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The dorsolateral prefrontal cortex reflects the impact of anxiety on drift rates during cognitive processing

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Declaration of Interests: The authors declare no competing interests.

Abstract

Generally, anxiety is thought to impair ongoing cognitive operations. Surprisingly, however, anxiety has been shown to improve performance during the Go/No-Go task. Understanding how anxiety can facilitate task performance may shed light on avenues to address the cognitive deficits commonly associated with anxiety. Here, we set out to identify the computational processes and neural mechanisms underlying the impact of anxiety on Go/No-Go task performance using a combination of computational drift diffusion models and ultra-high field (7T) functional MRI. Hierarchical Bayesian analysis suggest that anxiety, induced using the delivery of unpredictable electrical shock, was associated with a higher drift rate process which is thought to reflect increased informational uptake. Additionally, changes in drift rate during the anxiety condition were associated with enhanced BOLD responses within the dorsolateral prefrontal cortex and posterior cingulate cortex during No-Go trials. This relationship may reflect the impact of induced anxiety on the activity of ramping neurons within the dorsolateral prefrontal cortex, whose activity patterns mimic the drift rate process. Collectively, these results shed light on the mechanisms underlying facilitated task performance and suggest that anxiety can improve cognitive processing by enhancing information uptake and increasing activity within prefrontal and posterior cingulate cortices.

Introduction

One of the functions of emotion is to prepare organisms to cope with challenges in the environment (Levenson, 2011). Anxiety is characterized by an attentional bias towards threat and researchers have suggested that anxiety impairs cognitive performance unless the task involves the processing of threatening stimuli (Eysenck et al., 2007; Pessoa, 2009). Consistent with this view, experimental anxiety from the unpredictable delivery of electrical shock (i.e. induced anxiety) has been shown to impair working memory (Vytal et al., 2013; Balderston et al., 2017b), cognitive flexibility (Yancey et al., 2019), and measures of response inhibition assessed using the stop signal paradigm (Roxburgh et al., 2019, 2020). Contrary to this view however, induced anxiety has been consistently shown to improve performance during Go/No-Go paradigms (Robinson et al., 2013a; Torrisi et al., 2016; Aylward and Robinson, 2017; Grillon et al., 2017; Mkrtchian et al., 2017), a finding which is difficult to reconcile with existing theories of how anxiety and cognition interact. Identifying the mechanisms underlying the impact of induced anxiety on Go/No-Go paradigms may provide a deeper understanding of the divergent effects of anxiety on task performance and may shed light on how threat impacts neural circuits which support cognitive processes in the human brain.

Although researchers have suggested that induced anxiety can enhance Go/No-Go performance by facilitating response inhibition (Robinson et al., 2013a; Grillon et al., 2017), recent evidence suggests a more complicated relationship. First, induced anxiety impairs measures of response inhibition during the stop-signal task (Roxburgh et al., 2019, 2020). Second, research has demonstrated that induced anxiety improves accuracy during both go trials and no-go trials when Go/No-Go paradigms involve variable inter-trial intervals (Torrisi et al., 2016). Collectively, these data suggest that the impact of induced anxiety on Go/No-Go task performance is not solely attributable to improvements in response inhibition. Importantly, changes in accuracy between different experimental conditions can reflect multiple processes. One potential approach to understanding how induced anxiety impacts Go/No-Go performance is to utilize computational models to identify the mechanisms underlying changes in task processing between conditions.

The drift diffusion model (DDM) is the most common computational model for characterizing performance during the Go/No-Go paradigm. The DDM is comprised of four parameters and is designed to implement an optimal solution strategy for any two alternative (A or B) forced choice task. These four parameters are drift rate, boundary separation, starting point, and non-decision parameters. The drift rate parameter corresponds to a random walk process that proceeds from an initial starting point and eventually crosses the upper boundary to trigger response A (i.e. a Go response) or eventually crosses the lower boundary to trigger response B (i.e. a No-Go response) (See Figure 1 for illustration). The drift rate parameter corresponds to information uptake with higher drift rates reflecting faster arrival at the threshold for making

a decision. The boundary separation parameter corresponds to how much information is required to make a decision. A higher boundary parameter means that more evidence accumulation is necessary for that information to trigger a decision. The third parameter is the starting point for the random walk process, and corresponds to a response bias for either response A or response B. Finally, the non-decision parameter reflects aspects of processing unrelated to decision making and represents sensory encoding and motor execution. Here, we set out to estimate model parameters explaining variability in Go/No-Go accuracy and reaction time to identify the processes underlying improved task performance during experimentally induced anxiety.

