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Fast Evidence Accumulation in Social Anxiety Disorder Enhances Decision Making in a Probabilistic Reward Task

Daniel G. Dillon[1, 2], Amit Lazarov[3], Sarah Dolan[4], Yair Bar-Haim[3], Diego A. Pizzagalli[1, 2], and Franklin R. Schneier[4, 5]

[1] McLean Hospital, Belmont, Massachusetts, United States
[2] Department of Psychiatry, Harvard Medical School
[3] School of Psychological Sciences, Tel Aviv University
[4] New York State Psychiatric Institute, New York, NewYork, United States
[5] Vagelos College of Physicians and Surgeons, Columbia University

Choices and response times in two-alternative decision-making tasks can be modeled by assuming that individuals steadily accrue evidence in favor of each alternative until a response boundary for one of them is crossed, at which point that alternative is chosen. Prior studies have reported that evidence accumulation during decision-making tasks takes longer in adults with psychopathology than in healthy controls, indicating that slow evidence accumulation may be transdiagnostic. However, few studies have examined perceptual decision making in anxiety disorders, where hypervigilance might enhance performance. Therefore, this study used the Hierarchical Drift Diffusion model to investigate evidence accumulation in adults with social anxiety disorder (SAD) and healthy controls as they performed a probabilistic reward task (PRT), in which social rewards were delivered for correct perceptual judgments. Adults with SAD completed the PRT before and after gaze-contingent music reward therapy (GCMRT), which trains attention allocation and has shown efficacy for SAD. Healthy controls also completed the PRT twice. Results revealed excellent performance in adults with SAD, especially after GCMRT: relative to controls, they showed faster evidence accumulation, better discriminability, and earned more rewards. These data highlight a positive effect of attention training on performance in anxious adults and show how a behavioral trait that is typically problematic—hypervigilance in SAD—can nevertheless confer advantages in certain contexts. The data also indicate that, in contrast to other forms of psychopathology, SAD is not characterized by slow evidence accumulation, at least in the context of the social PRT.

Keywords: social anxiety disorder, drift diffusion model, probabilistic reward, attention bias modification, gaze contingent music reward therapy

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Daniel G. Dillon https://orcid.org/0000-0002-1977-700X
Amit Lazarov https://orcid.org/0000-0002-2811-2739
Sarah Dolan https://orcid.org/0000-0002-7202-8008
Yair Bar-Haim https://orcid.org/0000-0002-4630-9180
Diego A. Pizzagalli https://orcid.org/0000-0002-7772-1143
Franklin R. Schneier https://orcid.org/0000-0002-2938-2693

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Correspondence concerning this article should be addressed to Daniel G. Dillon, McLean Hospital, 244 DeMarneffe Building, 115 Mill Street, Belmont, MA 02478, United States. Email: ddillon@mclean.harvard.edu

Watching a movie, we simultaneously apprehend color, motion, and form, and the experience feels seamless. Separate brain areas represent each of these object qualities (Seymour et al., 2010; Zeki et al., 1991), however, and thus while perception seems instantaneous and unitary, in fact it depends on continuously integrating multiple streams of information. A similar understanding has emerged for decision making. Presented with two options, we do not choose between them at once. Instead, the drift diffusion model (DDM; Ratcliff, 1978) proposes that we extract evidence in support of each option, compute a difference score to determine whether the evidence favors Option 1 or Option 2, and then take a step toward a threshold for the better option. These processes are referred to as "evidence accumulation," and they are performed repeatedly until the evidence for Option 1 or 2 crosses its threshold, at which point that option is chosen. The DDM can explain a wide range of choice behaviors (Ratcliff & McKoon, 2008), and the speed of evidence accumulation, captured by the DDM's drift rate parameter, has emerged as a valuable measure of the rate and quality of information processing (Lerche et al., 2020).

The mechanistic account of decision making provided by the DDM can also provide insight into psychopathology (White et al., 2010). Indeed, a recent study found that, relative to healthy controls, adults with attention deficit hyperactivity disorder, schizophrenia, and bipolar disorder showed slower evidence accumulation across three different tasks, leading to the proposal that slow evidence accumulation may be a "transdiagnostic vulnerability factor" for psychopathology (Sripada & Weigard, 2021). Consistent with this conceptualization, we recently used the hierarchical drift diffusion model (HDDM; Wiecki et al., 2013), a Bayesian implementation of the DDM, to uncover slow evidence accumulation in unmedicated adults with Major Depressive Disorder (MDD; Lawlor et al., 2020) as they performed a probabilistic reward task (PRT; Pizzagalli et al., 2005). In the current study, we built on this work by using the HDDM to analyze social PRT data collected from adults with social anxiety disorder (SAD).

The original PRT was designed to assess reward system function: it involves rapidly distinguishing between short and long lines, and correct identifications of lines of one length (the "rich" stimulus) are reinforced with monetary gains three times more frequently than correct identifications of lines of the other length (the "lean" stimulus). Due to the asymmetric reinforcement, psychiatrically healthy participants typically develop a response bias—they tend to respond "rich" more than "lean", regardless of whether the rich or lean stimulus is actually shown (Pizzagalli et al., 2005)—and several studies report that adults with anhedonia display weak response biases (Liu et al., 2016; Pizzagalli et al., 2008; Vrieze et al., 2013). Unexpectedly, our recent study (Lawlor et al., 2020) did not reveal a weaker response bias in adults with MDD versus healthy controls. The HDDM, however, indicated that evidence accumulation occurred more slowly in the MDD group than in the nondepressed control group, and this had important consequences. Specifically, individual differences in drift rate and discriminability (i.e., response accuracy) were strongly positively correlated, and both variables positively predicted cumulative reward totals. In other words, fast evidence accumulation supported response accuracy, and because rewards in the PRT are delivered for accurate identification of both the rich and lean stimuli, albeit at different rates, participants with faster drift rates tended to earn more rewards in the task. This led to an interesting finding: although there was no group difference in response bias, slow evidence accumulation (low drift rate) in adults with MDD led them to earn significantly fewer rewards than the controls did (Lawlor et al., 2020). In short, this study supports the claim that slow evidence accumulation may be transdiagnostic (Sripada & Weigard, 2021), and application of the HDDM revealed effects of depression on the speed of evidence accumulation, response accuracy, and cumulative reward totals that would not otherwise have been identified.

Administering the PRT to adults with SAD allowed us to test two contrasting sets of predictions that were informed by this earlier work, and by prior studies of social anxiety. The first set of predictions was guided by the hypothesis that SAD is associated with weak reward responses. Prior studies indicate that SAD is associated with diminished positive experiences (Brown et al., 2007; Kashdan, 2004, 2007), possibly due to abnormalities in brain reward circuity (Schneier et al., 2000; but see Schneier et al., 2009). As mentioned earlier, several prior PRT studies have found weaker response biases in adults with anhedonia relative to healthy controls (e.g., Liu et al., 2016; Pizzagalli et al., 2008). Moreover, in two community samples, Chevallier and colleagues (2016) found that social anhedonia was negatively correlated with response bias in a "social" PRT, where the rewards were video clips of smiling actors rather than monetary gains. Although social anhedonia and social anxiety are different they are related concepts (Brown et al., 2007), such that on balance this work suggested that social anxiety might be associated with elevated social anhedonia and weaker responses to social rewards. Therefore, we used the social PRT developed by Chevallier et al. (2016) in this study, to test the prediction that response bias magnitude would be lower in adults with SAD versus controls.

The second set of predictions was focused on visual perception. As noted above, the PRT demands rapid judgments about two similar stimuli. The literature emphasizes that adults with SAD readily make such judgements—they show excellent visual perception, even when nonemotional stimuli are used (e.g., Berggren et al., 2015). Moreover, event-related potential (ERP) studies point to a likely underlying mechanism: relative to healthy controls, adults with SAD generate higher amplitude P100 components in response to a variety of stimuli (Kolassa et al., 2007, 2009; Santesso et al., 2008). As the P100 is generated in extrastriate cortex (Clark et al., 1994), these data suggest that the visual system is particularly responsive in SAD, possibly due to hypervigilance (Bögels & Mansell, 2004). This prior work suggested that, relative to controls, adults with SAD would show better discriminability in the PRT. In other words, adults with SAD should more accurately classify the lines presented in the PRT as short or long.

Because our prior PRT study in MDD (Lawlor et al., 2020) found that discriminability and drift rate were strongly positively correlated, this reasoning led to an interesting prediction: contrary to what has been observed in most studies of psychopathology to date, drift rate should be faster in adults with SAD than it is in healthy controls. As noted above, our prior study in MDD (Lawlor et al., 2020) also showed that high discriminability and fast drift rates—because they allow participants to respond accurately on rich and lean trials—positively predicted cumulative reward in the PRT. This supported another prediction: reward totals should be higher in adults with SAD. Finding support for this second set of predictions—namely, that SAD would be associated with better discriminability, faster drift rates, and higher reward totals—would indicate that although the speed of evidence accumulation may be reduced in many conditions (Lawlor et al., 2020; Sripada & Weigard, 2021), this may not be so for anxiety disorders, at least in tasks that call for difficult perceptual decisions.

The study also afforded an opportunity to examine the impact of attentional training on PRT performance. A subset of participants in the SAD group completed the PRT twice, before and after undergoing gaze-contingent music reward therapy (GCMRT; Lazarov et al., 2017). GCMRT is an intervention designed to reduce threat bias in anxious individuals (Bantin et al., 2016; Bar-Haim et al., 2007; Chen & Clarke, 2017) using musical reward as reinforcement. During GCMRT, gaze is tracked as the participant views matrices of neutral and threatening faces. Rewarding music plays when gaze is directed at one of the neutral faces, but the music stops when the participant looks at threatening faces. This manipulation is intended to train attention allocation away from threat and onto neutral stimuli, and a randomized control trial yielded support for using GCMRT to treat SAD (Lazarov et al., 2017); relative to participants in a control condition, those receiving GCMRT demonstrated stronger reductions in threat bias and SAD symptoms, with symptom reduction remaining at 3-month follow-up.

