37	1.51	8.07	1.51	891	342	.28
75% (congruent)	6.40	0.19	6.22	0.15	-269	97	.344	8.42	0.20	8.40	0.13	1117	466	.228
75% (incongruent)	6.66	0.19	6.43	0.15	112	43	.723	8.16	0.20	8.22	0.13	no clusters found		
50% (congruent)	6.22	0.22	6.43	0.22	-123	53	.629	8.00	0.04	7.97	0.37	477	184	.509
50% (incongruent)	5.91	0.22	6.12	0.22	123	49	.378	7.95	0.04	7.46	0.37	1536	535	.15

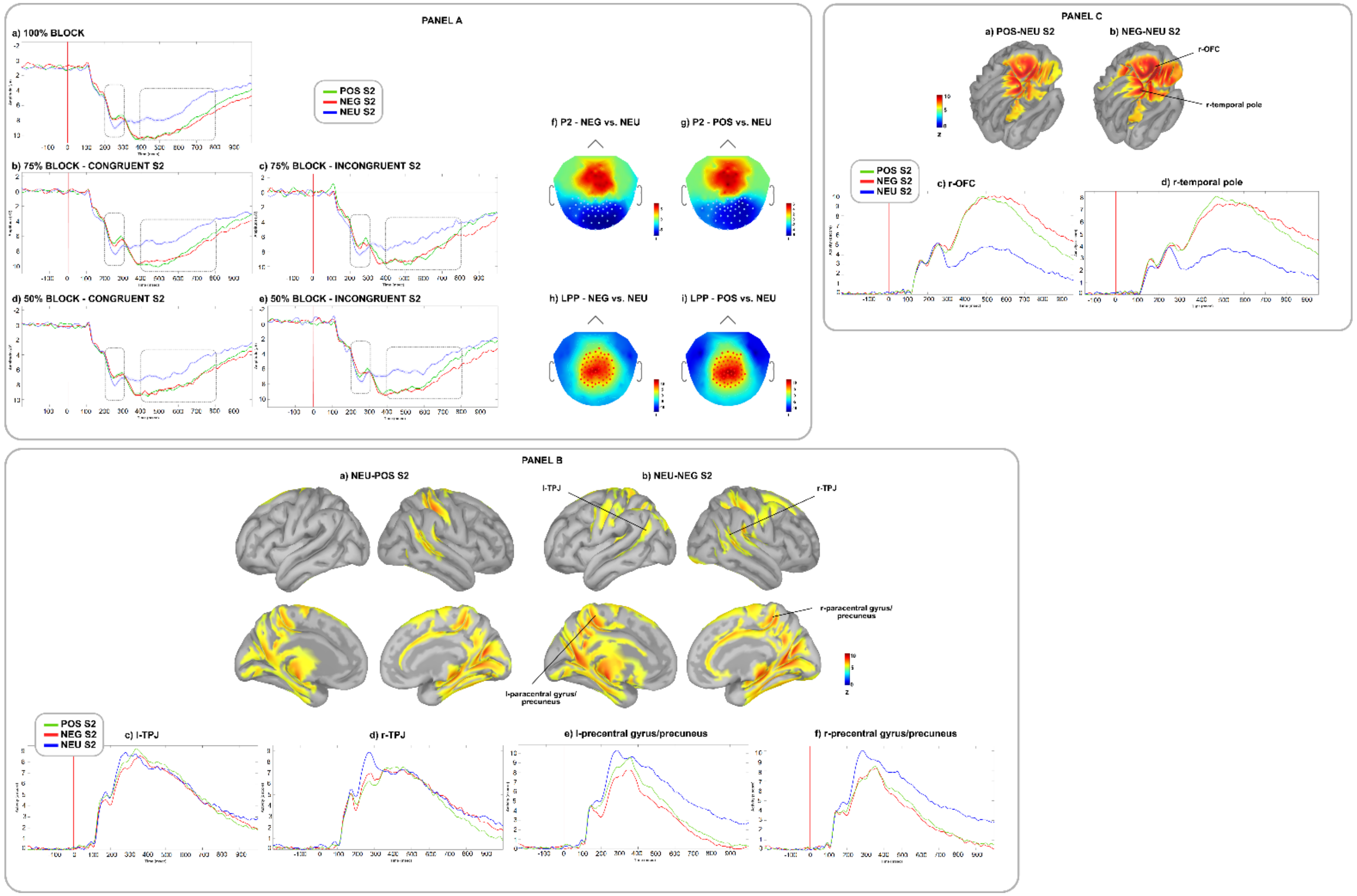

Figure 2.4 Modulation of ERPs and brain sources during prediction *updating* stage in Study 1.
Panel A. On the left, grand average ERP waveforms following NEG (red lines), POS (green lines), and NEU (blue lines) pictures (S2) in the (a) 100%, (b, c) 75%, and (d, e) 50% blocks for congruent and incongruent S2s. Waveforms are plotted from a central cluster of electrodes (E60, E61, E62, E67, E72, E77, E78, E85). Shaded areas denote *SE*. P2 was computed between 200 and 300 msec, and LPP between 400 and 800 msec from S2 onset (time 0). On the right, cluster-based (f, g) P2 and (h, i) LPP ERP activity averaged across the electrodes exceeding the critical *t*-score threshold for statistical significance for the contrasts (f, h) NEG vs. NEU and (g, i) POS vs. NEU. **Panel B.** On the top, cortical maps reconstruction of the (a) NEU-POS and (b) NEU-NEG differences in brain activations in the P2 temporal window (200-300 msec). On the bottom, time course of (c) left TPJ, (d) right TPJ, (e) left paracentral gyrus/precuneus, (f) right paracentral gyrus/precuneus activations to POS (green lines), NEG (red lines), and NEU (blue lines) pictures, regardless of blocks. l-TPJ = left temporoparietal junction, r-TPJ = right temporoparietal junction. **Panel C.** On the top, cortical maps reconstruction of the (a) POS-NEU and (b) NEG-NEU differences in brain activations in the total LPP temporal window (400-800 msec). On the bottom, time course of (c) right OFC and (d) right temporal pole activations to POS (green lines), NEG (red lines), and NEU (blue lines) pictures, regardless of blocks. r-OFC = right orbitofrontal cortex.

2.3.2 Mixed-effects models

No significant effects of the predictors were found on S2-P2 amplitude, and only weak effects were found including the S1-N170 predictor. In fact, the inclusion of S1-N170 amplitude as predictor improved the model fit for the late S2-LPP in 100% block (χ^2 (14) = 12.684, p = .005, ΔAIC = -0.864), and for the early and late S2-LPP in 50% block for congruent S2s (early LPP: χ^2 (14) = 10.977, p = .012, ΔAIC = -1.198; late LPP: χ^2 (14) = 10.918, p = .012, ΔAIC = -1.336). Furthermore, including the S1-N170 × S2 valence interaction, an improvement of the model fit for early and late S2-LPP emerged in 75% block for congruent S2s (early LPP: χ^2 (14) = 6.382, p = .041, ΔAIC = -2.374; late LPP: χ^2 (14) = 6.375, p = .041, ΔAIC = -1.935). Nevertheless, ΔAIC values were small and negative, so the actual fit improvements reported are weakly supported. For this reason, the results of these models, suggesting a negative correlation between S1-N170 and S2-LPP amplitudes, will not be further commented.

The late CNV predictor improved the model fit for the early and late S2-LPP in 50% block for congruent S2s (early LPP: χ^2 (14) = 8.996, p = .03, ΔAIC = 7.952; late LPP: χ^2 (14) = 9.522, p = .023, ΔAIC = 8.507), suggesting a positive correlation between late CNV and S2-LPP, regardless of S2 valence.

2.4 Discussion

Study 1 aimed to explore the temporal dynamics and the underlying neural signatures of the construction of affective predictions as a function of *contextual information* of different predictive value (see RQ1, § 1.5). To our knowledge, this was the first study in the literature using an uninstructed experimental task, in which participants could implicitly construct their own predictive models. As a further element of novelty, we analyzed the relationships between the three stages of prediction construction (generation-implementation-updating).

As expected (H1a), during prediction *generation* S1 valence modulated the N170, leading to a processing advantage for fearful faces. This effect was subtended by a higher cortical activity in the right STS, consistent with the estimated brain sources of N170 and signaling the perceptual coding of changeable facial properties, among which emotional facial expression (Haxby et al., 2000). In contrast with our hypothesis (H1b), however, the emotional modulation on N170 was apparent in presence of sufficiently reliable predictive information (100% and 75% blocks), maybe due to the different (highly social) nature of face stimuli as compared to the symbolic cues used in other studies (Lin, Gao, et al., 2014). It seems that in the uncertain condition (50%), where the face (and the emotional information it conveyed) was not helpful to construct a valid prediction, the generation stage was replaced by a process of resources saving, in line with a general cognitive economy principle proposed by predictive coding (Clark, 2013). The N170/right STS modulation could signal the extraction of sensory (i.e., perceptual and affective) and contextual (i.e., predictive) information from the environment, subtended by domain-specific brain circuits, and crucial to continuously generate predictions (Bar, 2007; Knill & Pouget, 2004).

In the *implementation* stage, a between-blocks modulation emerged on CNV, regardless of valence. The 50% block elicited the maximum allocation of anticipatory resources, as reflected by a larger CNV and a higher activation within a left-lateralized domain-general network composed by ACC, SMA, dPCC/sbps. This result, though in conflict with our hypothesis (H2), is in line with previous studies suggesting that valence-independent anticipatory neural activity increases with uncertainty, both at the scalp and at the source level (Catena et al., 2012; Greenberg et al., 2015; Sarinopoulos et al., 2010). ACC activation is also coherent with previous EEG and fMRI evidence, in which ACC has been found to be involved in the anticipation of unexpected stimuli during the implementation stage (Duma et al., 2020; Greenberg et al., 2015; Onoda et al., 2008; Sarinopoulos et al., 2010; Ueda et al., 2003). Thus, in the uncertain condition, where a stable expectancy is impossible to generate because of the unavailability of reliable predictive models, the valence-independent pre-allocation of anticipatory resources served at tuning the implementation stage with all the potential forthcoming environmental demands. This interpretation is supported by the functional meaning of the neural network subtending the CNV. ACC, SMA and dPCC/sbps are all areas involved in the large-scale brain system which supports allostasis (Barrett, 2017), and they partially overlap with the DMN (Raichle, 2015). They are implied in integrating sensory and visceromotor information with prior experience, thus supporting the selection of appropriate action plans and the pre-allocation of resources necessary to anticipate all the relevant features of forthcoming events (Barrett, 2017; Raichle, 2015). Moreover, the absence of a detectable emotional modulation on CNV in sufficiently predictive conditions (100%, 75%) is consistent with some previous studies (Recio et al., 2014; Tamm et al., 2014), and it can be explained according to the cognitive economy principle (Clark, 2013): it might be a useless effort to allocate wide anticipatory resources in conditions in which all the information needed to prepare to S2 is already extracted as S1 processing ends.

Finally, during prediction *updating*, and in contrast with our hypothesis (H3a) no effects were found on the MMN, probably due to the complexity of the stimuli employed as S2s, and to the large overlapping positive activity. A strong emotional modulation emerged instead on the P2 and LPP components across all the blocks and S2 congruency levels: larger LPPs were found for emotional than neutral pictures, whereas the opposite was observed for P2s. The latter effect could index the infrequency of neutral S2s, and the consequent updating of the overall predictive model. Since in all blocks the number of emotional stimuli was twice the number of neutral ones, neutral S2s could represent unexpected stimuli requiring an updating of the predictive model. This could have elicited a larger P2 and a coherent modulation both in the TPJ, an area involved in contextual updating (Geng & Vossel, 2013; Gómez et al., 2019), and in the paracentral gyrus/precuneus, areas belonging to the *frontoparietal control network* (Dosenbach et al., 2007) and subtending the top-down adjustment of predictions. The LPP modulation replicated a well-established effect in the literature, signaling a greater motivated attention towards emotional stimuli, supported by domain-specific neural circuits responsible for the interoceptive-autonomic integration performed by the *salience network* (Hajcak et al., 2010; Schupp et al., 2000; Seeley et al., 2007). Difference waves revealed that the effect of emotion, coherently with our hypothesis (H3b) and previous ERP findings (Johnen & Harrison, 2020; Lin et al., 2018; Lin, Jin, et al., 2015), was stronger with a fully predictive ratio. A larger late LPP and higher corresponding brain activations emerged when comparing difference waves between 100% and 50% blocks. This result suggests that in presence of fully predictive cues the emotional evaluation of congruent forthcoming stimuli is enhanced, resulting in greater motivated attention towards them. This could seem in contrast with predictive coding (Clark, 2013; Friston, 2010), according to which an expected stimulus processing should be silenced, and it could represent a peculiar specificity of implicit affective expectancy (cf. Lin et al., 2018).

Interestingly, when comparing congruent with incongruent pictures, contrasting results emerged from ERPs and source analyses. In the moderately predictive condition (75%) no processing difference between congruent and incongruent S2s was found, thus violating our hypothesis (H3a) and predictive coding assumptions (Clark, 2013; Friston, 2010). This controversial result might be explained by the inevitably different number of trials between congruent and incongruent S2s in 75% block. Over the 120 trials, only 30 were incongruent and their number might be too low to allow prediction errors to exert a strong (and statistically detectable) influence. In the uncertain condition (50%), instead, a larger late LPP was found to positive congruent than positive incongruent S2s, whereas a higher cortical activation was found in the right hemisphere for incongruent S2s, and in the left OFC for congruent S2s regardless of emotional valence. These results can reflect two complementary processes: a greater motivated attention towards expected positive S2s, partially consistent with some ERP studies (Gole et al., 2012; Lin et al., 2012, 2020) (cf. H3c); and a later detection of residual prediction error, signaled by a right-hemisphere activation, and consistent with predictive coding models (Clark, 2013; Friston, 2010). Therefore, two different processes seemed to develop during prediction updating: at early neurocomputational stages, in all conditions a coarse expectancy updating (subtended by the P2/TPJ-precuneus modulation) allowed to signal infrequent neutral stimuli; while at later processing stages, the residual prediction error related to incongruent S2s (signaled by the right OFC activity) was detected in the uncertain condition.

Lastly, it is worth noting that the uncertain (50%) was the only condition in which a reliable relationship was found between the implementation and the updating stages. The late CNV amplitude positively predicted the LPP amplitude to congruent S2s, regardless of emotional valence (cf. Brown et al., 2008). Thus, it seems that in absence of reliable predictive models the valence-independent anticipatory resources may be relocated to a facilitation of the subsequent information processing when a congruent S2 occurs by chance.

To summarize, results of Study 1 contributed to unveil the neural correlates of affective predictions constructed under different probabilistic *contextual information* (see RQ1, § 1.5). During prediction *generation*, the emotional information conveyed by faces was extracted by domain-specific neural circuits in presence of certain or moderately predictive contextual information. During the *implementation* stage, the unavailability of a reliable predictive model in the uncertain context led to a valence-independent pre-allocation of anticipatory resources, subtended by neural activity within domain-general cortical networks. During prediction *updating*, besides the preferential processing of emotional stimuli which consistently replicated across all the contexts (but to a greater extent in the certain one), higher-order association cortices signaled both an early and late detection of prediction error in the presence of uncertain contextual information.

Concluding, some limitations of Study 1 must be addressed. First, a passive viewing task might have contributed to an overall decrease of ERP amplitudes, thus preventing some weaker modulations to reach statistical significance (Gaillard & Perdok, 1980). Second, a "congruent" S2 does not necessarily correspond to a "predicted" S2, even though it is likely that S1-S2 congruency results in a stronger predictive model than incongruency. Third, due to the peculiarities of EEG spatial resolution, any further speculation on brain sources must be treated with caution. Last, in the present paradigm only the *currently available* contextual information was manipulated between-blocks. Nevertheless, affective contingencies experienced in the *past* (i.e., prior experience, see Figure 1.1) may impact on the construction of affective predictions, too.

Therefore, building on the latter limitation, and given that the literature has not yet answered how affective predictions can be modulated by more or less reliable *prior experience* (see RQ2, §

1.5), in Studies 2 to 5 we decided to focus on the role of previous learnings. In particular, we targeted subjective affective experience and we developed an experimental design combining the emotional S1-S2 paradigm with a learning component, with the aim to investigate the impact of (un)certain prior experience in constructing affective predictions in a new, moderately certain predictive context.

CHAPTER 3

THE ROLE OF PRIOR EXPERIENCE

"The best predictor of future behavior is past behavior, which I find very depressive"

Lisa Feldman Barrett

3.1 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 prior certain vs. uncertain scenarios could affect people's expectancies and subjective reactions to new affective events.

According to predictive models of emotion (Barrett, 2017; Seth & Friston, 2016), people use their *prior experience* to construct affective predictions. Affective predictive models are generative, probabilistic, and mostly implicit (see § 1.1 and 1.2). Thus, the continuous cycle of generation-implementation-updating of (affective) predictions allows to (i) extract relevant information from the environment, (ii) combine it with previously acquired knowledge, (iii) pre-allocate resources to face all the potential future scenarios, and (iv) consistently adjust future predictions (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 prior experience (see § 1.2). 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 are probabilistic (Clark, 2013; Friston, 2010; Shipp, 2016), it follows that subjective experience may be crucially affected by the degrees of uncertainty experienced in the past, and thus by the degree of confidence on 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 prior 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, there are still some open questions in the literature. First, it is unclear how (un)certain prior experience may affect future affective predictions at the level of subjective experience. Second, it is yet to be unraveled 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 (un)certain environments. Third, it is still unknown if (un)certain prior experience interacts with environmental cues ambiguity in shaping new affective predictions. Last, it is unclear whether the influence of prior experience may act at an implicit level (i.e., without an explicit focus of attention) in shaping subjective expectancies and reactions to new affective stimuli. Studies 2 to 5 aimed to answer the abovementioned open questions. As a first goal (Study 2) we wanted to examine if being exposed to certain vs. uncertain probabilistic relationships between stimuli would lead to an intensification of subjective reactions during future predictions. Our second goal (Study 3) was to examine whether new affective predictions developed similarly across the visual and auditory sensory modalities. The third goal (Study 4) was investigating if (un)certain prior experience might influence the subjective expectancies and reactions to new affective stimuli as a function of cues ambiguity. As the fourth goal (Study 5), we investigated whether people were able to implicitly extract (un)certain probabilistic information from the environment, and use it later to predict new affective events. Last, at the exploratory level, in all the studies we wanted to examine whether individual differences in IU could modulate the subjective affective experience as a function of prior (un)certain learnings (this latter goal is presented and discussed in Chapter 4).

Most studies in the extant literature have not manipulated prior experience directly, but have focused on how explicit contextual probabilistic information (based on the instructed meaning of cues) may impact emotional processing. These studies mostly employed affective cueing paradigms in the visual modality (see § 1.3). They focused on the role of currently available contextual information, by manipulating explicitly labeled certain (100%) vs. uncertain (50%) affective contingency between S1 and S2. Thus, in existing paradigms participants are explicitly instructed about the probabilistic ratios they will be exposed to. Such paradigms do not implement the role of *actual prior 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 literature employing such paradigms (see Table 1.1) 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 the uncertain condition 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). Moreover, the only study manipulating cue ambiguity found that ambiguous cues (i.e., cues with uninstructed 50% predictive value) elicited less negative expectancy ratings than unambiguous (i.e., instructed) cues (Chen & Lovibond, 2016).

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 (Bermpohl et al., 2006a; Dieterich et al., 2016; Greenberg et al., 2015; Grupe & Nitschke, 2011; Lin et al., 2018; Qiao et al., 2018). Ambiguous cues were found to elicit more unpleasant post-experiment mood ratings than unambiguous cues (Chen & Lovibond, 2016). The only study assessing emotional intensity found a stronger self-reported arousal after certain as compared to uncertain emotional S2s (Bermpohl et al., 2006a). Two studies 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 (Lin et al., 2017; Lin, Xiang, et al., 2015). 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.

A last S1-S2 study 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) (Lin et al., 2018). 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.

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 predictive models of emotion (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.

This brief literature review unveils some important gaps that Studies 2 to 5 of the present project aim to fill. First, the impact of prior experience on new affective predictions has never been systematically investigated. Second, subjective affective ratings in the extant paradigms have mainly assessed the valence dimension, while arousal is under-represented, despite being an equally important dimension of affective experience. Third, affective cueing paradigms are typically instructed: participants are explicitly informed about the probabilistic ratios between S1 and S2 prior to the experiment. Fourth, cross-modality effects have never been studied within the extant literature. Last, 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.

In the light of these considerations, in Studies 2 to 5 we proposed a novel online experimental design, which combined traditional emotional S1-S2 paradigms with a learning component. In our paradigm, we implemented a *direct manipulation of prior experience* in terms of uninstructed affective contingency between stimuli. The paradigm aimed to investigate 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 S1-S2 paradigm was employed as a *learning phase*, in which prior experience was manipulated via uninstructed (Studies 2, 3, and 4) or implicit (Study 5) certain vs. uncertain S1-S2 affective contingency. Participants were assigned to the *certain* (CG) or *uncertain* group (UG), in which they were presented with a 100% vs. 50% probabilistic ratio between visual stimuli (i.e., colored dots as S1s, and affective negative or neutral pictures as S2s), respectively. A second S1-S2 paradigm with a fixed 75% S1-S2 affective contingency, unambiguous (Study 2, 3, and 5) or ambiguous (Study 4) S1s, and visual (Studies 2, 4, and 5) or auditory (Study 3) 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*). Through this purposely developed paradigm, Studies 2 to 5 aimed to investigate the role of *prior experience* on the subjective reactions to new affective predictions, within and across sensory modalities (see RQ2, § 1.5).