In addition to identifying the processes that underlie induced anxiety's impact on Go/No-Go performance, computational models can help shed light on the role of neural circuits in processing interactions between anxiety and cognition. Computational models can facilitate the search for neural circuits underlying complex cognitive processes (Wang et al., 2020). Evidence suggests that neurons within the lateral prefrontal and parietal cortices exhibit ramping activity that terminates at response selection, consistent with patterns characterizing the drift rate process of the DDM model (Shadlen and Newsome, 2001; Ding and Gold, 2012). Consistent with the idea that these circuits reflect drift rate processes, evidence suggests that Go/No-Go paradigms preferentially engage fronto-parietal cortices (Swick et al., 2011) and that variability in BOLD responses within these regions are associated with Go/No-Go task performance (Sakai et al., 2013). Although previous research has demonstrated that induced anxiety enhances BOLD activity within the lateral prefrontal and parietal cortices during Go/No-Go paradigms, these responses were not significantly associated with changes in task performance during the anxiety condition (Torrissi et al., 2016). It is possible that testing for associations between neural activity and model parameters, rather than univariate measures of accuracy, would help to identify the neural circuits underlying the impact of induced anxiety on task performance during the Go/No-Go paradigm.

In the present study, we utilized a combination of hierarchical Bayesian analysis and ultra-high field (7 tesla) functional magnetic resonance imaging (fMRI) to investigate the mechanisms underlying the impact of induced anxiety on cognitive performance during the Go/No-Go paradigm. We collected behavioral responses and BOLD signal while participants performed a Go/No-Go paradigm during periods of safety and periods of anxiety induced by the delivery of unpredictable electrical shock. We calculated estimates of (1) drift rate, (2) boundary separation, (3) starting point, and (4) non-decision time by fitting computational drift-diffusion models to trial-by-trial measures of accuracy and reaction time. We then tested the impact of induced anxiety on the estimation of model parameters. Additionally, we tested whether differences in BOLD responses within the fronto-parietal circuit were associated with changes in model

parameters during the anxiety condition. Previous research has demonstrated that induced anxiety increases activity within the lateral prefrontal and parietal cortex (Torrissi et al., 2016), and that these regions contain ramping neurons which mimic drift rate processes (Shadlen and Newsome, 2001; Ding and Gold, 2012). Based on this evidence, we hypothesized that induced anxiety would enhance drift rates during the Go/No-Go paradigm and that increased drift rates would be reflected in enhanced activity within the fronto-parietal circuit.

Results

Subjective state

Self-reported anxiety

Paired t-tests demonstrated that retrospective self-reported anxiety was greater [$t(34) = 10.31$, $p < 0.001$] during the anxiety condition ($M = 6.23 \pm 2.33$ SD) than the safe condition ($M = 2.11 \pm 1.62$ SD).

Go/No-Go task performance

Accuracy

Repeated measure ANOVAs revealed two main effects, for trial-type [$F(1,38) = 77.07$, $P < 0.001$] and for threat [$F(1,38) = 5.03$, $P < 0.05$]. Accuracy was higher for go trials ($M = 0.937 \pm 0.098$ SD) than no-go trials ($M = 0.737 \pm 0.164$ SD). Accuracy was higher during the anxiety condition ($M = 0.848 \pm 0.124$ SD) than the safe condition ($M = 0.826 \pm 0.114$ SD). The interaction between trial-type and threat was not significant [$F(1,38) = 1.49$, $P = 0.23$].

Reaction Times

Repeated measure ANOVAs showed no main effects for trial type or threat, and no interactions between trial-type and threat (all P 's > 0.12).