In the current analysis, we examined whether GCMRT affected PRT performance in adults with SAD. Two possible effects of GCMRT were considered, to parallel the two sets of predictions described earlier. The first possibility was that reduction of SAD symptoms after GCMRT would be associated with improved reward system function. If this were the case, then response bias magnitude would increase from pre- to posttreatment. This possibility was suggested by small studies indicating that successful treatment of SAD with cognitive behavioral therapy (Cervenka et al., 2012) and selective serotonin reuptake inhibitors (Warwick et al., 2012) was associated with changes in the dopamine system, which supports reward processing (Schultz, 1998). The second possibility was that, because GCMRT reward fast, controlled allocation of attention among perceptually similar stimuli (i.e., away from threatening and toward neutral faces), it might further enhance perceptual decision making in the SAD group. This possibility is supported by numerous studies revealing that training attentional control yields generalizable benefits (Bherer et al., 2005; Ducrocq et al., 2016; Slagter et al., 2007), including in adults with anxiety (Sari et al., 2016). If GCMRT led to improved attentional control in the current study, then discriminability and drift rate, but not response bias, should increase from pre- to posttreatment in the SAD group.

To summarize, PRT data were collected from adults with SAD before and after GCMRT, and healthy controls also completed the task twice with a similar delay between sessions. The analysis was oriented around two sets of predictions. The first set concerned reward system dysfunction in SAD: relative to controls, socially anxious adults were expected to show a weaker response bias in the PRT, with this group difference (controls > SAD) growing smaller after GCMRT. The second set of predictions concerned perceptual ability and the speed of evidence accumulation: relative to controls, socially anxious adults were expected to show better discriminability, faster evidence accumulation, and higher reward totals in the PRT. Because GCMRT reinforces the controlled allocation of attention among similar stimuli (i.e., threatening and neutral faces), and because this attentional training might generalize to the PRT, the predicted group differences (SAD > controls) were expected to grow larger after GCMRT.

Materials and Method

Participants

PRT data were collected in two sessions separated by about 4 weeks (mean ± *SD* = 27 ± 12 days between sessions), hereafter referred to as "Session 1" and "Session 2." Adults with a principal diagnosis of SAD were recruited—via online advertisements, local media, and community postings—to complete a randomized control trial testing the efficacy of GCMRT. Based on prior work (Lazarov et al., 2017), GCMRT was expected to reduce dwell time on threatening faces with an effect size of $d = .68$. A sample size of 40 adults with SAD was thus planned, as this would yield 98% power to detect an effect this large. As described below, some participants completed the PRT in Session 1 but did not initiate GCMRT, which resulted in an increased sample size for the PRT analysis. Specifically, Session 1 was completed by 81 adults with SAD. Twenty age-, sex-, and race-matched adults with no lifetime psychiatric disorders were recruited as a healthy control (HC) group; the size of the HC group was not planned in advance. Session 2 was completed by 48 adults with SAD and 18 healthy controls. A quality control assessment, described below, was used to exclude problematic PRT data sets: 10 from Session 1 (3 HC, 7 SAD) and 13 from Session 2 (3 HC, 10 SAD). This left 74 SAD and 17 HC participants with usable PRT data in Session 1, and 38 SAD and 15 HC participants with usable PRT data in Session 2.

Participants were recruited from the New York metropolitan area; no detailed data on culture/geographic background were collected. The SAD sample was ethnically diverse (16% of Hispanic origin; 18% Black or African American; 23% Asian; 42% Caucasian; 14% more than one race; 4% other), as was the HC sample (16% of Hispanic origin; 32% Black or African American; 21% Asian; 42% Caucasian; 5% more than one race). For both groups, a roughly equal percentage indicated yearly household incomes above versus below $50,000 (HC: 53% above vs. 47% below; SAD: 51% above vs. 49% below). Additional demographic and clinical data are in Table 1. All participants provided written, informed consent to protocols approved by the New York State Psychiatric Institute Institutional Review Board (#7598 and #7527), and they were paid for their time.

Clinical Assessments

Psychiatric diagnoses were made by a psychiatrist using the Mini-International Neuropsychiatric Interview (Sheehan et al., 1998). The severity of social anxiety and depression were assessed with the clinician-rated Liebowitz Social Anxiety Scale (LSAS; Liebowitz, 1987) and the clinician-rated Hamilton Rating Scale for Depression (HAMD; Hamilton, 1960), respectively. A subset of participants (see the Table 1 note) also completed additional self-report measures—namely, the Snaith Hamilton Pleasure Scale (SHAPS; Snaith et al., 1995), the Revised Social Anhedonia Scale (RSAS; Eckblad et al., 1982), and the Quality of Life Enjoyment and Satisfaction Questionnaire (QLESQ; Endicott et al., 1993). Controls completed questionnaires in Session 1 only, whereas adults with SAD completed them at Sessions 1 and 2.

Eligibility Criteria

To be included in the SAD group, participants had to: have a primary *DSM–5* diagnosis of SAD; have an LSAS score ≥ 50; be between 18 and 60 years old; speak fluent English; and have normal

Table 1
Mean (SD) Demographic and Clinical Data for Participants With Usable PRT Data

Variable	HC	SAD	*t*-value	*p*-value	Cohen's *d*
		Session 1			
Gender*	10 f, 7 m	41 f, 31 m, 1 o	0.26	.88	0.00
Age (years)	27.71 (6.17)	27.62 (6.44)	0.05	.96	0.01
Education (years)	15.65 (2.03)	15.75 (1.70)	0.20	.84	0.06
LSAS	6.71 (6.89)	83.73 (14.98)	31.80	<.001	5.56
HAMD	0.47 (0.72)	6.01 (4.37)	10.32	<.001	1.40
RSAS	5.33 (3.50)	18.74 (5.99)	11.15	<.001	2.40
SHAPS	16.69 (4.13)	23.28 (5.79)	5.14	<.001	1.20
QLESQ	86.69 (9.36)	60.68 (13.58)	8.09	<.001	2.08
		Session 2			
Gender	7 f, 8 m	22 f, 16 m	0.19	.66	0.22
Age (years)	28.13 (6.40)	26.26 (5.50)	1.00	.33	0.32
Education (years)	15.40 (2.29)	15.47 (1.84)	0.11	.91	0.04
LSAS	—	76.21 (20.94)	—	—	—
HAMD	—	5.03 (3.64)	—	—	—
RSAS	—	15.17 (8.15)	—	—	—
SHAPS	—	22.52 (4.72)	—	—	—
QLESQ	—	64.17 (9.57)	—	—	—

Note. In Session 1, one participant in the SAD group was missing data for gender, education, and the LSAS. In Session 2, four participants in the SAD group were missing data for the LSAS and HAMD. The *t*-values, *p* values, and Cohen's *d* values correspond to between-group tests. PRT = probabilistic reward task; HC = healthy controls; SAD = adults with Social Anxiety Disorder; LSAS = Liebowitz Social Anxiety Scale; RSAS = Revised Social Anhedonia Scale; SHAPS = Snaith Hamilton Pleasure Scale; QLESQ = Quality of Life Enjoyment and Satisfaction Questionnaire. Only a subset of participants completed the RSAS (Session 1: 15 HC, 57 SAD; Session 2: 23 SAD), the SHAPS (Session 1: 16 HC, 58 SAD; Session 2: 23 SAD) and the QLESQ (Session 1: 16 HC, 38 SAD; Session 2: 23 SAD).
*For gender, count data are listed (f = female, m = male, o = other) and a χ^2 value is given instead of a *t*-value.

or corrected-to-normal vision (excluding multifocal eye wear) for eye tracking. An LSAS cutoff score of 50 was used as this identifies SAD with an optimal balance of specificity and sensitivity (Amir & Taylor, 2012; Mennin et al., 2002). Exclusion criteria were: (a) current severe depression (HAMD score > 20); (b) clinically significant suicidal ideation or behavior; (c) current or past psychosis; (d) current or past diagnosis of posttraumatic stress disorder, obsessive–compulsive disorder, bipolar disorder, manic episode, tic disorder, or attention deficit hyperactivity disorder; (e) severe alcohol or cannabis use disorder, or any other substance use disorder (except nicotine use disorders); (f) current unstable or untreated medical illness; (g) current or past organic mental disorder, seizure disorder, or brain injury; (h) use of any psychotropic medication in the past month, with the exception of serotonin reuptake inhibitors, serotonin-norepinephrine reuptake inhibitors, or zolpidem for sleep, if taken at a stable dose for at least 3 months; and (i) concurrent psychotherapy initiated within the past 3 months. To qualify for the HC group, participants had to be 18–60 years old, fluent in English, have normal or corrected-to-normal vision (excluding multifocal eye wear), and have an LSAS score < 30. Exclusion criteria for the HC group were: (a) current or past history of any *DSM–5* psychiatric disorder; (b) current or past organic mental disorder, seizure, or brain injury; and (c) current unstable or untreated medical illness. Of the 74 participants with SAD who had usable PRT data in Session 1, seven also met criteria for Major Depressive Disorder, four met criteria for Generalized Anxiety Disorder, and four met criteria for Panic Disorder. Eight participants were on stable medication (7 SSRI, 1 SNRI).

PRT

Participants completed three 100-trial blocks of the social PRT (Chevallier et al., 2016); which is depicted in Figure 1A. On each trial, participants viewed a central fixation cross (duration: 500 ms) followed by an empty circle (500 ms). A "short" (11.5 mm) or "long" (13.0 mm) line was then briefly presented (100 ms) in the circle. The task was to indicate, by button press, whether a short or long line had been shown. There was no time limit for responding. Once a response was made, participants saw a blank screen or a silent video clip of a smiling, nodding actor giving a "thumbs up" gesture for 1,750 ms; the video clips constituted social reward. The task was coded in E-Prime Version 2.0 (Schneider et al., 2002) and presented on a 17" monitor (38 × 21 cm; 1,152 × 864 pixels resolution). Participants were seated about 50 cm away from the monitor and responded on a keyboard.