STUDY 2

Study 2 focused on how being exposed to certain vs. uncertain probabilistic relationships between visual stimuli may influence subjective affective experience to new affective predictions in the same (i.e., visual) sensory modality.

We performed confirmatory analyses to test three a-priori formulated hypotheses (as pre-registered on OSF, https://osf.io/ef9q7/). The first hypothesis (H1) was that participants in the *UG* would show more negative expectancy ratings (Dieterich et al., 2016; Grupe & Nitschke, 2011; Herwig, Kaffenberger, et al., 2007; Qiao et al., 2018; Schumacher et al., 2015), as compared to participants in the CG. The second hypothesis (H2a) was that participants in the *UG* 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 CG. The third hypothesis (H2b), opposed to H2a, was that participants in the *CG* would show higher *arousal* and more unpleasant *valence ratings* to S2s (Bermpohl et al., 2006a; Johnen & Harrison, 2019; Lin et al., 2020; Lin, Jin, et al., 2015; Lin, Xiang, et al., 2015), as compared to participants in the UG.

We also explored whether *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%).

3.2 Methods

3.2.1 Participants

We recruited 200 adult English-speaking 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 § 3.2.2.2), reporting experienced technical issues in more than 25% of the experimental trials.

The final sample included 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.

3.2.2 Stimulus material and procedure

3.2.2.1 Stimuli and rating scales

Two emotional S1-S2 paradigms were employed as learning and 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 Table 3.1. Negative and neutral pictures did not differ in terms of luminance, contrast, complexity, and color space (see Table 3.2). 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.

The English short form (12-item) of the Intolerance of Uncertainty Scale (IUS) (Carleton et al., 2007) was used to measure IU.

Table 3.1. List of NAPS picture names used as S2s in Studies 2, 4, and 5, sorted by valence.
NEG = negative, NEU = neutral

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 3.2. Means (*M*), standard deviations (*SD*), test statistics (*t*) and associated *p*-values (*p*) of NAPS pictures employed as S2s in Studies 2, 4, and 5.
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) vs. neutral (NEU) S2s revealed no significant results.

Measure	NEG		NEU		*t*(118)	*p*
	M	*SD*	*M*	*SD*		
luminance	114.149	27.503	116.943	27.615	-0.555	.58
contrast	65.682	11.569	66.225	11.490	-0.258	.797
complexity						
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
color space						
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

3.2.2.2 Learning phase

Before the learning phase, participants were randomly assigned to one of two experimental groups: the CG, and the 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 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 affective contingency: 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% affective contingency: 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 ratio.

3.2.2.3 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 affective contingency 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 ratio 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 3.1 for a schematic representation of the experimental paradigm).

3.2.2.4 S2 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 fully reliable predictive context (100%, experienced during the learning phase), to a new, less predictive 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 fully unreliable predictive context (50%), to a more predictive one. 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%.

3.2.2.5 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), and the IUS. 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.

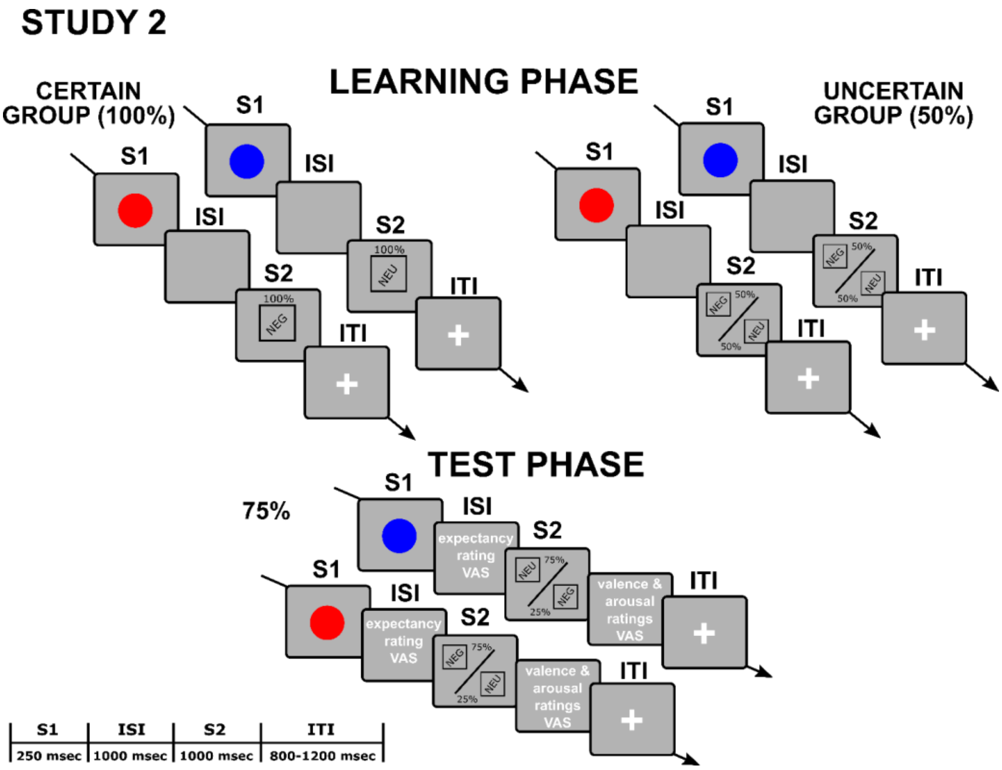

Figure 3.1 Schematic representation of Study 2 experimental paradigm.
Example sequence of events and their duration for a trial, according to the phase (learning, test), and the group (CG, UG). During the *learning phase* participants experienced a 100% (CG) vs. 50% (UG) affective contingency between S1s (red or blue circles) and S2s (NEG or NEU pictures), according to the group. During the *test phase* the S1-S2 affective contingency 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. ISI = inter-stimulus interval, ITI = inter-trial interval, VAS = visual analogue scale. The text is not drawn to scale.

3.2.3 Data analysis

The study has a 2 (*group*, between-subjects: CG vs. UG) × 2 (*S2 valence*, within-subjects: NEG vs. 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 group. Each color had an actual predictive meaning for participants in the CG, since they experienced a fully reliable S1-S2 affective contingency 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 re-coded 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 circle's 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 DV we fitted the following LMMs (R package: lme4; Bates et al., 2015):

- *expectancy ratings* (H1): *group*, *S1 color* and their interaction as fixed factors, random slopes for *S1 color* within participant;
- *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.

3.3 RESULTS

All confirmatory models are summarized in Table 3.3 and Figure 3.2. For the *expectancy* model ($R^2_{marginal} = 0.216$, $R^2_{conditional} = 0.496$), we found a main effect of *S1 color* ($F(1, 183) = 90.2$, $p < .001$) and an interaction between *S1 color* and *group* ($F(1, 183) = 65.30$, $p < .001$). 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 vs. red = -35.2, $t(183) = -13.12$, $p < .001$, 95% *CI* = [-40.54, -29.94]), whereas in the UG no differences in expectancy ratings as a function of the S1 color emerged (blue vs. red = -2.8, $t(183) = -0.96$, $p = .34$, 95% *CI* = [-8.72, 3.03]). Contrary to H1, however, we did not find any significant main effect of *group* ($F(1, 183) = 0.02$, $p = .9$). 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* ($R^2_{marginal} = 0.622$, $R^2_{conditional} = 0.723$) and *arousal* ($R^2_{marginal} = 0.293$, $R^2_{conditional} = 0.556$) models testing H2a vs. H2b, we found a main effect of *S2 valence*, with both groups reporting significantly greater unpleasantness ($F(1, 183) = 1393$, $p < .001$; NEG vs. NEU = -47.55, $t(183) = -37.32$, $p < .001$, 95% *CI* = [-50.06, -45.03]) and higher arousal ($F(1, 183) = 332.68$, $p < .001$; NEG vs. NEU = 26.69, $t(183) = 18.24$, $p < .001$, 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* ($F(1, 183) = 0.07$, $p = .799$) and *arousal ratings* (F(1,

183) = 0.82, *p* = .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 3.4.

Table 3.3 Results of confirmatory LMMs on *expectancy*, *valence* and *arousal ratings* in Study 2.
For each model, we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated *t*-test.

Model	**Parameter**	**Estimate**	***SE***	***t***	***DF***	***p***	**95% *CI***	
Expectancy ratings	Intercept	52.96	0.57	93.46	183.00	< .001	51.84	54.08
	UG - CG	-0.15	1.13	-0.13	183.00	.897	-2.38	2.09
	blue - red	-19.04	2.00	-9.50	182.99	**< .001**	-23.00	-15.09
	color × group	-32.40	4.01	-8.08	182.99	**< .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	< .001	44.69	46.28
	UG - CG	-0.73	0.81	-0.90	183.00	.369	-2.33	0.87
	NEG - NEU	-47.55	1.27	-37.32	183.00	**< .001**	-50.06	-45.04
	valence × group	0.65	2.55	0.26	183.00	.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	< .001	46.42	48.93
	UG - CG	0.17	1.27	0.13	183.00	.894	-2.33	2.67
	NEG - NEU	26.69	1.46	18.24	183.00	**< .001**	23.80	29.57
	valence × group	-2.66	2.93	-0.91	183.00	.364	-8.44	3.11
	σ ID	8.19						
	σ valence	19.11						
	σ residual	16.37						

Table 3.4 Results of exploratory LMMs investigating the effect of *S2 congruency* on *valence* and *arousal ratings* in Study 2.
For each model, we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated *t*-test.

Model	**Parameter**	**Estimate**	***SE***	***t***	***DF***	***p***	**95% *CI***	
Valence ratings	Intercept	46.44	0.42	111.05	208.84	< .001	45.62	47.27
	UG - CG	-0.52	0.84	-0.62	208.84	.535	-2.17	1.13
	NEG - NEU	-45.60	1.29	-35.30	193.21	**< .001**	-48.14	-43.05
	congruent - incongruent	-3.83	0.42	-9.06	7,026.01	**< .001**	-4.66	-3.00
	valence × group	1.10	2.58	0.43	193.21	.669	-3.99	6.20
	group × congruency	-0.84	0.85	-0.99	7,026.01	.322	-2.50	0.82
	valence × congruency	-7.82	0.85	-9.24	7,026.01	**< .001**	-9.47	-6.16
	group × valence × congruency	-1.82	1.69	-1.07	7,026.01	.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	< .001	46.06	48.60
	UG - CG	0.17	1.29	0.13	194.20	.893	-2.37	2.71
	NEG - NEU	25.53	1.48	17.26	191.40	**< .001**	22.62	28.45
	congruent - incongruent	1.36	0.44	3.09	7,026.00	**.002**	0.50	2.23
	valence × group	-2.47	2.96	-0.83	191.40	.405	-8.31	3.37
	group × congruency	-0.01	0.88	-0.02	7,026.00	.987	-1.74	1.71
	valence × congruency	4.61	0.88	5.22	7,026.00	**< .001**	2.88	6.33
	group × valence × congruency	-0.77	1.76	-0.44	7,026.00	.663	-4.22	2.69
	σ ID	8.19						
	σ valence	19.11						
	σ residual	16.33						

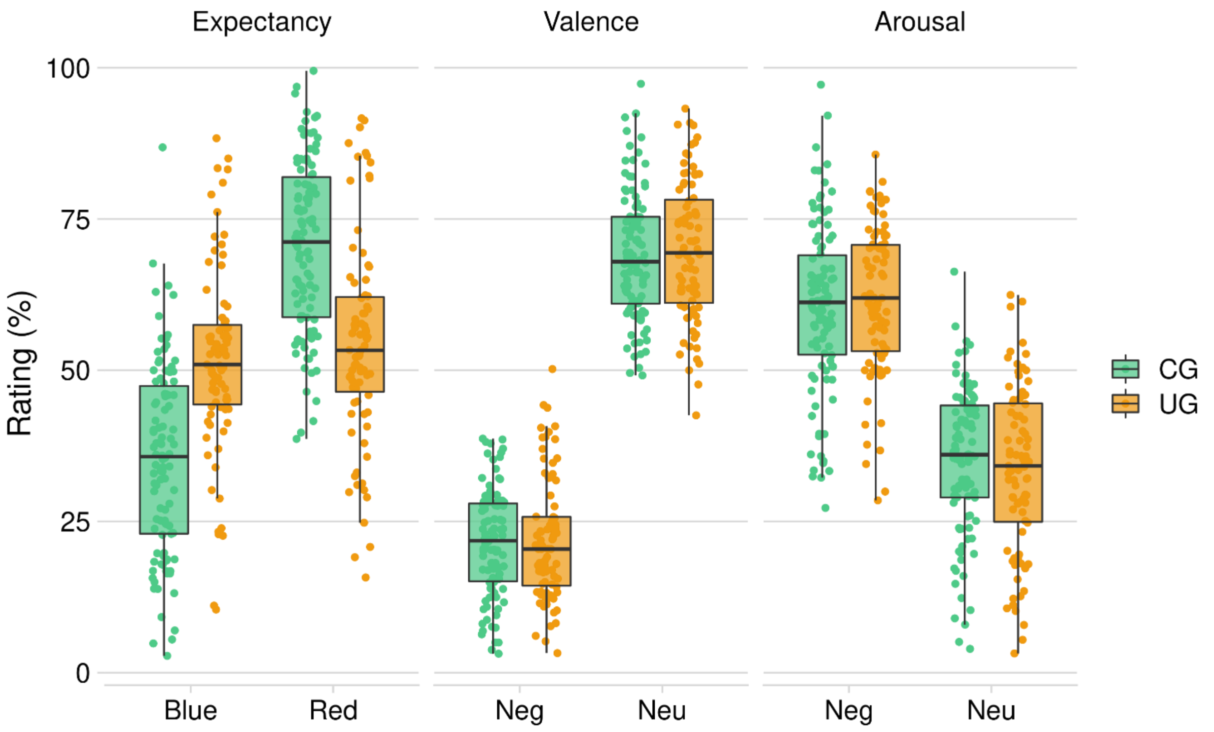

Figure 3.2 Box-plot of *expectancy*, *valence* and *arousal ratings* in Study 2.
Points represent the mean value for each participant according to the *group* (CG vs. UG), and the *S1 color* (red vs. blue, for expectancy ratings) or the *S2 valence* (NEG vs. NEU, for valence and arousal ratings).

3.4 Discussion

Study 2 demonstrated that within the visual sensory modality prior probabilistic information shaped the subjective experience of the expected valence of future stimuli (i.e., the *generation-implementation* stages), 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 fully 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 contextual 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, Kaffenberger, 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* may push subjective experience towards a negative bias (as it has been found in the literature), while this effect may 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 prior 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 contextual information and subjective valence ratings (Bermpohl et al., 2006a; 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 learnings, 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 Study 2 suggested that previous experience shaped the subjective reactions to new affective predictions only with regards to the generation-implementation stages, in Study 3 we tested if these results hold when previous experience and new predictions tap into *different sensory modalities*.

STUDY 3

Study 3 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). In fact, if previously learned visual contingencies effectively generalize to novel auditory stimuli, then we can expect to find similar patterns of results in Study 2 (visual to visual) and Study 3 (visual to auditory).

We tested the same a-priori and pre-registered (https://osf.io/wcy9r/) hypotheses as in Study 2 (H1, H2a, H2b). Furthermore, we explored whether the influence of previous experience on subjective affective ratings differed between Study 2 and Study 3.

3.5 Methods

3.5.1 Participants

According to an a-priori power-analysis (see § 3.2.1), we recruited 200 adult English-speaking participants through Prolific (Prolific, Oxford, UK; www.prolific.co). In order to be included in Study 3, participants must not have taken part in Study 2. Data from 17 participants were discarded according to the pre-registered exclusion criteria (https://osf.io/wcy9r/) (see § 3.2.1). Furthermore, data from 3 participants were incomplete 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 included 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.

3.5.2 STIMULUS MATERIAL AND PROCEDURE

The experiment was run online through OpenSesame (Mathôt et al., 2012), and hosted in JATOS (Lange et al., 2015). Two S1-S2 paradigms were employed as a learning and a test phase, respectively. S1s were the same as in Study 2 (see § 3.2.2.1). 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 Table 3.5. 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 Table 3.6). 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*. The English short form of the IUS (Carleton et al., 2007) was used to measure IU.

Table 3.5 List of NAPS pictures names and IADS-2 sounds numbers used as S2s in Study 3, sorted by valence. NEG = negative, NEU = neutral

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 3.6 Means (*M*), standard deviations (*SD*), test statistics (*t*), and associated *p*-values (*p*) of NAPS pictures and IADS-2 sounds employed as S2s in Study 3.
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) S2s showed no significant results.

Measure	**NEG**		**NEU**		***t*(38)**	***p***
	M	*SD*	*M*	*SD*		
luminance	110.232	23.168	121.242	24.168	-1.471	.150
contrast	65.834	10.017	61.919	10.617	1.199	.238
jpeg_size	345480.200	115725.462	357945.550	111068.563	-0.348	.730
entropy	7.623	0.399	7.663	0.216	-0.394	.695
LABL	45.552	9.136	50.539	9.667	-1.677	.102
LABA	2.089	4.294	-1.576	10.822	1.408	.167
LABB	5.316	5.992	6.630	15.278	-0.358	.722
Measure	**NEG**		**NEU**		***t*(78)**	***p***
	M	*SD*	*M*	*SD*		
min dB	-0.673	0.058	-0.657	0.094	-0.916	.362
max dB	0.668	0.052	0.681	0.116	-0.638	.526
peak dB	-93.125	566.920	-3.582	1.347	-0.999	.321

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 Study 2 (see § 3.2.2.2).

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 Study 2 (adapting the wording from visual to auditory modality, see § 3.2.2.3). S1, ISI, and ITI timings were unchanged, whereas S2s were presented in their full length of 6000 msec (see Figure 3.3 for a schematic representation of the experimental paradigm).

At the end of the test phase, participants were redirected to the Qualtrics survey (see § 3.2.2.5), and then back to Prolific to complete the study submission and receive their payment.

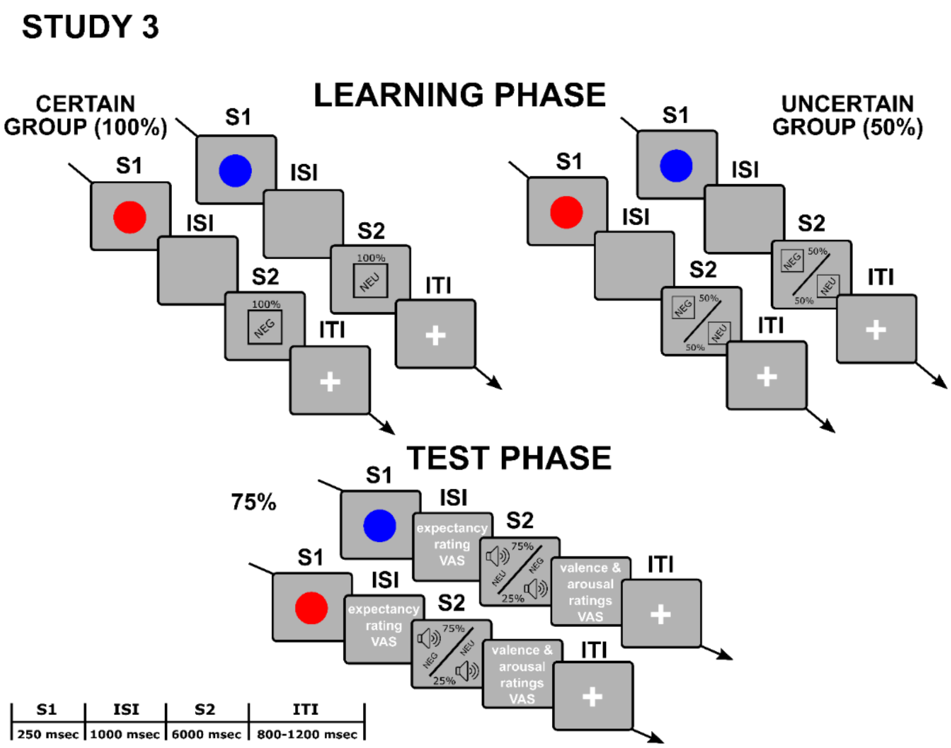

Figure 3.3 Schematic representation of Study 3 experimental paradigm.
Example sequence of events and their duration for a trial, according to the phase (learning, test), and the group (CG, UG). During the *learning phase* participants experienced a 100% (CG) vs 50% (UG) affective contingency between S1s (red or blue circles) and S2s (NEG or NEU pictures), according to the group. During the *test phase* S2s were negative or neutral sounds, 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. ISI = inter-stimulus interval, ITI = inter-trial interval, VAS = visual analogue scale. The text is not drawn to scale.

3.5.3 Data analysis

The study has a 2 (*group*, between-subjects: CG vs. UG) × 2 (*S2 valence*, within-subjects: NEG vs. 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, 7 of them were identified as "error outliers" (cf. Leys et al., 2019) and 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 an "error outlier" and removed from data analysis. The remaining 57 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 as "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):

- *expectancy ratings* (H1): *group*, *S1 color* and their interaction as fixed factors, random slopes for *S1 color* within participant;
- *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 Study 2 and Study 3, we merged the two datasets, and added the *study* (between-subjects: Study 2 vs. Study 3) 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 (α = .05, R package: lmerTest; Kuznetsova et al., 2017). For each model we reported the estimated parameters with 95% *CI*, marginal and conditional R^2 (estimated as in Nakagawa et al., 2017).