Drift Diffusion Model

Model selection

The winning model (i.e., lowest deviance information criterion (DIC) value) was characterized by: (1) drift rate, boundary separation, and non-decision time parameters were estimated separately for the safe and

anxiety conditions and (2) starting point parameters were estimated jointly across both conditions (see **Supplemental Material: Results: Model Selection** for full details).

Assessment of model fit

R-hat statistics did not detect problems with Monte Carlo Markov Chain (MCMC) convergence (all R-hats > 1.01). Additionally, MC error statistics suggested acceptable model convergence (all Monte Carlo (MC) error statistics are < 1% of the posterior standard deviation). Finally, visual inspection of traces, autocorrelations and histograms of all parameters of the model suggested acceptable chain convergence (see **Supplemental Figure S1-S4**). Individual model parameters were associated with between-subject differences in accuracy for each trial and condition (**Supplemental Material: Results: Associations between model parameters and observed data**).

Impact of induced anxiety on model parameters

Bayesian hypothesis testing suggested that there was moderate evidence that the anxiety condition increased the drift diffusion parameter compared to the safe condition (90.8% probability). Bayesian hypothesis testing suggested that there was inconclusive evidence that the anxiety condition increased other model parameters (boundary separation: 67.9% probability; non-decision time: 65.1% probability).

BOLD fMRI

Impact of trial type on BOLD responses

Whole brain analyses demonstrated that BOLD responses during the safe condition were consistent with prior work (for full details, see **Supplemental Material**). Briefly, Go trials elicited enhanced BOLD in left primary motor cortex, the supplemental motor area, and the anterior cerebellum (**Supplemental Table S1, Supplemental Figure S5**). No-Go trials elicited enhanced BOLD responses within the dorsal anterior cingulate cortex/supplemental motor area, anterior insular cortex, and inferior parietal cortex (**Supplemental Table S2, Supplemental Figure F6**).

Impact of induced anxiety on BOLD responses

Whole brain analyses demonstrated that during Go trials, induced anxiety enhanced BOLD responses within the right inferior frontal gyrus, anterior cerebellum, and lateral parietal cortex (for full details, see Table 1, Figure 3). During No-Go trial, anxiety enhanced BOLD responses within the anterior cerebellum, the right inferior frontal gyrus, and the right dorsolateral prefrontal cortex (for full details, see Table 2, Figure 4).

Associations between model parameters and BOLD responses

During No-Go trials, changes in the drift rate parameter were positively associated with enhanced activity within the dorsolateral prefrontal cortex (BA 9) [$F = 29.92$, $kE = 30$, $x = 50$, $y = 19$, $z = 26$] and posterior cingulate cortex (BA 23) [$F = 21.56$, $kE = 32$, $x = 5$, $y = -60$, $z = 12$] (Figure 5). Whole brain analyses failed to detect any significant relationship between changes in the drift rate parameter and changes in BOLD responses to Go trials during the anxiety condition after correction for multiple comparisons.

Discussion

We used the DDM to identify the mechanisms underlying the impact of induced anxiety on task performance during a Go/No-Go paradigm. As expected, anxiety improved accuracy during the task. Here, a hierarchical Bayesian analysis suggests that anxiety increased the drift rate parameter, reflecting faster information uptake. Additionally, increased drift rates during the anxiety condition were positively associated with BOLD activity within the dorsolateral prefrontal cortex and posterior cingulate cortex during No-Go trials. Researchers have suggested that induced anxiety promotes an external focus of attention and may function to enhance vigilance and facilitate the detection of environmental threat (Balderston et al., 2017a). The results suggest that anxiety facilitates cognitive processing during Go/No-Go paradigms by increasing the rate of information uptake. This facilitation is associated with enhanced neural activity within prefrontal and posterior cingulate cortex. Collectively, these data shed light on the mechanisms underlying interactions between anxiety and cognitive processing in the human brain.