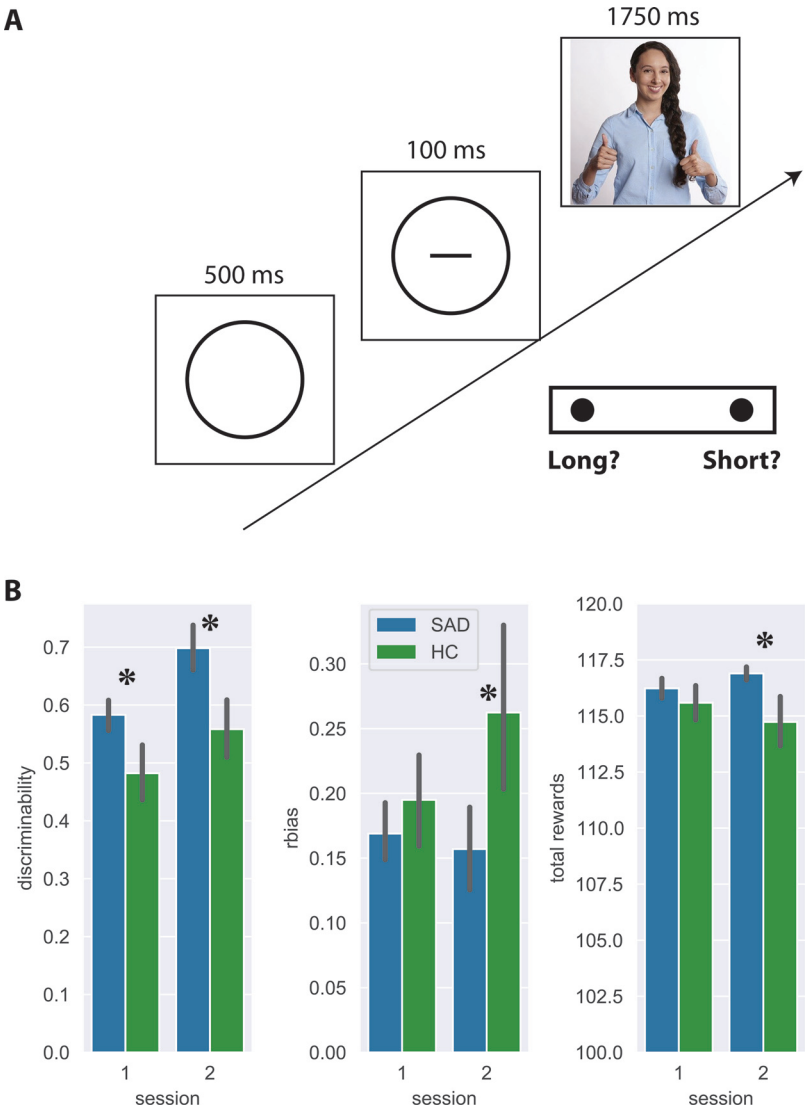
An equal number of short and long lines was presented in each block, but asymmetric reinforcement was delivered: correct identifications of one line length, the rich stimulus, were rewarded three times more frequently than correct identifications of the other line length, the lean stimulus. This manipulation consistently induces a response bias such that participants respond "rich" more than "lean." Assignment of long and short lines to the rich and lean conditions was counterbalanced across participants. After receiving instructions, participants completed five practice trials and were then left alone to finish the PRT.

GCMRT

In between Sessions 1 and 2, adults with SAD were invited to complete four 20-min sessions, twice per week, of GCMRT (Lazarov et al., 2017); the HC group received no intervention. At the outset of each GCMRT session, participants selected the background music that would be used during the session from a menu of popular recordings. Next, a 5-point gaze calibration, followed by 5-point validation, was completed. Calibration was repeated if visual deviation was > .5 °F on the X or Y axis of any of the validation points, and training began only when these parameters were achieved. Following

Figure 1

The Social PRT (A) and Group Differences in Discriminability, Response Bias, and Cumulative Reward by PRT Session (B)



Note. Asterisks mark significant ($p < .05$) group differences. Error bars show S.E.M. The picture in Figure 1A is from http://www.pixabay.com (contributor: Robin Higgins) and is free for use without permission; in the task, silent video clips were used. PRT = probabilistic reward task; HC = healthy controls; SAD = adults with Social Anxiety Disorder. See the online article for the color version of this figure.

calibration/validation, the GCMRT session started; this comprised 30 consecutive trials during which gaze data were recorded, each trial showing a 4 × 4 matrix of color faces from the Karolinska Directed Emotional Faces database (Lundqvist et al., 1998) for 24 seconds. Each matrix included 16 unique actors (8 female, 8 male), with half expressing no emotion (neutral faces) and half expressing disgust (threatening faces). The spatial assignment of neutral versus threatening faces was randomized, but the four inner faces always included two neutral and two threatening expressions (whose location was also randomized). Participants were free to view the faces however they wished, but music played only when gaze was directed at neutral faces; when participants gazed at threatening faces, it stopped. Participants were seated about 70 cm away from a 24-in. monitor (resolution: 1,920 × 1,080 pixels) and their eye movements were recorded (sampling rate: 500 Hz) with an Eyelink 1000+ eye tracker (SR Research Ltd., Mississauga, Ontario, Canada).

Many participants in the SAD group who completed the PRT in Session 1 did not initiate GCMRT, and some participants with usable PRT data from Sessions 1 or 2 did not have usable gaze data from the corresponding—first or fourth—GCMRT session. The

final data set included: 74 adults with SAD with usable Session 1 PRT data (37 of whom also had gaze data from the first GCMRT session); 38 adults with SAD with usable Session 2 PRT (28 of whom also had gaze data from the fourth GCMRT session); and 28 adults with SAD who had both usable PRT data from Sessions 1 and 2, and usable gaze data from the first and fourth GCMRT sessions. Note that while PRT Session 1 occurred before the first GCMRT session, PRT Session 2 occurred within a week after the fourth GCMRT session. PRT data were thus collected before (Session 1) and after (Session 2) GCMRT was administered.

Data Analysis

Clinical Assessments

All statistical analyses were conducted using the R software package (R Core Team, 2016). Group differences in demographics and clinical measures at Session 1 were examined using *t*-tests and are shown in Table 1. Changes in the SAD group from Session 1 to 2 were assessed with paired *t*-tests and are presented in the Results. The SHAPS was scored by summing all items (Franken et al., 2007), so higher scores indicate greater anhedonia.

GCMRT

The efficacy of GCMRT in reducing attention bias toward threat was assessed by comparing the percent dwell time on threatening faces in the fourth GCMRT session versus the first. The percentage of time spent dwelling on threatening faces relative to all faces was calculated and analyzed in a linear mixed model with *session* as a fixed effect and subjects modeled as random intercepts, using the R package *lmerTest* (Kuznetsova et al., 2017). In the first GCMRT session, only the first five trials were used in this analysis, as in our prior work (Lazarov et al., 2017); this provides an approximate baseline measure of threat bias in the first session, before any improvement associated with GCMRT can emerge. In the fourth GCMRT session, all the trials were used to calculate the percentage dwell time on threat. All SAD participants with usable gaze data from either session (GCMRT Session 1, $n = 37$; GCMRT Session 4, $n = 28$) were included in this analysis.

PRT

As in prior studies (Pizzagalli et al., 2005), the PRT data were cleaned by removing trials where the raw response time (RT) was faster than 150 ms or slower than 2,500 ms, or where the participant's log-transformed RT exceeded their mean ± 3 SD log-transformed RT (computed separately for rich vs. lean trials, as RT is typically shorter on rich trials). This resulted in the removal of 5.11% of trials. Quality control checks were performed next using prespecified cutoffs. Data sets were excluded if, in any block: more than 20 trials were removed as RT outliers; fewer than 20 rewards were earned on rich trials; fewer than six rewards were earned on lean trials; or the rich/lean reward ratio—the number of rewards earned on rich trials, divided by the number of rewards earned on lean trials—was lower than 2.0. These checks ensured that the analyzed PRT data came from participants who attended to the task, performed it correctly, and experienced the asymmetric rewards contingency. As noted earlier, this resulted in the removal of 10 data sets from Session 1 (3 HC, 7 SAD) and 13 from Session 2 (3 HC, 10 SAD).

Following many prior studies, analysis initially considered cumulative reward, response bias, and discriminability, each calculated by block (Lawlor et al., 2020; Pizzagalli et al., 2005, 2008). Cumulative reward corresponds to the total number of rewards received. Response bias quantifies the tendency to more frequently respond "rich" versus "lean" due to the asymmetric reinforcement. It was computed as:

$$response\ \ bias = \frac{1}{2} log\left(\frac{Rich_{correct} \times Lean_{incorrect}}{Rich_{incorrect} \times Lean_{correct}}\right)$$

Discriminability quantifies the capacity to respond accurately. It was computed as:

$$discriminability = \frac{1}{2} log\left(\frac{Rich_{correct} \times Lean_{correct}}{Rich_{incorrect} \times Lean_{incorrect}}\right)$$

Note that the cell labels (e.g., "$Rich_{correct}$") in the formulas above correspond to the number of trials of that type per block. To enable calculation of response bias and discriminability in cases where accuracy was at ceiling or floor, each cell was initialized to .5 (Hautus, 1995).