3.6 RESULTS

All confirmatory models are summarized in Table 3.7 and Figure 3.4. For the *expectancy* model ($R^2_{marginal} = 0.145$, $R^2_{conditional} = 0.468$) replicating the finding from Study 2, we found a main effect of *S1 color* ($F(1, 183) = 73.25$, $p < .001$), and an interaction between *S1 color* and *group* ($F(1, 183) = 18.45$, $p < .001$). 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 vs. red = -27.97, $t(183) = -8.86$, $p < .001$, 95% $CI = [-34.20, -21.73]$) and in the UG (blue vs. red = -9.28, $t(183) = -3.09$, $p = .002$, 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 (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* ($F(1, 183) = 0.35$, $p = .56$). 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* ($R^2_{marginal} = 0.471$, $R^2_{conditional} = 0.540$) and *arousal* ($R^2_{marginal} = 0.274$, $R^2_{conditional} = 0.398$) models testing H2a vs. H2b, we found a main effect of *S2 valence*, with both groups reporting significantly greater unpleasantness ($F(1, 169) = 1490.65$, $p < .001$; NEG vs. NEU = -37.67, $t(183) = -38.61$, $p < .001$, 95% $CI = [-39.59, -35.74]$) and higher arousal ($F(1, 169) = 870.40$, $p < .001$; NEG vs. NEU = 25.24, $t(183) = -37.32$, $p < .001$, 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 = .031) and *arousal* models (F(1, 169) = 5.30, p = .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 vs. UG = 2.54, t(169) = 1.92, p = .056, 95% CI = [-0.06, 5.14]; NEG: CG vs. UG = -1.70, t(169) = -1.39, p = .166, 95% CI = [-0.22, 0.03]) and *arousal ratings* (NEU: CG vs. UG = -2.07, t(169) = -1.58, p = .117, 95% CI = [-4.67, 0.52]; NEG: CG vs. UG = 1.86, t(169) = 1.19, p = .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.

Study 3 exploratory models are summarized in Table 3.8.

Table 3.7 Results of confirmatory LMMs on *expectancy*, *valence* and *arousal ratings* in Study 3.
For each model we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated *t*-test.

Model	Parameter	Estimate	*SE*	*t*	*DF*	*p*	95% *CI*	
Expectancy ratings	Intercept	53.40	0.54	99.62	169	< .001	52.34	54.46
	UG - CG	0.63	1.07	0.59	169	.557	-1.48	2.75
	blue - red	-18.62	2.18	-8.56	169	**< .001**	-22.92	-14.33
	color × group	-18.69	4.35	-4.30	169	**< .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	< .001	40.65	42.26
	UG - CG	0.42	0.82	0.51	169	.609	-1.19	2.03
	NEG - NEU	-37.67	0.98	-38.61	169	**< .001**	-39.59	-35.74
	valence × group	-4.24	1.95	-2.17	169	**.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	< .001	58.79	61.09
	UG - CG	-0.10	1.17	-0.09	169	.931	-2.41	2.20
	NEG - NEU	25.24	0.86	29.50	169	**< .001**	23.55	26.93
	valence × group	3.94	1.71	2.30	169	**.022**	0.56	7.32
	σ ID	7.03						
	σ valence	9.48						
	σ residual	18.68						

Table 3.8 Results of exploratory LMMs investigating the effect of *S2 congruency* on *valence* and *arousal ratings* in Study 3.
For each model, we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated *t*-test.

Model	Parameter	Estimate	*SE*	*t*	*DF*	*p*	95% *CI*	
Valence ratings	Intercept	42.13	0.43	98.30	204.39	< .001	41.29	42.98
	UG - CG	0.44	0.86	0.52	204.39	.607	-1.25	2.13
	NEG - NEU	-35.69	1.01	-35.36	193.50	**< .001**	-37.68	-33.70
	congruent - incongruent	-2.70	0.52	-5.22	6,494.00	**< .001**	-3.71	-1.69
	valence × group	-3.52	2.02	-1.74	193.50	.083	-7.50	0.46
	group × congruency	-0.09	1.03	-0.09	6,494.00	.929	-2.12	1.93
	valence × congruency	-7.93	1.03	-7.68	6,494.00	**< .001**	-9.96	-5.91
	group × valence × congruency	-2.87	2.07	-1.39	6,494.00	.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	< .001	58.30	60.66
	UG - CG	-0.15	1.20	-0.12	186.22	.903	-2.51	2.21
	neg - neu	23.85	0.89	26.67	201.72	**< .001**	22.09	25.61
	congruent - incongruent	1.83	0.52	3.52	6,494.00	**< .001**	0.81	2.86
	valence × group	3.40	1.79	1.90	201.72	.058	-0.12	6.93
	group × congruency	0.18	1.04	0.17	6,494.00	.866	-1.87	2.22
	valence × congruency	5.56	1.04	5.34	6,494.00	**< .001**	3.52	7.60
	group × valence × congruency	2.15	2.08	1.03	6,494.00	.303	-1.94	6.23
	σ ID	7.03						
	σ valence	9.49						
	σ residual	18.62						

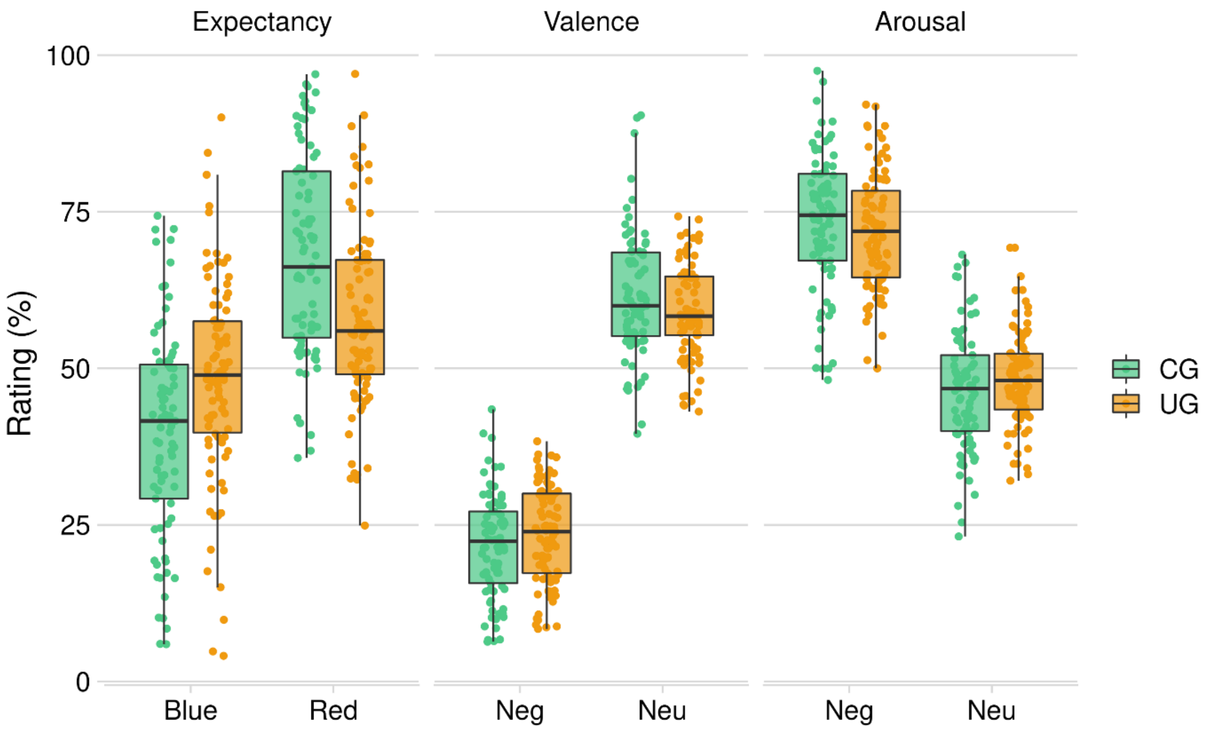

Figure 3.4 Box-plot of *expectancy*, *valence* and *arousal ratings* in Study 3.
Points represent the mean value for each participant according to the *group* (CG vs. UG), and the *S1 color* (red vs. blue, for expectancy ratings) or the *S2 valence* (NEG vs. NEU, for valence and arousal ratings).

Exploratory models comparing results of Study 2 and 3 are summarized in Figure 3.5. For the *expectancy* model ($R^2_{marginal} = 0.184$, $R^2_{conditional} = 0.483$) we found evidence for a three-way interaction ($F(1, 352) = 5.385$, $p = .021$) between *study*, *group* and *S1 color*. However, none of the post-hoc comparisons between Study 2 and Study 3 emerged as statistically significant. For the *valence* model ($R^2_{marginal} = 0.559$, $R^2_{conditional} = 0.645$) we found an interaction between *study* and *S2 valence* ($F(1, 352) = 37.09$, $p < .001$). In particular, neutral sounds were rated as more unpleasant than neutral pictures (NEU: Study 2 vs. Study 3 = 8.969, $z = 8.508$, $p < .001$)[1]. Finally, for *arousal* model ($R^2_{marginal} = 0.327$, $R^2_{conditional} = 0.512$) we only found a main effect of *study* ($F(1, 352) = 202.64$, $p < .001$), with sounds rated overall as more arousing than visual stimuli independently from valence (Study 2 vs. Study 3 = -12.3, $z = -14.16$, $p < .001$)[1]. Thus, none of the exploratory comparisons

[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.

between Study 2 and Study 3 yielded evidence in favor of a different effect of previous experience as a function of the sensory modality involved.

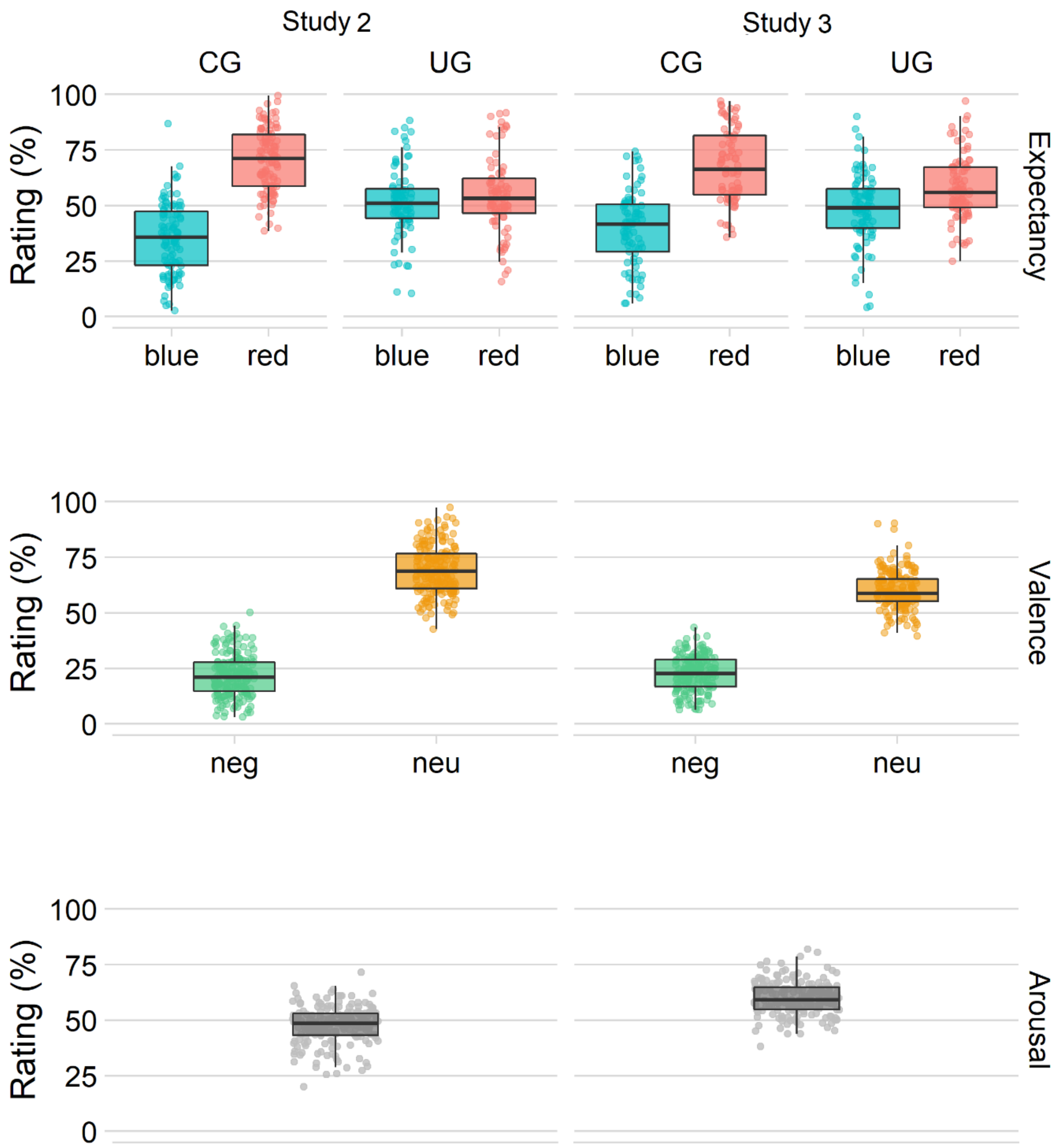

Figure 3.5 Box-plots of the comparison of *expectancy*, *valence* and *arousal ratings* between Study 2 and Study 3. Top: Points represent the mean value of *expectancy ratings* for each participant according to the *study* (Study 2 vs. Study 3), the *group* (CG vs. UG), and the *S1 color* (red vs. blue). Middle: Points represent the mean value of *valence ratings* for each participant according to the *study* (Study 2 vs. Study 3), and *S2 valence* (NEG vs. NEU). Bottom: Points represent the mean value of *arousal ratings* for each participant according to the *study* (Study 2 vs. Study 3).

3.7 DISCUSSION

Study 3 (visual to auditory) demonstrated that prior 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 Study 2 (visual to visual). In Study 3 we replicated the results of Study 2, 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 vs. 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 Study 2 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 (Study 2 + Study 3). Thus, consistently with the predictive framework (Barrett, 2017; Friston, 2010; Seth & Friston, 2016; Shipp, 2016), the claim that affective predictions develop similarly across sensory modalities seems to be supported by our results. 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).

Summarizing, Studies 2 and 3 suggested that relying on a certain prior experience can shape subjective expectancies toward a coherent labeling of the predicted valence of future stimuli, and that this process generalizes across sensory modalities. However, affective predictions must generalize also from the specific features of the learning context (from which they are constructed) to new, and potentially ambiguous, contextual features (in which they are implemented), in order to be effective in promoting survival and allostatic balance with our environment (cf. § 1.1 and 1.2). Therefore, we implemented a follow-up study (Study 4) in which we investigated how (un)certain prior experience may influence new affective predictions, as a function of cues *ambiguity*.

STUDY 4

Study 4 investigated how being exposed to certain vs. uncertain probabilistic relationships between stimuli might influence the subjective reactions to new affective stimuli, as a function of S1s ambiguity.

We performed confirmatory analyses to test two a-priori formulated hypotheses (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*.

3.8 Methods

3.8.1 Participants

We recruited 125 adult English-speaking participants through Prolific (Prolific, Oxford, UK; www.prolific.co). The sample size was estimated through an a priori pre-registered (https://osf.io/gdr3b/) power analysis (see § 3.2.1), estimating parameters from data of Study 2 (N = 185). In order to be included in Study 4 participants must not have taken part in Studies 2 and 3. One participant was discarded according to the pre-registered exclusion criteria (https://osf.io/gdr3b/) (see § 3.2.1). Data from 3 participants were discarded because of data collection failure.

The final sample included 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).

3.8.2 Stimulus material and procedure

Two S1-S2 paradigms were employed as learning and test phase, respectively. S1s in the learning phase were identical to the ones employed in Study 2 (see § 3.2.2.1). In the test phase, new ambiguous S1s were added: same-sized reddish and bluish (i.e., coral- and turquoise-colored) circles. In both learning and test phases, S2s were the same negative or neutral NAPS pictures employed in Study 2 (see Tables 3.1 and 3.2). As in Study 2 (see § 3.2.2.1), the yellow circle and the striped pattern picture were used as S1 and S2, respectively, in attention check trials. Three VASs were used to collect *expectancy*, *valence* and *arousal ratings* (see § 3.2.2.1). The English short form of the IUS (Carleton et al., 2007) was used to measure IU.

The experiment was run online through OpenSesame (Mathôt et al., 2012), and hosted in JATOS (Lange et al., 2015). Before the learning phase participants were randomly assigned to the CG or the UG. The learning phase was identical to Study 2 (see § 3.2.2.2). 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, structure and timing of the test phase were the same as in Study 2 (see § 3.2.2.3). *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 (see Figure 3.6 for a schematic representation of the experimental paradigm). At the end of the test phase, participants were redirected to the Qualtrics survey (see § 3.2.2.5), and then back to Prolific to complete the study submission and receive their payment.

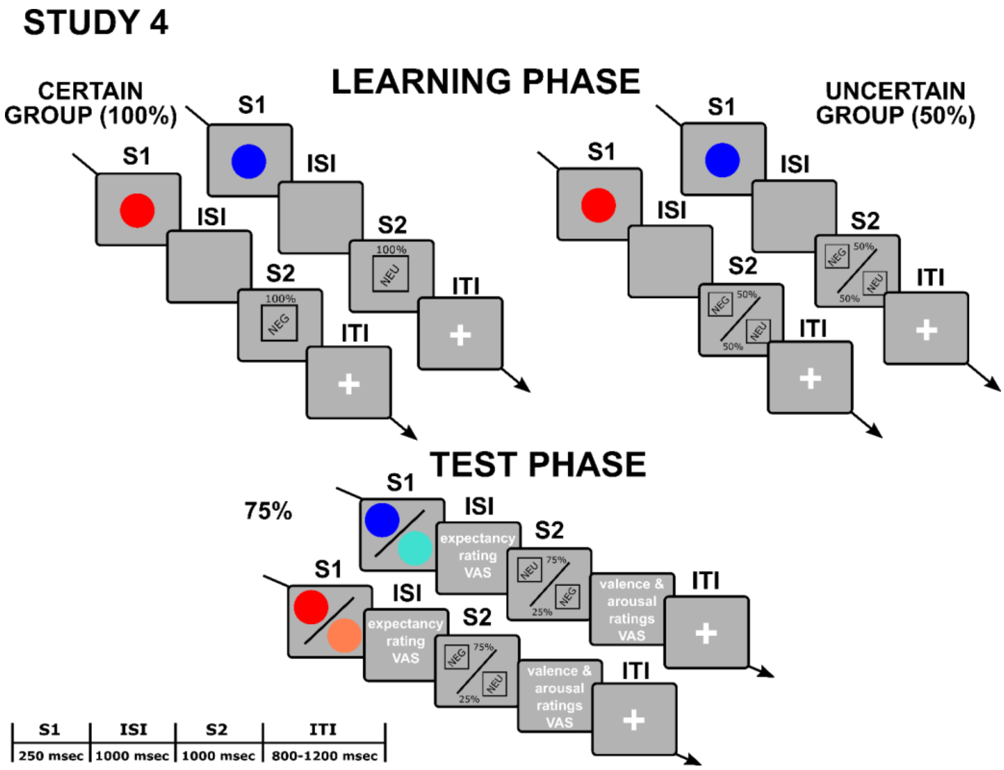

Figure 3.6 Schematic representation of Study 4 experimental paradigm.
Example sequence of events and their duration for a trial, according to the phase (learning, test), and the group (CG, UG). During the *learning phase* participants experienced a 100% (CG) vs. 50% (UG) affective contingency between 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. ISI = inter-stimulus interval, ITI = inter-trial interval, VAS = visual analogue scale. The text is not drawn to scale.

3.8.3 Data analysis

The study has a 2 (*group*, between-subjects: CG vs. UG) × 2 (*cue*, within-subjects: ambiguous vs. unambiguous) × 2 (*S2 valence*, within-subjects: NEG vs. NEU) mixed design. The analysis plan was pre-registered on OSF (https://osf.io/gdr3b/).

We detected 12 univariate outliers (MAD > 3). We visually inspected their ratings, we identified them as "error outliers" (cf. Leys et al., 2019), and we chose to remove them from data analysis. We also detected 21 multivariate outliers (MMCD, breakdown point 0.25). 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). 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 LMMs for each DV (R package: lme4; Bates et al., 2015):

- *expectancy ratings* (H1): *group*, *cue* and their interaction as fixed factors, random slopes for *cue* within participant;
- *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% *CI*, marginal and conditional R^2 (estimated as in Nakagawa et al., 2017).

3.9 Results

Study 4 models are summarized in Table 3.9 and Figure 3.7. For the *expectancy* model ($R^2_{marginal} = 0.006$, $R^2_{conditional} = 0.056$) 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 ($R^2_{marginal} = 0.155$, $R^2_{conditional} = 0.453$) 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. § 3.3 and 3.6), 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 ($R^2_{marginal} = 0.621$, $R^2_{conditional} = 0.704$) 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 vs. 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 vs. 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 ($R^2_{marginal} = 0.325$, $R^2_{conditional} = 0.566$) 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 vs. unambiguous = -1.52, $t(4138) = -2.98$, $p = .003$, 95% CI = [-2.53, -0.52]).

Table 3.9 Results of LMMs on *expectancy*, *valence* and *arousal ratings* in Study 4.
For each model, we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated *t*-test.

