Irrelevant threats linger in high anxiety

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Abstract

Threat-related information attracts attention and disrupts on-going behavior, and particularly so for more anxious individuals. Yet, it is unknown how and to what extent threat-related information leave lingering influences on behavior, e.g. by impeding on-going learning processes. Here, human male and female participants (N=47) performed probabilistic reinforcement learning tasks where irrelevant distracting faces (neutral, happy, or fearful) were presented together with relevant monetary feedback. Behavioral modeling was combined with fMRI data (N=27) to explore the neurocomputational bases of learning relevant and irrelevant information. In two separate studies, individuals with high trait anxiety showed increased avoidance of objects previously paired with the combination of neutral monetary feedback and fearful faces (but not neutral or happy faces). Behavioral modeling revealed that high anxiety increased the integration of fearful faces during feedback learning, and fMRI results (regarded as provisional, due to a relatively small sample size) further showed that variance in the prediction error signal - uniquely accounted for by fearful faces - correlated more strongly with activity in the right dorsolateral prefrontal cortex for more anxious individuals. Behavioral and neuronal dissociations indicated that the threat-related distractors did not simply disrupt learning processes. By showing that irrelevant threats exert long-lasting influences on behavior, our results extend previous research that separately showed that anxiety increases learning from aversive feedbacks and distractibility by threat-related information. Our behavioral results, combined with the proposed neurocomputational mechanism, may help explain how increased exposure to irrelevant affective information contributes to the acquisition of maladaptive behaviors in more anxious individuals.

Significance statement

In modern-day society people are increasingly exposed to various types of irrelevant information, e.g. intruding social media announcements. Yet, the neurocomputational mechanisms influenced by irrelevant information during learning, and their interactions with increasingly distracted personality types, are largely unknown. Using a reinforcement learning task, where relevant feedback is presented together with irrelevant distractors (emotional faces), we reveal an interaction between irrelevant threat-related information (fearful faces) and inter-individual anxiety levels. Functional neuroimaging (fMRI) show provisional evidence for an interaction between anxiety levels and the coupling between activity in the dorsolateral prefrontal cortex and learning signals specifically elicited by fearful faces. Our study reveals how irrelevant threat-related information may become entrenched in the anxious psyche and contribute to long-lasting abnormal behaviors.

Introduction

In modern-day society people are increasingly exposed to emotionally loaded information that is irrelevant for on-going and prospective behaviors (e.g. via online news and social media). Moreover, efficient everyday learning requires the ability to ignore peripheral information that is not indicative of, but presented in the vicinity of, actual performance feedback (e.g. intrusive social media notifications). The ability to filter out irrelevant information is therefore important for an individual's everyday function and well-being, even when not experienced first-hand. For example, media exposure to disasters and violence relate to negative psychological outcomes (Holman et al., 2014; Hopwood and Schutte, 2017), and information regarding potential threats, obtained via social interactions, may induce maladaptive behaviors (Atlas, 2019; Lindstrom et al., 2019). Finally, distracted learning has detrimental effects on learning performance in general (for a review, see Schmidt, 2020). Surprisingly, the neurocomputational mechanisms influenced by affective irrelevant information during learning, and how these interact with personality types that are more easily distracted by affective information, are largely unknown.

Threat-related distractors attract attention and disrupt on-going behavior, and particularly so for more anxious individuals (Bishop et al., 2004; Bar-Haim et al., 2007; Cisler and Koster, 2010). While there are obvious adaptive advantages of being more attuned to potential threats, e.g. increased survivability (Ohman, 1986; Grillon, 2002; Robinson et al., 2012), such a sensitivity may have maladaptive properties if subsequent behaviors are guided by irrelevant threat-related information. More generally, failures to ignore irrelevant aversive feedback information could compromise future decision by assigning inappropriate aversive properties to stimuli and the actions that elicited them.

Three different behavioral hypotheses were considered. First, the null-hypothesis that affective distractors has no impact on the learning. Second, affective distractors disrupt the learning, i.e. learning performance in conditions with affective distractors should be reduced. Finally, affective distractors are integrated during learning, i.e. learning performance respectively increases and

decreases when affective distractors are congruent / incongruent with the relevant feedback. Because anxious individuals are more distracted by threat-related information, we predicted an interaction between inter-individual anxiety levels and irrelevant threat-related information during learning.

To explore the neuronal correlates, our a priori analyses focused on the dorsolateral prefrontal cortex (DLPFC) given that it has been implicated in attentional selection, such that the DLPFC is engaged when distractors consist of threat-related stimuli, or stimuli to which participants attended in a previous experimental phase (Fales et al., 2008; Browning et al., 2010). For example, Browning et al. (2010) first trained participants to attend either neutral or fearful faces, and reported increased activity in the DLPFC when the attuned stimulus types were subsequently presented as distractors in a different task. Second, converging evidence suggests that aberrant prediction error encoding in the right DLPFC is involved in the acquisition of irrelevant associations (Corlett et al., 2007, 2016), with the prediction error being the mismatch between an experienced and a predicted outcome (Sutton and Barto, 1998). Accordingly, some studies report that prediction error encoding in the R DLPFC correlated with an individual's tendency to learn associations in conditions that normally prevent the formation of stimulus-outcome associations (Corlett and Fletcher, 2012, 2015). As such, abnormal updating of stimulus-outcome contingencies in the R DLPFC may cause learning about stimuli and events that should normally be ignored, eventually leading to the formation of maladaptive beliefs and behaviors. Following reviewer suggestions, we also performed post-hoc analyses to elucidate potential roles for the amygdala. This is relevant because the amygdala is activated by emotional distractors (for a review, see Carretie, 2014a), plays a role in emotional learning (for a review, see Phelps, 2006), and has been implicated in encoding prediction errors (Averbeck and Costa, 2017; Aberg et al., 2020b). Additionally, amygdala activation during aversive learning and the presentation of irrelevant distractors has been correlated with differences in anxiety levels (for reviews, see Bishop et al., 2004; Lissek et al., 2005; Bishop, 2007; Aupperle and Paulus, 2010; Duval et al., 2015).

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Methods and Materials

Participants

After having provided written consent according to the ethical regulations of the Weizmann Institute of Science, fifty-one participants joined the experiment (behavioral pilot study/fMRI study: 20/31). All participants were right-handed, native Hebrew speakers, and without any previous history of psychiatric or neurological disorders. The study was performed in accordance with the Declaration of Helsinki.

To ensure sufficient power regarding the behavioral effects in the fMRI study, a power analysis was conducted using data from the behavioral pilot study. This analysis showed that 16 participants are required to detect a one-tailed Pearson correlation coefficient of 0.548 (as obtained in the pilot study) with a power (1-β) of 0.8 and error probability (α) of 0.05. However, because 16 participants are not sufficient to detect inter-individual differences in fMRI activation, we recruited additional participants to be more in-line with previous fMRI studies that investigated fMRI activation as a function of trait anxiety in learning and decision making tasks, e.g. n=31 (Browning et al., 2015b), n=32 (Bijsterbosch et al., 2015), n=25 (Xu et al., 2013), n=30 (Fung et al., 2019), and n=28 (Aberg et al., 2022).

Two participants frequently fell asleep in the MRI scanner (as indicated by frequently missed trials and post-task interviews). One participant did not perform the task satisfactorily (they pressed the same button in all trials of a block), and one participant displayed excessive movement in all three blocks of learning (as indicated by translational movements in a direction larger than the relevant voxel dimension; Wylie et al., 2014). Therefore, data from 27 participants were included in the subsequent analyses of fMRI data (20 females; average age ± STD: 25.667 ± 4.961), while data from 20 different participants were included in the behavioral pilot study (11 females; average age ± STD: 27.350 ± 4.171). Trait anxiety was estimated using the State-Trait Anxiety Inventory (Spielberger et al., 1983).

Experimental design and statistical analyses

Reinforcement learning task with distracting emotional faces

Task description

In each trial, participants were presented with a pair of objects and selected the object believed to be more likely to provide Correct feedback (Fig. 1A). The best object in each pair provided Correct feedback with a probability of 0.7 (pilot study) or 0.8 (fMRI study) while the other object provided Correct feedback with a 0.3 (pilot study) or 0.2 (fMRI study) probability.

A schematic of a trial progression is shown in Fig. 1B. If no response was made within 2.5s after the presentation of the objects, the letters 'Too slow' appeared on the screen and one shekel was deducted. The jittered durations were drawn from a truncated exponential distribution; Dale, 1999), with an average duration of 3s and a maximum duration of 10s. To prevent difficulties in identifying the numerical feedback, the location of the feedback number on the screen was identical to the location of the preceding fixation cross.

The different feedback types provided in the experiment are shown in Fig. 1C (pilot study) and Fig. 2A (fMRI study). To test for learning differences between appetitive and aversive conditions the Correct and Incorrect feedbacks were respectively +1₪ (a gain of one shekel) or 0₪ (no shekel gained) in a Gain condition, while in a Loss condition the Correct and Incorrect feedbacks were respectively 0₪ (no shekel lost) or -1₪ (one shekel lost). The accumulated sum of shekels corresponded to a monetary bonus provided at the end of the experiment. To assess the impact of affective distractors on associative learning, the numerical feedbacks were superimposed on fearful, neutral, or happy faces (Fig. 1C; Fig. 2A). In Affirmative pairs, the facial expression was matched with the feedback type (e.g. a positive face was presented together with Correct feedback), while in Contradictory pairs the contingencies were reversed (e.g. a positive faces was presented with Incorrect feedback). Please observe that there were slight differences in the different feedback types presented in the pilot and in the fMRI study. Specifically, in the fMRI study only emotional faces were presented in the

Affirmative and Contradictory conditions because we wanted to add a control condition (Neutral pairs) with only neutral faces to provide a baseline of learning performance without affective distractors.