Our results show that induced anxiety improved task performance during the Go/No-Go paradigm, consistent with previous research (Robinson et al., 2013a; Torrisi et al., 2016; Aylward and Robinson, 2017; Grillon et al., 2017; Mkrtchian et al., 2017). In contrast to suggestions that anxiety impairs cognitive performance unless the task involves the processing of threatening stimuli (Eysenck et al., 2007; Pessoa, 2009) our results demonstrate that under certain circumstances, anxiety can facilitate cognitive processing. There is mixed evidence that threat of unpredictable shock can improve performance on Stroop paradigms, however it is unclear whether these results are confounded by speed-accuracy tradeoffs (for discussion, see Robinson et al., 2013b). The drift diffusion model may be able to resolve the question of how induced anxiety impacts Stroop performance by estimating model parameters using a combination of accuracy and reaction times. Additionally, the DDM model can facilitate research investigating the divergent effects of anxiety on cognition by providing a common framework to investigate the impact of induced anxiety on Go/No-Go, stop-signal, Stroop, and other cognitive paradigms.

The increased drift rates during the anxiety condition were also associated with larger BOLD responses within the DLPFC during No-Go trials. The DLPFC is part of a network of brain regions involved with cognitive processing (Cieslik et al., 2013). Previous research has demonstrated that neurons in the lateral prefrontal cortex exhibit ramping activity that terminates at response selection, consistent with patterns characterizing the drift rate process of the DDM model (Ding and Gold, 2012). Additionally, disruption of DLPFC function using transcranial magnetic stimulation results in reduced drift rates during task processing (Philiastides et al., 2011). Taken together, these results suggest that anxiety may facilitate cognitive performance by enhancing drift rate activity within the dorsolateral prefrontal cortex during response selection. However, previous research has also demonstrated that between-subject differences in drift rates during Go/No-Go task processing are related to increased BOLD activity in lateral PFC during commission errors. Consequently, an alternative possibility is that the relationship between BOLD responses and drift rate reflects neural activity following, rather than during, response selection. Future work will require neuroimaging techniques with better temporal resolution to differentiate whether anxiety directly impacts ramping activity during response selection or whether anxiety impacts neural activity following commission errors on No-Go trials.

Increased drift rates during the anxiety condition were associated with larger BOLD responses in the posterior cingulate cortex during No-Go trials. The posterior cingulate cortex receives afferent projections from the dorsolateral prefrontal cortex (Morecraft et al., 2004). However, in contrast to the DLPFC, the posterior cingulate cortex, which is part of the default network, is frequently de-activated during cognitive tasks (Raichle, 2015). Consistent with this idea, our results demonstrate that No-Go trials significantly reduced BOLD responses in the posterior cingulate cortex during both safe and threat conditions (see Supplemental Material, for full details). Neurons within the lateral parietal cortex exhibit ramping activity that terminates at response selection (Shadlen and Newsome, 2001), consistent with patterns characterizing the drift rate process of the DDM model. However, it is unclear from our results whether responses within the posterior cingulate cortex are involved with emotional modulation of the drift rate during anxiety, or whether these neural responses directly reflect enhancement of the drift rate process *per se*. Future research will be required to shed light on the nature of the relationship between neural activity within the posterior cingulate cortex and improved Go/No-Go performance during induced anxiety.

Researchers have suggested that computational models can facilitate research addressing how neural circuits underlying complex cognitive processes (Wang et al., 2020). Our results demonstrated that BOLD responses within the DLPFC and posterior cingulate cortex reflect changes in drift rate during the anxiety condition. This suggests that computational parameters can aid research that seeks to understand the

relationship between brain function and behavior. Additionally, although anxiety did not significantly impact BOLD deactivation within the posterior cingulate cortex, there was a significant association between changes in drift rate and between-subject differences in posterior cingulate activity. The role of individual variability in brain function is often obscured in group level analyses, and our results can broaden our understanding of how neural circuits process interactions between anxiety and cognition at different levels of performance.