Model	**Parameter**	**Estimate**	***SE***	***t***	***DF***	***p***	**95% *CI***	
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						
	σ valence	14.43						
	σ residual	16.03						
Arousal ratings	Intercept	49.59	0.86	57.89	107.19	< .001	47.89	51.29
	UG - CG	-1.62	1.71	-0.95	107.19	.346	-5.02	1.78
	ambiguous - unambiguous	-1.52	0.51	-2.97	4,138.00	**.003**	-2.53	-0.52
	NEG – NEU	28.71	1.83	15.68	107.17	**< .001**	25.08	32.34
	group × cue	-0.35	1.02	-0.34	4,138.00	.733	-2.36	1.66
	valence × group	4.67	3.66	1.27	107.17	.205	-2.59	11.93
	cue × valence	-1.66	1.02	-1.62	4,138.00	.105	-3.67	0.35

group × cue × valence	1.69	2.05	0.83	4,138.00	.409	-2.32	5.70
σ ID	8.53						
σ valence	18.34						
σ residual	16.80						

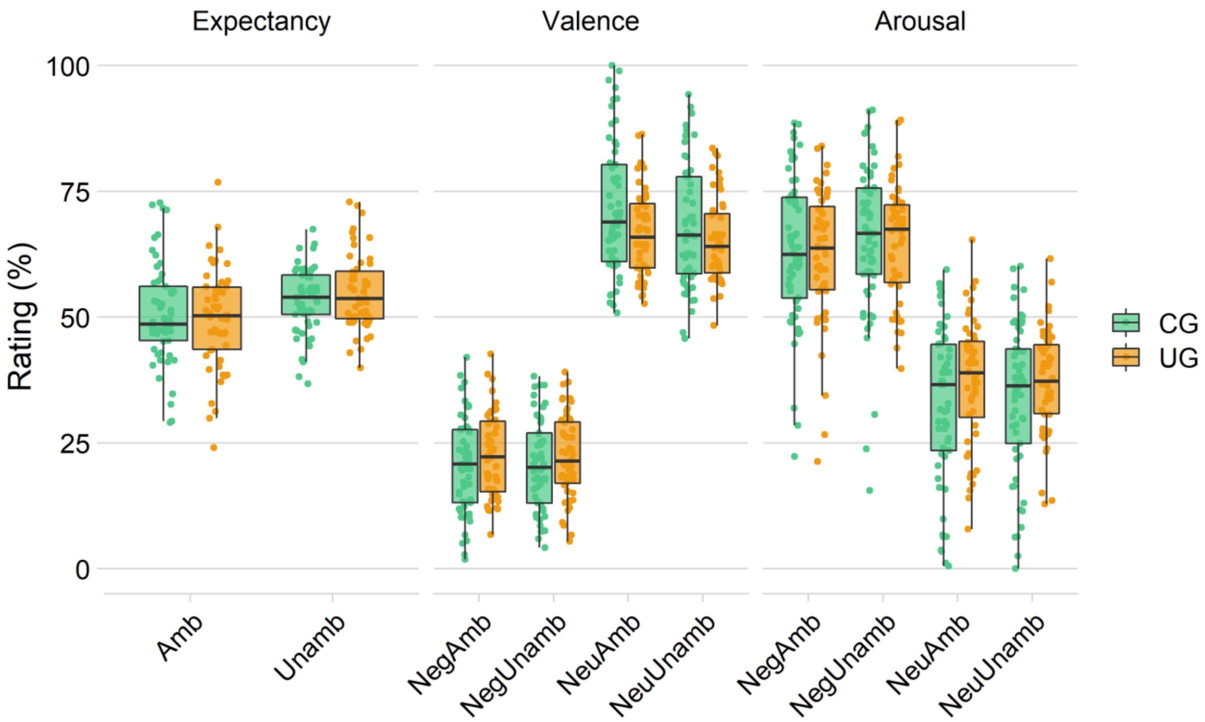

Figure 3.7 Box-plot of *expectancy*, *valence* and *arousal ratings* in Study 4.
Points represent the mean value for each participant according to the *group* (CG vs. UG), the *cue* (ambiguous vs. unambiguous), and *S2 valence* (NEG vs. NEU, for valence and arousal ratings only).

3.10 Discussion

Results of Study 4 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 manipulating ambiguity of the target affective pictures, found that ambiguous pictures were rated as less unpleasant and less arousing than unambiguous pictures (Kirschner et al., 2016), 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 Study 4, 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, it might be that when it comes to evaluating environmental ambiguity *current* (i.e., ambiguous vs. unambiguous) information prevailed over *past* information (i.e., certain vs. uncertain) in shaping subjective affective experience. When presented with unambiguous cues (for which one might have formerly constructed a reliable internal model), indeed, 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; 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, 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).

Thus, Study 4 suggested that subjective affective experience under ambiguity is dampened in all the stages, and that previous reliable learnings may be used in a later moment to predict and give meaning both to unambiguous and ambiguous environmental cues. Finally, as a last investigation, in Study 5 we explored whether it is possible to extract (un)certain probabilistic information from the environment at an *implicit* level (i.e., without explicitly focusing attention) and use this information to predict/react to new affective events.

STUDY 5

Study 5 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 S1-S2 affective contingency, during the learning phase we engaged participants in a distracting task (a parity judgement task, see § 3.11.2). Then, we tested if they 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 pre-registered (https://osf.io/z5esb/) 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 subjective ratings during 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, Kaffenberger, 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 (as previously found in Studies 2 and 3). 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 (Bermpohl et al., 2006a; 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 group (Lin et al., 2018).

3.11 Methods

3.11.1 Participants

We computed the required sample size through an a priori pre-registered (https://osf.io/z5esb/) power analysis for GLMMs (see § 3.2.1), estimating parameters from pilot data (N = 18). We recruited 126 adult English-speaking participants through Prolific (Prolific, Oxford, UK; www.prolific.co). In order to be included in Study 5, participants must not have taken part in Studies

2, 3, and 4. 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 ratio between S1 color and S2 valence during the learning phase. The final sample included 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).

3.11.2 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 Study 2 (see § 3.2.2.1). 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*, *valence* and *arousal ratings* during the test phase (see § 3.2.2.1). The English short form of the IUS (Carleton et al., 2007) was used to measure IU.

The experiment was run online through OpenSesame (Mathôt et al., 2012), and hosted in JATOS (Lange et al., 2015). Before the learning phase participants were assigned to the CG or the UG. The learning phase was the same as in Study 2 (see § 3.2.2.2), 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 Study 2 (see § 3.2.2.2). 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 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 Study 2 (see § 3.2.2.3). In Figure 3.8 a schematic representation of the experimental paradigm is displayed. At the end of the test phase, participants were directed to the Qualtrics survey (see § 3.2.2.5). Here, we added a manipulation check question: participants were asked whether they have 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.

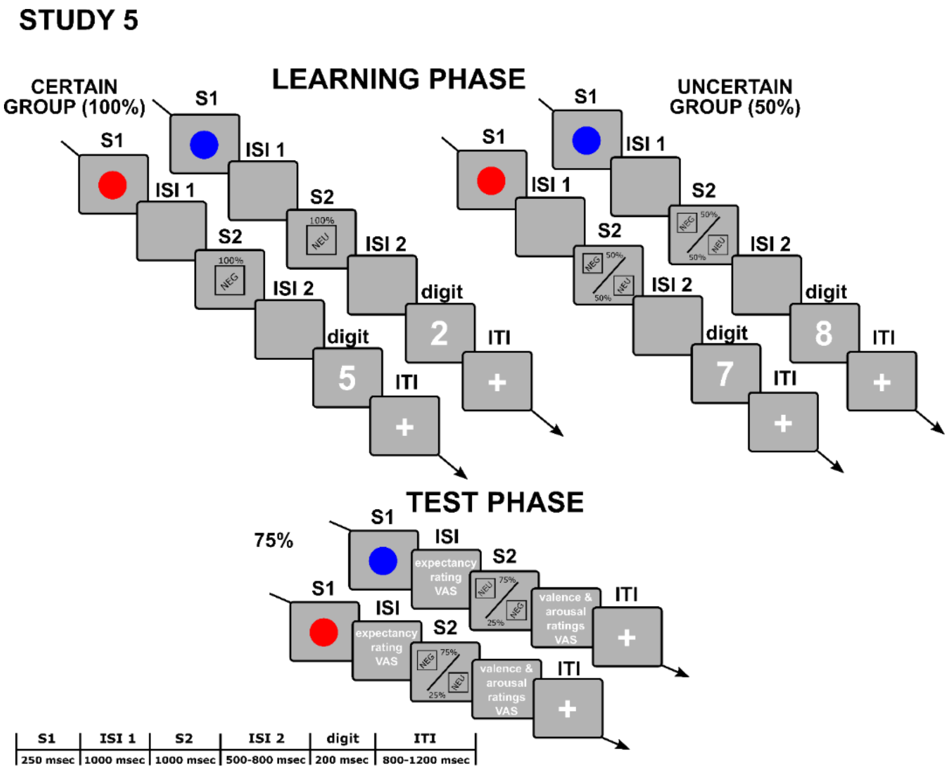

Figure 3.8 Schematic representation of Study 5 experimental paradigm.
Example sequence of events and their duration for a trial, according to the phase (learning, test), and the group (CG, UG). During the *learning phase* participants experienced a 100% (CG) vs 50% (UG) affective contingency between 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.

3.11.3 Data analysis

The study has a 2 (*group*, between-subjects: CG vs. UG) × 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 § 3.11.2) 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, 2 of them emerged as "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 subjective ratings), for each DV we fitted the following (G)LMMs (R package: lme4; Bates et al., 2015):

- *log-transformed IES* (H1a): *group* as fixed factor, random intercept for participant;
- *accuracy* (H1b): logistic regression with *group* as fixed factor, random intercept for participant;
- *expectancy ratings* (H2a, H2b): *group*, *S1 color* and their interaction as fixed factors, random slopes for *S1 color* within participant;
- *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 (α = .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 models parameters are reported in the logit scale), marginal and conditional R^2 (estimated as in Nakagawa et al., 2017).

3.12 RESULTS

Study 5 models are summarized in Table 3.10 and Figure 3.9. For the *IES* model ($R^2_{marginal}$ = 0.018, $R^2_{conditional}$ = 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 ($R^2_{marginal}$ = 0.012, $R^2_{conditional}$ = 0.506) testing H1b, with no significant effect of *group* emerging (χ^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 ($R^2_{marginal}$ = 0.033, $R^2_{conditional}$ = 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 we found evidence for the difference between blue (i.e., circles preceding neutral pictures) and red (i.e., circles preceding negative pictures) colors within the CG group, which reported significantly more negative expectancy ratings after the red color as compared to the blue one (blue vs. 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 vs. 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* ($R^2_{marginal}$ = 0.593, $R^2_{conditional}$ = 0.669) and *arousal* ($R^2_{marginal}$ = 0.351, $R^2_{conditional}$ = 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 vs. 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 vs. 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).

Table 3.10 Results of confirmatory (G)LMMs on *IES*, *accuracy*, *expectancy*, *valence* and *arousal ratings* in Study 5. For each model we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated statistics (*t*-test for LMMs, *z*-test for GLMMs).

Model	Parameter	Estimate	*SE*	statistics	*DF*	*p*	95% *CI*	
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						

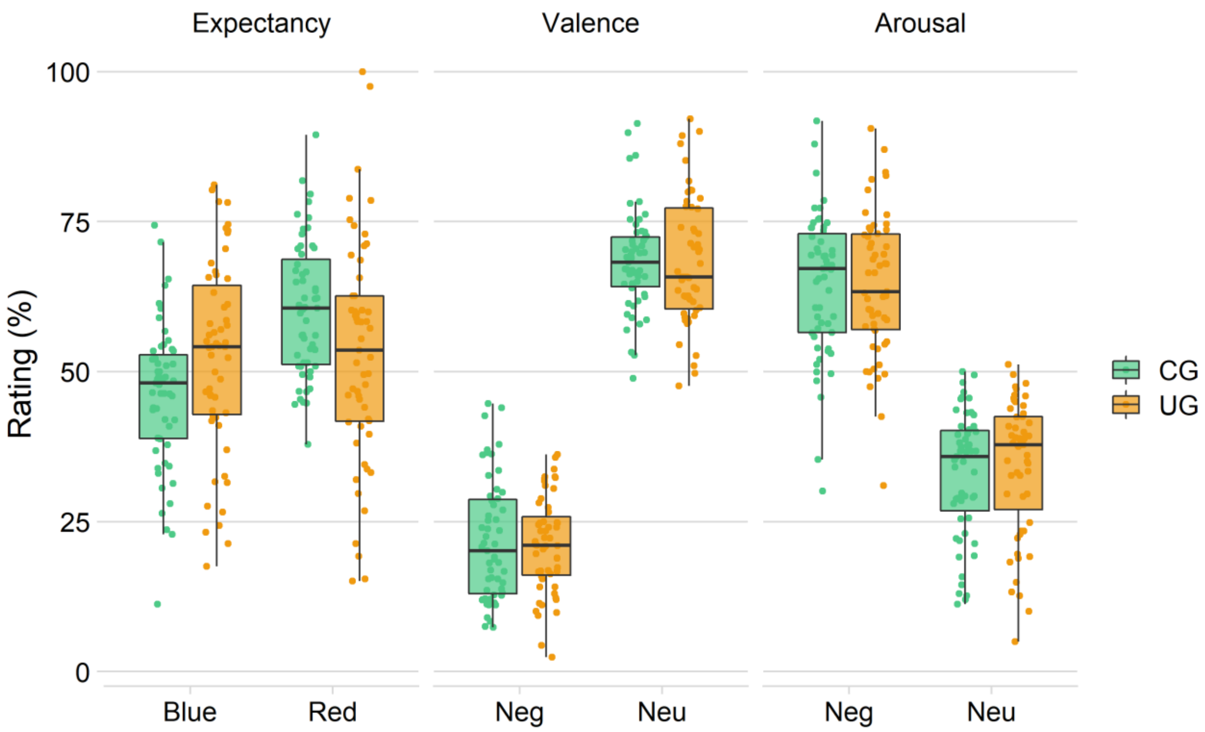

Figure 3.9 Box-plot of *expectancy*, *valence* and *arousal ratings* in Study 5.
Points represent the mean value for each participant according to the *group* (CG vs. UG), and the *S1 color* (red vs. blue, for expectancy ratings) or the *S2 valence* (NEG vs. NEU, for valence and arousal ratings).

3.13 Discussion

Study 5 demonstrated that contextual 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, as it happens when the same information is extracted at an explicit level (cf. § 3.4 and 3.7). As hypothesized (H2b), experiencing a fully reliable

S1-S2 affective contingency 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, consistently with our previous findings (cf. § 3.3 and 3.6) 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 difference in the way implicit affective learning occurred in the two groups. In fact, no significant group effects emerged on the performance in 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 § 3.11.2), 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 the results of Study 5 reflect the effects of actual implicit previous experience, and that they must be specifically ascribable to the different contextual probabilistic information (100% vs. 50%) formerly experienced by the two groups.

To summarize, Studies 2 to 5 represent an attempt to empirically investigate the role of actual *prior experience* in the construction of new affective predictions, with a specific focus on subjective ratings. In these studies, we employed a purposely developed experimental paradigm, filling some of the gaps in the existing literature (see § 3.1). First, our experimental design combined the logic of emotional S1-S2 paradigms with a learning component. This allowed us to implement the role of actual prior experience in constructing new predictions, by manipulating the (un)certain probabilistic relationships between stimuli experienced in the past (i.e., learning phase), and measuring the effects on subjective ratings in a subsequent moment (i.e., test phase). Second, it targeted all the stages of (affective) prediction construction (generation-implementation-updating). Third, it allowed to study cross-modality generalization between the visual and auditory modalities. Fourth, it allowed to explore the effects of cue ambiguity on subjective affective ratings. Last, by leaving the S1-S2 affective contingencies uninstructed (Studies 2, 3, 4) or implicit (Study 5), 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 all the Studies, participants who had previously experienced a certain affective contingency, reported more negative expectancy ratings after the specific cues which were formerly paired with negative stimuli. Interestingly, this process emerged to develop similarly (and thus, to be generalizable) across the visual and auditory sensory modalities (cf. Studies 2 and 3). Furthermore, 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 (cf. Study 4). Last, we confirmed that statistical knowledge can be actually inferred from the environment also at an implicit level (cf. Study 5).

Surprisingly, we found no evidence in any Study about an intensification of subjective reactions during the *updating* stage as a function of the uncertainty degrees previously experienced. According to predictive models of emotion (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 all the studies 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 of Studies 2 and 3, assessing the differences between expected and unexpected S2s by comparing affective ratings between congruent and incongruent test trials (see Tables 3.4 and

3.8). In both the groups, congruent negative stimuli (i.e., negative stimuli more strongly expected) were rated as more unpleasant and more arousing than incongruent (i.e., negative stimuli violating expectancies), thus leading to an intensification of subjective experience. 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, subjective experience in the updating stage may be more prominently modulated by currently available contextual information rather than by past learnings. This explanation is further supported considering the evolutionary value of emotions (and affective predictions) as "tools" to promote survival and adaptation to the environment (see § 1.2).

Concluding, some limitations of the present set of studies must be addressed. First, we employed unimodal affective stimuli as S2s. Although this choice makes our paradigm similar to (and thus, comparable with) the existing affective cueing paradigms, it remains quite artificial as compared to daily environments. Employing multimodal or dynamic affective stimuli, and/or different surrounding environments might allow future paradigms to reach a better ecological validity. Second, prior experience is manipulated only in terms of (un)certain probabilistic relationships between stimuli (i.e., S1-S2 affective contingency). However, other characteristics of prior 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. Last, in this group of studies we only focused on subjective experience, as overtly rated by participants, but more subtle modulations may be caught by measuring also covert processing indices (e.g., psychophysiological measures, neural activity).

Hence, studies 1 to 5 contributed to elucidate the neural and subjective mechanisms involved in the construction of affective predictions, as they are influenced by currently available contextual information or prior experience (see RQ1 and RQ2, § 1.5). As a final goal of this project, in the next

Chapter we will focus on the role of IU as a potential (and still understudied) modulating factor on the construction of affective predictions (see RQ3, § 1.5).

CHAPTER 4

THE MODULATION OF INTOLERANCE OF UNCERTAINTY

"The oldest and strongest emotion of mankind is fear, and the oldest and strongest kind of fear is fear of the unknown"

Howard Phillips Lovecraft

4.1 INTRODUCTION

The world is an uncertain place, and the uncertainty we experience in everyday life can have a dramatic influence on our emotional life. For example, the COVID-19 pandemic outbreak, and the associated risk of contracting the virus, carried a huge amount of uncertainty, substantially impacting over the affective experience and mental health of people worldwide. Or else, not knowing how the plot is going to develop while watching a new TV series usually increases the rewarding value of the series itself (that's why we all hate spoilers!). From both examples, it is clear how dealing with uncertainty can intensify affective experience.

The literature has suggested that uncertainty pushes to a polarization of the impact of positive and negative affect, leading to increased attention and emotional engagement towards uncertain events (Einstein, 2014). Individual differences in the subjective predisposition to tolerate uncertainty may play a non-negligible role in shaping emotional processing within uncertain environments. Intolerance of uncertainty (IU) is the dispositional characteristic that reflects individual differences in tolerating and adapting to uncertain situations (Carleton, 2016a). It has been defined as the inability to tolerate the aversive reaction triggered by a perceived lack of sufficient or salient information, sustained by the correlated perception of uncertainty (Carleton, 2016b). IU is characterized by cognitive, affective, and behavioral facets that may have a broad influence on affective experience (see § 1.4), e.g., inflated estimates of threat probability, increased attention to threat and hypervigilance, deficient safety learning, behavioral and cognitive avoidance of uncertainty, heightened physiological reactivity to threat uncertainty (Grupe & Nitschke, 2013). Moreover, the fear of the unknown (FOTU, which is assumed to be the key feature at the basis of IU) has been proved to be a lower-order construct able to account for several higher-order constructs (Carleton, 2012, 2016a; Hong & Cheung, 2015). Indeed, it is positively associated with neuroticism (Carleton, 2016b; Mahoney & McEvoy, 2012), and with symptoms of different anxiety disorders (see Carleton, 2016b for a review); and it can act as a trigger for the activation of the behavioral inhibition system (BIS) (Carleton, 2016a, 2016b), and the fight-flight-freeze defensive response (Carleton, 2016a, 2016b). For these reasons, IU has been proposed as a trans-diagnostic risk and maintaining factor, potentially crucial for vulnerability assessment and/or as a target for clinical treatment, for a wide range of emotional traits and disorders (Carleton, 2016a, 2016b; Einstein, 2014; Shihata et al., 2016; Tanovic, Gee, et al., 2018) (see § 1.4).

In the last years, the degree of uncertainty conveyed by contextual information has been targeted as an influential feature in shaping affective prediction construction (see § 1.2). According to predictive models of emotion (Barrett, 2017; Seth & Friston, 2016), in fact, emotions have been redescribed as interoceptive predictive models, developing across the stages of *generation*, *implementation*, and *updating* (see Figure 1.1). Contextual differences in the relative balance of the amount of information between certain and uncertain situations are assumed to be crucial in determining whether uncertainty is appraised as threatening (Carleton, 2016b). Moreover, it has been proposed that biases in the anticipation of affective stimuli (e.g., inflated threat estimates) characterizing high-IU individuals could result from a disrupted prediction error signaling, which turns in a failure to update affective predictions (Grupe & Nitschke, 2013). For these reasons and given the significance of IU as a trans-diagnostic risk factor, a better understanding of how individual differences in IU may affect affective predictions construction could represent a valuable contribution to advancing knowledge in the field, leading to promising clinical and preventive implications.

Assessing the neural and subjective correlates of individual differences in IU across the different neurocomputational stages of affective prediction construction would allow to identify potential targets to treat, or to early intervene on, thus preventing high-IU from developing into clinically relevant conditions.