Figure 1 around here

The learning task was divided into three separate blocks, each consisting of four (pilot) or six (fMRI study) different types of pairs: Affirmative Gain, Affirmative Loss, Contradictory Gain, and Contradictory Loss (as well as Neutral Gain and Neutral Loss for the fMRI study). In total, 12/18 different pairs of objects were used and participants performed 120 trials per block (30 trials per pair in the pilot, and 20 trials per pair in the fMRI study) for a total of 360 trials. Participants were allowed a break between each block. Pairs were presented in an interleaved fashion, such that each pair was presented once before any other pair was repeated. Moreover, the object pairs were randomly assigned to a condition for each participant, and each object was presented equally many times to the left and to the right. Finally, no facial identity was repeated until all facial identities has been presented. For more information regarding the stimuli, see 'Stimulus selection' below.

To get familiarized with the task and the different facial identities, all participants performed one block of the task outside the scanner. Here, two pairs of objects were presented in one Loss and one Gain pair for a total of 40 trials. These two objects were not used for the main task. Critically, to ensure that all participants understood the goal of the task, they were explicitly instructed that they should try to collect as many shekels as possible and that the faces, including their emotional expression, were irrelevant for performing the task well.

Statistical analyses

Learning performance was defined as the average proportion of selections of the best object in each pair for trials 16-20 (as well as trials 26-30 for the pilot study). Correlations with trait anxiety were conducted using Pearson's correlation coefficient, as well as Spearman's rank-order correlation. Tests

were one-tailed when testing directed predictions (i.e. positive or negative correlations), while two-tailed tests were used when no direction was predicted. The Bonferroni-correction for multiple comparisons were applied where required.

Categorization task

To provide a functional localization of the right dorsolateral prefrontal cortex (DLPFC) and the amygdala, participants performed a categorization task prior to the learning task. This task was inspired by a previous task in which participants categorized attended neutral and fearful faces, and which showed increased DLPFC activation for neutral (vs. fearful) faces for participants that had been previously been attuned to fearful faces (as compared participants that had been attuned to neutral faces; see Browning et al. (2010), Figure 4B: Face Attended condition). Furthermore, the amygdala is robustly engaged by faces, suggesting it should be activated more strongly by faces than by numbers (Todorov, 2012). We selected a task in which participants attended the faces, rather than presenting them as distractors, because we wanted to prevent any task-related perceived difficulty to confound the results. For example, a differential brain activity between distracting fearful and neutral faces could be wrongly attributed to increased task-difficulty caused by, for example, a disruptive attentional bias towards fearful faces. Because it is hard to disentangle these processes, we took advantage of previous reports of differential brain activation when faces were in attentional focus.

Task description

Stimuli were classified as negative, neutral, or positive (Fig. 4A). In each trial, one stimulus was presented from one of six different stimulus types, which could be either a number (-1, 0, or +1) or an emotional face (fearful, neutral, or happy). The classification was performed in the absence of feedback and no specific instructions about the 'correct' classification was provided. The six different stimulus types were presented pseudorandomly interleaved in fifteen blocks of six trials each, where one stimulus from each category was presented in each block. The emotional and the neutral faces were exactly those used for the learning task (see 'Stimulus selection'). A schematic of trial-

progressions are shown in Fig. 4A. The ITI durations were drawn from a truncated exponential distribution; Dale, 1999), with an average duration of 3s and a maximum duration of 10s. In total, 90 trials were performed (15 trials for each stimulus type). Each facial identity was presented once in each of the fearful, neutral, and happy categories. Of note, the position of the numbers and the faces directly overlapped with the positions of the same stimuli used in the learning task.

Data analysis

The R DLPFC was defined by contrasting fearful and neutral faces (Browning et al., 2010), while the amygdala was defined by contrasting faces and numbers. After defining the ROI on a group-level, the average activity within the identified R DLPFC and amygdala clusters was correlated with trait anxiety scores. Because the ROI selections were blind to trait anxiety scores, this procedure conforms to recommendations on how to correlate fMRI data with inter-individual factors (Vul et al., 2009).

Stimulus selection

Objects

Eighteen different pairs of objects were created from a colored version of the Snoddgrass and Vanderbilt object data set, and only familiar objects were selected, as determined by a familiarity rating > 4.0 (Rossion and Pourtois, 2004). All pairs of objects used in the reinforcement learning experiment are presented in Table 1.

Table 1 around here

Faces

Fearful, neutral, and happy faces from fifteen different identities (7 males and 8 females) were selected from the Karolinska Directed Emotional Faces (KDEF) data set (Lundquist et al., 1998). To ensure that the different facial expressions could be easily identified, only facial identities with a high degree of correspondence between the expressed and the rated emotion were selected. Specifically, only identities with a correct identification > 85% for all of the three facial expressions (Neutral,

Fearful, and Happy) were selected (Calvo and Lundqvist, 2008). This resulted in seven male and eight female identities (AF01, AF02, AF09, AF16, AF19, AF20, AF29, AF31, AM08, AM10, AM11, AM13, AM17, AM31, AM35). All face stimuli were normalized by rotating and changing the size of each face in accordance with a template image that ensured that the relative locations of the eyes and the tip of the nose were aligned across identities and facial expressions. Finally, the faces were cropped using a rectangular mask which allowed part of the hair to be included in the image.

Behavioral modeling

Q-learning

Following standard reinforcement learning theory, each object *i* in a pair was assigned an expected value Q*i* which represents the expected outcome if that object is selected in a trial. Qi is updated when object i has been selected and there is a mismatch between the expected outcome (Qi) and the actual feedback received (φ), i.e. the so called prediction error (δ). The update of Qi is regulated by a learning rate α:

$$Q(t+1)_i = Q(t)_i + \alpha \cdot \delta(t)_i$$

$$\delta(t)_i = \varphi - Q(t)_i$$

The probability of selecting object i in a given trial t can be estimated by a soft-max choice probability function (Sutton and Barto, 1998):

$$p(t)_i = e^{Q(t)_i \cdot \beta} / (e^{Q(t)_i \cdot \beta} + e^{Q(t)_j \cdot \beta})$$

The β parameter estimates the trade-off between exploration and exploration / randomness of choice.

Modeling the influence of distractor type

To include distractor types in the model, it was presumed that emotional faces alter the subjective value of the received feedback. For example, happy faces may increase the subjective value of any feedback type, or fearful faces could specifically reduce the subjective value of neutral feedback, et

cetera. To test these notions, the subjective value of the feedback term φ was fitted separately for different types of feedback.

In the '12φ' model, 12 different φ's were fitted: one φ for each type of face for +1₪ feedback (3 φ's), -1₪ feedback (3 φ's), 0₪ feedback in Gain pairs (3 φ's), and 0₪ feedback in Loss pairs (3 φ's).

In the '9φ' model, 9 φ's were fitted: one φ for each type of face for +1₪ feedback (3 φ's), -1₪ feedback (3 φ's), and for 0₪ feedback across Gain and Loss pairs (3 φ's).

In the '6φ_0' model, 8 φ's were fitted: one φ collapsed across faces for +1₪ feedback (1 φ) and -1₪ feedback (1 φ), and one φ for each type of face separately for 0₪ feedback in Gain (3 φ's) and Loss pairs (3 φ's).

In the '3φ_0' model, 5 φ's were fitted: one φ collapsed across faces for +1₪ feedback (1 φ) and -1₪ feedback (1 φ), and one φ for each type of face for 0₪ collapsed across Gain and Loss pairs (3 φ's).

In the 'φ_{0FF}, φ_{0NH}' model, 4 φ's were fitted: one φ collapsed across faces for +1₪ feedback (1 φ) and -1₪ feedback (1 φ), one φ_{FF} for fearful faces paired with 0₪ feedback, and one φ_{NH} for neutral/happy faces paired with 0₪ feedback.

In the 'φ_{0FFG}, φ_{0FFL}, φ_{0NH}' model, 5 φ's were fitted: one φ collapsed across faces for +1₪ feedback (1 φ) and -1₪ feedback (1 φ), one φ_{FFG} for fearful faces paired with 0₪ feedback in Gain pairs, one φ_{FFL} for fearful faces paired with 0₪ feedback in Loss pairs, and one φ_{NH} for neutral/happy faces paired with 0₪ feedback.

In the 'φ_{+1},φ_{-1}' model, 5 φ's were fitted: one φ collapsed across faces for 0₪ feedback (1 φ), one φ for happy faces paired with +1₪ feedback (1 φ), one φ for happy faces paired with -1₪ feedback (1 φ), one φ for fearful/neutral faces paired with +1₪ feedback (1 φ), and one φ for fearful/neutral faces paired with -1₪ feedback (1 φ).

We also tested another set of models which fit separate subjective values for each numerical feedback (-1, 0, +1) independent of face type. The impact of irrelevant affect is then added via constant 'bias' terms (ε's).