Cumulative reward, response bias, and discriminability results were analyzed by: (a) using the R function *lm* to estimate a first linear model with main effects of Group and Block, plus a second model including a Group × Block interaction; (b) comparing the two models by using the R function *anova* to compute a chi-square test on likelihood ratios; and (c) reporting on the parameters of the better fitting model. Unless stated otherwise, this and all other PRT analyses described below were conducted separately for Session 1 and Session 2.

Recent PRT research revealed a dependency between accuracy and RT: there was a larger effect of stimulus type (rich > lean) on accuracy for fast RTs versus slower RTs (Lawlor et al., 2020), indicating that response bias is primarily carried by trials with fast responses (White & Poldrack, 2014). To test whether this finding was replicated in the current sample, and to gain additional insight into group differences in discriminability, trial-level accuracy (0 = incorrect, 1 = correct) data from each session were analyzed using generalized linear models computed with *lme4*. The models included main effects and all interactions of Group (HC, SAD), Stimulus type (rich, lean), and Response type (fast RT, slow RT), where—as in our prior study (Lawlor et al., 2020)—fast RTs were defined as those faster than the .3 quantile of the participant's RT distribution. Participants were modeled with random intercepts.

Finally, we examined relationships between cumulative reward and response bias versus discriminability, averaged over all trials within a session. The strength of these relationships was compared using a test for dependent correlations (Meng et al., 1992). To determine whether session effects on PRT performance were directly related to GCMRT, we also computed correlations relating (a) changes in threat bias (percent dwell time on threat, fourth minus first GCMRT session) to (b) changes in response bias and discriminability (PRT Session 2 minus Session 1). This last set of analysis was restricted to the 28 adults with SAD who had usable

PRT data from Sessions 1 and 2, and usable gaze data from GCMRT Sessions 1 and 4.

Computational Modeling

The HDDM (Wiecki et al., 2013) was fit to the PRT data to quantify the speed of evidence accumulation and to characterize the underlying cognitive processes that supported behavior. As in our prior study (Lawlor et al., 2020), we used the HDDM "Stim-Coding" model, coded the stimuli and responses as "rich" or "lean", included starting point bias, and allowed all four model parameters—decision threshold (a), nondecision time (t), drift rate (v), and starting point bias (z)—to vary by Group. It is important to determine if a model has converged on a stable fit before interpreting its parameters. Consequently, the models were initially run three times (2,000 samples, 500 burn-in, every fifth sample retained) and the Gelman Rubin statistic was computed (Gelman & Rubin, 1992). This exercise yielded across-run maximum $\hat{R}$ values of 1.03 (Session 1) and 1.02 (Session 2), which are below the recommended threshold of 1.1 and indicate convergence. For improved visualization of parameter distributions, the final model involved drawing 10,000 samples from the posterior (5,000 burn-in, every fifth sample retained); visual inspection of posterior plots from this model also indicated convergence. Finally, the HDDM *post_pred_gen* tool was used to run 500 simulations in which parameters were randomly drawn from participants' posterior distributions and used to generate simulated responses and RTs for 300 trials per participant. Summary statistics were computed, and we verified that the actual results in each session were within the 95% credible interval of the simulated data. These posterior predictive checks indicated that the models adequately captured behavior.

To examine group differences, we plotted the posterior distributions for each parameter and quantified the degree of between-group overlap. Although this comparison of Bayesian posterior distributions does not constitute a statistical significance test, we refer to the percentage overlap as a q-value and emphasize results with q-value $< .05$ (Lawlor et al., 2020).

To examine changes within the SAD group, we used the procedures described above to generate another model using data from the 37 adults with SAD who completed PRT Session 1 and Session 2. This model was identical to those described above, except parameters were allowed to vary by session rather than group. This allowed us to determine which HDDM parameters, if any, had changed after GCMRT.

Finally, to better understand the practical importance of the HDDM parameters, we regressed the standard PRT measures—response bias, discriminability, and cumulative reward, all averaged across blocks at the participant level—on the model parameters and group.

Psychometrics

To examine internal consistency, the PRT data were split into odd and even trials to generate two estimates of response bias, discriminability, and the HDDM parameters for each participant. Agreement between these estimates was quantified with the Spearman-Brown correlation coefficient (Brown, 1910; Spearman, 1910), computed as

$$SB = \frac{2 \times r}{1 + r}$$

where r is the Pearson correlation coefficient for the odd versus even data. To examine retest reliability, Pearson correlation coefficients comparing Session 1 versus 2 were calculated for response bias, discriminability, and HDDM parameters for participants who completed both PRT sessions (13 HC, 37 SAD). These analyses were computed across groups to maximize power, but also in controls alone given that the SAD group was exposed to an intervention.

Because GCMRT is designed to drive changes in gaze within and across sessions, an analysis of internal consistency or retest reliability would not be appropriate. However, prior studies (Lazarov et al., 2016, 2021) found that when participants freely gaze at the matrices used in GCMRT, but without music playing, the percentage of time spent dwelling on threatening versus neutral faces is higher in adults with SAD than in controls and this metric shows excellent internal consistency. Indeed, Lazarov et al. (2021) reported a Cronbach's alpha of .99 for this measure in adults with SAD and a sample of community controls, with a two-week retest reliability of $r(20) = .92$ in the control group; retest reliability was not assessed in the SAD group. These findings replicated earlier results obtained in adults with SAD, students with subclinical social anxiety, and students with minimal anxiety (Lazarov et al., 2016). In short, the gaze measures used here have strong psychometric properties.

Transparency and Openness

We report how we determined our sample sizes; we describe all date exculsions, all manipulations and measures, and the software used for analyses, and we follow JARS (Appelbaum et al., 2018). The data are available at the Open Science Framework website: https://osf.io/6mnzx, and analysis code is available upon request. The study's design and its analysis were not preregistered but closely follow methods used in prior reports.

Results

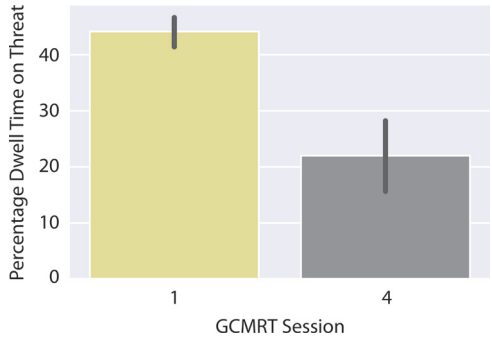
Clinical Assessments

Table 1 shows no group differences in age, gender, or education at Session 1 or 2. Relative to the HC group, at Session 1 the SAD group reported greater social anxiety, depression, overall anhedonia, and social anhedonia, as well as lower life satisfaction. Table 1 also shows a significant reduction in LSAS scores, $t(32) = 2.65$, $p = .01$, $d = .44$, and a nonsignificant reduction in HAMD scores, $t(32) = 1.79$, $p = .08$, $d = .38$, from Session 1 to 2 in the SAD group. From Session 1 to 2, adults with SAD also showed increased QLESQ scores (i.e., improved life satisfaction) and decreased SHAPS and RSAS scores (i.e., reduced anhedonia and social anhedonia). These changes were not statistically significant, $ts < 1.58$, $ps > .12$, but power was limited because only a subset of participants completed these measures.

GCMRT

As shown in Figure 2, the percentage of dwell time on threatening faces decreased from the first to the fourth GCMRT session

Figure 2
Dwell Time on Threatening Faces From First to Last GCMRT Session



Note. Error bars show S.E.M. GCMRT = gaze-contingent music reward therapy. See the online article for the color version of this figure.

(Session effect: $B = -16.62$, 95% CI [−22.40, −10.84], $SE = 2.95$, $t = -5.64$, $p < .001$). Control analyses confirmed that these results held when the number of trials analyzed was equated across sessions (i.e., first five trials from first GCMRT session vs. last five trials from fourth GCMRT session; Figure S2 in the online supplemental materials).

PRT

Discriminability, Response Bias, and Cumulative Reward

Figure 1B reveals group differences in the PRT data. Discriminability was greater in the SAD versus HC group in both sessions, and adults with SAD earned more rewards than controls in Session 2. By contrast, response bias—the tendency to respond "rich" more than "lean"—was higher in controls versus adults with SAD in Session 2.

These impressions were supported by the statistical analysis. For all three dependent variables, adding Group × Block interactions did not improve on the "main effects only" models in either session, $ps > .09$. Consequently, findings from the main effects models are presented; see Table 2 for detailed results. For discriminability, the group effect was reliable in Sessions 1 and 2 as discriminability was higher in adults with SAD. For response bias, the Session 1 data did not reveal a group effect, but response bias magnitude was greater in Block 3 versus Block 1. In Session 2, only the group effect was significant due to a weaker response bias (across all blocks) in adults with SAD. Analysis of cumulative reward in Session 1 did not reveal a group effect but reward totals were higher in Blocks 2 and 3 versus Block 1. In Session 2, reward totals were again higher in Blocks 2 and 3 versus Block 1, but here the group effect was also significant: adults with SAD received more rewards than the controls did. Paired t-tests conducted within the SAD group showed that the increase in cumulative reward from Session 1 to 2 was not significant, $t < 1$, $d = .11$, but the improvement in discriminability was, $t(36) = 3.34$, $p = .002$, $d = .40$.