Nevertheless, experimental studies investigating the effects of IU on emotional processing as a function of contextual information are still scarce (see Table 1.2) and provided conflicting results. Moreover, no study to our knowledge has investigated how IU may interact with (un)certainty of prior experience in shaping subjective reactions to new affective predictions. Finally, as a further potential flaw, extant studies typically split their samples into two groups (high- vs. low-IU) according to the IUS (Carleton et al., 2007; Freeston et al., 1994) scores distribution, risking some slighter IU individual differences to be lost in a dichotomization of the variable (Royston et al., 2006).

As stated above, extant literature collected fragmentary results, sometimes in conflict with the predictions formulated by the theoretical models of IU (Carleton, 2016a; Einstein, 2014; Grupe & Nitschke, 2013; Shihata et al., 2016). Regarding the *generation* stage, some studies found no differences between high- and low-IU participants in S1-locked SCR and corrugator EMG activity as a function of cue predictive meaning (Chen & Lovibond, 2016; Morriss, 2019). Other studies found that high-IU participants showed a larger P2 to S1s irrespective of their predictive meaning (Gole et al., 2012; Tanovic, Pruessner, et al., 2018), reflecting a heightened early automatic attention allocation towards cues and their potential threatening meaning. Focusing on prediction *implementation*, most of the studies found no significant effects of IU on ERPs amplitude, SCR, EMG activity, and expectancy ratings measured during the ISI (Grupe & Nitschke, 2011; Morriss et al., 2020; Tanovic, Pruessner, et al., 2018). Contra, other studies reported that high-IU participants showed higher threat expectancy ratings following uncertain cues (Chen & Lovibond, 2016); that IU predicted higher self-reported anxiety when expecting an electrical shock (Nelson & Shankman, 2011); and that higher IU was associated with heightened certainty in anticipating the negative outcomes of a future event (Miranda et al., 2008; Pepperdine et al., 2018). These latter results are consistent with the overestimation of threat predicted by the theoretical models of IU (Grupe & Nitschke, 2013). As for the prediction *updating* stage, some studies failed to find significant effects of IU on S2-locked SCR (Grupe & Nitschke, 2011; Morriss, 2019). Other studies found that in the uncertain condition IU negatively predicted neural activity within posterior frontomedian cortex (PFMC) (Schienle et al., 2010), and the magnitude of the startle response (Nelson & Shankman, 2011), thus unexpectedly suggesting that as IU increases, the aversive reactions to uncertain threat attenuate, probably due to the perceived lack of controllability typical of uncertain contexts. Furthermore, in high-IU participants uncertain negative S2s were found to elicit smaller LPP amplitudes, reflecting a dampening effect on the emotional processing of uncertain stimuli (Gole et al., 2012). Finally, IU was found to be associated with either no effects on S2-valence and arousal ratings (Gole et al., 2012; Morriss et al., 2020, 2021); or with more unpleasant valence ratings, higher arousal and more negative mood/self-reported anxiety in uncertain or threatening conditions (Chen & Lovibond, 2016; Chin et al., 2016; Kirschner et al., 2016; Morriss et al., 2021). Altogether, results regarding the *updating* stage are mixed: ERPs and psychophysiological indices suggest a dampened physiological reactivity to uncertain threat, contrary to theoretical models of IU (Carleton, 2016a; Einstein, 2014; Grupe & Nitschke, 2013; Shihata et al., 2016); whereas subjective ratings support the hypothesis that uncertainty is associated with affect intensification, as predicted by theoretical models of IU (Carleton, 2016a; Einstein, 2014; Grupe & Nitschke, 2013; Shihata et al., 2016).

Therefore, as the last aim of the present project (see RQ3, § 1.5), we investigated the relationships between IU and two distinct facets of affective predictions construction, thus helping to untangle the mixed pattern of results shown in the literature. More in detail, we ran a hd-EEG study (Study 6) in which we targeted the neural activity developing in conditions of different *contextual information*, and we investigated whether IU could predict it. Further, we re-analyzed Studies 2 to 5 focusing on IU, investigating whether subjective affective experience could be differently predicted by individual differences in IU as a function of (un)certainty of *prior experience*.

STUDY 6

Study 6 investigated through hd-EEG whether and how IU predicted the neural activity, both at the scalp and at the source level, which develops in presence of *contextual information* of different predictive value along the generation, implementation and updating stages. We employed the same experimental paradigm as in Study 1 (see § 2.2). In the analyses, we used IU scores as a continuous predictor rather than dichotomizing participants into two groups. This allowed us to avoid flattening individual differences in IU and losing information and power (Royston et al., 2006).

For each neurocomputational stage of affective prediction construction, we targeted specific ERP components, which in Study 1 have shown to respond to our experimental manipulation (see § 2.3.1). We focused on S1-N170 for prediction *generation*; on the CNV for the *implementation* stage; and on the P2 and the LPP as regards prediction *updating*.

We hypothesized higher IU scores to predict (H1) a larger N170 irrespective of the predictive context (Gole et al., 2012; Tanovic, Pruessner, et al., 2018) during prediction *generation*; (H2) larger early and late CNV amplitudes following negative S1s (reflecting the anticipatory processes elicited by inflated threat estimates, cf. (Chen & Lovibond, 2016)) in uncertain contexts (75% and 50%) during the *implementation* stage; either (H3a) smaller (according to ERP findings, e.g., (Gole et al., 2012)) or (H3b) larger (according to IU theories, e.g., (Einstein, 2014)) P2 and LPP amplitudes to emotional S2s in uncertain contexts (75% and 50%) during prediction *updating*.

4.2 METHODS

4.2.1 PARTICIPANTS

A total of 294 Italian-speaking undergraduates at University of Padua were initially screened for participation through an online survey evaluating the inclusion criteria for the study, which were the same as in Study 1 (see § 2.2.1). Thirty-six right-handed participants met the inclusion criteria, and took part in the study as volunteers (16 males, age: *M* = 23.25, *SD* = 1.85, range = 20-29). The sample size was based on previous ERP research measuring IUS within S1-S2 paradigms (Gole et al., 2012). All participants signed an informed consent. All experimental procedures were approved by the Ethical Committee for the Psychological Research of the University of Padua (protocol no. 2859) and were conducted in accordance with the Declaration of Helsinki.

4.2.2 Stimulus material and procedure

The stimulus material and experimental procedures were the same of Study 1 (see § 2.2.2). The IUS, in its Italian 12-item validated adaptation (Bottesi et al., 2019; Carleton et al., 2007), was administered online to all participants, before their arrival. Participants were instructed to answer the survey alone, in a silent room, taking all the time needed.

4.2.3 Electrophysiological recordings, brain source modelling and data analysis

The study has a 3 (*block*: 100%, 75% and 50%) × 3 (*S1* or *S2 valence*: POS, NEG, NEU) within-subjects design.

EEG recordings and signal pre-processing were performed as in Study 1 (see § 2.2.3). Experimental conditions did not differ for final number of epochs accepted (see Table 4.1).

Table 4.1 Means (*M*), standard deviations (*SD*), test statistics (*F*), and associated *p*-values (*p*) of the final number of epochs accepted for each experimental condition in Study 6.
Results showed no significant differences between conditions.

Block	**100%**		**75%**		**50%**		***F*(2,105)**	***p***
	M	*SD*	*M*	*SD*	*M*	*SD*	0.42	.66
	113.33	5.87	114.56	6.39	114.17	5.07		
Valence	**POS**		**NEG**		**NEU**		***F*(2, 105)**	***p***
S1	*M*	*SD*	*M*	*SD*	*M*	*SD*	0.52	.6
	113.64	4.87	114.67	4.34	113.75	4.90		
S2	*M*	*SD*	*M*	*SD*	*M*	*SD*	0.26	.78
	113.72	4.93	114.47	4.62	113.86	4.64		

The ERPs statistical analysis was performed via Brainstorm software, using the Fieldtrip functions (Oostenveld et al., 2011; Tadel et al., 2011). A whole-brain paired two-tailed *t*-test ($\alpha = .05$) permutation approach (Fields & Kuperberg, 2020; Groppe et al., 2011) was used, performing 1000 Monte-Carlo cluster-based corrected permutations over all 128 channel locations (see § 2.2.3). The permutations were computed over 6 a-priori time windows, corresponding to 4 distinguishable ERP components: S1-locked N170 (140-180 msec) for prediction *generation*; S1-locked early CNV (eCNV, 1500-2000 msec) and late CNV (lCNV, 2000-2500 msec) for prediction *implementation*; S2-locked P2 (200-300 msec), early LPP (eLPP, 400-600 msec) and late LPP (lLPP, 600-800 msec) for prediction *updating*. Interaction effects were tested through difference waves (see § 2.2.3). To test for the presence of overall predictive effects, we performed the pairwise comparisons 100% vs. 75%, 100% vs. 50%, 50% vs. 75% blocks, collapsing emotional valence across blocks. In order to assess the interaction effect between S1/S2 valence and blocks, the contrasts POS vs. NEU, NEG vs. NEU, and NEG vs. POS were performed separately per blocks (100%, 75%, 50%). Furthermore, for both S1- and S2-ERPs, difference waves were computed (POS-NEU, NEG-NEU, and NEG-POS) and compared between blocks. Based on the results of the permutation analysis, ERPs were extracted as the mean voltage amplitude in the abovementioned time windows from the following electrode clusters: an occipital cluster (E70, E74, E75, E81, E82, E83) for the N170, a left-central cluster (E40, E41, E42, E46, E47) for eCNV and lCNV, a parietal cluster (E67, E71, E72, E75, E76, E77) for the P2, and a slightly different parietal cluster (E60, E61, E62, E67, E72, E77, E78, E85) for eLPP and lLPP.

Brain source analysis was performed as in Study 1 (see § 2.2.3). Based on each ERP source reconstruction, source map vertices were clustered in the following ROIs: right STS for the N170; left ACC, SMA, and dPCC for the CNV; bilateral TPJ for the P2; right OFC and temporal pole for the LPP. Absolute values of each ROI were time-averaged from the pertaining ERP time windows, extracted for each participant, and transformed using a natural logarithm.

To assess whether IUS score predicted the neural activity during the task both at the scalp and at the source level, separate LMMs (R package: lme4 (Bates et al., 2015) with individual random intercept were estimated, with each averaged ERP and ROI activity as DVs, *IUS* as a fixed continuous predictor, *S1/S2 valence*, *block*, and the interaction *IUS* × *S1/S2 valence* × *block* as fixed factors. 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 both marginal and conditional R^2 (as estimated in (Nakagawa et al., 2017). The slopes of the *IUS* trend for each level of the factors (*block*, *S1/S2 valence*) were estimated, and their pairwise differences were tested by means of post-hoc Tukey test (R package: emmeans; (Lenth, 2020).

4.3 RESULTS

4.3.1 ERPS AND CORTICAL SOURCES RECONSTRUCTION

4.3.1.1 Prediction generation stage – N170 (140-180 msec) to S1 onset

A significant negative occipital cluster, reflecting a larger N170, was found in 100% block when comparing emotional with neutral faces (POS vs. NEU: $c = -476$, $s = 153$, $p = .024$; NEG vs. NEU: $c = -871$, $s = 246$, $p = .004$), in 75% block when comparing fearful with positive and neutral faces (NEG vs. NEU: $c = -1080$, $s = 306$, $p = .002$; NEG vs. POS: $c = -455$, $s = 178$, $p = .018$), and in 50% block when comparing positive with neutral faces (POS vs. NEU: $c = -413$, $s = 164$, $p = .03$) (see Figure 4.1, panel A). No significant effects were found when comparing difference waves between blocks.

N170 source reconstruction highlighted an emotional modulation on the right STS, showing a maximum pattern of activation after fearful faces (see Figure 4.1, panel B). This pattern replicated consistently across blocks.

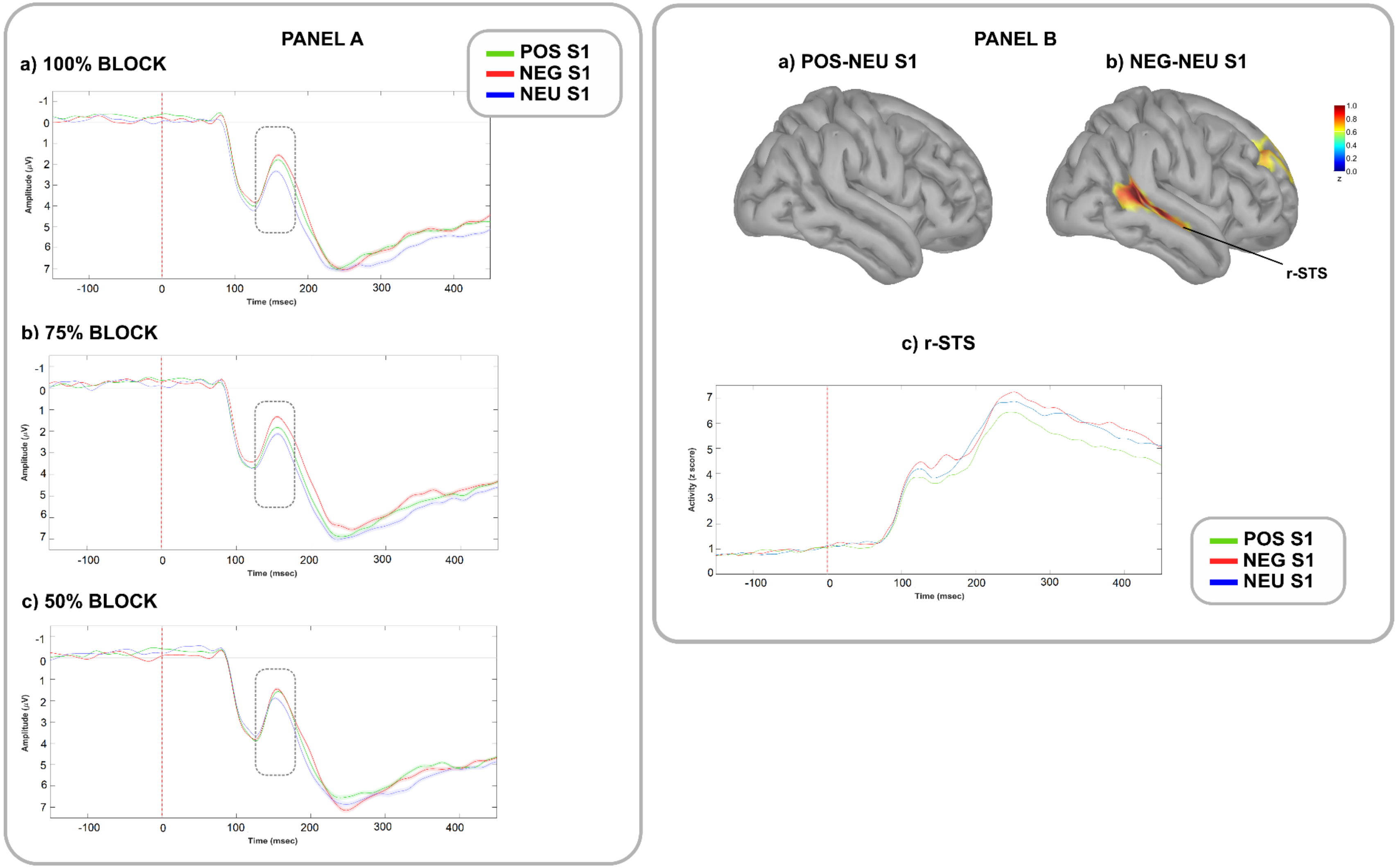

Figure 4.1 Modulation of ERPs and brain sources during prediction *generation* stage in Study 6.
Panel A. Grand average ERP waveforms following NEG (red lines), POS (green lines) and NEU (blue lines) faces (S1) in the (a) 100%, (b) 75% and (c) 50% blocks. Waveforms are plotted from an occipital cluster of electrodes (E70, E74, E75, E81, E82, E83). Shaded areas denote *SE*. The N170 was computed between 140 and 180 msec from S1 onset (time 0). **Panel B**. On the top, cortical maps reconstruction of the (a) POS-NEU and (b) NEG-NEU differences in brain activations in the N170 temporal window (140-180 msec), regardless of blocks. On the bottom, time course of (c) right STS activations to POS (green lines), NEG (red lines), and NEU (blue lines) faces, regardless of blocks. r-STS = right superior temporal sulcus.

4.3.1.2 Prediction implementation stage – eCNV (1500-2000 msec) and lCNV (2000-2500 msec) to S1 onset

Permutation analyses showed no significant effects of block, nor interaction effects with S1 valence on both early and late CNV. Nevertheless, visual inspection of grand average ERP waveforms from a central-left cluster of electrodes showed some amplitude differences, suggesting that a slightly larger CNV could have been elicited in the 50% block as compared to the others. However, since this result is not supported by statistics, it will not be further discussed.

CNV source analysis showed the involvement of a left network, extending over the ACC, the SMA, and the dPCC.

4.3.1.3 Prediction updating stage – P2 (200-300 msec), eLPP (400-600 msec), and lLPP (600-800 msec) to S2 onset

A significant negative parietal cluster was found, signaling a reduced positivity to positive and negative, and so a larger P2 to neutral pictures in all the blocks. Furthermore, a larger P2 was found in 100% block comparing negative to positive pictures (see Table 4.2 and Figure 4.2, panel A). No significant effects were found when comparing difference waves between blocks.

P2 source reconstruction highlighted a larger activation of bilateral TPJ to neutral than emotional pictures in all the blocks (see Figure 4.2, panel B).

A significant positive parietal cluster was found, confirming the effect of S2 valence on LPP: positive and negative pictures elicited a larger early and late LPP than neutral pictures in all the blocks. Furthermore, a larger lLPP was found in 100% block comparing negative with positive pictures (see Table 4.2 and Figure 4.2, panel A). No significant effects were found when comparing difference waves between blocks.

LPP source analysis showed that, as compared with neutral, emotional stimuli elicited a larger activation of the right OFC and temporal pole in all the blocks (see Figure 4.2, panel C).

Table 4.2 ERP results from Study 6 during the prediction *updating* stage in the P2 (200-300 msec), eLPP (400-600 msec) and lLPP (600-800 msec) time windows. Means (*M*), standard deviations (*SD*), cluster statistic (*c*), cluster size (*s*), and associated *p*-values for each planned comparison (POS vs. NEU, NEG vs. NEU, NEG vs. POS) within each block (100%, 75%, 50%) are reported.