In the '3φ, 3ε' model, 3 φ's were fitted: one φ for each numerical feedback type (-1, 0, +1; 3 φ's), and one ε for each emotional face type (fearful, neutral, happy; 3 ε's).

In the '3φ, ε_{FF}, ε_{NH}' model, 3 φ's were fitted: one φ for each numerical feedback type (-1, 0, +1; 3 φ's), one ε_{FF} for fearful faces (1 ε), and one ε_{NH} for neutral/happy faces combined (1 ε).

Finally, in the '3φ, ε_{0FF}, ε_{0NH}' model, 3 φ's were fitted: one φ for each numerical feedback type (-1, 0, +1; 3 φ's), one ε_{0FF} for fearful faces paired with 0₪ feedback (1 ε), and one ε_{0NH} for neutral/happy faces combined and paired with 0₪ feedback (1 ε).

Model fitting and model selection procedures

For each model, the free parameters were fitted individually to each participant's learning behavior by minimizing the negative log-likelihood estimate:

$$LLE = -\ln(\prod_{1}^{n} p(t)_i)$$

Given n trials, $p(t)_i$ is the soft-max choice probability of selecting object i in trial t. To avoid local minima, each fit was repeated 10,000 times with different random starting points for each free parameter. All model fits were compared by calculating the Bayesian Information Criterion (BIC; Schwarz, 1978), which penalizes model-fits based on their complexity:

$$BIC = 2 * LLEm + k * \ln(n)$$

LLEm is the minimal log-likelihood estimate, k is the number of fitted parameters and n is the total number of trials. The most parsimonious model is the model with the lowest BIC.

To further validate the selection of the most parsimonious model, a protected exceedance probability for each model being the best model was calculated using a Bayesian model selection procedure (Rigoux et al., 2014).

Model simulations

Two different model-simulations of behavior were performed to validate the most parsimonious model.

First, a model-derived probability for selecting the best object in each trial was calculated using each participant's fitted parameters and the history of previous actions and outcomes (Palminteri et al., 2017). To confirm that these model-simulated behaviors reproduce the observed effects-of-interest, we calculated the same correlations between trait anxiety and learning performance in the different conditions.

Second, to determine whether specific computational parameters drive the observed effects-of-interest, another set of simulations were performed. These simulations first set all fitted parameters to their average value across participants. Next, the value of the parameter-of-interest is gradually changed to see if there are associated changes in the simulated behavioral effect-of-interest. Performance improvements in all conditions were simulated, and 1000 simulations were conducted for each data point.

MRI Data

Image Acquisition

MRI images were acquired using a 3T whole body MRI scanner (Prisma, Siemens, Germany) with a 20-channel head coil. Standard structural images were acquired with a T1 weighted 3D sequence (MPRAGE, Repetition time (TR)/Inversion delay time (TI)/Echo time (TE)=2300/900/2.32 ms, flip angle=8 degrees, voxel dimensions=0.9 mm isotropic, 192 slices). Functional images were acquired with a susceptibility weighted EPI sequence (TR=2000, TE=30 ms, flip angle=75 degrees, voxel dimensions=3x3x3.5 mm, 32 slices). The phase encoding direction was anterior-posterior, the slice order was all even (2 to 32) followed by all odd (1 to 31), with a 0% distance factor. No acceleration technique was applied. The MRI scanner was stopped between each block of the learning task (each block lasted~15 minutes), while the functional localizer task lasted ~7 minutes.

Preprocessing

Functional MRI data were preprocessed and then analyzed using the general linear model (GLM) for event-related designs in SPM12 (Welcome Department of Imaging Neuroscience, London, UK; http://www.fil.ion.ucl.ac.uk/spm). During preprocessing, all functional volumes were realigned to the mean image (with auto-masking applied), co-registered to the structural T1 image, corrected for slice timing, resampled to 2x2x2 mm voxel size (upsampling of the voxel size to these dimensions has been suggested to increase the sensitivity of fMRI analyses; Hopfinger et al., 2000), normalized to the MNI EPI-template, and smoothed using a 6 mm FWHM Gaussian kernel. Please observe that the resampling of voxels is mainly relevant for ROI identification in the functional localizer task.

First-level analyses

General procedure

At the first level, individual event-types, e.g. feedbacks, stimuli, or button presses (depending on task, see below), were modelled by a standard synthetic hemodynamic response function (HRF). A 24-parameter model was used to regress out head motion effects from the realigned data (i.e. six head motion parameters, six head motion parameters calculated as the difference between time points *t* and *t-1*, and the twelve corresponding squared items; Friston et al., 1996). Statistical analyses were performed on a voxel-wise basis across the whole brain.

First-level analysis of the categorization task

An event-related design was created with two different event-types (stimulus onset and response onset) for each of the six stimulus types (the numbers -1, 0, and +1, and fearful faces, neutral faces, and happy faces). In total, twelve different event-types were created, together with a regressor of no interest which included the onset of trials in which no response was made.

Region of interest (ROI)

To test the a priori hypothesis regarding an involvement of the DLPFC in the present study, an initial R DLPFC mask was created by intersecting the union of Broadmann areas 9 and 46 with the

middle frontal gyrus in the right hemisphere. The resulting ROI was then dilated by a factor of 1. All of these steps were performed using the WFU PickAtlas toolbox which also provided pre-defined ROIs for Broadmann areas 9, 46, and the middle frontal gyrus (Tzourio-Mazoyer et al., 2002; Maldjian et al., 2003; Maldjian et al., 2004). For the post-hoc analysis regarding amygdala involvement, an initial amygdala mask was obtained by including all available amygdala sub-regions provided by the SPM Anatomy toolbox (Eickhoff et al., 2005).

Statistical Analyses

To localize the R DLPFC, we contrasted the BOLD signal evoked by neutral and fearful faces, while the amygdala was localized by contrasting BOLD signal evoked by faces and numbers. Significant differential activations within the initial R DLPFC and amygdala masks were tested via t-tests implemented in SPM using an initial search threshold of $p=0.001$, and small volume correction (SVC) using a threshold of $p<0.05$ Family-Wise Error rate (FWE) to correct for multiple comparisons. For display purposes and follow-up analyses (e.g. correlation with individual anxiety levels), beta parameter estimates were extracted and averaged from all voxels within significant clusters of activation.

First-level analysis of the learning task

An event-related fMRI design was created with three different event-types (stimulus onset, response onset, and feedback onset) for each of four trial types (Gain Correct feedback, Gain Incorrect feedback, Loss Correct feedback, and Loss Incorrect feedback). Besides these twelve event-types for each of three blocks, trials in which no response was made during the picture display were included as a regressor of no interest. To isolate the contribution of the distractors to the prediction error signal, the prediction error term for the selected model (δFull) was separated into two parts (see Wittman et al., 2008; Eldar and Niv, 2015, for similar procedures). In brief, a 'Basic' prediction error term (δBasic) accounted for variance in the prediction error signal when there is no differential modulation by distractor type, i.e. the values of parameters-of-interest are set to be equal. Next, a prediction error 'Boost' term (δBoost) was created to account for variance above and beyond

variance the δBasic term; the δBasic term was subtracted from δFull in each trial *t*, i.e. δBoost(t)= δFull(t)- δBasic(t). To study the fMRI correlates of the two prediction error types δBasic and δBoost, their respective values were added as parametric modulators to the feedback onsets. Critically, to elucidate unique variance explained by δBoost, the values of δBoost was orthogonalized with respect to the values of δBasic (Mumford et al., 2015).

Regions of interest (ROIs)

The R DLPFC and amygdala ROIs identified in the separate categorization task.

Statistical Analyses

Correlations between prediction errors and BOLD signal in the ROIs was tested using a ROI approach were the average beta parameter estimates for each type of prediction error (δ_{Basic}, δ_{Boost}) were extracted from all voxels within the ROIs. These beta parameters were then entered into two separate repeated measures ANOVAs (i.e. one for each prediction error type) with factors Gain/Loss (Gain, Loss pairs) and Feedback (Correct, Incorrect), and Trait anxiety as continuous covariate. Follow-up analyses were conducted using paired *t*-tests and Pearson correlations.

Results

Behavior

Behavioral pilot study

An initial pilot study was conducted with twenty participants to explore interactions between trait anxiety and affective distractors during learning. Learning performance was assessed as the average proportion of correct choices in trials 16-20 and in trials 26-30. Furthermore, we tested the relationship between anxiety and learning performance separately in each of the four conditions (i.e. Affirmative Loss, Affirmative Gain, Contradictory Loss, and Contradictory Gain). The average learning curve for each condition is shown in Fig. 1D,E. Trait anxiety scores correlated negatively with the average performance only in the Contradictory Loss condition (trials 16-20: Pearson's r=-0.548,

p=0.0125, trials 26-30: Pearson's r=-0.438, p=0.053, two-tailed tests), but not in any other condition (all p-values>0.08; see Table 2). To replicate these results, we conducted a follow-up study where participants also underwent fMRI scanning to provide initial insights into the neurocomputational correlates of the behavioral effects.

Table 2 around here

fMRI study

The behavioral paradigm of the fMRI study was similar to the one used in the pilot study, with the main addition of a control condition used to normalize learning performance by subtracting the learning performance in the absence of affective distractors (i.e. with neutral faces; Fig. 2A). Learning curves are shown in Fig. 2B, and normalized average learning performances are shown in Fig. 2C-F.