Trial-Level Accuracy Analysis

Analysis of trial-level accuracy data provided two additional insights. First, Figure 3 shows that when participants responded quickly ("fast RTs", < .3 quantile), they were substantially more accurate on rich versus lean trials, but this effect was smaller for

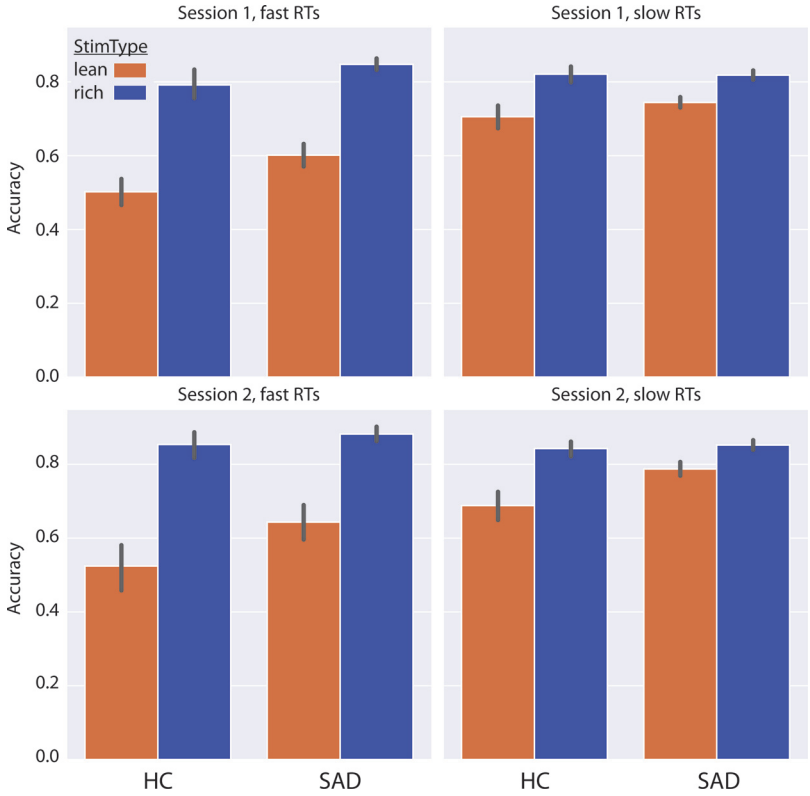
Table 2
Results of Regression Analyses on Discriminability, Response Bias, and Cumulative Reward

Variable	*B* [95% CI]	*SE*	β	*t*-value	*p*-value
		Discriminability: Session 1			
Block 2	−0.01 [−0.08, 0.06]	0.04	−0.03	−0.22	.822
Block 3	0.01 [−0.06, 0.09]	0.04	0.06	0.40	.686
Group (SAD)	0.10 [0.03, 0.18]	0.04	0.40	2.62	.009
		Discriminability: Session 2			
Block 2	0.04 [−0.07, 0.14]	0.05	0.13	0.70	.483
Block 3	−0.01 [−0.11, 0.09]	0.05	−0.03	−0.14	.888
Group (SAD)	0.14 [0.05, 0.23]	0.05	0.52	3.02	.003
		Response bias: Session 1			
Block 2	0.02 [−0.05, 0.10]	0.04	0.10	0.69	.491
Block 3	0.08 [0.01, 0.15]	0.04	0.31	2.12	.035
Group (SAD)	−0.03 [−0.10, 0.05]	0.04	−0.11	−0.70	.487
		Response bias: Session 2			
Block 2	0.10 [0.00, 0.21]	0.05	0.37	1.96	.052
Block 3	0.03 [−0.07, 0.14]	0.05	0.11	0.59	.557
Group (SAD)	−0.11 [−0.20, −0.01]	0.05	−0.38	−2.20	.029
		Cumulative reward: Session 1			
Block 2	1.71 [1.06, 2.37]	0.33	0.71	5.13	<.001
Block 3	2.01 [1.35, 2.67]	0.33	0.83	6.02	<.001
Group (SAD)	0.21 [−0.48, 0.90]	0.35	0.09	0.61	.542
		Cumulative reward: Session 2			
Block 2	1.91 [1.29, 2.52]	0.31	1.06	6.11	<.001
Block 3	1.23 [0.61, 1.84]	0.31	0.68	3.93	<.001
Group (SAD)	0.72 [0.16, 1.28]	0.28	0.40	2.55	.012

Note. SAD = adults with Social Anxiety Disorder.

Figure 3

Accuracy by Group, Stimulus Type, Response Time, and PRT Session



Note. Error bars show S.E.M. PRT = probabilistic reward task; HC = healthy controls; SAD = adults with Social Anxiety Disorder. See the online article for the color version of this figure.

slower responses ("slow RTs", > .7 quantile). Second, Figure 3 shows that accuracy was generally higher in the SAD group.

These interpretations were supported by the linear models, which returned two main findings; see Table 3 for detailed results. First, in both sessions there were Stimulus Type × Response Type interactions. Follow-up comparisons revealed that lean accuracy was substantially lower for fast versus slow RTs (Session 1: $Z = -12.75$, $p < .001$; Session 2: $Z = -10.34$, $p < .001$), while rich accuracy

Table 3

Results of Regression Analysis Conducted on Trial-Level Accuracy Data

Variable	*B* [95% CI]	*SE*	*z*-value	*p*-value
	Session 1			
Stimulus type (rich)	1.34 [1.11, 1.57]	0.12	11.37	<.001
Response type (slow)	0.80 [0.61, 1.00]	0.10	8.12	<.001
Group (SAD)	0.40 [0.11, 0.70]	0.15	2.68	.007
Stimulus Type × Response Type	−0.67 [−0.95, −0.38]	0.14	−4.62	<.001
Group × Stimulus Type	0.01 [−0.26, 0.26]	0.13	0.02	.987
Group × Response Type	−0.19 [−0.41, 0.02]	0.11	−1.75	.080
Group × Stimulus Type × Response Type	−0.22 [−0.54, 0.09]	0.16	−1.38	.168
	Session 2			
Stimulus type (rich)	1.70 [1.43. 1.97]	0.14	12.45	<.001
Response type (slow)	0.73 [0.51, 0.95]	0.11	6.61	<.001
Group (SAD)	0.61 [0.25, 0.97]	0.18	3.35	<.001
Stimulus Type × Response Type	−0.77 [−1.09, −0.45]	0.16	−4.68	<.001
Group × Stimulus Type	−0.23 [−0.55, 0.10]	0.16	−1.37	.170
Group × Response Type	−0.09 [−0.35, 0.17]	0.13	−0.66	.510
Group × Stimulus Type × Response Type	−0.26 [−0.64, 0.13]	0.20	−1.30	.194

Note. SAD = adults with Social Anxiety Disorder. The use of a logit link function in the generalized linear models used to analyze these data complicates the calculation of standardized betas. However, the unstandardized coefficients correspond to log-odds ratios that can serve as measures of effect size.

for fast versus slow RTs was more similar (Session 1: $Z = 1.09$, $p = .69$; Session 2: $Z = 2.61$, $p = .045$). Moreover, although the rich > lean accuracy effect was always robust, it was larger for trials marked by fast RTs (Session 1: $Z = 20.20$; Session 2: $Z = 19.29$) versus slow RTs (Session 1: $Z = 12.20$; Session 2: $Z = 12.51$). Second, the group effect was significant in both sessions due to higher accuracy in the SAD group.

Correlations

In Session 1, cumulative reward was predicted by discriminability, $r(89) = .52$, $p < .001$, but not by response bias, $r(89) = .11$, $p = .28$, and these correlations differed significantly, $Z = 3.06$, $p = .002$. The same pattern held in Session 2: cumulative reward was predicted by discriminability, $r(51) = .51$, $p < .001$, but not by response bias, $r(51) = -.06$, $p = .66$, and these two correlations were again significantly different $Z = 2.75$, $p = .006$. As noted above, a linear model confirmed that Session 2 cumulative reward totals were higher in the SAD group. To determine if this result reflected the group difference in discriminability, we computed a second model where Session 2 cumulative reward was predicted by Group and Discriminability. The second model improved on the first, $F(1) = 13.74$, $p < .001$, and while Discriminability predicted cumulative reward ($B = 5.44$ [2.49, 8.38], $SE = 1.47$, $\beta = .45$, $t = 3.71$, $p < .001$), Group was no longer a significant predictor ($B = 1.40$ [−.12, 2.93], $SE = .76$, $\beta = .49$, $t = 1.84$, $p = .071$). Thus, the group difference in Session 2 reward totals was driven by better discriminability in SAD.

Finally, larger decreases in the percentage of time spent dwelling on threatening faces from the first to last GCMRT session predicted larger increases in discriminability from PRT Session 1 to Session 2, $r(26) = -.40$, $p = .03$, but they did not predict changes in response bias, $r(26) = .06$, $p = .75$. These correlations, however, did not differ significantly, $Z = 1.65$, $p = .10$.

HDDM

Figure 4 displays posterior distributions of HDDM parameters. The first row shows that a modest group difference (SAD > HC) in Session 1 drift rate (q-value = .17) grew larger in Session 2 (q-value = .04), and the drift rate increased substantially in the SAD group from Session 1 to Session 2 (q-value = .006). The second row shows that the starting point of the evidence accumulation process was biased toward the "rich" boundary (coded 1) in both groups and sessions, as expected given the asymmetric reinforcement rates. Group differences were not pronounced, however, with no q-values < .05. The third row shows that decision thresholds in the SAD group were larger than in the HC group at Session 1 but declined from Session 1 to 2. Finally, the fourth row shows that nondecision times were longer in the SAD group at both sessions and increased from Session 1 to 2, although no q-value was below .05.

Figure S1 in the online supplemental materials shows that, as in our prior study (Lawlor et al., 2020), the zero-order correlation between drift rate and discriminability was remarkably strong in Session 1, $r(89) = .92$, and Session 2, $r(51) = .90$, $ps < .001$. Accordingly, of the four model parameters, drift rate most strongly predicted discriminability in Session 1 and 2; see Table 4 for detailed results. Threshold also positively predicted discriminability in Sessions 1 and 2, and starting point bias was a reliable, positive predictor in Session 2 (see Table 4). With the HDDM parameters in the model, group did not predict discriminability in either session. Table 4 shows that the one reliable predictor of response bias was starting point bias in Sessions 1and 2; group did not predict response bias in these models. Finally, Table 4 also shows that cumulative reward in Session 1 was predicted by drift rate, whereas cumulative reward in Session 2 was predicted by drift rate, nondecision time and group.