	P2							**eLPP**							**lLPP**						
	POS		**NEU**		*c*	*s*	*p*	**POS**		**NEU**		*c*	*s*	*p*	**POS**		**NEU**		*c*	*s*	*p*
	M	*SD*	*M*	*SD*				*M*	*SD*	*M*	*SD*				*M*	*SD*	*M*	*SD*			
100%	7.64	4.02	8.58	3.81	-3075	754	**.002**	8.46	3.89	6.24	3.44	14375	2712	**.002**	6.34	3.23	4.14	2.71	13257	2567	**.002**
75%	7.45	4.33	8.73	4.18	-3989	958	**.002**	8.41	4.23	5.98	3.46	15735	2673	**.002**	6.390	3.73	4.31	3.24	12491	2385	**.002**
50%	7.64	3.91	8.35	3.81	-2931	842	**.002**	8.15	3.37	6.15	3.46	13251	2711	**.002**	6.022	3.12	4.55	3.12	12987	2525	**.002**
	NEG		**NEU**		*c*	*s*	*p*	**NEG**		**NEU**		*c*	*s*	*p*	**NEG**		**NEU**		*c*	*s*	*p*
	M	*SD*	*M*	*SD*				*M*	*SD*	*M*	*SD*				*M*	*SD*	*M*	*SD*			
100%	7.46	3.91	8.58	3.81	-4745	1088	**.002**	8.57	3.99	6.24	3.44	15813	2782	**.002**	6.87	3.43	4.14	2.71	16155	2770	**.002**
75%	7.66	3.92	8.73	4.18	-4642	1036	**.002**	8.34	3.91	5.98	3.46	16376	2928	**.002**	6.72	3.48	4.31	3.24	16235	2930	**.002**
50%	7.40	3.67	8.35	3.81	-3285	915	**.002**	8.269	3.685	6.154	3.458	15592	2980	**.002**	6.64	3.28	4.55	3.12	16310	2951	**.002**
	NEG		**POS**		*c*	*s*	*p*	**NEG**		**POS**		*c*	*s*	*p*	**NEG**		**POS**		*c*	*s*	*p*
	M	*SD*	*M*	*SD*				*M*	*SD*	*M*	*SD*				*M*	*SD*	*M*	*SD*			
100%	7.46	3.91	7.64	4.02	-1926	571	**.002**	8.57	3.99	8.46	3.89	670	287	.228	6.87	3.43	6.34	3.23	1701	657	**.04**
75%	7.66	3.93	7.45	4.33	-215	85	.382	8.34	3.91	8.41	4.23	391	161	.414	6.72	3.48	6.39	3.73	268	105	.545
50%	7.40	3.67	7.64	3.91	-441	176	.158	8.27	3.69	8.15	3.37	774	297	.194	6.64	3.28	6.02	3.12	1132	434	.08

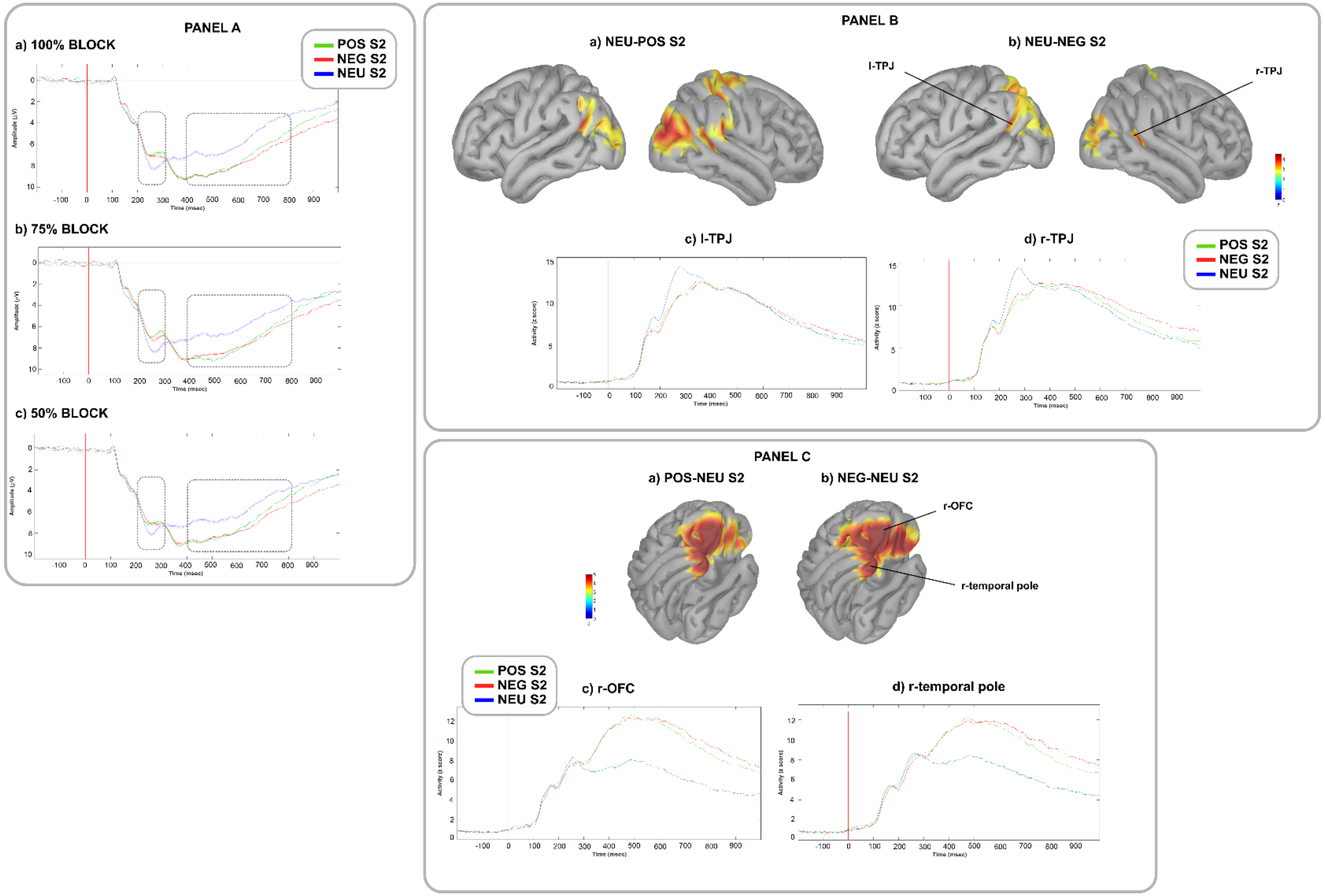

Figure 4.2 Modulation of ERPs and brain sources during prediction *updating* stage in Study 6.
Panel A. Grand average ERP waveforms following NEG (red lines), POS (green lines), and NEU (blue lines) pictures (S2) in the (a) 100%, (b) 75%, and (c) 50% blocks. Waveforms are plotted from a parietal cluster of electrodes (E60, E61, E62, E67, E71, E72, E75, E76, E77, E78, E85). Shaded areas denote *SE*. P2 was computed between 200 and 300 msec, and LPP between 400 and 800 msec from S2 onset (time 0). **Panel B.** On the top, cortical maps reconstruction of the (a) NEU-POS and (b) NEU-NEG differences in brain activations in the P2 temporal window (200-300 msec). On the bottom, time course of (c) left TPJ, and (d) right TPJ activations to POS (green lines), NEG (red lines), and NEU (blue lines) pictures, regardless of blocks. l-TPJ = left temporoparietal junction, r-TPJ = right temporoparietal junction. **Panel C.** On the top, cortical maps reconstruction of the (a) POS-NEU and (b) NEG-NEU differences in brain activations in the total LPP temporal window (400-800 msec). On the bottom, time course of (c) right OFC and (d) right temporal pole activations to POS (green lines), NEG (red lines), and NEU (blue lines) pictures, regardless of blocks. r-OFC = right orbitofrontal cortex.

4.3.2 Mixed-effects models

4.3.2.1 Prediction generation stage – N170 and right STS activity (140-180 msec to S1 onset)

LMMs on prediction *generation* stage DVs are summarized in Table 4.3. No significant main nor interaction effects of the predictors (IUS, S1/S2 valence, block, and their interaction) were found for N170 and right STS activity.

Table 4.3 Results of LMMs on the prediction *generation* stage DVs in Study 6.
F-values (*F*), degrees of freedom (*DF*) and *p*-values (*p*) for each main and interaction effects of predictors on N170, and r-STS activity are reported.

DVs	Predictors	*F*	*DF*	*p*	$R^2_{marginal}$	$R^2_{conditional}$
N170	block	0.68	2, 272	.505	0.016	0.872
	valence	2.27	2, 272	.106		
	IUS	0.08	1, 34	.777		
	block × valence	0.41	4, 272	.798		
	block × IUS	1.00	2, 272	.369		
	valence × IUS	0.55	2, 272	.580		
	block × valence × IUS	0.20	4, 272	.940		
r-STS	block	0.04	2, 272	.959	0.012	0.566
	valence	0.25	2, 272	.778		
	IUS	0.05	1, 34	.832		
	block × valence	0.97	4, 272	.425		
	block × IUS	0.08	2, 272	.919		
	valence × IUS	0.35	2, 272	.704		
	block × valence × IUS	1.23	4, 272	.300		

4.3.2.2 Prediction implementation stage – early (1500-2000 msec to S1 onset) and late (2000-2500 msec to S1 onset) CNV, left ACC, SMA, and dPCC activity

LMMs on prediction *implementation* stage DVs are summarized in Table 4.4. In the early time window (1500-2000 msec), a significant main effect of IUS was found for eCNV amplitude ($F(1, 34) = 4.4$, $p = .044$; see Figure 4.3 A) and early left ACC activity ($F\ (1, 34) = 6.29$, $p = .017$; see Figure 4.3 B): higher IUS score predicted larger eCNV negativity and smaller early left ACC activity regardless of block and S1 valence. No other significant main effects or interactions were found for eCNV, and early left ACC, SMA and dPCC activity.

As for the late time window (2000-2500 msec), analysis of lCNV showed significant main effects of IUS ($F\ (1, 34) = 6.92$, $p = .013$) and block ($F\ (2, 272) = 4.07$, $p = .018$), better explained by a significant IUS × block interaction ($F\ (2, 272) = 3.48$, $p = .032$; see Figure 4.3 C): a statistically significant difference in the relationship between IUS and lCNV was found between blocks, regardless of S1 valence. The slope analysis revealed that the slope of the relationship between IUS score and lCNV amplitude was statistically different from 0 only in the 75% block ($b = -0.061$, $b_{SE} = 0.017$, *95% CI* = [-0.0940, -0.0286]), suggesting that higher IUS score predicted larger lCNV amplitude only in the 75% block, regardless of S1 valence. Post-hoc contrasts showed a significant difference between the slopes in the 75% vs 100% block ($t(272) = -2.42$, $p = .043$), with more negative values in the first. A significant main effect of IUS was found for late left ACC ($F(1, 34) = 4.69$, $p = .037$; see Figure 4.3 D) and left SMA activity ($F(1, 34) = 4.17$, $p = .049$; see Figure 4.3 E): higher IUS score predicted smaller late left ACC and SMA activity regardless of block and S1 valence. No other significant main effects or interactions were found for lCNV, and late left ACC, SMA and dPCC activity.

Table 4.4 Results of LMMs on the prediction *implementation* stage DVs in Study 6.
F-values (*F*), degrees of freedom (*DF*) and *p*-values for each main and interaction effects of predictors on early and late CNV amplitude, early and late left ACC, SMA, and dPCC activity are reported.

DVs	Predictors	*F*	*DF*	*p*	$R^2_{marginal}$	$R^2_{conditional}$
eCNV	block	1.73	2, 272	.179	0.063	0.147
	valence	0.58	2, 272	.560		
	IUS	4.40	1, 34	**.044**		
	block × valence	0.51	4, 272	.732		
	block × IUS	1.68	2, 272	.189		
	valence × IUS	0.63	2, 272	.534		
	block × valence × IUS	0.51	4, 272	.728		
early left ACC	block	1.12	2, 272	.328	0.085	0.318
	valence	0.02	2, 272	.976		
	IUS	6.29	1, 34	**.017**		
	block × valence	0.77	4, 272	.545		
	block × IUS	0.48	2, 272	.618		
	valence × IUS	0.07	2, 272	.929		
	block × valence × IUS	0.61	4, 272	.654		
early left SMA	block	2.38	2, 272	.094	0.057	0.236
	valence	0.32	2, 272	.724		
	IUS	3.59	1, 34	.067		
	block × valence	0.74	4, 272	.563		
	block × IUS	1.86	2, 272	.158		
	valence × IUS	0.36	2, 272	.695		
	block × valence × IUS	0.56	4, 272	.691		
early left dPCC	block	0.27	2, 272	.767	0.046	0.311
	valence	0.39	2, 272	.674		
	IUS	3.84	1, 34	.058		
	block × valence	0.35	4, 272	.847		
	block × IUS	0.45	2, 272	.641		
	valence × IUS	0.41	2, 272	.662		
	block × valence × IUS	0.48	4, 272	.750		

lCNV	block	4.07	2, 272	**.018**	0.101	0.187
	valence	0.54	2, 272	.584		
	IUS	6.92	1, 34	**.013**		
	block × valence	0.81	4, 272	.519		
	block × IUS	3.48	2, 272	**.032**		
	valence × IUS	0.75	2, 272	.475		
	block × valence × IUS	0.71	4, 272	.587		
late left ACC	block	1.27	2, 272	.283	0.075	0.333
	valence	0.37	2, 272	.691		
	IUS	4.69	1, 34	**.037**		
	block × valence	0.57	4, 272	.686		
	block × IUS	0.32	2, 272	.725		
	valence × IUS	0.42	2, 272	.659		
	block × valence × IUS	0.48	4, 272	.749		
late left SMA	block	1.89	2, 272	.153	0.060	0.276
	valence	0.84	2, 272	.431		
	IUS	4.17	1, 34	**.049**		
	block × valence	0.60	4, 272	.665		
	block × IUS	1.51	2, 272	.223		
	valence × IUS	0.76	2, 272	.467		
	block × valence × IUS	0.66	4, 272	.618		
late left dPCC	block	0.48	2, 272	.620	0.038	0.311
	valence	1.40	2, 272	.249		
	IUS	1.59	1, 34	.215		
	block × valence	1.05	4, 272	.384		
	block × IUS	0.33	2, 272	.716		
	valence × IUS	1.33	2, 272	.265		
	block × valence × IUS	1.02	4, 272	.399		

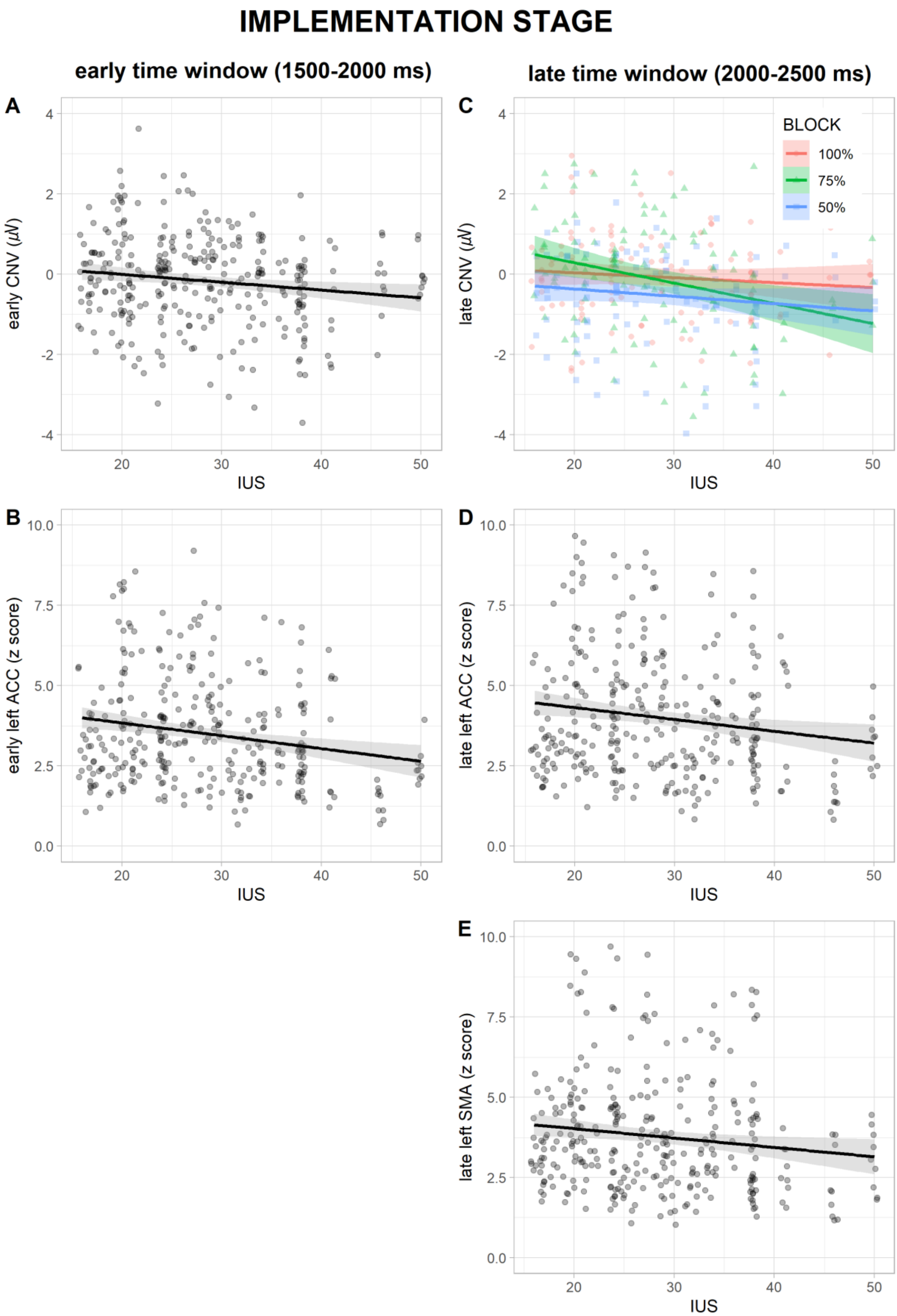

Figure 4.3 Regression plots in the two time windows of the prediction *implementation* stage in Study 6. Relationships between IUS scores and (A) early CNV amplitude, (B) early left ACC activity, (C) late CNV amplitude in 100% (in red), 75% (in green), and 50% (in blue) blocks, (D) late left ACC and (E) late left SMA activity are displayed. Shaded areas denote the 95% *CI*.

4.3.2.3 Prediction updating stage – P2 and bilateral TPJ (200-300 msec to S2 onset), early (400-600 msec to S2 onset) and late (600-800 msec to S2 onset) LPP, right OFC and temporal pole activity

LMMs on prediction *updating* stage DVs are summarized in Table 4.5. In the first time window (200-300 msec), analysis of P2 showed a significant main effect of block ($F(2, 272) = 4.12$, $p = .017$), better explained by the significant IUS × block interaction ($F(2, 272) = 3.98$, $p = .02$; see Figure 4.4 A), and a significant IUS × S2 valence interaction ($F(2, 272) = 4.45$, $p = .013$; see Figure 4.4 B): a statistically significant difference in the relationship between IUS and P2 amplitude was found between blocks regardless of S2 valence, and between S2 valence levels regardless of block. Nevertheless, the slope analysis revealed that the slopes of the relationship between IUS score and P2 amplitude were not statistically different from 0 in any of the block and S2 valence levels. Post-hoc contrasts showed significant differences between the slopes in the 75% vs 100% block ($t(272) = -2.72$, $p = .019$), and between POS vs. NEU S2 valence levels ($t(272) = -2.9$, $p = .011$), with more negative slope values for the former. Furthermore, a significant main effect of block ($F(2, 272) = 3.44$, $p = .034$) was found for left TPJ activity. Nevertheless, since overall predictive effects have already been tested by means of permutation analyses, and no effects of block were found on P2 amplitude and its corresponding neural sources, this result will not be further commented. No other significant main effects or interactions were found for P2, and bilateral TPJ activity.

In the second time window (400-600 msec), analysis of the eLPP showed a significant main effect of *block* ($F(2, 272) = 3.82$, $p = .023$), better explained by the significant IUS × block interaction ($F(2, 272) = 4.69$, $p = .01$; see Figure 4.4 C), and a main effect of S2 valence ($F(2, 272) = 17.15$, $p < .001$): a statistically significant difference in the relationship between IUS and eLPP amplitude was found between blocks regardless of S2 valence, while the main effect of S2 valence replicates the results of the permutation analysis suggesting a larger eLPP for emotional as compared to neutral S2s. Nevertheless, the slope analysis revealed that the slopes of the relationship between IUS score and eLPP amplitude were not statistically different from 0 in any of the blocks. Post-hoc contrasts showed significant differences between the slopes in the 75% vs 100% block ($t(272) = -2.92$, $p = .011$), with more negative slope values for the former. Furthermore, a significant main effect of S2 valence ($F(2, 272) = 23.15$, $p < .001$), better explained by the significant IUS × S2 valence interaction ($F(2, 272) = 8.77$, $p < .001$; see Figure 4.4 D) was found for the early right OFC activity: a statistically significant difference in the relationship between IUS and early right OFC activity was found between S2 valence levels regardless of blocks. Nevertheless, the slope analysis revealed that the slopes of the relationship between IUS score and early right OFC activity were not statistically different from 0 in any of the S2 valence levels. Post-hoc contrasts showed significant differences between the slopes in the POS vs. NEU and NEG vs. NEU S2 valence levels ($t(272) = -3.89$ and -3.29, $p < .011$ and $= .003$, respectively), with more negative slope values for the emotional as compared to the neutral S2 valence levels. Lastly, a significant main effect of S2 valence ($F(2, 272) = 4.74$, $p = .01$) was found for right temporal pole activity, replicating the larger activation to emotional stimuli already shown by LPP source reconstruction. No other significant main effects or interactions were found for eLPP, and early right OFC and temporal pole activity.

In the third time window (600-800 msec), analysis of the late right OFC activity showed a significant main effect of S2 valence ($F(2, 272) = 19.12$, $p < .001$), better explained by a significant IUS × S2 valence interaction ($F(2, 272) = 6.45$, $p = .002$; see Figure 4.4 E): a statistically significant difference in the relationship between IUS and late right OFC activity was found between S2 valence levels regardless of blocks. Nevertheless, the slope analysis revealed that the slopes of the relationship between IUS score and late right OFC activity were not statistically different from 0 in any of the S2 valence levels. Post-hoc contrasts showed significant differences between the slopes in the POS vs. NEU and NEG vs. NEU S2 valence levels ($t(272) = -3.14$ and -3.08, $p = .005$ and $.006$, respectively), with more negative slope values for the emotional as compared to the neutral S2 valence levels. A significant main effect of S2 valence was found for lLPP ($F(2, 272) = 13.11$, $p < .001$) and right temporal pole activity ($F(2, 272) = 9.47$, $p < .001$), replicating results already shown by permutation analyses and corresponding source reconstruction. No other significant main effects or interactions were found for lLPP, and late right OFC and temporal pole activity.

Table 4.5 Results of LMMs on the prediction *updating* stage DVs in Study 6.
F-values (*F*), degrees of freedom (*DF*) and *p*-values for each main and interaction effects of predictors on P2, early and late LPP amplitude, bilateral TPJ, early and late right OFC and temporal pole activity are reported.