Strengths of the current study involve the use of a well-validated experimental paradigm, hierarchical Bayesian modeling, and ultra-high field (7T) fMRI. However, this study is not without limitations. First, our experimental design did not entail a sufficient number of trials to estimate separate model parameters for Go trials vs No-go trials or for accurate vs inaccurate responses. Additionally, our BOLD fMRI measurements did not have sufficient temporal resolution to dissociate activity following stimulus onset from activity following response initiation. Future research will be required to determine how induced anxiety impacts drift rates as a function of accuracy and trial type and to clarify how DLPFC and posterior cingulate activity support these processes. Additionally, the observation of a positive, rather than a negative, relationship between drift rates and BOLD activity within the posterior cingulate cortex is surprising. Previous research has suggested that deactivations within the posterior cingulate cortex support cognitive operations. However, our results suggest that posterior cingulate activity is positively associated with heightened drift rates during anxiety, which are thought to correspond to enhanced information uptake and presumably facilitate cognitive processing. In contrast to deactivations during cognitive paradigms, ongoing work has demonstrated that posterior cingulate cortex is activated during autobiographical memory, imagining the future, spatial navigation, and scene processing (Rolls, 2019). Although somewhat unexpected, our results demonstrating that posterior cingulate cortex activity is associated with enhanced drift rates during anxiety can inform ongoing theoretical work addressing the role of the posterior cingulate in emotional and cognitive processing.

These limitations notwithstanding, our results shed light on the mechanisms underlying induced anxiety facilitation of cognitive processing during the Go/No-go paradigm. Induced anxiety was associated with improved accuracy and enhanced drift rates during task processing. Additionally, enhanced drift rates during anxiety were associated with increased BOLD responses within the DLPFC and posterior cingulate cortex. These patterns may reflect enhanced information uptake and increased activity within cognitive neural circuits during anxiety induced using the delivery of unpredictable electrical shock. Collectively, our results suggest that computational models can help identify the mechanisms underlying the impact of

emotion on cognitive processes and shed light on the role of neural circuits in supporting interactions between anxiety and cognition in the human brain.

Methods

Participants

The sample reported here overlaps with the sample reported in (Torrissi et al., 2018). Whereas Torrissi et al.' study was a methodological paper focused on the main effects of "Go" trials to directly compare the statistical power resulting from 3T vs 7T fMRI, the present study is focused on differences in the computational processes and BOLD responses during the safe and threat conditions. Fifty right-handed volunteers were recruited via flyers, print advertisements and internet listservs for participation in this study. Written informed consent was obtained from all participants and approved by the National Institute of Mental Health (NIMH) Combined Neuroscience Institutional Review Board. All participants were free from the following exclusion criteria: (i) current or past Axis I psychiatric disorder as assessed through a clinician administered SCID-I/NP (First et al., 2002), (ii) first-degree relative with a psychotic disorder, (iii) medical condition conflicting with safety or design of the study, (iv) brain abnormality on magnetic resonance imaging (MRI) as assessed by a radiologist, (v) positive toxicology screen, or (vi) MRI contraindication. Eleven participants in total were excluded from functional magnetic resonance imaging (fMRI) analysis owing to problems with the reverse phase encoding EPI sequence (N=7), excessive head motion during fMRI (N=2), and failure to complete the behavioral task because of time constraints (N=2). The final sample for fMRI analysis consisted of 39 participants ($M = 27.5 \pm 7.22$ SD years; 18 women). Four participants did not complete self-reported measures of subjective state during the task and consequently the assessment of self-reported anxiety consisted of 35 participants.

Experimental paradigm

The experimental paradigm was based on the Sustained Attention to Response Task (SART) (Robertson et al., 1997). During the task, participants were presented with two stimuli: 1) a "=" symbol denoting a "Go" trial, during which participants were instructed to make a button press using the index finger of their right hand; and 2) a "0" symbol denoting a "No-Go" trial, during which participants were instructed to refrain from making a button press. Stimuli were presented for 250ms and trials were interleaved with a jittered intertrial interval of 1500, 2000, 2500, or 3000ms. To develop a strong prepotent motor response, 91% of trials were "Go" trials and 9% were "No-Go" trials. Trials were presented in blocks (51 trials per block) and there were 6 blocks in each run and 2 runs during the experiment (12 blocks / 612 trials in total). The task consisted of interleaved blocks of an experimentally induced anxiety condition and blocks of a safe

condition (3 blocks of each condition per run). Participants were told, during anxiety condition, that they could receive an electrical stimulus at any time. A total of two aversive electrical stimuli were delivered during the task (one stimulus in each run). Text stating that “You are now safe from shock” or “You are now at risk of shock” was displayed at the beginning of each block. A blue border surrounded the screen during safe blocks and a red border during threat blocks.