First, we replicated the main result of the pilot study, namely a negative correlation between trait anxiety and learning performance in the Contradictory (vs. Neutral) Loss condition [Fig. 1F; r=-0.394, p=0.021, one-tailed Pearson correlation]. Because anxiety increases the tendency to display behavioral switching following aversive feedbacks (Aberg and Paz, 2022), we tested whether anxious participants displayed a reduced proportion of win-stay decisions for the Correct feedback in the Contradictory Loss condition (i.e. because the fearful faces were paired with the neutral 0₪ feedback). As predicted the proportion of win-stay decisions correlated negatively with trait anxiety in Contradictory (vs. Neutral) Loss pairs [Fig. 2J; r=-0.420, p=0.015, one-tailed Pearson-correlation]. A similar trend was observed in the Contradictory Loss condition of the pilot study [r=-0.359, p=0.060, one-tailed Pearson-correlation].

In contrast to the pilot study, we observed a positive correlation between anxiety and learning performance in Affirmative (vs. Neutral) Gain pairs [Figure 2C; r=0.640, p=0.001, two-tailed Pearson correlation, p-value was corrected for three unplanned comparisons]. Notably, in the fMRI study (but not the pilot study), the neutral 0₪ feedback in Affirmative Gain pairs was presented together with a

fearful face, therefore providing another opportunity to test whether fearful faces increase the averseness of the neutral 0₪ feedback. Indeed, trait anxiety correlated positively with the proportion of lose-shift decisions in Affirmative (vs. Neutral) Gain pairs [r=0.343, p=0.040, one-tailed Pearson-correlation; Fig. 2G].

Finally, trait anxiety did not correlate significantly with learning performance in the remaining two conditions [Fig. 2D,E, all uncorrected p-values > 0.05, two-tailed Pearson-correlations; Table 3], nor with the behavioral switching for neutral 0₪ feedbacks paired with happy faces [Fig. 2H,I; all uncorrected p-values > 0.05, two-tailed Pearson-correlations; Table 4].

Table 3 around here

Table 4 around here

In summary, the behavioral results from the pilot and the fMRI study suggest that distracting fearful faces increases the averseness of the neutral 0₪ feedback for more anxious individuals. This was demonstrated by increased behavioral switching following this feedback combination, both when it signaled a Correct and when it signaled an Incorrect outcome, which respectively caused reduced and improved learning performance.

Behavioral modeling

To explain how anxiety interacts with the distractors, several different behavioral models were designed. To support the aforementioned behavioral result, different subjective feedback values φ were fitted for different feedback combinations (for details about the different models and the model-fitting procedures, see Methods).

A fixed-effect analysis showed an overall lower BIC for the 'φ_{0FF}, φ_{0NH}' model (Fig. 3A), indicating a better fit to behavior on average. Additionally, a random-effects analysis indicated a protected exceedance probability of 1.0 for the same model (Inset, Fig. 3A), a result which suggests that the

selected model is the most likely model to generate the observed behavior (Stephan et al., 2009). Together, these two complementary ways of comparing model indicate the 'φ_{0FF}, φ_{0NH}' model as being the most parsimonious model.

The selected 'φ_{0FF}, φ_{0NH}' model contains six free parameters: one learning rate α, one randomness of choice/exploration parameter β, and four feedback parameters (φ_{+1}, φ_{-1}, φ_{0FF}, and φ_{0NH}). To clarify, φ_{+1} and φ_{-1} respectively estimate the subjective value of +1₪ and -1₪ feedbacks and are independent of the distracting faces, while φ_{0FF} and φ_{0NH} respectively estimates the subjective value of the neutral 0₪ feedback paired with fearful (φ_{0FF}) and neutral/happy (φ_{0NH}) faces. Average fitted model parameters for all models are displayed in Table 5.

Table 5 around here

To validate the model, and to conform to recent recommendations that effects-of-interest need to be recovered using model-simulated performance data (Palminteri et al., 2017), the performance of the selected model was simulated using each participant's fitted model parameters. For visualization purposes, the fitted learning curves of the selected model are shown in Fig. 3B. More importantly, the model successfully reproduced the behavioral effects-of-interest (Fig. 3C-F, c.f. Fig. 2C-F).

One possible explanation for the behavioral results is that the interaction between fearful faces and anxiety reduces the subjective value of the neutral 0₪ feedback. Corroborating this notion, trait anxiety correlated negatively with the difference in the fitted subjective values of the 0₪ feedback paired with fearful and neutral/happy faces [φ_{0FF}-φ_{0NH}, r=-0.467, p=0.007, one-tailed Pearson-correlation; Figure 2G]. These parameters do not correlate significantly with trait anxiety individually [φ_{0FF}: r=-0.242, p=0.223; φ_{0NH}: r=0.051, p=0.802, two-tailed Pearson-correlations].

Additional model simulations were performed to ensure that the impact of the interaction between distractor type and anxiety on learning can actually be attributed to the differential

subjective values of φ_{0FF} and φ_{0NH}. In these simulations, all model parameters are initially set to the average values of the fitted parameters across participants' values (i.e. α=0.25, φ_{+1}=-0.25, φ_{0FF}=0.35, φ_{0NH}=0.35, φ_{+1}=0.80, and β=0.15). The values are held constant, except for the values of φ_{0FF} and φ_{0NH}, which are gradually decreased and increased, respectively, in order to simulate the modulation by trait anxiety (Fig. 3G). Simulated performance improvements are calculated for all conditions, and visualized as a comparison between conditions (see Methods for further details). As would be expected, decreases in the difference between φ_{0FF} and φ_{0NH}, improved performance in Affirmative Gain pairs (relative Contradictory and Neutral Gain pairs; Fig. 2H) while reducing performance in Contradictory Loss pairs (relative Affirmative and Neutral Loss pairs; Fig. 2I).

Finally, to illustrate the robustness of the main modeling result, we demonstrate that the negative correlation between trait anxiety and the relative difference between fitted 0₪ feedback values for fearful (vs. neutral and happy) faces are present across different behavioral models. First, the 'φ_{0FFG}, φ_{0FFG}, φ_{0NH}' model differs from the most parsimonious model by estimating separate φ_{0FF}'s in Gain and Loss pairs (i.e. φ_{0FF} was separated into two parameters, φ_{0FFL} and φ_{0FFG}). Trait anxiety correlated negatively with the difference between φ_{0FFL} and φ_{NH} [r=-0.426, p=0.013, one-tailed Pearson correlation; Fig. 3J], and with the difference between φ_{0FFG} and φ_{NH} [r=-0.448, p=0.010, one-tailed Pearson correlation; Fig. 3K], with a positive correlation between φ_{0FFL} and φ_{0FFG} [r=0.412, p=0.016, one-tailed Pearson correlation]. Second, the '$3\varphi_0$' model differs from the most parsimonious model by separating the φ_{0NH} term into two terms, one term corresponding to the combination of 0₪ feedback paired with neutral faces (φ_{0N}) and one term for happy faces (φ_{0H}). Trait anxiety correlated negatively with the difference between φ_{0FF} and φ_{0N} [r=-0.535, p=0.002, one-tailed Pearson-correlation; Fig. 3L], as well as for the difference between φ_{0FF} and φ_{0H} [r=-0.335, p=0.044, one-tailed Pearson correlation; Fig. 3M], and φ_{0N} and φ_{0H} were positively correlated [r=0.816, p<0.001].

In summary, the selected 'φ_{0FF}, φ_{0NH}' model provides the most parsimonious fit to behavior and provides a plausible and robust explanation for how anxiety interacts with threat-related distractors to modulate learning performance, namely via a reduced subjective value of neutral 0₪ feedbacks.

Functional neuroimaging

A priori, we hypothesized that atypical prediction error encoding in the R DLPFC, caused by the presence of threat-related distractors, contributes to the learning bias displayed by more anxious individuals. Based on reviewer suggestions, we also conducted a post-hoc analysis with focus on the amygdala. To this end, we first used a separate task to functionally define the ROIs to be used when analyzing the learning task. Notably, by selecting ROIs in a separate task, we avoid issues of double-dipping (Kriegeskorte et al., 2009), and by selecting ROIs based on group-level data, we minimize the possibility of inflated effect sizes when analyzing inter-individual differences in brain activation (Vul et al., 2009).

Functional localization of the R DLPFC and the amygdala via the categorization task

In the functional localizer task, participants categorized numbers (-1, 0, +1) and faces (fearful, neutral, happy) as either negative, neutral, or positive (Fig. 4A). The contrast between neutral and fearful faces revealed a region within an initial a priori defined R DLPFC mask which responded more strongly to neutral (versus fearful) faces [peak voxel coordinate: x=46 y=44 z=18, T(25)=5.151, pFWE,SVC=0.013; one-tailed paired *t*-test, Fig. 4B,C]. A negative correlation with trait anxiety shows that the difference in DLPFC BOLD signal between fearful and neutral faces is larger for more anxious individuals [Fig. 4D; r=-0.514, p=0.006, two-tailed Pearson correlation].