DVs	Predictors	*F*	*DF*	*p*	$R^2_{marginal}$	$R^2_{conditional}$
P2	block	4.12	2, 272	**.017**	0.025	0.905
	valence	2.15	2, 272	.119		
	IUS	0.17	1, 34	.68		
	block × valence	0.97	4, 272	.423		
	block × IUS	3.98	2, 272	**.02**		
	valence × IUS	4.45	2, 272	**.013**		
	block × valence × IUS	1.01	4, 272	.405		
right TPJ	block	2.53	2, 272	.082	0.041	0.702
	valence	0.92	2, 272	.401		
	IUS	0.06	1, 34	.805		
	block × valence	0.27	4, 272	.897		
	block × IUS	2.11	2, 272	.124		
	valence × IUS	1.68	2, 272	.188		
	block × valence × IUS	0.63	4, 272	.64		
left TPJ	block	3.44	2, 272	**.034**	0.038	0.636
	valence	0.83	2, 272	.436		
	IUS	0.07	1, 34	.787		
	block × valence	1.76	4, 272	.138		
	block × IUS	2.33	2, 272	.099		
	valence × IUS	2.22	2, 272	.111		
	block × valence × IUS	1.87	4, 272	.116		

eLPP	block	3.82	2, 272	**.023**	0.086	0.882
	valence	17.15	2, 272	**< .001**		
	IUS	0.29	1, 34	.596		
	block × valence	0.53	4, 272	.715		
	block × IUS	4.69	2, 272	**.01**		
	valence × IUS	2.06	2, 272	.13		
	block × valence × IUS	0.78	4, 272	.537		
early right OFC	block	1.18	2, 272	.308	0.157	0.636
	valence	23.15	2, 272	**< .001**		
	IUS	1.13	1, 34	.296		
	block × valence	0.75	4, 272	.56		
	block × IUS	1.01	2, 272	.367		
	valence × IUS	8.77	2, 272	**< .001**		
	block × valence × IUS	0.5	4, 272	.738		
early right temporal pole	block	0.94	2, 272	.392	0.100	0.649
	valence	4.74	2, 272	**.01**		
	IUS	1.2	1, 34	.28		
	block × valence	1.85	4, 272	.119		
	block × IUS	0.51	2, 272	.603		
	valence × IUS	0.65	2, 272	.523		
	block × valence × IUS	1.55	4, 272	.189		
lLPP	block	1.28	2, 272	.281	0.098	0.843
	valence	13.11	2, 272	**< .001**		
	IUS	0.11	1, 34	.748		
	block × valence	0.41	4, 272	.798		
	block × IUS	1.26	2, 272	.285		
	valence × IUS	1.94	2, 272	.145		

	block × valence × IUS	0.58	4, 272	.681		
late right OFC	block	0.97	2, 272	.382	0.184	0.514
	valence	19.12	2, 272	**< .001**		
	IUS	0.96	1, 34	.335		
	block × valence	0.84	4, 272	.503		
	block × IUS	0.87	2, 272	.418		
	valence × IUS	6.45	2, 272	**.002**		
	block × valence × IUS	0.62	4, 272	.649		
late right temporal pole	block	0.83	2, 272	.438	0.149	0.536
	valence	9.47	2, 272	**< .001**		
	IUS	1.57	1, 34	.219		
	block × valence	2.16	4, 272	.073		
	block × IUS	0.47	2, 272	.625		
	valence × IUS	2.75	2, 272	.066		
	block × valence × IUS	1.94	4, 272	.103		

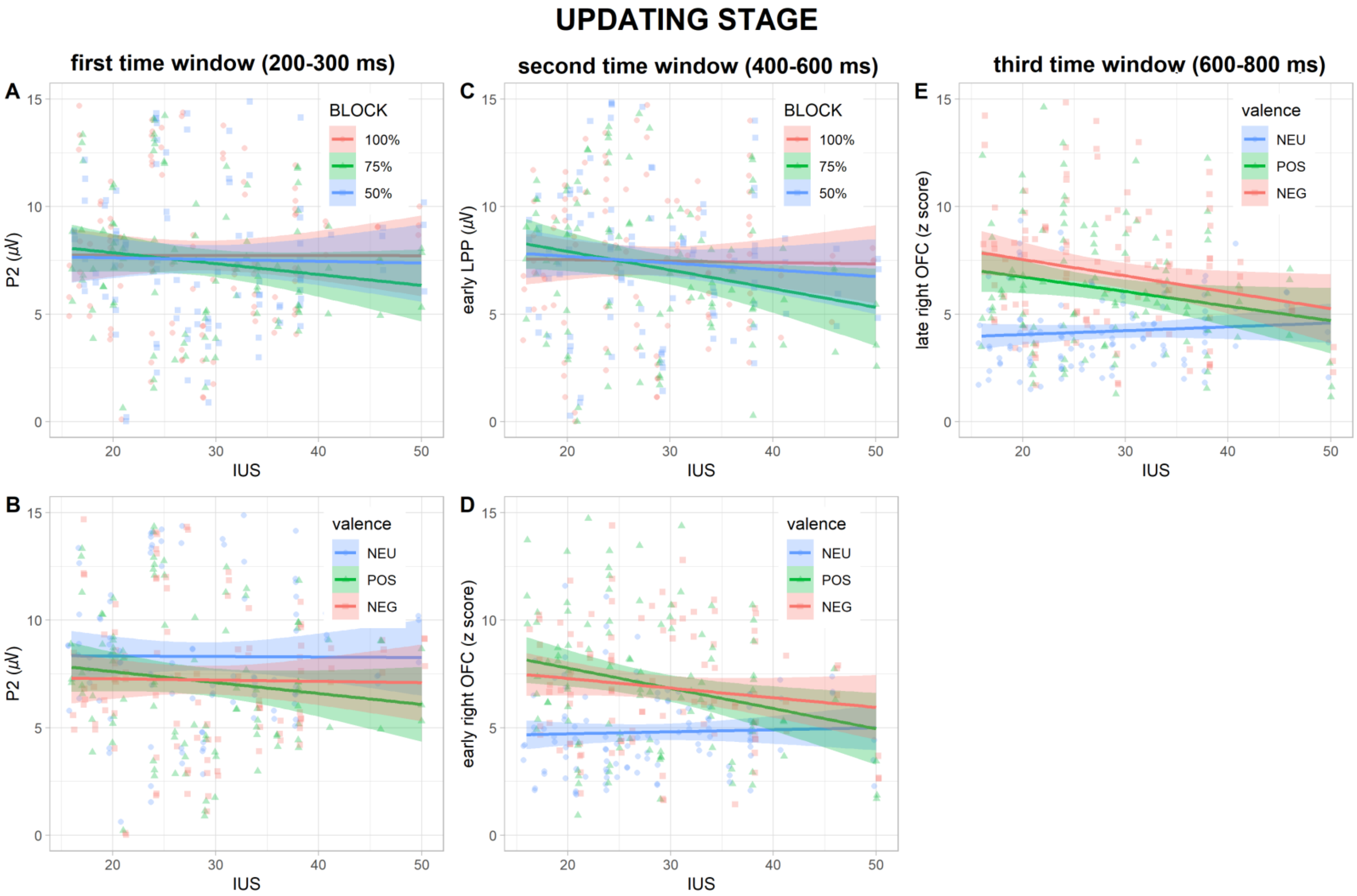

Figure 4.4 Regression plots in the three time windows of the prediction *updating* stage in Study 6.
Relationships between IUS scores and (A) P2 amplitude in 100% (in red), 75% (in green), and 50% (in blue) blocks, (B) P2 amplitude to NEU (in blue), POS (in green), and NEG (in red) S2s, (C) early LPP amplitude in 100% (in red), 75% (in green), and 50% (in blue) blocks, (D) early and (E) late right OFC activity to NEU (in blue), POS (in green), and NEG (in red) S2s are displayed. Shaded areas denote the 95% *CI*.

4.4 Discussion

To our knowledge, Study 6 represents the first attempt to investigate the modulating role of IU on the neural activity elicited during the generation, implementation, and updating stages of affective prediction construction, as a function of contextual information with certain (100%), moderately valid (75%), or uncertain (50%) predictive value.

Contrary to what hypothesized (H1), but in line with some previous evidence (Chen & Lovibond, 2016; Morriss, 2019), individual differences in IU did not affect the prediction *generation* stage, either at the ERP or at the source level, suggesting that the extraction of emotional and contextual information conveyed by the faces develops in a similar manner along the different IU levels.

During the *implementation* stage, IU exerted a modulating role both on ERPs and sources activity, in partial consistency with our hypothesis (H2), and with interesting differences as a function of time. In the early implementation stage, a higher IU was associated with a context- and valence-independent decrease of neural activity within the left ACC, an area assumed to subtend the behavioral and cognitive avoidance of uncertainty exposure (Grupe & Nitschke, 2013), and the continuous assessment of environmental uncertainty levels (Peters et al., 2017). Net of the needed caution in interpreting brain sources activity as reconstructed from EEG, a reduced left ACC activation to increasing IU levels could signal a disrupted environmental assessment of uncertainty. This could in turn translate into a heightened deployment of anticipatory resources, as reflected in larger eCNV amplitudes, in order to try to solve uncertainty (Paulus & Stein, 2006). In the late implementation stage, instead, higher IU levels were found to predict a context- and valence-independent decrease of neural activity within both the left ACC and SMA. So, as the implementation stage proceeds, the disrupted environmental uncertainty assessment, subtended by ACC decreased activity, seems to match an inhibition in action plans programming, as suggested by the reduced SMA activity, thus potentially contributing to the behavioral inhibition typical of high-IU individuals (Shihata et al., 2016) (cf. Carleton, 2016a, 2016b for potential relationships with BIS activation).

Furthermore, the heightened deployment of anticipatory resources, subtended by a larger CNV and reflecting an attempt to solve uncertainty, specialized into a context-specific effect: IU scores were found to negatively predict larger lCNVs only within the moderately predictive (75%) as compared to the certain (100%) context. It can be suggested that, as IU increases more anticipatory resources are pre-allocated only in those contexts in which the amount of uncertainty is perceived as "solvable" (i.e., 75%), while in more certain contexts (i.e., 100%) it could be metabolically effective to save resources, since there is no uncertainty to solve. This interpretation is consistent with IU models suggesting that neural, cognitive and behavioral peculiarities of high-IU individuals are aimed to increase perceived certainty and to reduce uncertainty exposure (Shihata et al., 2016; Tanovic, Gee, et al., 2018).

Within prediction *updating*, results were partially consistent with our hypotheses (H3a, H3b): higher IU levels were found to be associated both with valence-specific effects, such as smaller P2s to positive S2s and smaller right OFC activity to emotional S2s, and with context-specific effects, such as smaller P2s and eLPPs to S2s in the moderately predictive (75%) context. Although slope analyses failed to find significant differences, and so these results should be considered with caution, some explanations could still be suggested. The valence-specific decrease of P2 amplitude to positive as compared to neutral S2s, reflecting a reduced automatic attention allocation, could represent an early neural correlate of the deficient safety learning which characterizes high-IU individuals (Grupe & Nitschke, 2013). This, in turn, could prevent emotional predictive models from being efficiently updated, by integrating environmental safety cues, because of the reduced attention allocation towards them. Furthermore, higher IU was found to be associated with a context-specific decrease in P2s and eLPPs when comparing the moderately predictive (75%) with the certain (100%) contexts. This result, suggesting a dampening in S2 processing both at early and later stages, could reflect the uncertainty avoidance and a disrupted prediction error signaling typical of high-IU individuals (Grupe & Nitschke, 2013). Moreover, this result specifically arises in a context in which the updating of emotional predictive models is required (i.e., 75%), as compared to a context in which there is no need to update internal models since no expectancy violation occurs (i.e., 100%). Lastly, both in the early and late stages of prediction updating, IU was found to be associated with a smaller right OFC activity to emotional as compared to neutral S2s. Since OFC is involved in emotion regulation (Goldin et al., 2008; Golkar et al., 2012), its reduced activity may subtend a limited access to emotion regulation strategies, which is assumed to be a peculiar facet of high-IU traits (Ouellet et al., 2019), and which seems to spread across positive and negative valence and also across all predictive contexts.

Thus, in Study 6 we have covered the first facet of affective predictions construction (see § 4.1), by exploring IU influence on the neural activity which develops in conditions of different contextual information. We then re-analyzed Studies 2 to 5 in relation to IU to cover the second facet, i.e., prior experience.

STUDIES 2 TO 5

4.5 METHODS

Studies 2 to 5 aimed to investigate primarily the impact of *prior experience* on subjective affective ratings to new affective predictions (cf. Chapter 3). As exploratory pre-registered analyses (see Table 1.3), we re-analyzed data in relation to IUS scores to investigate whether individual differences in IU could affect the subjective affective experience as a function of prior (un)certain learnings.

Participants, stimulus material and procedures are described in Chapter 3. In order to investigate the relationships between IU and the DVs (*expectancy*, *valence* and *arousal ratings*), in each Study and for each DV we fitted separate LMMs (R package: lme4; Bates et al., 2015) with individual random intercept, adding *IUS* total score (mean centered) as a continuous predictor, and the *group* (CG vs. UG) and its interaction with IUS scores as fixed factors.

Influential cases for each 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% *CI*, marginal and conditional R^2 (estimated as in Nakagawa et al., 2017). Post-hoc pairwise comparisons between the slopes of the IUS scores trend for each level of the fixed factors (CG vs. UG) were tested by means of estimated marginal means (EMMs) contrasts (R package: emmeans; Lenth, 2020), Tukey adjusted for multiple comparisons.

4.6 RESULTS

Study 2 models are summarized in Table 4.6 and Figure 4.5. For the *expectancy* model ($R^2_{marginal} = 0.002$, $R^2_{conditional} = 0.051$), we found interactions between IUS total score and group ($F(1, 180) = 4.27$, $p = .04$): a statistically significant difference in the relationship between IUS and expectancy ratings was found between groups. The slope analysis revealed that the slope of the relationship between IUS score and expectancy ratings was statistically different from 0 only in the CG (CG: $b = 0.167$, $b_{SE} = 0.077$, 95% $CI = [0.014, 0.32]$; UG: $b = -0.075$, $b_{SE} = 0.088$, 95% $CI = [-0.249, 0.099]$), suggesting that higher IUS total scores predicted more negative expectancy ratings only in participants in the CG. Post-hoc contrasts showed a significant difference between the slopes in the CG as compared to the UG ($t(180) = 2.07$, $p = .04$), with higher values in the CG.

For the *valence* model ($R^2_{marginal} = 0.003$, $R^2_{conditional} = 0.009$), we found a main effect of IUS total score ($F(1, 180) = 5.83$, $p = .017$), better explained by a significant interaction with group ($F(1, 180) = 8.41$, $p = .004$): a statistically significant difference in the relationship between IUS total scores and valence ratings was found between groups. The slope analysis revealed that the slope of the relationship between IUS total scores and valence ratings was statistically different from 0 only in the CG (CG: $b = -0.216$, $b_{SE} = 0.054$, 95% $CI = [-0.322, -0.11]$; UG: $b = 0.02$, $b_{SE} = 0.061$, 95% $CI = [-0.101, 0.14]$), suggesting that higher IUS total scores predicted more unpleasant valence ratings only in participants in the CG. Post-hoc contrasts showed a significant difference between the slopes in the CG as compared to the UG ($t(180) = -2.9$, $p = .004$), with lower values in the CG.

For the *arousal* model ($R^2_{marginal} = 0.004$, $R^2_{conditional} = 0.101$), we did not find any significant effect. However, from the visual inspection of the regression plot (see Figure 4.5) it can be noticed that the trend of the slopes seems to suggest that higher IUS scores are associated with higher arousal ratings in the CG.

Studies 3, 4 and 5 models are summarized in Tables 4.7, 4.8 and 4.9, respectively. No significant effects of IUS scores emerged in any of these models.

Table 4.6 Results of LMMs investigating IU effect on *expectancy*, *valence* and *arousal ratings* in Study 2. For each model we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated *t*-test.

Model	**Parameter**	**Estimate**	***SE***	***t***	***DF***	***p***	**95% *CI***	
Expectancy ratings	Intercept	53.09	0.57	93.54	180	< .001	51.97	54.21
	UG - CG	-0.12	1.14	-0.10	180	.918	-2.36	2.12
	IUS	0.05	0.06	0.78	180	.435	-0.07	0.16
	group × IUS	0.24	0.12	2.07	180	**.04**	0.01	0.47
	σ ID	6.25						
	σ residual	27.54						
Valence ratings	Intercept	45.36	0.39	115.34	180	< .001	44.58	46.13
	UG - CG	-0.84	0.79	-1.07	180	.288	-2.39	0.71
	IUS	-0.10	0.04	-2.41	180	**.017**	-0.18	-0.02
	group × IUS	-0.24	0.08	-2.90	180	**.004**	-0.40	-0.08
	σ ID	2.29						
	σ residual	30.08						
Arousal ratings	Intercept	47.73	0.63	75.32	180	< .001	46.48	48.98
	UG - CG	0.43	1.27	0.34	180	.735	-2.07	2.93
	IUS	0.13	0.07	1.93	180	.055	0.00	0.26
	group × IUS	0.18	0.13	1.41	180	.16	-0.07	0.44
	σ ID	7.66						
	σ residual	23.34						

Table 4.7 Results of LMMs investigating IU effect on *expectancy*, *valence* and *arousal ratings* in Study 3.
For each model we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated *t*-test.

Model	**Parameter**	**Estimate**	***SE***	***t***	***DF***	***p***	**95% *CI***	
Expectancy ratings	Intercept	53.41	0.54	98.76	162	< .001	52.35	54.48
	UG - CG	0.73	1.08	0.68	162	.5	-1.40	2.87
	IUS	0.10	0.07	1.47	162	.145	-0.03	0.23
	group × IUS	-0.09	0.13	-0.70	162	.484	-0.35	0.17
	σ ID	5.57						
	σ residual	26.18						
Valence Ratings	Intercept	41.45	0.42	98.49	162	< .001	40.62	42.29
	UG - CG	0.40	0.84	0.47	162	.639	-1.27	2.06
	IUS	-0.07	0.05	-1.32	162	.189	-0.17	0.03
	group × IUS	0.06	0.10	0.61	162	.543	-0.14	0.27
	σ ID	3.26						
	σ residual	27.24						
Arousal ratings	Intercept	60.15	0.59	102.40	162	< .001	58.99	61.31
	UG - CG	0.12	1.17	0.10	162	.92	-2.20	2.44
	IUS	0.14	0.07	1.95	162	.053	0.00	0.28
	group × IUS	0.19	0.14	1.30	162	.194	-0.10	0.47
	σ ID	6.59						
	σ residual	23.18						

Table 4.8 Results of LMMs investigating IU effect on *expectancy*, *valence* and *arousal ratings* in Study 4.
For each model we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated *t*-test.

Model	**Parameter**	**Estimate**	***SE***	***t***	***DF***	***p***	**95% *CI***	
Expectancy ratings	Intercept	52.10	0.63	82.22	104	< .001	50.85	53.36
	UG - CG	-0.70	1.27	-0.55	104	.582	-3.21	1.81
	IUS	0.12	0.07	1.69	104	.093	-0.02	0.25
	group × IUS	-0.09	0.14	-0.69	104	.489	-0.37	0.18
	σ ID	4.83						
	σ residual	27.60						
Valence ratings	Intercept	44.62	0.51	88.36	104	< .001	43.62	45.62
	UG - CG	0.98	1.01	0.97	104	.332	-1.02	2.99
	IUS	0.01	0.05	0.10	104	.924	-0.10	0.11
	group × IUS	-0.08	0.11	-0.69	104	.489	-0.29	0.14
	σ ID	2.34						
	σ residual	29.30						
Arousal ratings	Intercept	49.52	0.87	56.96	104	< .001	47.80	51.24
	UG - CG	-1.85	1.74	-1.06	104	.29	-5.30	1.60
	IUS	0.13	0.09	1.41	104	.162	-0.05	0.32
	group × IUS	0.18	0.19	0.96	104	.34	-0.19	0.55
	σ ID	8.08						
	σ residual	24.03						

Table 4.9 Results of LMMs investigating IU effect on *expectancy*, *valence* and *arousal ratings* in Study 5. For each model we reported the unstandardized regression coefficients, *SE*, 95% *CI*, and the associated *t*-test.

Model	**Parameter**	**Estimate**	***SE***	***t***	***DF***	***p***	**95% *CI***	
Expectancy ratings	Intercept	53.34	0.91	58.65	99.00	< .001	51.53	55.14
	UG - CG	0.00	1.82	0.00	99.00	.998	-3.61	3.60
	IUS	0.03	0.13	0.24	99.00	.814	-0.22	0.29
	group × IUS	-0.03	0.26	-0.11	99.00	.915	-0.54	0.48
	σ ID	8.10						
	σ residual	26.79						
Valence ratings	Intercept	44.97	0.58	76.87	99.02	< .001	43.81	46.13
	UG - CG	0.14	1.17	0.12	99.02	.904	-2.18	2.46
	IUS	0.06	0.08	0.79	99.04	.434	-0.10	0.23
	group × IUS	0.08	0.17	0.48	99.04	.633	-0.25	0.41
	σ ID	3.41						
	σ residual	30.30						
Arousal ratings	Intercept	48.89	0.80	60.82	98.91	< .001	47.29	50.48
	UG - CG	-0.47	1.61	-0.29	98.91	.77	-3.66	2.72
	IUS	0.06	0.11	0.55	98.92	.587	-0.16	0.29
	group × IUS	-0.16	0.23	-0.68	98.92	0.496	-0.61	0.30
	σ ID	7.04						
	σ residual	25.01						

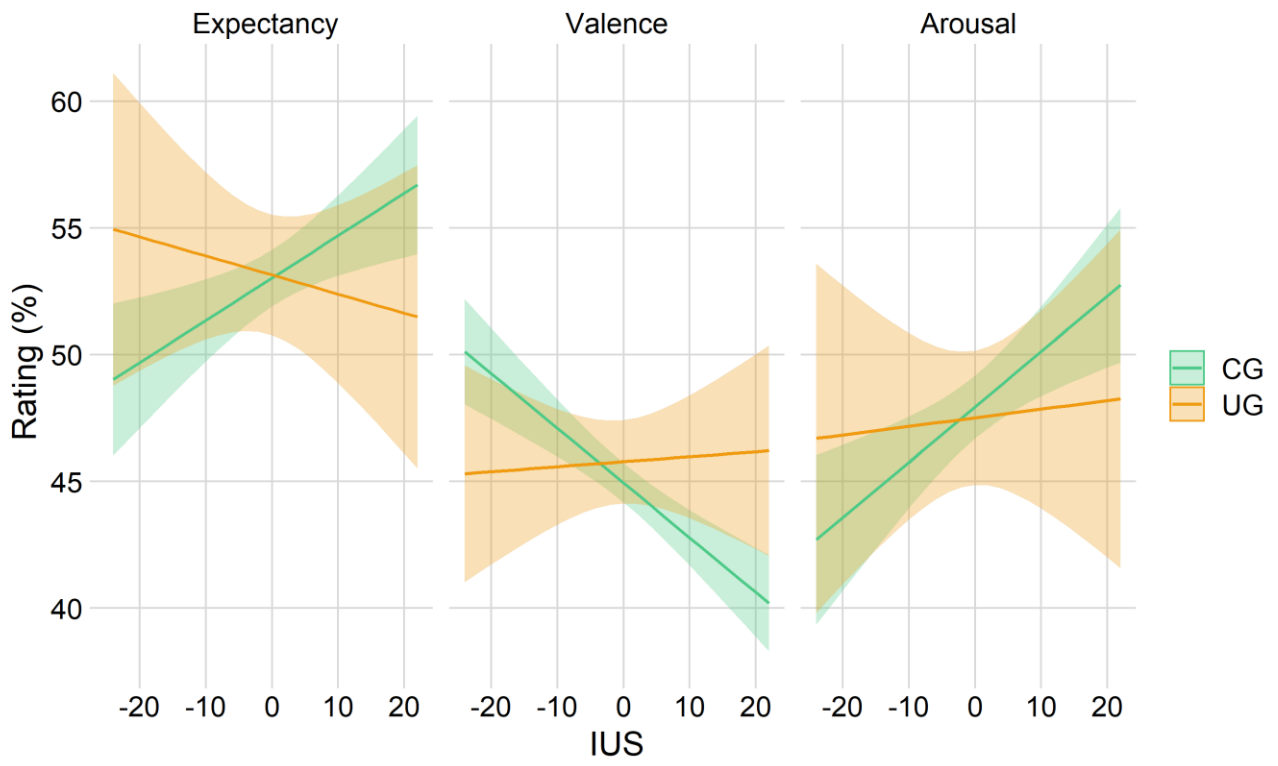

Figure 4.5 Regression plots of *expectancy*, *valence* and *arousal ratings* in Study 2.
Lines represent the mean estimated slope of the relationship between IUS scores and the DVs (*expectancy*, *valence* and *arousal ratings*) according to the *group* (CG vs. UG). Shaded areas denote 95% *CI*.