Shock procedure

The intensity of aversive electrical stimuli was calibrated to account for individual differences in subjective experience of the shock prior to the task. Participants identified a level of electrical stimulation that was “highly uncomfortable and aversive but not painful” using a 1-5 Likert scale. Electrical stimuli were delivered for 100 ms to the subject’s left wrist using a Digitimer constant current stimulator (DS7A; Digitimer, UK) via 2 Ag/AgCl 6 mm electrodes.

Self-reported anxiety

Following the scan, participants were asked to retrospectively report how anxious they felt during the safe condition and during the anxiety condition, using a 10-point Likert scale.

Computational modeling

Computational models were implemented in Python 3.0, using the Hierarchical Bayesian estimation of the Drift-Diffusion Model (HDDM) toolbox (Wiecki et al., 2013). Drift diffusion models were fit to trial-by-trial measures of accuracy and reaction times. Reaction times during incorrect Go trials and correct No-Go trials were coded as not a number (NaN). Four model parameters (i.e. drift rate, boundary separation, starting point, and non-decision time) were estimated either jointly across both safe and anxiety conditions, or separately for each condition, for a total of sixteen possible models. Five percent of all trials were assumed to be outliers and modeled under a different process (See **Supplemental Materials: Model code** for details). Deviance information criterion (DIC) scores were used to assess model fit and the lowest DIC score indicated the winning model. Monte Carlo Markov Chain (MCMC) convergence diagnostics were conducted by computing R-hat (Gelman-Rubin) statistics and Monte Carlo (MC) error statistics and by visual inspection of the traces of the posteriors. Difference scores reflecting changes in model parameters during the anxiety condition (anxiety minus safe) ± 3 SD from the mean were winsorized prior to being entered into multiple regression models predicting BOLD responses.

MRI data acquisition

MRI data were acquired using a Siemens Magnetom 7T scanner and Nova 32-channel head coil. Third-order shimming was used to correct for field inhomogeneities. Blood oxygen level-dependent (BOLD) signal was acquired using T2*-weighted echo-planar imaging (EPI) across 32 ascending interleaved axial slices using the following parameters: TR=2000 ms, TE = 27 ms, flip angle = 70°, 1.8 mm³ voxels, 1.98mm gap between slices, acquisition matrix = 108×108; 430 volumes (860 seconds). A reverse phase encoded EPI (30 s) sequence was also acquired at 7T for geometric distortion correction (Schallmo et al., 2021). A 0.7 mm isotropic T1-weighted anatomical image was also collected using a gradient-echo sequence (TR = 2200 ms, TE = 3.01, flip angle 7°, acquisition matrix = 320×320).

MRI preprocessing and analysis

FreeSurfer (Fischl et al., 2002) was used to generate white matter and ventricular images from the T1 weighted anatomical scan. Ventricular and white matter images were then resampled to 1.8 mm isotropic resolution. The rest of pre-processing and analysis was performed using Analysis of Functional NeuroImages (Cox, 1996). The first four functional volumes were discarded to allow for steady-state equilibrium. The preprocessing pipeline was generated using the `afni_proc.py` script. Functional volumes were slice-time corrected, re-aligned to the last functional volume, co-registered to the corresponding T1 weighted anatomical image, non-linearly warped to the “MNIa_caez_colin27_T1_18” template with 3dQwarp, smoothed using a 3.6mm FWHM kernel. Functional volumes maintained their 1.8mm isotropic resolution.

First-level general linear models were used to statistically remove variance associated with head motion. The six head motion parameters and their first order derivatives were added as regressors into the model. Other individual regressors included the volumes where the Euclidean norm motion derivative was greater than 0.3 mm or 10% of the voxels were outliers. Participants whose head motion exceeded 0.3 mm on more than 10% of functional volumes were excluded from analysis. The first three principal components from the time series extracted from the lateral ventricles, the first three principal components from the time series extracted from the third and fourth ventricles, and local white matter signal from a 15 mm sphere surrounding each gray matter voxel using the fast ANATICOR approach (Jo et al., 2010) were then regressed from the functional volumes in order to remove nuisance signals. Predictors of interest included the onset of (i) safe/Go trials, (ii) safe/No-Go trials, (iii) anxiety/Go trials, (iv) anxiety/No-Go trials, (v) the instructions screens preceding experimental blocks, and (vi) the aversive electrical stimuli. General linear tests were used in the first-level analysis comparing anxiety/Go trials to safe/Go trials and comparing anxiety/No-Go trials to safe/No-Go trials.