Psychometrics

When data from both groups were considered, retest reliability was acceptable for drift rate ($r = .78$), decision threshold ($r = .73$), and discriminability ($r = .70$). It was lower for starting point bias ($r = .55$), response bias ($r = .53$), and nondecision time ($r = .52$). When only controls were considered, retest reliability was acceptable for drift rate ($r = .84$), decision threshold ($r = .79$), and response bias ($r = .77$), but lower for discriminability ($r = .54$), starting point bias ($r = .63$), and nondecision time ($r = .51$). Finally, Figure 5 shows excellent internal consistency for discriminability, response bias, and all HDDM parameters from Session 1. Session 2 results were similar, with SB coefficients between .90 (response bias) and .94 (drift rate).

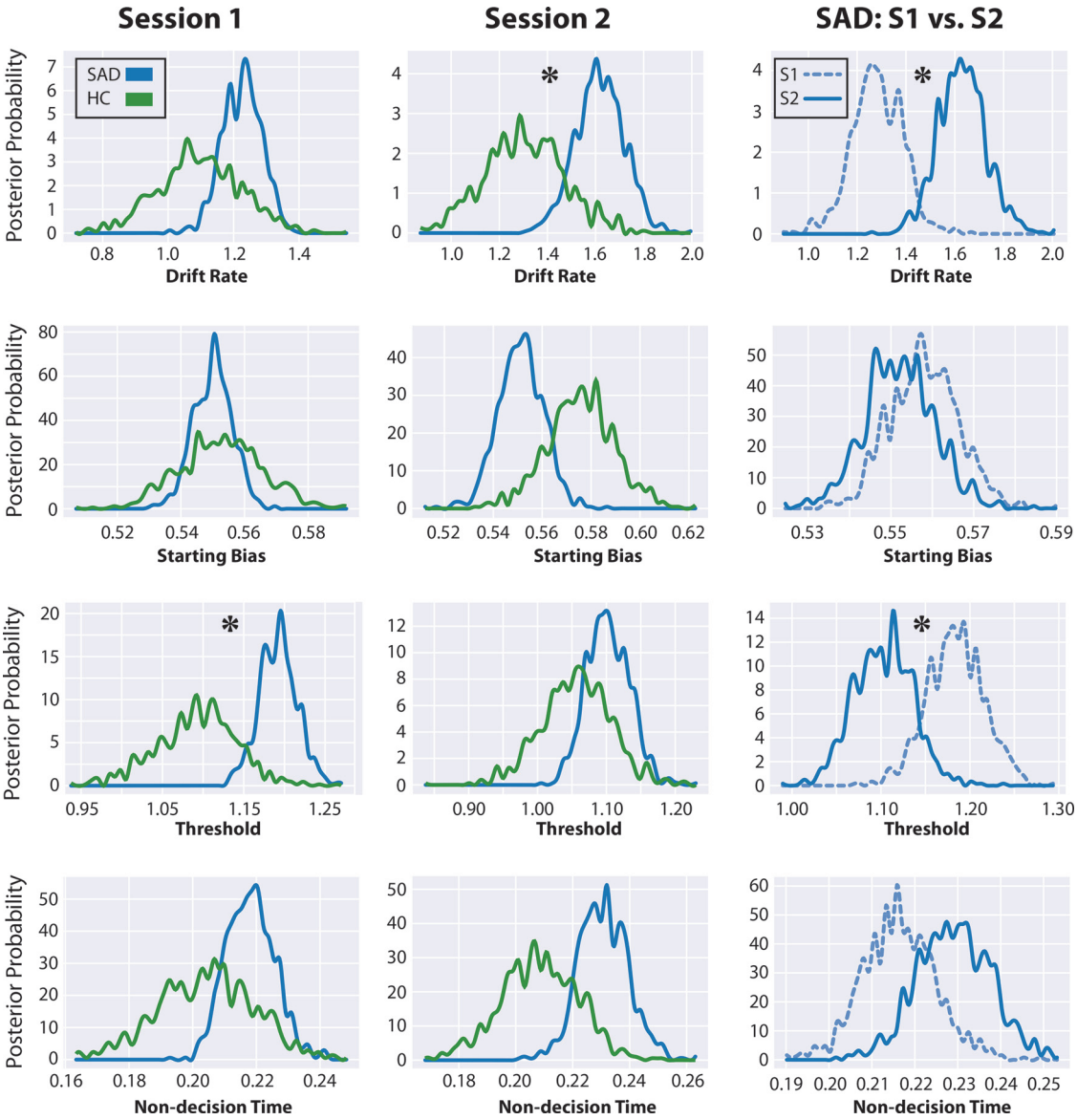
Discussion

In this analysis, we tested two sets of predictions regarding the impact of social anxiety disorder on reward responses versus perceptual decision making. The first set of predictions—that SAD would be associated with a blunted response bias that would increase after GCMRT—was not supported. There was no group difference in response bias in Session 1, and although the HDDM confirmed that the PRT induced a starting point bias toward the "rich" boundary, this model parameter did not differ strongly between groups and did not change in the SAD group from Session 1 to 2. The response to social rewards thus appears to have been intact in adults with SAD. This was somewhat surprising given that the SAD group generated elevated scores on a measure of social anhedonia, the RSAS (Eckblad et al., 1982), and that anhedonia is often associated with a weak response bias in the PRT (e.g., Pizzagalli et al., 2008; Vrieze et al., 2013). Prior research, however, indicates that while socially anxious individuals often endorse items that suggest social anhedonia (e.g., the RSAS item "I prefer watching TV to going out with other people"), they typically do so out of fear of rejection rather than lack of interest (Brown et al., 2007). In other words, reduced social engagement in adults with SAD is likely to be predominantly driven by avoidance, not loss of approach motivation. We speculate that, in the current study, the use of videotaped social feedback in the PRT did not trigger avoidance responses in the SAD group and thus their intact reward responses were able to emerge, unimpeded.

By contrast, the second set of predictions was supported. Relative to controls, the SAD group showed higher discriminability in Session 1, and in the SAD group discriminability was significantly higher after GCMRT (in Session 2) than it was before (in Session 1). A similar pattern emerged for drift rate: a modest group difference (SAD > HC) in Session 1 was enlarged in Session 2, and within the SAD group drift rate increased from the first to the second session. These findings help explain a result that might initially seem to support the first set of predictions—namely, the presence of a group difference (HC > SAD) in Session 2 response

Figure 4

Posterior Distributions of HDDM Parameters



Note. Asterisks mark less than 5% between-group overlap of the posterior distributions. HDDM = hierarchical drift diffusion model; HC = healthy controls; SAD = adults with Social Anxiety Disorder. See the online article for the color version of this figure.

bias. Analysis of trial-level accuracy data revealed that this finding was not due to reduced reward sensitivity in SAD, as might be expected. Instead, it emerged because the SAD group was highly accurate on both rich and lean trials, whereas in controls the stimulus effect on accuracy (rich > lean) was more pronounced. Because rewards are delivered for accurate rich and lean responses in the PRT, albeit at different rates, higher overall accuracy allowed the SAD group to earn more rewards than controls did in Session 2. Corroborating these findings, regression analyses further showed that the group difference in cumulative reward totals was explained, at least in part, by higher discriminability and faster drift rates in SAD. Overall, these findings indicate that evidence accumulation during the PRT was fast in socially anxious adults, especially after GCMRT, and this supported high discriminability which led them to earn more rewards than the controls did.

Attention and Perception in Social Anxiety

The current findings stand in contrast to prior reports of slow evidence accumulation in psychopathology (Lawlor et al., 2020; Sripada & Weigard, 2021), but they can be interpreted in light of extensive prior work on the cognitive impact of anxiety. A prominent hypothesis, Attentional Control Theory (Eysenck et al., 2007), proposes that anxiety is associated with working memory deficits: if working memory is overloaded, or if an anxious individual is confronted with internal or external distractors, their ability to direct

Table 4
Results of Regressing Behavior in the PRT Onto HDDM Parameters and Group

Variable	*B* [95% CI]	*SE*	β	*t*-value	*p*-value
		Discriminability: Session 1			
Drift rate (*v*)	0.46 [0.43, 0.48]	0.01	0.99	35.12	<.001
Starting point bias (*z*)	0.19 [−0.03, 0.41]	0.11	0.04	1.70	.092
Threshold (*a*)	0.37 [0.31, 0.43]	0.03	0.32	12.25	<.001
Nondecision time (*t*)	0.15 [−0.04, 0.33]	0.09	0.04	1.58	.118
Group (SAD)	0.00 [−0.02, 0.03]	0.32	0.02	0.32	.751
		Discriminability: Session 2			
Drift rate (*v*)	0.39 [0.36, 0.43]	0.02	0.98	24.25	<.001
Starting point bias (*z*)	0.51 [0.20, 0.82]	0.15	0.12	3.31	.002
Threshold (*a*)	0.44 [0.35, 0.54]	0.05	0.33	9.17	<.001
Nondecision time (*t*)	0.34 [−0.02, 0.70]	0.18	0.08	1.90	.064
Group (SAD)	0.01 [−0.03, 0.04]	0.02	0.03	0.38	.707
		Response Bias: Session 1			
Drift rate (*v*)	0.01 [−0.05, 0.07]	0.03	0.02	0.34	.738
Starting point bias (*z*)	3.19 [2.69, 3.70]	0.25	0.82	12.60	<.001
Threshold (*a*)	−0.09 [−0.22, 0.05]	0.07	−0.09	−1.27	.208
Nondecision time (*t*)	0.10 [−0.32, 0.52]	0.21	0.03	0.47	.639
Group (SAD)	−0.01 [−0.08, 0.05]	0.03	−0.06	−0.37	.714
		Response Bias: Session 2			
Drift rate (*v*)	−0.04 [−0.12, 0.04]	0.04	−0.11	−1.06	.294
Starting point bias (*z*)	2.95 [2.19, 3.72]	0.38	0.73	7.79	<.001
Threshold (*a*)	0.03 [−0.21, 0.27]	0.12	0.02	0.24	.814
Nondecision time (*t*)	−0.39 [−1.27, 0.49]	0.44	−0.09	−0.89	.380
Group (SAD)	−0.02 [−0.10, 0.07]	0.04	−0.07	−0.35	.728
		Cumulative Reward: Session 1			
Drift rate (*v*)	3.95 [2.35, 5.56]	0.81	0.51	4.89	<.001
Starting point bias (*z*)	13.38 [−0.38, 27.14]	6.92	0.18	1.93	.057
Threshold (*a*)	3.14 [−0.57, 6.85]	1.87	0.16	1.68	.096
Nondecision time (*t*)	6.31 [−5.22, 17.84]	5.80	0.11	1.09	.279
Group (SAD)	−0.27 [−2.02, 1.49]	0.88	−0.07	−0.30	.764
		Cumulative Reward: Session 2			
Drift rate (*v*)	1.43 [0.08, 2.78]	0.67	0.29	2.13	.039
Starting point bias (*z*)	8.86 [−3.97, 21.70]	6.38	0.17	1.39	.171
Threshold (*a*)	−1.04 [−5.06, 2.99]	2.00	−0.06	−0.52	.607
Nondecision time (*t*)	20.32 [5.49, 35.16]	7.37	0.38	2.76	.008
Group (SAD)	1.66 [0.16, 3.16]	0.75	0.59	2.22	.031