4.7 Discussion

Re-analyzing Studies 2 to 5 with regards to IUS scores allowed us to investigate whether individual differences in IU could affect the subjective experience developing along new affective predictions as a function of certain vs. uncertain *prior experience*. We found significant results only in Study 2 (visual to visual). Here, IU predicted more negative expectancy ratings during the *generation-implementation* stage, and more unpleasant valence ratings (and a slight tendency to higher arousal ratings) in the *updating* stage, within CG participants only. So, it seems that higher IU levels are associated with an intensification of the subjective affective experience during all the stages of affective prediction construction (generation-implementation-updating), as it might be expected according to theoretical models of IU (Carleton, 2016a; Einstein, 2014; Grupe & Nitschke, 2013; Shihata et al., 2016). Interestingly, this effect was present only in the CG, where participants transitioned from a fully certain context (100%, experienced during the learning phase) to an uncertain context (75%, experienced during the test phase), thus implying a shift from certainty to uncertainty. In the UG, instead, participants moved from an extremely uncertain context (50%, experienced during the learning phase) to another uncertain (although less extreme) context (75%, experienced during the test phase), thus implying only an adjustment to a different level of uncertainty (see § 3.2.2.4). As a result, CG participants may have experienced a sudden perception of uncertainty when they moved from learning to test phase, as their previously learned predictive models were sometimes disconfirmed during the test phase. This may have led to an increased anxious reaction, which eventually cascaded into a general affect intensification effect (Einstein, 2014). In contrast, UG participants may have experienced a decrease in perceived uncertainty when they transitioned from learning to test phase, potentially becoming able to develop a new, slightly reliable (75%) predictive model during the test phase. This may have contributed to a greater perceived controllability, which in turn may have diluted the anxious feelings triggered by uncertainty per se, and may have served as an efficient coping strategy to mitigate the adverse reaction (and thus the associated subjective experience) to the levels of uncertainty in the present moment (i.e., 75%, test phase) (Carleton, 2016b).

Oddly enough, IU did not exert a statistically significant modulation in any other study (Studies 3 to 5). If Study 5 null results can be explained by the differential effects of explicit vs. implicit uncertainty, with only the first being associated with a detectable effect (cf. Reuman et al., 2015); null results of Studies 3 and 4 are more tricky to interpret. In both studies, the common factor is that ambiguity of either S1s (Study 4) or S2s (Study 3, see § 3.7) was introduced in the test phase. Therefore, potential interactions between uncertainty and ambiguity may have contributed to complicating the full picture, ultimately pushing the focus more on the *here and now* (due to the need to process and disambiguate novelty in the present environment), and thus dampening the impact of IU on subjective ratings. According to some extant evidence (Chen & Lovibond, 2016), it might be expected the opposite of what we have found, since ambiguity should prevail over uncertainty, eliciting in turn a stronger affective response (either in terms of biased expectancies and negative affective reactions). However, Chen and Lovibond (2016) manipulated both ambiguity and uncertainty in the present moment (where they also collected participants' ratings); whereas in our paradigm we manipulated uncertainty in the past moment (i.e., during the learning phase, where participants were not asked any rating), and ambiguity in the present moment (i.e., during the test phase, where we asked for subjective affective ratings). Moreover, Chen and Lovibond (2016) split participants into high- and low-IU according to IUS scores distribution, while we treated IU as a continuous variable. These methodological differences may explain the opposite results found, suggesting a more complex relationship (and therefore worthy of further investigation in the future) between uncertainty and ambiguity, as they differently develop in the past vs. present moment.

To summarize, we found that IU may actually impact on the construction of new affective predictions (see RQ3, § 1.5), predicting both the neural activity developing in conditions of different *contextual information* (Study 6), and the subjective affective ratings subsequent to (un)certain *prior experience* (Study 2). Prediction *generation* stage was not affected at the neural level by individual differences in IU. During the *implementation* stage, instead, higher IU was associated with (i) a disrupted environmental uncertainty assessment, indexed by a reduced activity of the ACC; (ii) a consequent inhibition in anticipatory action plans programming, as signaled by a decreased activity in the SMA; and (iii) a facilitation in the deployment of computational resources, reflected by a larger CNV amplitude. These processes may serve to solve uncertainty, specifically arising in moderately predictive contexts (75%) in which uncertainty is perceived as solvable. Moreover, and only in the case of a fully reliable (100%) previous experience, higher IU was associated with more negative expectancy ratings during the generation-implementation stage. As regards the *updating* stage, at the neural level IU predicted (i) a context-dependent uncertainty avoidance in the moderately predictive context (75%), reflected by reduced P2 and LPP amplitudes; (ii) a context-independent reduced attention to safety cues, signaled by a reduced P2 to positive S2s; and (iii) disrupted access to emotion regulation strategies, as supported by decreased activity within the right OFC. Also, and again in the case of a fully reliable (100%) previous experience, higher IU was associated with more unpleasant valence ratings during updating. Net of the due caution in comparing results from different studies using different methodologies and measuring different DVs, it is nevertheless interesting to note that during prediction updating higher IU levels were found to be associated with apparently opposing results (as already emerged in the literature, cf. § 4.1): a dampened neural processing of affective stimuli, and an intensified subjective experience. This may suggest the existence of a potential dissociation in the effects of IU on overt (e.g., self-reported subjective experience) vs. covert (e.g., neural or peripheral physiological indices) affective processing, worth of further investigation.

Implications of our results are promising. First, our results contribute to move further our level of understanding about the mechanisms by which both contextual information and prior experience interact with IU in shaping the neural and subjective correlates of affective prediction construction. When assessing the relationships between IU and affective predictions, probabilistic *contextual information* should be taken into more careful account, since its amount has proved to have an impact on neural activity (cf. Study 6). Moreover, our results highlighted the importance of perceived (rather than actual) uncertainty levels, and of *prior experience* in shaping uncertainty perception (cf. Study 2). In fact, both CG and UG participants actually experienced the same exact amount of uncertainty (i.e., 25%) when giving their ratings in the present moment (i.e., test phase), but their previous learnings were different: only in case of a reliable prior experience IU exerted a modulation on subjective ratings (see § 4.7). Therefore, decreasing the perceived uncertainty from past to present moment may eventually contribute to reducing the aversive reaction triggered by uncertainty, and the associated affective experience intensification. These results support (and integrate well within) those clinical perspectives that propose treating anxiety-related psychopathology through the progressive minimization of perceived uncertainty (Carleton, 2016b; Shihata et al., 2016).

Second, given the conceptual relationships between IU, emotional traits and disorders (e.g., neuroticism, anxiety), and the activation of the associated behavioral patterns (e.g., BIS, fight-flight-freeze response), and being IU considered as the lower-order construct accounting for them (Carleton, 2016a, 2016b), it can be hypothesized that such emotional traits might share similar correlates of affective predictions construction. Thus, our results encourage broader considerations, useful for preventive and clinical applications within the domain of affective psychopathology. For instance, the CNV component and its neural sources, as well as the P2, the LPP and the right OFC activity could be considered as potential neural markers to assess, or to (early) intervene on, when developing preventive and treatment measures for clinical and subclinical populations.

Third and last, our results further support the hypothesized link between IU and a disrupted prediction updating, as proposed within the predictive framework (Barrett, 2017; Paulus & Stein, 2006; Seth & Friston, 2016; Tanovic, Gee, et al., 2018). This may encourage the development of future treatments for anxiety-related psychopathology, in which to target specifically the updating stage both at the neural (e.g., through biofeedback) and subjective experience level (e.g., through teaching/empowering cognitive reappraisal strategies).

In conclusion, besides the limitations of our studies that we have already discussed above, our paradigms brought several elements of novelty to the literature. First, we used fully uninstructed experimental tasks, in which participants were left free to implicitly construct their own predictive models. Second, IU was modeled as a continuous predictor, thus better approximating the construct, and preventing some slight individual differences to be lost in a dichotomization of the variable. Third, pleasant stimuli were included in Study 6, thus allowing to isolate valence-specific effects. Fourth, hd-EEG allowed to investigate both the scalp and, with due caution, the source level, thus conveying a comprehensive neurocomputational evidence. Fifth and last, combining the logic of emotional S1-S2 paradigms with an uninstructed learning component in Studies 2 to 5 allowed us to target the role of actual previous experience and its interaction with IU in constructing new predictions.

GENERAL DISCUSSION

SUMMARY OF THE FINDINGS

The present research project aimed to elucidate some underlying mechanisms of affective prediction construction at the neural and subjective experience level. We investigated the role of *contextual information* of different predictive value on the neural correlates of affective predictions construction (see RQ1, § 1.5); the role of *prior experience* on the subjective ratings to new affective predictions, within and across sensory modalities (see RQ2, § 1.5); and how *individual differences in IU* modulate this processes (see RQ3, § 1.5).

First, we demonstrated that the neural activity developing along affective prediction construction is differently modulated by the predictive value of **contextual information** (Study 1). When this latter conveys a *certain* probabilistic structure, it leads to the construction of a reliable predictive model. This model is used to generate predictions within domain-specific neural circuits, allowing to early detect emotional information in the present environment, prioritizing negatively-valenced stimuli because of their salience. Predictions allow to pre-sensitize the expected affective stimuli, in turn facilitating their subsequent neural processing during the updating stage. When contextual information conveys an *uncertain* probabilistic structure, it is impossible to construct a reliable predictive model. As a consequence, when generating predictions, emotional information in the present environment is silenced because it is unreliable; while, in the implementation stage, action plans selection and programming become crucial (and therefore they are assigned heightened anticipatory resources), in order to provide the organism with optimal resources for an efficient adaptation to the (unknown) environmental requests. Furthermore, it is also crucial to achieve an efficient prediction error signaling, thanks to which adjusting the generative model coherently.

Second, regarding the role of **prior experience**, we found that it shapes the subjective expectancies about the valence of future stimuli (Studies 2 to 5). When prior experience is *certain*, it leads future expectancies to accordingly label the predicted valence of future stimuli. This process is consistently replicated within and across sensory modalities, in presence of new ambiguous environmental cues, and in conditions of implicit prior learning. When prior experience is *uncertain*, instead, it exerts no modulation on subjective affective ratings in any of the stages of future prediction construction.

Third and last, **individual differences in IU** have been found to predict both context- and prior experience-specific effects (Studies 2 to 6). With regards to *context-specific effects*, when contextual information is *moderately reliable*, present uncertainty levels can be perceived as manageable (and thus, potentially solvable), leading individuals with higher IU to deploy more anticipatory resources in the implementation stage, and to a dampened affective processing (presumably serving an avoidance coping mechanism) in the following updating stage. As for the *prior experience-specific effects*, higher IU predicts an intensified subjective affective experience in all the stages only in presence of a *certain* previous knowledge.

THEORETICAL AND CLINICAL IMPLICATIONS

Overall, the present research project offers both a theoretical contribution to predictive models of emotion, and potential clinical implications for the early diagnosis and treatment of affective psychopathology (in particular anxiety disorders).

As a **theoretical contribution**, our results advance knowledge about the mechanisms underlying the construction of affective predictions, both at the neural and subjective experience level. Despite predictive models of emotion (Barrett, 2017; Seth & Friston, 2016) assume that the main theoretical principles of predictive coding (see § 1.1) can be effectively applied to the emotion domain as well, the present research project suggests some caution. In fact, some specificities of affective stimuli emerged, worth to be taken into further consideration. First, as regards the prediction *generation* stage, the overall picture derived from our results is mostly coherent with the neurocomputational processes already found to subtend this stage. Nevertheless, contrary to some previous evidence (cf. § 1.3), we found more neural processing resources to be allocated to extract the emotional information conveyed by cues when the available contextual information is sufficiently reliable. Second, for what concerns the *implementation* stage, the neural processes we found to be involved are qualitatively coherent with what has already been found in the literature; but in contrast with previous findings, we found that this process is maximally expressed in presence of unreliable contextual information (cf. § 1.3). Third and last, as for prediction *updating*, our results are coherent with previous evidence suggesting a prioritization in the neural processing of emotional over neutral stimuli, independently from them being predicted or not, and a prediction error signaling to stimuli mismatching predictions (see § 1.3). Nonetheless, matching stimuli do not seem to be silenced as it could be expected according to predictive coding principles (cf. Kok et al., 2019), and subjective affective experience is not influenced by the reliability of prior experience. Thus, predictive coding principles seem to apply more consistently to the generation and implementation stages. When it comes to prediction updating, instead, more weight (and, thus, more confidence) seems to be attributed to the affective nature of stimuli and to the contextual information available in the present moment, rather than to top-down predictions. This may be due to the evolutionary value of emotional stimuli, in that a prompt response to stimuli potentially impacting homeostasis, driven primarily by a quick bottom-up evaluation of present inputs, may cover a more efficient role in supporting allostasis and promoting survival (and thus, it must be prioritized).

Furthermore, given the links between IU and affective psychopathology (especially anxiety disorders) (see § 1.4), outlining the specificities of affective prediction construction with increasing IU levels may be crucial to narrowing future anxiety research toward a deeper understanding of the mechanisms that underpin affective predictions in anxious populations (and that may be shared with high-IU). In view of this, our results may support the following **preventive and clinical implications**. First, ERPs (and their estimated brain sources) found to be altered with increasing IU levels may be targeted as potential *neural markers* to assess, or to (early) intervene on, when developing preventive and treatment interventions for clinical and subclinical anxiety. Second, since reducing the perceived anxiety from past to present moment may contribute in decreasing the adverse reaction to uncertainty (and thus in dampening the associated affective experience), clinical approaches that implement progressive *minimization of perceived uncertainty* in their treatment routines may gain further support from our findings. Third and last, by confirming a *disrupted prediction updating* with increasing levels of IU, our results may encourage future clinical protocols to specifically target this stage at the neural and subjective experience levels, for instance through biofeedback treatments or cognitive reappraisal empowerment interventions.

STRENGTHS, LIMITATIONS AND FUTURE DIRECTIONS

Being developed and implemented at the turn of COVID-19 pandemic imposed some unavoidable limitations on the present research project, such as the inability to collect more EEG data due to the forced closure of the laboratories. Besides, some other **limitations** are worth to be addressed. First, as regards *contextual information*, we focused only on external probabilistic information, leaving out other external (e.g., specific features of the physical environment) or internal factors (e.g., interoceptive states) that may equally contribute in shaping affective predictions. Similarly, we outlined *prior experience* only in terms of probabilistic contingency between stimuli, but other features of prior experience such as the frequency of exposure, or the familiarity with the specific environments in which the learning occurs, may be of interest, too. Nonetheless, a research design that simultaneously included and manipulated all of the abovementioned features would have been too complex to manage, ultimately making it difficult to draw meaningful theoretical and applicative conclusions.

Second, despite the efforts to make our affective cueing paradigms more realistic, they still remain quite *artificial* as compared to the multisensory and dynamic environments we are embedded in our daily life. We employed static and unimodal stimuli, and one could wonder to what extent the sequential presentation of such stimuli on a computer screen may be effective in resembling the multifaceted human affective experience, as it develops within everyday situations. However, net of their potential fictitiousness, experimental paradigms employing visual affective stimuli are still considered as the most effective in inducing a subjective experience of emotion in the lab (Siedlecka & Denson, 2019). Moreover, affective cueing paradigms are particularly suitable to study affective predictions by targeting the three stages of prediction construction separately, and offering an optimal level of flexibility and control over stimuli manipulation (see § 1.3).

Third, none of our studies contemplated the collection of *neural and subjective measures simultaneously*. If for Studies 2 to 5 this was a choice forced by the pandemic situation, which precluded the collection of EEG data, for Studies 1 and 6 it was a deliberate decision. We are aware that a passive viewing task could arise some concerns about the experimental control of the attentional resources that participants deploy on the task. However, controlling participant's attention was not our primary purpose; rather, we wanted to leave them free to spontaneously develop their own predictive models throughout the task. It has been proved that prediction is generated (eliciting detectable ERPs) also in absence of an explicit response to S2s (Mento, 2013), and even when cues processing occurs unconsciously (Rozier et al., 2020). Further, asking for subjective ratings during affective experimental tasks can interfere with implicit emotional processing (Schupp et al., 2014), dampening emotion-related neural activity (Taylor et al., 2003). For these reasons, and in the light of the advantages offered by a passive task in ruling out any attentional or motor confound on the processes (and relative ERPs) under consideration, we chose not to collect subjective affective ratings in Studies 1 and 6.

Fourth, the *sample size* of Studies 1 and 6 was relatively small (N = 31 and 36, respectively), resulting in potentially underpowered studies. Nevertheless, this issue was at least partially counterbalanced by the large number of trials (N = 360) we employed in our S1-S2 paradigm, which enabled to heighten power by increasing the signal-to-noise ratio (Baker et al., 2020). Moreover, the peculiarities of *EEG spatial resolution* imply caution when interpreting (and speculating on) brain sources activations. We nonetheless ensured to minimize this issue by recording the EEG with a high-density (128-channels) system, and by estimating brain sources through the sLORETA algorithm, which leads to small localization errors even with low signal-to-noise ratio (Hedrich et al., 2017; Samuelsson et al., 2021).

Last, in Studies 3 and 4 the potential *interactions between uncertainty and ambiguity* may have contributed to complicating the full picture of results, preventing more subtle effects of prior learnings to be fully identifiable through our experimental manipulation. Even though disentangling the differential effects of those two factors on affective prediction construction was not our main goal, the resulting mixed picture invites future research to consider these aspects more carefully.

Net of these limitations, our research project still brought several elements of **novelty** to the literature. First of all, it represents to our knowledge the first attempt to empirically investigate affective predictions with affective cueing paradigms by referring to *predictive models of emotion* (Barrett, 2017; Seth & Friston, 2016) as a theoretical framework for interpreting results, and by investigating the relationships between all the three stages of prediction construction (generation-implementation-updating).

As a second novel feature, exposing participants to either *uninstructed* or *implicit* affective contingencies, and to *moderately predictive* contextual information, allowed us to investigate affective predictions more similarly to how they spontaneously develop in everyday life. In fact, uncertainty levels in the environment are rarely extreme, and people usually learn contingencies from the environment without any need to be explicitly instructed.

Third, in Studies 1 and 6 we employed *highly social* and arousing affective stimuli (i.e., faces) as cues, and we included pleasant as well as unpleasant stimuli, thus allowing *valence-specific* effects to be isolated. Moreover, the optimal compromise between spatial and temporal resolution offered by *hd-EEG* (Hedrich et al., 2017; Michel & Murray, 2012; Samuelsson et al., 2021) contributed to providing a compelling comprehensive evidence on the neural activity developing along the neurocomputational stages of affective predictions construction, narrowing the gap between low-density EEG and fMRI studies.

Fourth, the experimental design we developed in Studies 2 to 5 allowed to implement the role of *actual prior experience* in constructing new predictions, and to study *cross-modality generalization* between the visual and auditory modalities.

Last, in Studies 2 to 6 IU was modeled as a *continuous predictor*, thus better approximating the construct and preventing some slight individual differences to be lost in a dichotomization of the variable (Royston et al., 2006).

Concluding, and building on some of the limitations of the present research project, we encourage **future works** to (i) combine the assessment of the overt subjective ratings with the simultaneous measurement of more covert (psychophysiological or neural) indices; (ii) investigate interoceptive states as inner contextual factors potentially shaping affective prediction construction; (iii) isolate the potential mutual influences between uncertainty and ambiguity; (iv) maximize the generalization of results to real-life contexts by employing more ecologically valid experimental procedures, such as for instance ecological momentary assessment (Shiffman et al., 2008).

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