The contrast between faces and numbers revealed bilateral activation within an initial a priori defined amygdala mask, which responded more strongly to faces (versus numbers) [peak voxel coordinates: x=-20 y=-6 z=-14, T(25)=6.025, pFWE,SVC=0.001; x=20 y=-4 z=-14, T(25)=6.833, pFWE,SVC<0.001; one-tailed paired *t*-tests, Fig. 4E,F]. The collapsed activity within this bilateral ROI showed no correlation with trait anxiety [Fig. 4G; r=-0.005, p=0.981, two-tailed Pearson correlation].

The obtained R DLPFC cluster and the bilateral amygdala cluster are subsequently used as ROIs in the analyses of prediction error encoding in the learning task.

Neural correlates of prediction errors

To assess the neural correlates of the unique contribution of φ_{OFF} (vs. φ_{ONH}) to the prediction error signal, the prediction error term of the full model (δ_{Full}) is separated into two terms, δ_{Boost} and δ_{Basic} (see Methods). To assess their neuronal correlates, the beta parameter estimates of the δ_{Boost} and the δ_{Basic} terms were extracted from all voxels within the functionally defined R DLPFC and amygdala ROIs. The resulting average beta parameters for each ROI were entered into two separate repeated measures ANOVAs, one for each prediction error type, with factors Gain/Loss (Gain, Loss) and Feedback type (Correct, Incorrect), and Trait anxiety as continuous covariate.

R DLPFC activity correlates with the 'Basic' prediction error

For the δ_{Basic} term, a repeated measures ANOVA showed a significant intercept term [$F(1, 25)=18.39$, $p<0.001$, ANOVA], but no significant main effects or interactions [all p-values > 0.16, ANOVA; Table 6]. To illustrate this effect, the individual beta parameters for the δ_{Basic} term collapsed across the four feedback conditions for the R DLPFC ROI are shown in Fig. 5B.

Table 6 around here

This result shows that BOLD signal in the R DLPFC correlates significantly with the magnitude of the 'Basic' prediction error signal.

R DLPFC activity correlates with the prediction error 'Boost' in anxious individuals

For the δ_{Boost} term, a repeated measures ANOVA revealed significant interactions between Trait anxiety x Gain/Loss [$F(1, 25)=6.04$, $p=0.021$, ANOVA], and Trait anxiety x Feedback [$F(1, 25)=4.68$, $p=0.040$, ANOVA], but no significant Trait anxiety x Gain/Loss x Feedback interaction [$F(1,25)=0.62$, $p=0.438$, ANOVA]. Individual beta parameters for the δ_{Boost} term in the four feedback conditions are shown in Fig. 5C. Importantly, the two a priori hypotheses were confirmed via a positive correlation

between trait anxiety and the beta parameters of δ_{Boost} in the Gain Incorrect feedback condition [r=0.468, p=0.007, one-tailed Pearson correlation; Fig. 5D], and a negative correlation in the Loss Incorrect feedback condition [r=-0.697, p<0.001, one-tailed Pearson correlation; Fig. 5G]. By contrast, trait anxiety did not correlate with the beta parameters of δ_{Boost} in the Gain Correct feedback condition [r=-0.147, p=0.463, two-tailed Pearson correlation; Fig. 5E] nor in the Loss Incorrect feedback condition [r=-0.107, p=0.594, two-tailed Pearson correlation; Fig. 5F]. Besides a significant Gain/Loss x Feedback interaction [F(1, 25)=5.74, p=0.024], no other effects or interactions are significant (all p-values > 0.24; see Table 7 for a full ANOVA table).

Table 7 around here

In summary, these results confirm that threat-related distractors contribute to altered prediction error encoding in the R DLPFC for anxious individuals, and specifically so in conditions where anxiety correlated with learning performance.

Prediction error coding in the Amygdala

As in the previous analysis, the beta parameter estimates corresponding to the two prediction error terms, δ_{Boost} and δ_{Basic}, were extracted from all voxels within the amygdala ROI. The resulting average beta parameters where entered into the same ANOVAs used for the R DLPFC ROI analysis.

Amygdala activity does not correlate with the 'Basic' prediction error

For the δ_{Basic} term, the repeated measures ANOVA revealed no significant main effects or interactions [all p-values>0.14, ANOVA; Table 8]. The intercept term, collapsed across conditions and anxiety levels is shown in Fig. 5I for visualization purposes.

Table 8 around here

Amygdala activity does not correlate with the prediction error 'Boost'

For the δ_{Boost} term, the repeated measures ANOVA revealed no significant main effects or interactions [all p-values>.17, ANOVA; Table 9]. For visualization purposes, the beta parameters for each condition are shown in Fig. 5J, and correlations with trait anxiety are shown in Fig. 5K-N.

Table 9 around here

In summary, no evidence supported a role for the amygdala in prediction error coding.

Whole-brain correlates of the 'Basic' prediction error

To validate our model-based fMRI procedure, we tested whether activity in the ventral tegmental area (VTA), a region well known for its role in encoding different aspects of reward, including prediction errors (D'Ardenne et al., 2008; Bromberg-Martin et al., 2010; Aberg et al., 2015; Schultz, 2016; Aberg et al., 2020a), correlated with the δ_{Basic} term. This analysis was performed by averaging the beta parameters related to the δ_{Basic} term for all voxels within a recently developed probabilistic in vivo atlas of the VTA (Fig. 6A; Pauli, Nili, & Tyszka, 2018(Pauli et al., 2018)). Indeed, the average beta parameters of this VTA ROI was significantly larger than 0.0 [mean (±SEM)=0.068 (±0.021), t(26)=3.291, p=0.001, one-tailed *t*-test, Fig. 6B]. Next, correlations with the δ_{Basic} term were tested across the whole-brain using a FWE-corrected threshold of 0.05. A full list of regions correlating with δ_{Basic}, surviving a threshold of a FWE-corrected threshold of 0.05, is reported in Table 10. In short, significant activation was observed in a midbrain region close to the previously used VTA mask (Fig. 6C,D), in the dorsal anterior cingulate cortex (dACC)/dorsomedial prefrontal cortex (dmPFC; Fig. 6D), in the bilateral striatum (Fig. 6E,F), and in the bilateral anterior insula (Fig 6G,H). These regions have previously been implicated in the neuronal coding of prediction errors (Garrison et al., 2013).

Table 10 around here

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Discussion

An increased sensitivity to threat-related information is advantageous in the context of immediate and actual threat avoidance (e.g. when hearing a threatening growl in the forest; Ohman, 1986). However, it is maladaptive if neutral/safe cues in the environment acquire aversive associations based on irrelevant threat-related information, and these associations subsequently guide behavior.

Here, we report that anxious individuals avoided a neutral stimulus following its pairing with the feedback combination of relevant 0₪ neutral feedback and irrelevant fearful faces, even though participants were explicitly instructed that the faces are unrelated to task performance. By showing that exposure to irrelevant affective information lingers and affect behavior beyond the immediate situation, our study extends previous research which focused on the immediate impact of affective distractors, such as alterations in response times, hit rates, or brain activations (e.g. within the same trial; Bar-Haim et al., 2007).

Importantly, the threat-related distractors did not simply disrupt the learning process, as would be indicated by an overall reduced learning performance in conditions with the feedback combination of fearful faces and neutral 0₪ feedback. By contrast, anxious individuals displayed respectively reduced or improved performance in conditions where this feedback combination represented the Correct or the Incorrect outcome. In support, behavioral modeling further showed that high anxiety was associated with a reduced subjective value of the neutral 0₪ feedback when paired with fearful faces both when it signaled Correct and Incorrect outcomes (as compared to happy and neutral faces). A third dissociation was observed in the fMRI data, with a stronger / weaker coupling between the prediction error signal - uniquely accounted for by fearful faces – and R DLPFC BOLD signal for feedbacks where anxious individuals showed increased / decreased learning performance. Together, these results indicate that anxiety is associated with an increased integration of irrelevant threat-related information during feedback processing (and not just disrupted learning

processes). From an evolutionary perspective, it makes sense that information related to potential threats are integrated during learning, rather than disrupting it. However, this ability comes at the cost of increased avoidance of beneficial situations in which a potential treat was occasionally detected.

It has been suggested that anxiety disorders develop from abnormal learning processes, e.g. amplified fear learning (Lissek et al., 2005) and over-generalization (i.e. the transfer of aversive properties from a fear-conditioned neutral stimulus to other perceptually and conceptually similar neutral stimuli (Lissek et al., 2014). Additionally, trait anxiety (e.g. the general tendency to experience distress in everyday life situations), may indicate a vulnerability to develop a mental illness (Chambers et al., 2004; Weger and Sandi, 2018). The identification of abnormal learning processes in trait anxiety could therefore help understand external factors and internal mechanisms that contribute to the development of dysfunctional behaviors and mental illness. Based on the present results, we propose that this includes the maladaptive formation of associations between neutral stimuli/events and irrelevant threat-related information, as these may result in inappropriate avoidance behaviors.

Anxious individuals showed increased integration of fearful faces with the neutral 0₪ feedback, but not with +1₪ and -1₪ feedbacks. One potential explanation for this result could be that anxious individuals call upon additional, salient sources of information to resolve uncertain feedbacks. To clarify, in the present study the -1₪ and +1₪ feedbacks always indicated the worst and best possible outcomes, while the 0₪ feedback signaled either a correct (in Loss conditions) or an incorrect (in Gain conditions) outcome, causing it to be more uncertain. This interpretation is in-line with findings that anxiety increases aversion to uncertainty (Hartley and Phelps, 2012; Grupe and Nitschke, 2013), the motivation to reduce uncertainty (Aberg et al., 2022), and distractibility by threat-related information (Bar-Haim et al., 2007). Future research may profit from looking at how irrelevant salient information guides the processing of uncertain feedback in high anxiety.