Statistical analysis

Paired t-tests were used to compare retrospective self-reported anxiety during the safe and anxiety conditions. Repeated measure analyses of variance (ANOVA) models were used to assess the impact of trial type (Go vs. No-Go) and experimental condition (safe vs anxiety) on trial accuracy.

Bayesian post-hoc tests were used to calculate the probability that the posterior for each model parameter was higher during the experimental anxiety condition compared to the safe condition using the HDDM toolbox. Probabilities lower than 89% were considered to be “inconclusive evidence” for the hypothesis, probabilities higher than 89% were considered to be “moderate evidence” for the hypothesis, and probabilities higher than 95% were considered to be “strong evidence for the hypothesis” (Makowski et al., 2019; Romero and Sprenger, 2020).

Group level analysis testing for the main effect of trial-type during the safe condition were conducted using one-sample t-tests on beta images corresponding to safe/Go trials and safe/No-Go trials using the AFNI program 3dttest++. Similarly, the impact of induced anxiety on BOLD responses was assessed using one-sample t-tests conducted on the statistical images of general linear tests comparing anxiety/Go trials to safe/Go trials and comparing anxiety/No-Go trials to safe/No-Go trials. The relationship between changes in the drift-rate parameter and changes in BOLD responses to Go and No-Go trials during the anxiety condition was tested using the AFNI program 3dMVM (Chen et al., 2014). Gender, age, and difference scores for the boundary separation, and non-decision time parameters were entered as covariates of no interest. All group level statistical maps were thresholded at $P < 0.05$, corrected across the whole brain based on cluster extent, using a cluster-forming threshold of ($P < 0.0005$, $k = 23$). Correction for multiple comparisons was performed via updated versions of 3dFWHMx and 3dClustSim which incorporate a mixed autocorrelation function to better model non-Gaussian noise structure (Cox et al., 2016; Eklund et al., 2016).

Acknowledgements

This work utilized the computational resources of the NIH HPC Biowulf cluster (<http://hpc.nih.gov>). This work was supported by the Intramural Research Program of the National Institutes of Mental Health, project no. ZIAMH002798 (clinical protocol 02-M-0321, NCT00047853) to CG.

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Figures

Figure 1. Illustration of the drift diffusion model (DDM). Jagged black line represents an individual random walk corresponding to the drift rate parameter. A response is initiated when the random walk crosses the upper boundary (corresponding to Response A) or the lower boundary (corresponding to Response B). The distance between the starting point and the upper boundary corresponds to the boundary separation parameter. The relative distance between the starting point of the random walk process and the upper and lower boundaries corresponds to the starting point parameter. The time gap between the onset of a stimulus and start of the evidence accumulation and the time gap between the crossing of the boundary and the conclusion of the motor response correspond to the non-decision time

Figure 2. Accuracy (% of correct responses) during the Go/No-Go paradigm as a function of trial type and condition illustrating higher accuracy during Go trials and higher accuracy during the anxiety condition. Error bars represent ± 1 standard error.

Figure 3. Statistical parametric map illustrating significantly larger BOLD responses during the anxiety condition within (A) anterior cerebellum, (B) inferior frontal gyrus, and (C) and lateral parietal cortex during Go trials.

Figure 4. Statistical parametric map illustrating significantly larger BOLD responses during the anxiety condition within (A) anterior cerebellum, (B) inferior frontal gyrus, and (C) dorsolateral prefrontal cortex during No-Go trials.

Figure 5. Statistical parametric map illustrating positive relationship between change in drift rate parameter and enhanced BOLD responses during the anxiety condition within (A) dorsolateral prefrontal cortex and (B) posterior cingulate cortex during No-Go trials.