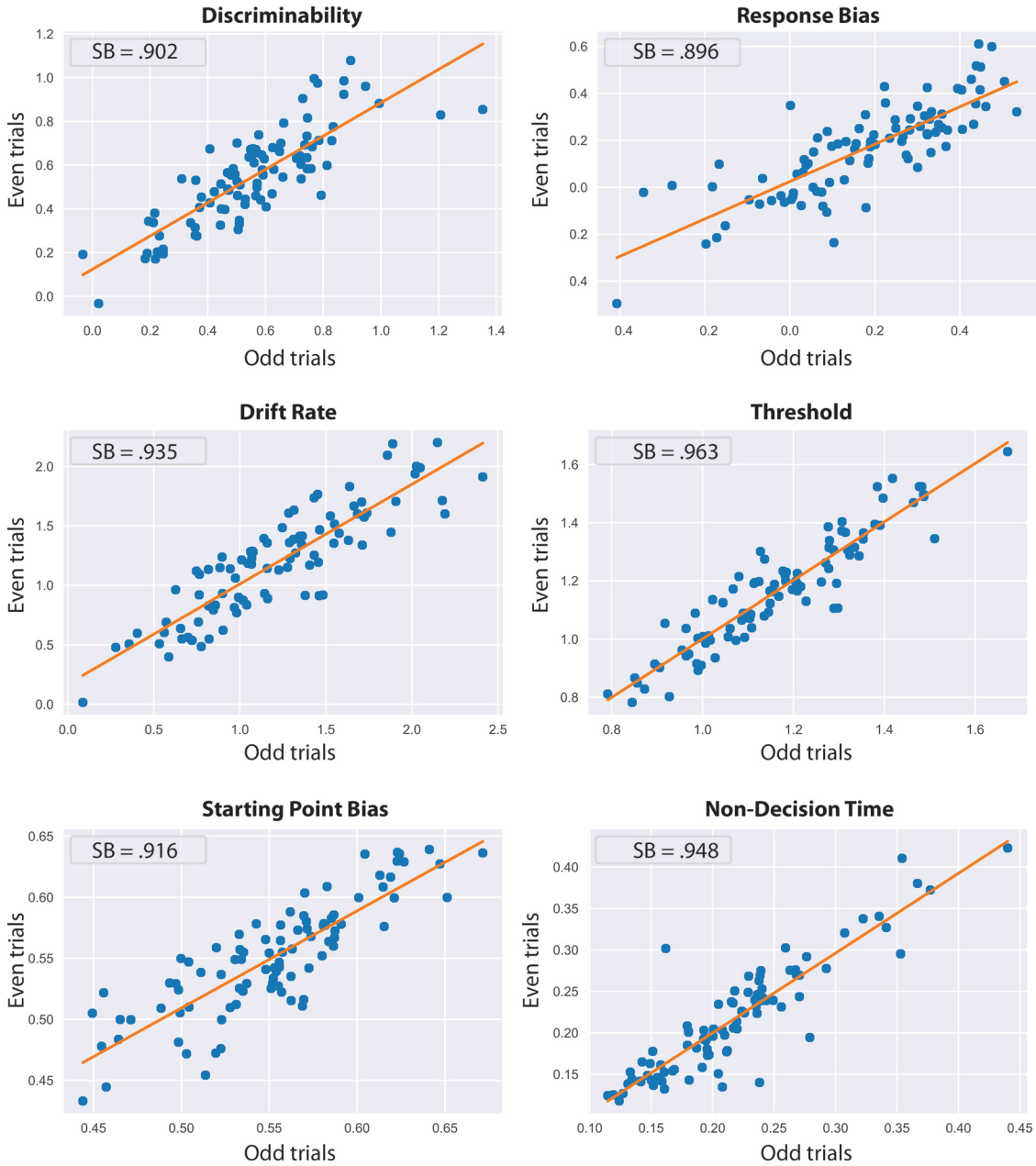
Note. SAD = adults with Social Anxiety Disorder; PRT = probabilstic reward task; HDDM = hierarchical drift diffusion model.

their attention in order to achieve goals suffers and attention is liable to be hijacked by task-irrelevant stimuli. This conceptualization has been supported by several behavioral studies. For example: Berggren et al. (2015) found that trait anxiety positively predicted detection of an extraneous stimulus presented in a visual search task; Gerdes et al. (2008) found that, relative to controls, persons with spider phobia were more easily distracted by task-irrelevant pictures of spiders but also mushrooms, flowers, and empty circles; and Wieser et al. (2009) reported that, relative to adults with minimal social anxiety, those with high social anxiety made more erroneous eye movements toward happy, sad, angry, fearful, and neutral faces in an antisaccade task. All these results are consistent with the hypothesis that, in anxious individuals, "top-down" (proactive) control of visual attention is decreased, whereas "bottom-up" (reactive) control of attention is increased, likely because of deficits in inhibitory functions associated with working memory (Eysenck et al., 2007; see also Sylvester et al., 2012).

Excessive reliance on bottom-up attention, and under use of top-down attentional control, is clearly a problem in tasks that include distractors or that require judicious use of working memory. It is important to recognize, however, that the PRT places virtually no load on working memory and does not include any distractors. The visual display is spartan, but the participant must quickly judge whether a briefly presented (100 ms) line is short (11.5 mm) or long (13.0 mm), where the difference between those two categories is quite modest (1.5 mm). In this tightly constrained but perceptually demanding context, a relative weakness in working memory is a minor problem. By contrast, an increase in "bottom-up", stimulus-driven attention—that is, hypervigilance—may be an asset. Meta-analyses of visual attention (Richards et al., 2014) and eye-tracking (Armstrong & Olatunji, 2012) indicate that hypervigilance characterizes adults with a wide range of anxiety disorders, including SAD. The current data are thus compatible with the argument that hypervigilance—repeatedly scanning the environment to quickly detect incoming stimuli—allows anxious adults to perform well on the PRT. This result also supports the broader point that it is difficult to make unequivocal value judgments about particular behavioral phenotypes, because value often

Figure 5

Internal Consistency of Discriminability, Response Bias, and HDDM Parameters in Session 1



Note. HDDM = hierarchical drift diffusion model. See the online article for the color version of this figure.

depends heavily on context (Holmes & Patrick, 2018; see also Chittka et al., 2009). In other words, although hypervigilance causes stress and can lead to poor performance on tasks that place demands on working memory, the current study highlights its utility in the context of the PRT.

ERP studies point to enhancement of early visual responses as a probable source of the perceptual advantage in SAD. For instance, Kolassa and colleagues collected ERPs as socially anxious adults viewed angry, happy, and sad faces (Kolassa et al., 2009) or flowers that morphed into spiders and vice versa (Kolassa et al., 2007; adults with spider phobia were also tested in this study). Over the wide range of stimuli used, a main effect of Group (but no Group × Stimulus interaction) emerged: the amplitude of the P100 component, which reflects early activity in extrastriate cortex (Clark et al., 1994), was larger in response to all stimulus types in adults with SAD versus healthy controls. Similarly, an ERP study in spider phobia presented spiders, butterflies, and flowers in a visual search task and found a main effect of group but no interaction: the C1, which is the earliest visual evoked component, was larger in response to all stimuli in phobics relative to controls (Weymar et al., 2014). This work

indicates that, in anxious adults, the visual system responds quickly and especially vigorously to new stimuli. Moreover, although it is assumed that hypervigilance occurs because anxious adults are scanning the environment to detect potential threats (Bar-Haim et al., 2007; Bögels & Mansell, 2004), the fact that early cortical potentials are larger in response to all kinds of stimuli—not just threatening ones—indicates that, as in the present study, neither the stimuli nor the task itself needs to be emotional for anxious adults to show a perceptual advantage (Berggren et al., 2015).