The present study used a between-subject design to study the interaction between anxiety and threat-related distractors during learning. A complementary way to assess behavioral interactions with anxiety is via alterations of stress and state anxiety, something which could be accomplished by, for example threat-of-shock manipulations (Schmitz and Grillon, 2012; Robinson et al., 2013). This approach is beneficial because it could be used to combine a powerful within-subject design (i.e. conditions with and without stress, or induced anxiety) with a between-subject design (e.g. trait anxiety measures, or patient versus control groups). This approach may be particularly fruitful to further research on findings that individuals with anxious predispositions respond differently in stressful situations (Meijer, 2001; Indovina et al., 2011; Aberg and Paz, 2022).

In accord with previous studies (for a review, see Garrison et al., 2013), a number of brain regions in the present study, including the ventral tegmental area, the striatum, anterior cingulate cortex, anterior insula, and the R DLPFC, encoded a 'basic' prediction error signal. However, only the R DLPFC of anxious individuals correlated with additional variance in the prediction error signal that was uniquely attributed to the fearful faces. This correlation was positive in conditions where anxiety improved performance, but negative when anxiety show impaired performance. These results are in accordance with previous research showing that the strength of neuronal prediction error encoding correlates with the amount of learning (Schönberg et al., 2007; Aberg et al., 2015, 2016a), and complement behavioral and physiological reports of links between personality traits and reinforcement learning biases (Browning et al., 2015b; Aberg et al., 2016b; Aberg et al., 2017). These results also bridge separate reports of an involvement of the DLPFC in attentional bias to threat (Bishop, 2009), prediction error encoding (Fletcher et al., 2001; Corlett et al., 2004), and the acquisition of irrelevant associations via altered prediction error encoding (Corlett and Fletcher, 2012, 2015). Indeed, similar and converging pieces of evidence support a theory in which aberrant prediction error encoding in the R DLPFC is believed to enable maladaptive learning about stimuli, events, and outcomes that are not related (Corlett et al., 2007, 2016). The present study adds to this theory by suggesting that one source of 'aberrancy' stems from failures in suppressing attention to

irrelevant sources of threat-related information, i.e. these stimuli may grab attention and engage learning processes like any other (relevant) stimulus, and particularly so with high anxiety.

By contrast, we did not observe any involvement of the amygdala in coding prediction errors, nor any interaction with trait anxiety. Although the amygdala plays a prominent role in fear learning and anxiety (Phelps, 2006; Duval et al., 2015; Tovote et al., 2015), only scarce evidence report correlations between amygdala activity and prediction errors (McHugh et al., 2014; Meffert et al., 2015; Aberg et al., 2020b). One possibility is that the amygdala codes for other features related to learning and the prediction error signal, such as surprise, sometimes defined as the unsigned prediction error signal (Li et al., 2011; Klavir et al., 2013). Further, although the amygdala is activated by affective distractors, and particularly so for more anxious individuals (Bishop et al., 2004; Bishop, 2009), it has to our best knowledge not been implicated in the learning of irrelevant information.

Limitations

Anxiety was estimated using the standard Spielberger's Trait-Anxiety Inventory (Spielberger et al., 1983), which provides a gradual scale for the normal (sub-clinical) range of anxiety. Using a continuous scale has the benefit of correlating behavior across a distribution of anxiety scores, rather than just comparing performance across two somewhat arbitrarily divided populations (patients vs. controls). Additionally, by studying anxiety within the normal range, we can determine how maladaptive decisions are mediated by irrelevant distractors even in healthy individuals. Because such maladaptive decision may have a huge impact on daily-life in all individuals, and definitely on societies and industry, we actually believe that more studies should use gradual scales over non-clinical populations (Browning et al., 2015a; Fung et al., 2019; Gagne et al., 2020). That said, Spielberger's Trait-Anxiety Inventory has been debated for its lack of convergent and discriminant validity, suggesting that it estimates 'negative affectivity' rather than proneness to anxiety per-se (Balsamo et al., 2013). Yet, because negative affectivity is closely linked to psychopathology (Kotov et

al., 2010; Stanton and Watson, 2014), and has been noted as a vulnerability factor for developing anxiety and depression (Clark et al., 1994), our results still bear significant relevance.

Our main behavioral results were replicated between two separate groups of participants (i.e. negative correlations between trait anxiety and learning performance in the Contradictory Loss condition was observed in both the pilot and in the fMRI study), and were replicated within another condition in the fMRI study (i.e. the feedback combination of fearful faces + neutral 0₪ feedback increased behavioral switching in both the Contradictory Loss and the Affirmative Gain condition). Furthermore, these latter results were associated with two dissociations in the fMRI results, namely opposite correlations with trait anxiety and the coupling between R DLPFC activity and the prediction error signal associated with fearful faces. Being able to replicate results across- and within groups speaks in favor of the robustness of our results.

Importantly, we would like to stress that our fMRI findings were obtained with a relatively small sample size (N=27), and therefore needs to be regarded as provisional. In particular, although many factors may contribute to the reliability of brain-behavior correlations in fMRI data, including behavioral task, amount of data per participant, targeted brain regions, and method-of-analysis, recent efforts suggest "… that with sample sizes in the range of those often used in fMRI studies (i.e., 20–30 participants), one cannot be confident that all of the regions appearing to correlate with individual differences in behavior are reliable, or that other regions have not been missed altogether." (Grady et al., 2021). Future studies should therefore expand on the issue and validate the robustness of the present fMRI results.

Conclusion

In conclusion, the present study displays a learning bias for individuals with high trait anxiety caused by an entanglement between threat-related distractors and on-going learning processes. This bias may be particularly unhealthy in modern society, where exposure to irrelevant threat-related information is increasingly prevalent via online news reporting and social networking sites. The

present study describes a new pathway for how threat-related information may become entrenched in the anxious psyche.

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Tables

Table 1. Object pairs used in the reinforcement learning task.

Pair	Object descriptions	Object numbers
1	Pen, Pencil	167, 168
2	Glasses, Book	105, 30
3	Chair, Table	53, 226
4	Candle, Light bulb	44, 138
5	Key, Door	128, 76
6	Tree, Flower	241, 91
7	Belt, Pants	26, 162
8	Carrot, Onion	48, 157
9	Apple, Pear	6, 166
10	Cat, Dog	49, 73
11	Car, Bus	47, 39
12	Lamp, Light switch	132, 139
13	Water Glass, Wine glass	104, 258
14	Shoe, Socks	204, 211
15	Telephone, Television	227, 228
16	Moon, Sun	146, 222
17	Pot, Pan	179, 101
18	Fork, Spoon	97, 215

Table 2. Correlations between trait anxiety and learning performance in the pilot study.

Condition	Trials 16-20		Trials 26-30	
	r	p-value	r	p-value
Affirmative Gain	0.241	0.305	0.160	0.501
Affirmative Loss	-0.393	0.086	-0.090	0.705
Contradictory Gain	0.179	0.451	0.288	0.219
Contradictory Loss	-0.548	0.013	-0.438	0.053

r: Two-tailed uncorrected Pearson's correlation coefficient.

Table 3. Correlations between trait anxiety and learning performance in the fMRI study. Data was normalized based on the Neutral condition.

Condition	Trials 16-20	
	r	p-value
Affirmative Gain	0.640	<0.001
Affirmative Loss	0.049	0.810
Contradictory Gain	0.351	0.073
Contradictory Loss	-0.394	0.042

r: Two-tailed uncorrected Pearson's correlation coefficient.

Table 4. Correlations between trait anxiety and the proportion of win-stay / lose-shift responses following neutral feedback in the fMRI study. Data was normalized based on the Neutral condition.

Condition	Win-stay		Lose-shift	
	r	p-value	r	p-value
Affirmative Gain	x	X	0.343	0.080
Affirmative Loss	x	X	0.108	0.591
Contradictory Gain	-0.134	0.505	x	X
Contradictory Loss	-0.420	0.029	x	x

r: Two-tailed uncorrected Pearson's correlation coefficient. X indicates that no such action was available for the neutral feedback in this condition.