Tables

Region	T statistic	Cluster size (kE)	X	Y	Z
Supplementary motor area (BA 6)	5.65	311	26.2	-9.7	65.5
Supplementary motor area (BA 6)	7.01	108	54.9	2.9	6.1
Supplementary motor area (BA 6)	4.82	33	-40.4	-6.1	51.1
Superior frontal gyrus (BA11)	6.43	91	13.6	58.7	-11.9
Middle frontal gyrus (BA 10)	5.2	28	27.9	53.3	22.3
Middle frontal gyrus (BA 10)	6.07	122	-35	46.1	22.3
Inferior frontal gyrus (BA 45), anterior insula	7.81	746	42.3	24.5	0.7
Inferior frontal gyrus (BA 44)	5.32	79	-42.2	17.3	9.7
Inferior frontal gyrus (BA 44)	4.81	38	-62	8.3	0.7
Orbital gyrus (BA 10)	5.93	26	47.8	51.5	-6.5
Subgenual anterior cingulate (BA 32)	-6.1	114	-13.4	31.7	-6.5
Subgenual anterior cingulate (BA 25)	-6.31	27	-2.7	13.7	-10.1
Precuneus (BA 7)	6.78	190	20.8	-49.3	61.9
Precuneus (BA 7)	5.15	60	2.8	-49.3	60.1
Precuneus (BA 7)	6.17	37	6.3	-78.1	45.7
Precuneus (BA 7)	6.01	28	2.8	-61.9	60.1
Precuneus (BA 7)	4.66	24	-4.4	-61.9	67.3
Angular gyrus (BA 39)	5.09	49	58.6	-49.3	11.5
Angular gyrus (BA 39)	4.93	26	-31.4	-54.7	40.3
Supramarginal gyrus (BA 40)	6.35	197	56.8	-24.1	18.7
Supramarginal gyrus (BA 40)	6.69	165	58.6	-40.3	27.7
Supramarginal gyrus (BA 40)	5.69	104	-58.4	-38.5	42.1
Supramarginal gyrus (BA 40)	5.66	101	-56.6	-31.3	22.3
Posterior cingulate cortex (BA 31)	5.28	44	-18.8	-34.9	40.3
Middle temporal gyrus (BA 21)	5.32	101	51.3	-31.3	-2.9
Inferior temporal gyrus (BA 37)	4.51	25	-56.6	-60.1	2.5
Anterior insula (BA 13)	5.35	54	-31.4	17.3	-10.1
Mid-insula (BA 13)	4.77	33	-38.6	8.3	4.3
Thalamus	6.44	60	1	-13.3	13.3
Anterior hippocampus	-4.85	24	29.8	-16.9	-15.5
Cerebellum	5.42	56	22.6	-49.3	-20.9
Cerebellum	5.48	40	29.8	-70.9	-22.7
Cerebellum	5.67	26	38.8	-81.7	-24.5
Cerebellum	7.76	1686	-26	-49.3	-26.3
Cerebellum	5.82	223	-33.2	-85.3	-24.5
Cerebellum	5.72	54	-53	-65.5	-24.5
Cerebellum	5.72	23	-35	-51.1	-33.5

Table 1. Coordinates, cluster sizes, and T statistics of brain areas exhibiting significantly larger BOLD responses during Go trials in the anxiety condition compared to the safe condition. Coordinates in MNI space.

Region	T statistic	Cluster size (kE)	X	Y	Z
Superior temporal gyrus (BA 22)	5.36	44	53.1	-13.3	-13.7
Dorsolateral prefrontal cortex (BA 9)	5.84	38	35.2	20.9	33.1
Inferior frontal gyrus (BA 47)	4.78	37	42.3	24.5	-1.1
Postcentral gyrus (BA 5)	4.51	23	26.2	-45.7	63.7
Angular gyrus (BA 39)	5.65	28	58.6	-45.7	29.5
Supramarginal gyrus (BA 40)	4.88	34	-65.6	-29.5	20.5
Cerebellum	5.97	52	1	-54.7	-22.7
Cerebellum	5.63	49	-0.8	-69.1	-11.9
Cerebellum	5.1	31	-26	-70.9	-17.3

Table 2. Coordinates, cluster sizes, and T statistics of brain areas exhibiting significantly larger BOLD responses during No-Go trials in the anxiety condition compared to the safe condition. Coordinates in MNI space.