Training Improves Performance in SAD by Enhancing Evidence Accumulation

PRT performance in the SAD group improved significantly after GCMRT was administered. Interpretation of this result is necessarily somewhat speculative, but the data are consistent with a training effect that transferred from GCMRT to the PRT. Although the specific underlying mechanisms that are trained by GCMRT and that could lead to improvements on the PRT are underspecified, two candidates stand out. The first is a direct improvement in perception. Threatening and neutral faces are visually similar, and GCMRT rewards participants for rapidly distinguishing between them. As a result, GCMRT may enhance perception. If so, then the improved PRT performance seen in SAD is easily explained: after GCMRT, adults with SAD are better able to distinguish the short lines from the long lines. There is some support for this idea, as repeated training with one set of stimuli can enhance early cortical responses to new stimuli (Casco et al., 2004; Ding et al., 2003; Zhang et al., 2015), and training on one perceptual task can facilitate learning of related tasks (Kattner et al., 2017). However, the field of perceptual learning emphasizes that training-related improvements in perception are often stimulus-specific (Fahle, 2005; Seitz & Watanabe, 2005). Given the many differences between the faces presented in GCMRT and the simple lines used in the PRT, a direct improvement in perception that transferred across these tasks seems somewhat unlikely.

The second candidate is attentional control. As noted earlier, adults with SAD are characterized by hypervigilance, which supports the detection of rapidly presented stimuli. But hypervigilance is, by definition, undirected: it involves attending to the entire visual field, either by maintaining a wide focus or by repeatedly scanning as much of the field as possible (Richards et al., 2014). By contrast, GCMRT trains participants to repeatedly and purposefully shift their attention away from threatening and toward neutral faces. This can be conceptualized as a form of attentional control, and it is possible that enhanced control led to improved PRT performance. Specifically, improved PRT performance after GCMRT would not reflect enhanced perception per se, but would instead be due to anxious adults being better able to control their focus of attention. This possibility is supported by several studies (e.g., Bherer et al., 2005; Ducrocq et al., 2016; Sari et al., 2016) showing that training attentional control can lead to generalizable benefits on tasks that differ in many respects from the training regimen, which need not involve a task at all (for instance, when meditation is used to train attention: Slagter et al., 2007, 2011). In other words, attentional training has been shown to support the sort of "far transfer" that was observed here.

It thus seems more likely that improved PRT performance after GCMRT in the SAD group reflects improved attentional control rather than better perception. This conclusion is also supported by the HDDM results. The DDM's nondecision parameter captures the time needed to perceive the stimulus before evidence accumulation begins, plus the time needed to execute a response once a boundary has been crossed. If the group difference in discriminability depended on a basic perceptual advantage in SAD, then the SAD group would be expected to show shorter nondecision times than controls. Moreover, nondecision times should grow shorter after GCMRT, assuming the time needed to execute a motor response remained constant. Nondecision times, however, were longer in the SAD group and grew longer still after GCMRT, the opposite of what would be expected if low-level perceptual mechanisms drove the results. By contrast, the speed of evidence accumulation is sensitive to attention (Nunez et al., 2017), and so a group difference (SAD $>$ controls) in bottom-up attention, together with improved attentional control in the SAD group after GCMRT, can explain the pattern of findings observed for drift rate. This argument may seem inconsistent with the ERP results mentioned earlier, as those reveal an effect of social anxiety on early visual potentials. It is important to note, however, that the P100 (Woldorff et al., 1997) and even the C1 (Kelly et al., 2008) are sensitive to attention, and thus the presence of a group difference in these ERPs may reflect an effect of anxiety on attention rather than low-level perception.

Importantly, however, these two candidate mechanisms are not mutually exclusive and they cannot be disambiguated using the current dataset. Determining how GCMRT affects perception and attentional control thus remains a goal for future work; future studies might consider collecting eye-tracking data while the PRT is performed, to shed light on these issues. Finally, we cannot rule out the possibility that the improvements also reflect, at least in part, greater facility with computer tasks in general rather than enhancements of attention or perception per se. To address this issue, future studies could include a second training condition that requires regular computer use but that does not target visual attention or perception, to test the hypothesis that this would not lead to the performance benefits observed here after GCMRT.

The Nature of Response Bias in the PRT

Although the study did not find evidence of reward insensitivity in SAD, the PRT elicited strong response biases, as it has in many prior studies. This was evident in the traditional PRT analysis but also in the HDDM results, which indicated that the starting point of the evidence accumulation process was shifted toward the "rich" boundary. This replicates our prior findings (Lawlor et al., 2020) and is the expected pattern when asymmetric reinforcement is delivered: the accumulator starts closer to the disproportionately rewarded option, so that only a small amount of evidence need be accumulated for that option to be selected (White & Poldrack, 2014).

This implies that participants prepare to press the "rich" button before trial onset, and examination of trial-level accuracy data supports this interpretation. Specifically, the rich $>$ lean accuracy difference was again larger for trials characterized by fast versus slow RTs (Lawlor et al., 2020). This pattern would emerge if, on many trials, the participant was poised to press the "rich" button before a stimulus appears. When the rich stimulus is actually presented, these rapid responses will be accurate—but when the lean

stimulus is shown, they will be inaccurate. Consequently, the rich > lean accuracy difference is large for trials marked by fast RTs. By contrast, when participants respond more slowly they presumably process the stimuli more fully, responses to the lean stimulus tend to be increasingly accurate, and the size of the rich > lean accuracy effect decreases.

These findings replicate our prior work and confirm that response bias in the PRT is mainly carried by fast RTs. This result can be contextualized with reference to prior work by White and Poldrack (2014), who distinguished between "response bias" and "stimulus bias." A response bias reflects a difference in response preparation that typically emerges when one response is required more frequently or rewarded more often than another. By contrast, a stimulus bias emerges when participants use a relatively lax or conservative decision criterion during stimulus processing (for example, told that most of the stimuli in an "old/new" recognition memory test will be new lures, a participant might adopt a conservative criterion such that only strong memory signals, extracted from the stimuli, will be counted as evidence for an "old" response). Critically, White and Poldrack (2014) used perceptual and memory tasks, as well as simulations, to show that response biases disproportionately affect fast versus slow responses, whereas stimulus biases affect both fast and slow responses. The presence of a substantially larger rich > lean accuracy difference for fast versus slow RTs in the current study, and in Lawlor et al. (2020), thus indicates that the PRT typically elicits a response bias, not a stimulus bias. This is important because it provides insight into how the PRT affects behavior, and also because it has implications for the analysis of PRT data. Specifically, electrophysiological or neuroimaging studies that use the PRT and that are interested in the neural correlates of response bias should focus their analyses on activity immediately *preceding* trial onset, as this is presumably when the brain systems that support response bias are active.

Psychometrics

An appealing aspect of the DDM is the potential for drift rate to serve as a reliable and temporally stable marker of individual differences in the quality and speed of information extraction. There is support for this proposal. For instance, Yap and colleagues (2012) used the DDM to analyze lexical decision data from over 800 students tested twice with a week between sessions, and their analysis indicate that within-session reliability (i.e., internal consistency) was high and retest reliability was good (rs > .80) for drift rates. Lerche and Voss (2017) obtained similar results in two experiments, each involving over 100 healthy participants completing three different paradigms twice within a week; they reported adequate retest reliability (rs > .70) for drift rate and threshold. Finally, Schubert and colleagues (2016) administered three tasks to 114 participants in two sessions separated by 8 months, finding that individual differences in drift rate were consistent across tasks and temporally stable. The current study cannot speak to across-task stability, but the internal consistency of the HDDM parameters, and of the traditional PRT measures, was excellent. Retest reliability was adequate, but the reliability analyses are limited by the fact that the control group was small. Because stable individual differences in information processing that cut across tasks are of great interest to clinicians and clinical researchers, it would be useful to conduct additional work examining the across-task consistency and temporal stability of diffusion model parameters in adults with psychopathology.

Limitations

This study has limitations. First, GCMRT was not compared to a control condition. It would be useful to include such a condition in a future PRT study because, as mentioned earlier, the post-GCMRT improvements in the PRT could reflect, at least in part, a practice effect as participants become increasingly used to performing computer tasks. Moreover, the current results make the prediction that that interventions which reduce SAD symptoms through nonattentional mechanisms should not lead to the pattern of results observed in the current study; it would be interesting to test this hypothesis in future work. Second, only a subset of participants completed certain self-report measures (SHAPS, RSAS, QLESQ), resulting in low power for analysis of those measures. Similarly, although the sample of SAD participants with usable Session 1 PRT data was large, many participants did not initiate GCMRT and so did not complete Session 2; moreover, only some participants had usable gaze data. The pattern of results was clear and interpretable despite the varying number of participants in different analyses, and some degree of attrition is unavoidable for a multisession study in participants with psychopathology. Nonetheless, follow-up work with larger samples across all measures would enhance power and the precision of estimated effects. Third, some participants in the SAD group were on stable medications or had comorbid conditions. We reran all analyses after excluding these participants. Encouragingly, the group differences in discriminability, cumulative reward totals, and drift rate remained significant when these participants were removed. However, the decrease in LSAS scores from Session 1 to 2 was reduced to a statistical trend (p = .08), albeit with a similar effect size (d = .43), and the negative correlation between changes in discriminability and changes in dwell time on threatening faces from Session 1 to 2 became nonsignificant (r = −.26, p = .26). We attribute these two changes to loss of power, which underscores the need for a larger follow-up study. Finally, the lack of detailed information on the cultural/geographic background of the participants is a limitation of the dataset.

Conclusion

This study revealed faster evidence accumulation in adults with SAD versus healthy controls, especially after GCMRT. The findings suggest that although slow evidence accumulation may characterize several disorders it is not characteristic of social anxiety, at least in the context of the social PRT. Future work linking model parameters to neurophysiological measures and examining the consistency of model parameters across a battery of tasks could provide additional insight into the pathophysiology of SAD. In the meantime, this study replicates prior work by showing that—by training attentional control and weakening threat bias—GCMRT can reduce symptoms in socially anxious adults. The study extends that work by demonstrating that excellent bottom-up attention in SAD can support performance of a perceptually demanding task, with GCMRT leading to additional improvements by enhancing evidence accumulation.

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