Table 5. Model fits and parameters. Mean (SEM)

Parameters	Models									
	12φ	9φ	$6\varphi_0$	$3\varphi_0$	**φ_{0FF}, φ_{0NH}**	φ_{0FFG}, φ_{0FFL}, φ_{0NH}	φ_{+1H}, φ_{-1H}	3φ, 3ε	3φ, ε_{FF}, ε_{NH}	3φ, ε_{0FF}, ε_{0NH}
Negative LLE	110.8 (7.8)	113.6 (7.8)	113.9 (7.8)	117.8 (7.8)	**118.7 (7.8)**	117.8 (7.7)	117.3 (7.7)	117.7(7.8)	118.5(7.8)	118.6 (7.8)
BIC	303.9 (15.6)	291.9 (15.6)	286.8 (15.5)	276.9 (15.5)	**272.8 (15.6)**	276.8 (15.5)	275.9(15.5)	282.4 (15.6)	278.3 (15.5)	278.5 (15.5)
α	0.22 (0.04)	0.21 (0.04)	0.25 (0.04)	0.23 (0.04)	**0.21 (0.03)**	0.24 (0.04)	0.23 (0.04)	0.23 (0.04)	0.24 (0.04)	0.24 (0.04)
β	0.07 (0.01)	0.07 (0.02)	0.10 (0.02)	0.13 (0.02)	**0.12 (0.01)**	0.12 (0.02)	0.10 (0.02)	0.19 (0.04)	0.19 (0.03)	0.14 (0.03)
φ_{-1}			-0.25 (0.06)	-0.27 (0.07)	**-0.23 (0.06)**	-0.21 (0.06)		-0.77 (0.05)	-0.78 (0.05)	-0.26 (0.07)
φ_0							0.21 (0.06)	0.05 (0.08)	0.03 (0.08)	0.26 (0.12)
φ_{+1}			0.70 (0.06)	0.81 (0.06)	**0.87 (0.04)**	0.76 (0.07)		0.80 (0.06)	0.74 (0.06)	0.82 (0.06)
φ_{0NH}					**0.37 (0.06)**					
φ_{-1FFL}	-0.40 (0.08)	-0.23 (0.07)								
φ_{-1NL}	-0.25 (0.08)	-0.15 (0.06)								
φ_{-1HL}	-0.26 (0.08)	-0.25 (0.07)					-0.25 (0.08)			
φ_{0FFL}	0.15 (0.03)		0.21 (0.05)			0.27 (0.07)				
φ_{0NL}	0.20 (0.06)		0.26 (0.06)							
φ_{0HL}	0.16 (0.07)		0.22 (0.05)							
φ_{+1FFG}	0.59	0.50								

	(0.06)	(0.06)							
φ_{+1NG}	0.69 (0.06)	0.59 (0.07)							
φ_{+1HG}	0.62 (0.06)	0.53 (0.07)					0.71 (0.07)		
φ_{0FFG}	0.08 (0.09)		0.15 (0.09)			0.14 (0.12)			
φ_{0NG}	0.10 (0.09)		0.14 (0.09)						
φ_{0HG}	0.26 (0.08)		0.30 (0.09)						
φ_{0FF}		0.09 (0.05)		0.29 (0.07)	**0.35 (0.06)**				
φ_{0N}		0.15 (0.04)		0.33 (0.06)		0.29 (0.06)			
φ_{0H}		0.14 (0.05)		0.32 (0.07)					
$\varphi_{-1FF,NL}$							-0.18 (0.07)		
$\varphi_{+1FF,NL}$							0.59 (0.07)		
ε_{FF}								0.40 (0.09)	0.45 (0.06)
ε_{N}								0.48 (0.08)	
ε_{H}								0.44 (0.09)	
ε_{NH}									0.49 (0.06)
ε_{0FF}									0.04 (0.12)
ε_{0NH}									0.07 (0.11)

LLE is the log-likelihood estimate. BIC is the Bayes Information Criterion. α denotes the learning rate, β determines the trade-off between exploration and exploitation, φ_X is the subjective value for feedback combination X. For example, φ_{+1} is the subjective value for -1₪ feedback, φ_{+1} is the subjective value for +1₪ feedback, φ_{0FF} is the subjective value for the feedback combining 0₪ and fearful faces, and φ_{0NH} is the subjective value for 0₪ + happy or fearful face. ε_X is the bias added for feedback combination X. For example, ε_{0FF} is the bias term for neutral 0₪ feedback presented together with fearful faces, and ε_H is the bias term for happy faces.

Table 6. Repeated measures ANOVA. R DLPFC beta parameter estimates for the 'Basic' prediction error term.

Predictor	Sum of Squares	*df*	Mean of Squares	F	p	η_p^2

(Intercept)	3.449	1	3.449	18.393	< 0.001	
TrAnx	0.386	1	0.386	2.056	0.164	0.076
Error	4.688	25	0.1875			
GaLo	0.0005	1	0.0005	0.001	0.972	<0.0001
TrAnx x GaLo	0.003	1	0.003	0.008	0.927	0.0003
Error(GaLo)	10.02	25	0.401			
Feedback	0.024	1	0.024	0.185	0.671	0.007
TrAnx x Feedback	0.227	1	0.227	1.776	0.195	0.066
Error(Feedback)	3.196	25	0.128			
GaLo x Feedback	0.26061	1	0.261	1.357	0.255	0.051
TrAnx x GaLo x Feedback	0.001	1	0.001	0.004	0.951	0.0002
Error(GaLo x Feedback)	4.801	25	0.192			

TrAnx = Continuous covariate Trait anxiety; GaLo = Factor Gain/Loss (Gain or Loss pair); Feedback = Factor Feedback (Good, Bad). p_{GG} = Greenhouse-Geisser corrected p-value. η_p^2 = Partial eta-squared. * $p < 0.05$.

Table 7. Repeated measures ANOVA. R DLPFC beta parameter estimates for the 'Boost prediction error term.

Predictor	Sum of Squares	*df*	Mean of Squares	F	p	η_p^2
(Intercept)	0.131	1	0.131	1.389	0.250	
TrAnx	0.055	1	0.055	0.584	0.452	0.023
Error	2.365	25	0.095			
GaLo	0.009	1	0.009	0.067	0.798	0.003
TrAnx x GaLo	0.763	1	0.763	6.041	0.021	0.195
Error(GaLo)	3.158	25	0.126			
Feedback	0.027	1	0.027	0.171	0.683	0.007
TrAnx x Feedback	0.737	1	0.737	4.676	0.040	0.158
Error(Feedback)	3.939	25	0.158			
GaLo x Feedback	0.802	1	0.802	5.742	0.024	0.187
TrAnx x GaLo x Feedback	0.087	1	0.087	0.622	0.438	0.024
Error(GaLo x Feedback)	3.492	25	0.140			

TrAnx = Continuous covariate Trait anxiety; GaLo = Factor Gain/Loss (Gain or Loss pair); Feedback = Factor Feedback (Good, Bad). p_{GG} = Greenhouse-Geisser corrected p-value. η_p^2 = Partial eta-squared. * $p < 0.05$.

Table 8. Repeated measures ANOVA. Amygdala beta parameter estimates for the 'Basic' prediction error term.

Predictor	Sum of Squares	*df*	Mean of Squares	F	p	η_p^2
(Intercept)	0.16818	1	0.16818	2.3112	0.14099	
TrAnx	0.008879	1	0.008879	0.12202	0.72978	0.004857
Error	1.8192	25	0.072768			
GaLo	0.05135	1	0.05135	0.73074	0.40076	0.028399
TrAnx x GaLo	0.001819	1	0.001819	0.025884	0.87348	0.001034

Error(GaLo)	1.7568	25	0.070272			
Feedback	0.068436	1	0.068436	1.1218	0.29966	0.042946
TrAnx x Feedback	0.004216	1	0.004216	0.069115	0.79478	0.002757
Error(Feedback)	1.5251	25	0.061006			
GaLo x Feedback	0.013725	1	0.013725	0.25587	0.61741	0.01013
TrAnx x GaLo x Feedback	0.007149	1	0.007149	0.13327	0.71814	0.005302
Error(GaLo x Feedback)	1.3411	25	0.053643			

TrAnx = Continuous covariate Trait anxiety; GaLo = Factor Gain/Loss (Gain or Loss pair); Feedback = Factor Feedback (Good, Bad). p_{GG} = Greenhouse-Geisser corrected p-value. η_p^2 = Partial eta-squared. * $p < 0.05$.

Table 9. Repeated measures ANOVA. Amygdala beta parameter estimates for the 'Boost prediction error term.

Predictor	Sum of Squares	*df*	Mean of Squares	F	p	η_p^2
(Intercept)	0.012961	1	0.012961	0.18998	0.66668	
TrAnx	0.11583	1	0.11583	1.6977	0.20446	0.063589
Error	1.7057	25	0.068226			
GaLo	0.11561	1	0.11561	1.9114	0.17903	0.071026
TrAnx x GaLo	0.040593	1	0.040593	0.67114	0.4204	0.026144
Error(GaLo)	1.5121	25	0.060483			
Feedback	0.011858	1	0.011858	0.274	0.60527	0.010842
TrAnx x Feedback	0.026619	1	0.026619	0.6151	0.44024	0.024013
Error(Feedback)	1.0819	25	0.043276			
GaLo x Feedback	0.044516	1	0.044516	0.54709	0.4664	0.021415
TrAnx x GaLo x Feedback	0.076804	1	0.076804	0.94392	0.34058	0.036383
Error(GaLo x Feedback)	2.0342	25	0.081367			

TrAnx = Continuous covariate Trait anxiety; GaLo = Factor Gain/Loss (Gain or Loss pair); Feedback = Factor Feedback (Good, Bad). p_{GG} = Greenhouse-Geisser corrected p-value. η_p^2 = Partial eta-squared. * $p < 0.05$.

968 **Table 10.** Brain regions showing significantly positive correlations between BOLD signal and the
969 basic prediction error term. p_{FWE} indicates familywise error rate (FWEr) corrected p-values for peak
970 voxel activities across the whole-brain. T-statistics were obtained from *t*-tests. Initial search
971 threshold: p=0.001, minimum cluster size: 5 voxels.

Brain region	Hemisphere	MNI peak coordinate			T-value	P_{FWE}
		x	y	z		
Thalamus	Right	12	-6	12	8.517	<0.001
Superior frontal gyrus	Left	-6	26	54	8.498	<0.001
Supplemental Motor Area	Left	-8	20	44	8.325	0.001
Medial Frontal Gyrus	Left	-4	28	38	8.282	0.002
Caudate	Right	18	12	12	8.396	0.001
Supplemental Motor Area	Left	-6	8	62	8.347	0.001
Superior Frontal Gyrus	Left	-28	56	20	8.343	0.001
Putamen	Left	-22	4	8	8.293	0.001
Caudate	Left	-18	12	12	6.897	0.034
Putamen	Left	-32	-12	-4	8.205	0.002
Putamen	Left	-26	-10	2	7.283	0.015
Superior Frontal Gyrus	Left	-28	56	0	8.093	0.002
Supramarginal Gyrus	Left	-54	-46	36	7.899	0.004
Insula	Right	28	20	-10	7.796	0.004
Insula	Left	-30	26	-4	7.609	0.007
Insula	Left	-34	18	-10	7.397	0.011
Superior Frontal Gyrus	Right	22	58	28	7.544	0.008
Medial Frontal Gyrus	Left / Right	0	36	46	7.390	0.011
Supramarginal Gyrus	Right	54	-50	38	7.330	0.013
White Matter	Left	-12	-8	4	7.252	0.016
Midbrain	Left	-8	-24	-16	7.131	0.021

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Figure legends

Figure 1. A. Principle of the learning task in the pilot study. In each trial, participants select one object in a pair of objects. The best and worst object in each pair respectively provides correct feedback with a probability of 0.7 and 0.3. Each pair is presented 30 times, allowing participants to learn which the best object is by trial-and-error. B. Illustration of a trial progression. C. Schematic of the outcomes provided in each pair type in the pilot study. In total four different pairs types were presented: Contradictory Loss, Affirmative Loss, Contradictory Gain, and Affirmative Gain. D,E. The average change in performance across participants for the different pair types in Gain (D) and Loss (E) conditions. A hit is defined as the selection of the best object in a pair. F-I. Correlations between Trait anxiety and the average learning performance for trials 16-20 in Affirmative and Contradictory pair types. Trait anxiety correlated significantly with learning performance in Contradictory Loss pairs only (I). *p<0.05, ns=not significant (p>0.05), r = Pearson's correlation coefficient, ρ = Spearman's rank-order correlation coefficient.

Figure 2. A. Schematic of the outcomes provided in each pair type in the fMRI study. Neutral pairs acted as control conditions by presenting Neutral faces for both Correct and Incorrect outcomes. In total six different pairs types were presented: Contradictory Loss, Affirmative Loss, Neutral Loss, Contradictory Gain, Affirmative Gain, and Neutral Gain. B. The average change in performance across participants for the different pair types in Gain and Loss conditions. A hit is defined as the selection of the best object in a pair. Learning was statistically assessed via the average performance in trials 16-20. C-F. Learning in Affirmative and Contradictory pair types relative the Neutral control condition. Trait anxiety significantly improved/impaired learning in Affirmative Gain pairs (C)/Contradictory Loss pairs (F). G-J. Win-stay and Lose-shift decisions in Affirmative and Contradictory pair types relative their Neutral counterparts. Trait anxiety significantly increased behavioral switching in Affirmative Gain pairs (J) and in Contradictory Loss pairs (M). *p<0.05, ***p<0.001, ns=not significant (p>0.05).

Figure 3. A. Difference in Bayesian Information Criterion relative the most parsimonious model (highlighted in red). The inset shows the protected exceedance probability (XPp) for these models. The most parsimonious model was the most likely model, as evidenced by an exceedance probability of 1.0. B. The average model-simulated change in performance for the different conditions in Gain and Loss pairs. C-F. Model-simulated learning in Affirmative and Contradictory pair types relative their Neutral control conditions. Trait anxiety significantly improved/impaired learning in Affirmative Gain pairs (C)/Contradictory Loss pairs (F). G. Trait anxiety correlated negatively with the difference in the model-fitted subjective values of the neutral 0₪ outcome paired with fearful faces (φ_{0FF}) versus neutral/happy faces (φ_{0NH}). H,I. Model-simulated performance improvements for gradual changes in the difference between φ_{0FF} and φ_{0NH}. Smaller values of φ_{0FF} (vs. φ_{0NH}) improves performance in Affirmative Gain pairs (H), but impairs performance in Contradictory Loss pairs (I). For illustration purposes, the performance improvements for when φ_{0FF} is equal to φ_{0NH} is subtracted from all data points, the x-axis shows φ_{0NH}-φ_{0FF}, and the separate lines for Neutral and Contradictory pairs (relative Affirmative pairs) in H were merged into one line, and similarly were the lines for Neutral and Affirmative pairs (relative Contradictory pairs) in I. J-K. For a model that estimates separate values for the neutral 0₪ outcome paired with fearful faces in Gain (φ_{0FFH}) and Loss (φ_{0FFL}) conditions, trait anxiety correlated negatively with the difference in the fitted subjective value between the neutral 0₪feedback paired with fearful faces in both Loss (J) and Gain (K) pairs, as compared to neutral/happy faces. L-M. For a model that estimates separate values for the neutral 0₪ outcome paired with neutral (φ_{0N}) or happy (φ_{0H}) faces, trait anxiety correlated negatively with the difference in the fitted subjective value between the neutral 0₪feedback paired with fearful faces, as compared to both neutral (L) and happy (M) faces. *p<0.05, ** p<0.01, *** p<0.001.

Figure 4 A. Schematic of the functional localizer task. In each trial a number (-1, 0, +1) or face (Fearful, Neutral, Happy) was presented for 2.5s. Participants indicated whether the stimulus was perceived as negative, neutral, or positive. No feedback was presented and participants were not given any particular instructions regarding how stimuli should be categorized. B. The contrast between Neutral and Fearful faces revealed a region in the a priori R DLPFC mask that was significantly more activated by Neutral versus Fearful faces. C. For visualization purposes, the average beta parameter estimates for Neutral and Fearful faces were extracted for all voxels within the R DLPFC cluster shown in B. D. Trait anxiety correlated negatively with the contrast between Fearful and Neutral faces for the R DLPFC cluster. E. The contrast between Faces and Numbers revealed bilateral regions in the a priori amygdala mask that was significantly more activated by Faces versus Numbers. F. For visualization purposes, the average beta parameter estimates for Faces and Numbers were extracted for all voxels within the bilateral amygdala cluster shown in E. G. Trait anxiety did not correlate significantly with the contrast between Faces and Numbers for the amygdala cluster.

Figure 5. A. The R DLPFC ROI used to analyze prediction error encoding in the learning task. B. The average (solid line) and individual (dots) beta parameters for the 'Basic' prediction error term, δ_{Basic}, averaged across voxels within the R DLPFC for the four different feedback types. On average, activity in the R DLPFC ROI correlated significantly with the 'Basic' prediction error term independent of Feedback type and Trait anxiety. C. The average (solid line) and individual (dots) beta parameters for the prediction error 'Boost' term, δ_{Boost}, averaged across voxels within the R DLPFC for the four different feedback types. On average, activity in the R DLPFC ROI did not correlate with δ_{Boost} across the four feedback types, but showed significant interactions with trait anxiety and feedback types (see main text and D-G). D-G.

Correlations between trait anxiety and δ_{Boost} within the four different feedback types. Trait anxiety correlated positively with δ_{Boost} for Incorrect feedback in Gain pairs (D) and negatively with δ_{Boost} for Correct feedback in Loss pairs (G). The different feedbacks presented in each feedback type is shown above the corresponding plot. The fitted subjective values for the 0₪ feedbacks differed between fearful and happy/neutral faces. H. The amygdala ROI used to analyze prediction error encoding in the learning task. I. The average (solid line) and individual (dots) beta parameters for the 'Basic' prediction error term, δ_{Basic}, averaged across voxels within amygdala for the four different feedback types. On average, activity in the amygdala ROI did not correlate with the 'Basic' prediction error term nor was there any interaction with trait anxiety or feedback types. J. The average (solid line) and individual (dots) beta parameters for the prediction error 'Boost' term, δ_{Boost}, averaged across voxels within the amygdala ROI for the four different feedback types. On average, activity in the amygdala ROI did not correlate with δ_{Boost} nor were there any interactions with trait anxiety or feedback types. K-N. For visualization purposes, correlations between trait anxiety and δ_{Boost} for the four different feedback types are displayed. **p<0.01, ***p<0.001, ns = not significant (p>0.05).

Figure 6. A. Schematic of the ventral tegmental area (VTA) ROI. B. Average (solid line) and individual (dots) beta parameter estimates for the 'Basic' prediction error term, δBasic, within the VTA ROI. On average, BOLD signal in the VTA ROI correlated significantly with δBasic (p=0.001, one-tailed t-test). C-H. BOLD signal in the Midbrain, Dorsomedial PFC, Bilateral Striatum, and Bilateral Anterior Insula correlated significantly with δBasic after applying FWEr correction for the whole-brain. For visualization purposes, average (solid line) and individual (dots) beta parameter estimates were extracted from the peak voxels within each respective cluster. ** p<0.01.